

Faculdade de Engenharia da Universidade do Porto

TSO–DSO Coordination: Distributed Frameworks for Harnessing DER Flexibility in Power System Operational Planning

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Doctoral Program in Sustainable Energy Systems

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Abstract

Electric power systems are undergoing a profound transformation driven by the large-scale integration of Renewable Energy Sources (RES) and Distributed Energy Resources (DER). Increasing shares of generation are now connected at the Distribution Network (DN) level, accompanied by the widespread deployment of Energy Storage Systems (ESS), Electric Vehicles (EV), and flexible demand. While these developments introduce significant new sources of flexibility, they also challenge traditional operating paradigms that rely on limited interaction between Transmission System Operators (TSOs) and Distribution System Operators (DSOs). Fully exploiting distribution-level flexibility therefore requires a fundamental rethinking of how TSO and participating DSOs interact, together with the establishment of effective coordination mechanisms.

This thesis proposes a set of tools for the coordinated operation and planning of transmission and distribution systems. Central to the proposed approach is a distributed TSO–DSO coordination framework that enables the joint exploitation of DER-based flexibility while respecting institutional separation, data privacy, and regulatory requirements. A key novelty is the introduction of shared resources installed at transmission-distribution interface nodes, whose operation can be coordinated between TSO and participating DSOs to improve coordination efficiency and overall system performance. To operationalize this framework, the thesis develops a suite of optimization-based tools spanning multiple time scales, including a TSO–DSO coordinated operational planning tool and a two-level planning framework for the optimal siting and sizing of shared resources. Distributed optimization methods are employed throughout to ensure scalability and preserve data confidentiality among participating agents.

The proposed methodologies are validated through extensive numerical studies on standard IEEE test systems and real-world network data, as well as experimental Hardware-In-the-Loop (HIL) testing for real-time operation. The results demonstrate that coordinated TSO–DSO operation significantly improves system efficiency, enhances renewable energy integration, and mitigates network constraints through the effective utilization of DER flexibility. Overall, this work shows that distributed TSO-DSO coordination constitutes a viable and practical pathway toward the secure, efficient, and sustainable operation of future power systems.

Resumo

Os sistemas elétricos de energia atravessam uma profunda transformação, impulsionada pela integração em larga escala de Fontes de Energia Renovável (FER) e de Recursos Energéticos Distribuídos (RED). Uma parcela crescente da produção encontra-se atualmente ligada ao nível da Rede de Distribuição (RD), acompanhada pela ampla integração de Sistemas de Armazenamento de Energia (SAE), Veículos Elétricos (VE) e carga flexível. Embora estes desenvolvimentos introduzam novas e significativas fontes de flexibilidade, colocam também desafios aos paradigmas operacionais tradicionais, que se baseiam numa interação limitada entre os Operadores da Rede de Transporte (ORT) e os Operadores da Rede de Distribuição (ORD). Assim, a plena exploração da flexibilidade ao nível da distribuição exige uma reformulação profunda da forma como ORT e ORD interagem, bem como o estabelecimento de mecanismos de coordenação eficazes.

Esta tese propõe um conjunto de ferramentas de operação e planeamento coordenados dos sistemas de transporte e de distribuição. No centro da abordagem proposta encontra-se uma estrutura de coordenação distribuída entre ORT e ORD, que permite a exploração conjunta da flexibilidade disponibilizada pelos RED, respeitando simultaneamente a separação institucional, a confidencialidade dos dados e os requisitos regulamentares. Uma inovação central consiste na introdução de *recursos partilhados* instalados nos nós de interface entre as redes de transporte e de distribuição, cuja operação pode ser coordenada entre o ORT e os ORD participantes com o objetivo de melhorar a eficiência da coordenação e o desempenho global do sistema. Para operacionalizar esta estrutura, a tese desenvolve um conjunto de ferramentas baseadas em otimização que abrangem múltiplas escalas temporais, incluindo uma ferramenta de planeamento operacional coordenado ORT-ORD e uma ferramenta de planeamento em dois níveis para o dimensionamento ótimo de recursos partilhados. Ao longo de todo o trabalho são aplicados métodos de otimização distribuída, assegurando simultaneamente a escalabilidade das soluções propostas e a preservação da confidencialidade da informação partilhada entre os agentes participantes.

As metodologias propostas são validadas através de extensos estudos numéricos em sistemas de teste IEEE e com dados de redes reais, bem como através de ensaios experimentais em ambiente “Hardware-in-the-Loop (HIL)” de simulação em tempo real. Os resultados demonstram que a operação coordenada ORT-ORD conduz a melhorias significativas na eficiência do sistema, promove uma maior integração de energias renováveis e mitiga violações de restrições de rede através da utilização eficaz da flexibilidade disponibilizada pelos RED. Em suma, este trabalho demonstra que a coordenação distribuída entre ORT e ORD constitui um caminho viável e prático para a operação segura, eficiente e sustentável dos sistemas elétricos do futuro.

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This thesis is dedicated to the memory of my father.

Thank you, dad. Without you, none of this would have been possible.

*“And those who were seen dancing were thought to be insane
by those who could not hear the music.”*

– Friedrich Nietzsche

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Glossary

AC	Alternating Current
ACER	Agency for the Cooperation of Energy Regulators
ADMM	Alternating Direction Method of Multipliers
ADN	Active Distribution Network
AEMO	Australian Energy Market Operator
aFRR	automatic Frequency Restoration Reserve
AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
ANM	Active Network Management
API	Application Programming Interface
AS	Ancillary Service
ATC	Analytical Target Cascading
AVR	Automatic Voltage Regulator
BEMS	Building Energy Management System
CB	Capacitor Bank
CCO	Chance-Constrained Optimization
CDF	Cumulative Distribution Function
CIM	Common Information Model
CGMES	Common Grid Model Exchange Standard
DC	Direct Current
DER	Distributed Energy Resource
DG	Distributed Generation
DEP	Distribution Expansion Planning

DLR	Dynamic Line Rating
DN	Distribution Network
DNN	Deep Neural Network
DQA	Diagonal Quadratic Approximation
DR	Demand Response
DRO	Distributionally Robust Optimization
DSO	Distribution System Operator
ED	Economic Dispatch
ENTSO-E	European Network of Transmission System Operators for Electricity
ESS	Energy Storage System
EU	European Union
EV	Electric Vehicle
FCR	Frequency Containment Reserve
FFR	Fast Frequency Response
FL	Flexible Load
FM	Foundation Model
FOR	Feasible Operating Region
FPR	Flexible Planning Region
FRR	Frequency Restoration Reserve
FRS	Fast Ramping Service
FSP	Flexibility Service Provider
GDP	Gross Domestic Product
GEP	Generation Expansion Planning
GHG	Greenhouse Gas
GL	Guideline
GMSS	Generalized Master–Slave Splitting
GNN	Graph Neural Network
GPU	Graphics Processing Unit
HGD	Heterogeneous Decomposition
HEMS	Home Energy Management System

HIL	Hardware-In-the-Loop
HVAC	Heating, Ventilation, and Air-Conditioning
ICT	Information and Communication Technologies
ICPF	Interval-Constrained Power Flow
IEA	International Energy Agency
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
i.i.d.	independent and identically distributed
IMO	Independent Market Operator
IPM	Interior Point Method
ISO	Independent System Operator
KDE	Kernel Density Estimation
KKT	Karush-Kuhn-Tucker
LMP	Locational Marginal Price
LR	Lagrangian Relaxation
mFRR	manual Frequency Restoration Reserve
MG	Microgrid
MGO	Microgrid Operator
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Nonlinear Programming
ML	Machine Learning
MPCC	Mathematical Program with Complementary Constraints
MPEC	Mathematical Programming with Equilibrium Constraints
MO	Market Operator
NC	Network Code
NLP	Nonlinear Programming
NN	Neural Network
NP	Nondeterministic Polynomial time
NPV	Net Present Value
OECD	Organisation for Economic Co-operation and Development

OPF	Optimal Power Flow
OLTC	On-Load Tap Changer
PCC	Point of Common Coupling
PF	Power Flow
PMU	Phasor Measurement Unit
PQ	Active–Reactive power
PV	Photovoltaic
P2P	Peer-to-Peer
QC	Quadratic Convex
QCQP	Quadratically Constrained Quadratic Program
QP	Quadratic Programming
R&D	Research and Development
R&D&I	Research, Development, and Innovation
RES	Renewable Energy Source
RL	Reinforcement Learning
RO	Robust Optimization
RR	Replacement Reserve
RTU	Remote Terminal Unit
SC	Sensitivity Coefficient
SCADA	Supervisory Control and Data Acquisition
SCOPF	Security-Constrained Optimal Power Flow
SDP	Semi-Definite Programming
SE	State Estimation
SGU	Significant Grid User
SLP	Sequential Linear Programming
SLR	Surrogate Lagrangian Relaxation
SME	Small and Medium-sized Enterprise
SMOPF	Stochastic Multi-period Optimal Power Flow
SO	System Operator
SoC	State-of-Charge

SOC	Second-Order Cone
SOCP	Second-Order Cone Programming
SoH	State-of-Health
SP	Stochastic Programming
SPC	Smart Power Cell
SQP	Sequential Quadratic Programming
SVC	Static VAr Compensator
TEP	Transmission Expansion Planning
TES	Total Energy Supply
TN	Transmission Network
TSO	Transmission System Operator
UC	Unit Commitment
UK	United Kingdom
USA	United States of America
VPP	Virtual Power Plant
V2G	Vehicle-to-Grid

List of Symbols

Sets

Ω_m	Set of market scenarios
Ω_o	Set of operational scenarios
Ω_c	Set of investment cost scenarios
N	Set of network buses
$N^{\text{PV}} \subseteq N$	Subset of PV buses
$N^I \subseteq N$	Subset of TN-DN interface nodes
G	Set of generators
$G^C \subseteq G$	Subset of conventional generators
$G^R \subseteq G$	Subset of RES generators
L	Set of loads
$L^F \subseteq L$	Subset of flexible loads
B	Set of branches (lines, transformers)
$B^T \subseteq B$	Subset of controllable (OLTC) transformers
E	Set of ESSs
$E^S \subseteq E$	Subset of shared ESSs
C	Set of CBs
P	Set of control stages (real-time OPF)
K	Set of ADMM iterations
L^B	Set of Benders' algorithm iterations
T	Set of discrete time instants
Y	Set of representative years in the planning horizon
D	Set of representative days in the planning horizon

Parameters

Stochastic Multi-Period Optimal Power Flow

ω_m	Probability of market scenario $m \in \Omega_m$
ω_o	Probability of operational scenario $o \in \Omega_o$
ω_c	Probability of investment scenario $c \in \Omega_c$
$c_{m,t}^G$	Wholesale energy price in market scenario $m \in \Omega_m$ and time instant $t \in T$
$c_{m,t}^{F,P}$	Cost of active power flexibility in market scenario $m \in \Omega_m$ and time instant $t \in T$

$c_{m,t}^{F,Q}$	Cost of reactive power flexibility in market scenario $m \in \Omega_m$ and time instant $t \in T$
$c_{y,c}^{\text{Inv},S}$	Shared ESS investment cost (power) in year $y \in Y$ and scenario $c \in \Omega_c$
$c_{y,c}^{\text{Inv},E}$	Shared ESS investment cost (energy) in year $y \in Y$ and scenario $c \in \Omega_c$
c_g^{GC}	Penalty (cost) of curtailing generator $g \in G^R$
c_l^{LC}	Penalty (cost) of curtailing load $l \in L^C$
c^V	Penalty coefficient associated with voltage magnitude violations
c^I	Penalty coefficient associated with branch overloads
c^E	Penalty coefficient associated with violations of ESSs' complementarity constraints
$V_i^{\max}$	Maximum admissible voltage magnitudes at bus $i \in N$
$V_i^{\min}$	Minimum admissible voltage magnitudes at bus $i \in N$
V_i^{Base}	Base voltage of bus $i \in N$
ϕ^V	Parameter that bounds voltage slack variables as a fraction of $V_i^{\max}$
$P_g^{G,\max}$	Maximum active power output of generator $g \in G$
$P_g^{G,\min}$	Minimum active power output of generator $g \in G$
$Q_g^{G,\max}$	Maximum reactive power output of generator $g \in G$
$Q_g^{G,\min}$	Minimum reactive power output of generator $g \in G$
S_e^{Rated}	Rated apparent power of storage unit $e \in E$
$Q_c^{C,\text{Nom}}$	Nominal reactive power rating of CB $c \in C$
n_c^C	Number of discrete steps of CB $c \in C$
g_{ij}	Series conductance of branch $(i,j) \in B$
b_{ij}	Series susceptance of branch $(i,j) \in B$
b_{ij}^{Sh}	Half-line shunt susceptance of branch $(i,j) \in B$, modeled using the standard Π -equivalent representation
$r_{ij}^{\max}$	Maximum admissible tap ratio of transformer $(i,j) \in B^T$
$r_{ij}^{\min}$	Minimum admissible tap ratio of transformer $(i,j) \in B^T$
$t_{ij}^{\Delta,B}$	Incremental ratio change per tap of transformer $(i,j) \in B^T$
n_{ij}^B	Number of discrete tap positions available on transformer $(i,j) \in B^T$
$\hat{t}_{ij,p}^B$	Tap position of transformer $(i,j) \in B^T$ at control stage $p \in P$
$t_c^{C,\max}$	Maximum number of transformer tap changes allowed per control stage $p \in P$
F_{ij}^{Rated}	Thermal rating of branch $(i,j) \in B$
$P_{l,m,o,t}^L$	Active power demand of load $l \in L$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$Q_{l,m,o,t}^L$	Reactive power demand of load $l \in L$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$P_{l,o,t}^{L,\max}$	Maximum upward active power flexibility that FL $l \in L^F$ can provide in operational scenario $o \in \Omega_o$, and time instant $t \in T$
$P_{l,o,t}^{L,\min}$	Maximum downward active power flexibility that FL $l \in L^F$ can provide in operational scenario $o \in \Omega_o$, and time instant $t \in T$
$Q_{l,o,t}^{L,\max}$	Maximum upward reactive power flexibility that FL $l \in L^F$ can provide in operational scenario $o \in \Omega_o$, and time instant $t \in T$
$Q_{l,o,t}^{L,\min}$	Maximum downward reactive power flexibility that FL $l \in L^F$ can provide in operational scenario $o \in \Omega_o$, and time instant $t \in T$
$P_{l,o,t}^{L,\text{Curt},\max}$	Maximum upward active power curtailment limit of load $l \in L^C$ in operational scenario $o \in \Omega_o$, and time instant $t \in T$

$P_{l,o,t}^{L,Curt,min}$	Maximum downward active power curtailment limit of load $l \in L^C$ in operational scenario $o \in \Omega_o$, and time instant $t \in T$
$Q_{l,o,t}^{L,Curt,max}$	Maximum upward reactive power curtailment limit of load $l \in L^C$ in operational scenario $o \in \Omega_o$, and time instant $t \in T$
$Q_{l,o,t}^{L,Curt,min}$	Maximum downward reactive power curtailment limit of load $l \in L^C$ in operational scenario $o \in \Omega_o$, and time instant $t \in T$
$V_{i,t}^S$	Voltage magnitude set-point for bus $i \in N^{PV}$ at time period $t \in T$
$\varphi_g^{G,max}$	Maximum phase angle limit of the inverter associated with generator $g \in G^R$
$\varphi_g^{G,min}$	Minimum phase angle limit of the inverter associated with generator $g \in G^R$
$\hat{\varphi}_{g,o,t}^G$	Forecasted phase angle of generator $g \in G^R$, in operational scenario $o \in \Omega_o$ and time instant $t \in T$
$\hat{P}_{g,o,t}^G$	Forecasted active power output of generator $g \in G^R$, in operational scenario $o \in \Omega_o$ and time instant $t \in T$
$\hat{Q}_{g,o,t}^G$	Forecasted reactive power output of generator $g \in G^R$, in operational scenario $o \in \Omega_o$ and time instant $t \in T$
$\hat{S}_{g,o,t}^G$	Forecasted apparent power output of generator $g \in G^R$, in operational scenario $o \in \Omega_o$ and time instant $t \in T$
$\varphi_e^{E,max}$	Maximum phase angle limit of the inverter associated with storage unit $e \in E$
$\varphi_e^{E,min}$	Minimum phase angle limit of the inverter associated with storage unit $e \in E$
η_e^{Ch}	Charging efficiency of storage unit $e \in E$
η_e^{Dch}	Discharging efficiency of storage unit $e \in E$
SoC_e^{max}	Maximum allowable SoC of storage unit $e \in E$
SoC_e^{min}	Minimum allowable SoC of storage unit $e \in E$

TSO-DSO Coordinated Operational Planning

$\hat{V}_{i,t}^{I,k}$	Local copy of voltage magnitude at interface node $i \in N^I$, time instant $t \in T$, at iteration $k \in K$
$\hat{P}_{i,t}^{I,k}$	Local copy of active power flow at interface node $i \in N^I$, time instant $t \in T$, at iteration $k \in K$
$\hat{Q}_{i,t}^{I,k}$	Local copy of reactive power flow at interface node $i \in N^I$, time instant $t \in T$, at iteration $k \in K$
$\hat{P}_{i,t}^{E,k}$	Local copy of active power output of the shared ESS installed in interface node $i \in N^I$, time instant $t \in T$, at iteration $k \in K$
$\hat{Q}_{i,t}^{E,k}$	Local copy of reactive power output of the shared ESS installed in interface node $i \in N^I$, time instant $t \in T$, at iteration $k \in K$
$\rho^{I,V,k}$	ADMM penalty parameter associated with the interface voltage magnitude at iteration $k \in K$
$\rho^{I,P,k}$	ADMM penalty parameter associated with interface active flow at iteration $k \in K$
$\rho^{I,Q,k}$	ADMM penalty parameter associated with interface reactive flow at iteration $k \in K$

$\rho^{E,P,k}$	ADMM penalty parameter associated with the active power of shared ESSs at iteration $k \in K$
$\rho^{E,Q,k}$	ADMM penalty parameter associated with the reactive power of shared ESSs at iteration $k \in K$
$r^{I,V}$	Update rate associated with interface voltage magnitude's penalty parameter
$r^{I,P}$	Update rate associated with interface active power's penalty parameter
$r^{I,Q}$	Update rate associated with interface reactive power's penalty parameter
$r^{E,P}$	Update rate associated with shared ESSs' active power penalty parameter
$r^{E,Q}$	Update rate associated with shared ESSs' reactive power penalty parameter
$c^{I,V}$	Weighting coefficient that discourages large deviations of the scenario-specific voltage magnitudes from their expected values
$c^{I,P}$	Weighting coefficient that discourages large deviations of the scenario-specific active power flows from their expected values
$c^{I,Q}$	Weighting coefficient that discourages large deviations of the scenario-specific reactive power flows from their expected values
$c^{E,P}$	Weighting coefficient that discourages large deviations of the scenario-specific shared ESSs active powers from their expected values
$c^{E,Q}$	Weighting coefficient that discourages large deviations of the scenario-specific shared ESSs reactive powers their expected values
$\varepsilon^{I,V}$	User-defined ADMM tolerance (primal) for interface voltage magnitude
$\varepsilon^{I,PQ}$	User-defined ADMM tolerance (primal) for interface power flows
$\varepsilon^{E,PQ}$	User-defined ADMM tolerance (primal) for shared ESSs
$n^{I,V}$	Residual dimension (primal) of interface voltage magnitude
$n^{I,PQ}$	Residual dimension (primal) of interface power flows
$n^{E,PQ}$	Residual dimension (primal) of shared ESSs
$\theta^{I,V}$	User-defined ADMM tolerance (dual) for interface voltage magnitude
$\theta^{I,PQ}$	User-defined ADMM tolerance (dual) for interface power flows
$\theta^{E,PQ}$	User-defined ADMM tolerance (dual) for shared ESSs
$m^{I,V}$	Residual dimension (dual) of interface voltage magnitude
$m^{I,PQ}$	Residual dimension (dual) of interface power flows
$m^{E,PQ}$	Residual dimension (dual) of shared ESSs

Shared Resources Planning

$T_{e,y}^{\text{cal}}$	Calendar lifetime of the ESS installed at node $e \in E^S$, in year $y \in Y$
$E_{e,y}^{\text{Max}}$	Maximum installable capacity for ESS $e \in E^S$ in year $y \in Y$
ϕ_e^{Max}	Maximum admissible energy-to-power ratio for the shared ESS $e \in E^S$
ϕ_e^{Min}	Minimum admissible energy-to-power ratio for the shared ESS $e \in E^S$
$y^{(k)}$	Benders' subproblem objective value at iteration k (upper bound in the Benders' algorithm)
$\mu_{e,y}^{S(l)}$	Sensitivity coefficient (dual variable) associated with the rated power of the shared ESS $e \in E^S$ in year $y \in Y$, and iteration $l \in L^B$
$\mu_{e,y}^{E(l)}$	Sensitivity coefficient (dual variable) associated with the energy capacity of the shared ESS $e \in E^S$ in year $y \in Y$ and iteration $l \in L^B$

α^{Down}	Predefined lower bound ensuring numerical stability of Benders' master problem
c^{Inv}	Total investment budget available for shared ESSs
r	Annual discount rate
$\hat{S}_{e,y}^{\text{Inv}}$	Expected investment in power rating in shared ESS $e \in E^S$ in year $y \in Y$
$\hat{E}_{e,y}^{\text{Inv}}$	Expected investment in energy capacity in shared ESS $e \in E^S$ in year $y \in Y$
CL_e^{Nom}	Nominal cycle life of unit $e \in E^S$
$\text{SoH}_{e,y}^{\text{min}}$	Minimum admissible SoH for unit e , installed in year y^{Inv}
Y_y	Number of years represented by representative year $y \in Y$
D_d	Number of calendar days represented by day $d \in D$

Variables

Stochastic Multi-Period Optimal Power Flow

$e_{i,m,o,t}$	Real component of voltage at bus $i \in N$, under market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$f_{i,m,o,t}$	Imaginary component of voltage at bus $i \in N$, under market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$P_{g,m,o,t}^G$	Active power output of generator $g \in G^C$ in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$Q_{g,m,o,t}^G$	Reactive power output of generator $g \in G^C$ in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$S_{g,m,o,t}^{G,\text{Curt}}$	Apparent power curtailment of generator $g \in G^R$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$P_{f,m,o,t}^{L,\text{Up}}$	Upward active power flexibility provided by FL $f \in L^F$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$P_{f,m,o,t}^{L,\text{Down}}$	Downward active power flexibility provided by FL $f \in L^F$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$Q_{f,m,o,t}^{L,\text{Up}}$	Upward reactive power flexibility provided by FL $f \in L^F$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$Q_{f,m,o,t}^{L,\text{Down}}$	Downward reactive power flexibility provided by FL $f \in L^F$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$P_{l,m,o,t}^{L,\text{Curt},\text{Up}}$	Upward active power curtailment of load $l \in L^C$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$P_{l,m,o,t}^{L,\text{Curt},\text{Down}}$	Downward active power curtailment of load $l \in L^C$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$Q_{l,m,o,t}^{L,\text{Curt},\text{Up}}$	Upward reactive power curtailment of load $l \in L^C$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$Q_{l,m,o,t}^{L,\text{Curt},\text{Down}}$	Downward reactive power curtailment of load $l \in L^C$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$r_{ij,m,o,t}$	Tap ratio of OLTC transformer $(i,j) \in B^T$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and instant $t \in T$
$t_{ij,m,o,t}^B$	Integer tap position of transformer $(i,j) \in B^T$ in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$

$P_{e,m,o,t}^{E,Ch}$	Charging active power of storage unit $e \in E$ in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$P_{e,m,o,t}^{E,Dch}$	Discharging active power of storage unit $e \in E$ in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$Q_{e,m,o,t}^{E,Ch}$	Charging reactive power of storage unit $e \in E$ in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$Q_{e,m,o,t}^{E,Dch}$	Discharging reactive power of storage unit $e \in E$ in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$SoC_{e,m,o,t}$	SoC of storage unit $e \in E$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$Q_{c,m,o,t}^C$	Reactive power injection from CB $c \in C$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$t_{c,m,o,t}^C$	Integer tap position of CB $c \in C$ in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$P_{ij,m,o,t}$	Active power flow in the “from” direction of branch $(i,j) \in B$, under market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, instant $t \in T$
$Q_{ij,m,o,t}$	Reactive power flow in the “from” direction of branch $(i,j) \in B$, under market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, instant $t \in T$
$e_{i,m,o,t}^{Up}$	Upward slack variable associated with the real component of bus $i \in N$'s voltage in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$e_{i,m,o,t}^{Down}$	Downward slack variable associated with the real component of bus $i \in N$'s voltage in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$f_{i,m,o,t}^{Up}$	Upward slack variable associated with the imaginary component of bus $i \in N$'s voltage in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$f_{i,m,o,t}^{Down}$	Downward slack variable associated with the imaginary component of bus $i \in N$'s voltage in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$
$F_{ij,m,o,t}^{S^2}$	Slack variable associated with the violation of the branch $ij \in B$ power flow limit in market scenario $m \in \Omega_m$, operation scenario $o \in \Omega_o$, and time instant $t \in T$
$S_{e,m,o,t}^{S,E}$	Slack variable associated with ESS $e \in E$, in market scenario $m \in \Omega_m$, operation scenario $o \in \Omega_o$, and time instant $t \in T$

TSO-DSO Coordinated Operational Planning

$V_{i,t}^I$	Expected voltage magnitude at interface node $i \in N^I$ and time instant $t \in T$
$P_{i,t}^I$	Expected active power flow at interface node $i \in N^I$ and time instant $t \in T$
$Q_{i,t}^I$	Expected reactive power flow at interface node $i \in N^I$ and time instant $t \in T$
$P_{i,t}^E$	Expected active power output of the shared ESS installed in interface node $i \in N^I$ and time instant $t \in T$

$Q_{i,t}^E$	Expected reactive power output of the shared ESS installed in interface node $i \in N^I$ and time instant $t \in T$
$\pi_{i,t}^{I,V}$	Dual variable associated with the voltage magnitude at interface node $i \in N^I$ and time instant $t \in T$
$\pi_{i,t}^{I,P}$	Dual variable associated with active power flow at interface node $i \in N^I$ and time instant $t \in T$
$\pi_{i,t}^{I,Q}$	Dual variable associated with reactive power flow at interface node $i \in N^I$ and time instant $t \in T$
$\pi_{i,t}^{E,P}$	Dual variable associated with the active power output of the shared ESS installed in interface node $i \in N^I$ and time instant $t \in T$
$\pi_{i,t}^{E,Q}$	Dual variable associated with the reactive power output of the shared ESS installed in interface node $i \in N^I$ and time instant $t \in T$
$\mathcal{L}^{I,V}$	Augmented Lagrangian associated with the interface node voltage magnitude
$\mathcal{L}^{I,P}$	Augmented Lagrangian associated with the interface node active power exchange
$\mathcal{L}^{I,Q}$	Augmented Lagrangian associated with the interface node reactive power exchange
$\mathcal{L}^{E,P}$	Augmented Lagrangian associated with the active power output of shared ESSs
$\mathcal{L}^{E,Q}$	Augmented Lagrangian associated with the reactive power output of shared ESSs

Shared Resources Planning

$S_{e,y,c}^{\text{Inv}(l)}$	Installed rated power in shared ESS $e \in E^S$, in year $y \in Y$ and scenario $c \in \Omega_c$, at Benders' iteration $l \in L$
$E_{e,y,c}^{\text{Inv}(l)}$	Installed energy capacity in shared ESS $e \in E^S$, in year $y \in Y$ and scenario $c \in \Omega_c$, at Benders' iteration $l \in L$
$S_{e,y,c}^{\text{Rated}(l)}$	Total rated power available at node $e \in E^S$, in year $y \in Y$, under investment scenario $c \in \Omega_c$, at Benders' iteration $l \in L$
$E_{e,y,c}^{\text{Rated}(l)}$	Total energy capacity available at node $e \in E^S$, in year $y \in Y$, under investment scenario $c \in \Omega_c$, at iteration $l \in L$
$\alpha^{(l)}$	Underestimator of the Benders' subproblem objective function at iteration $l \in L$
$S_{e,y}^{\text{S,Up}}$	Slack variable associated with deviation in rated power (upward) of shared ESS $e \in E^S$ in year $y \in Y$
$S_{e,y}^{\text{S,Down}}$	Slack variable associated with deviation in rated power (downward) of shared ESS $e \in E^S$ in year $y \in Y$
$E_{e,y}^{\text{E,Up}}$	Slack variable associated with deviation in energy capacity (upward) of shared ESS $e \in E^S$ in year $y \in Y$
$E_{e,y}^{\text{E,Down}}$	Slack variable associated with deviation in energy capacity (downward) of shared ESS $e \in E^S$ in year $y \in Y$
$S_{e,y^{\text{Inv}},y}^{\text{Av,Unit}}$	Available rated power of unit $e \in E^S$, installed in year $y^{\text{Inv}} \in Y$, in the subsequent year $y \in Y$

$E_{e,y^{\text{Inv}},y}^{\text{Av,Unit}}$	Available energy capacity of unit $e \in E^S$, installed in year $y^{\text{Inv}} \in Y$, in the subsequent year $y \in Y$
$SoH_{e,y^{\text{Inv}},y}$	SoH of unit $e \in E^S$, installed in year $y^{\text{Inv}} \in Y$, in the subsequent year $y \in Y$
$\delta_{e,y^{\text{Inv}},y}$	Annual fractional capacity degradation of unit $e \in E^S$, installed in year y^{Inv} and operating in year y
$E_{e,y^{\text{Inv}},y}^{\text{Ch,Dch}}$	Auxiliary variable representing the total annual charge–discharge energy throughput of unit $e \in E^S$, averaged over representative days in year $y \in Y$

Chapter 1

Introduction

Electric power systems are undergoing a profound transformation, driven primarily by the large-scale integration of Renewable Energy Sources (RESs), which are progressively displacing conventional synchronous generation in the overall energy mix. This transition is accompanied by an increasing decentralization of electricity production, as a growing share of generation is connected to the Distribution Network (DN), predominantly through variable RESs such as solar and wind. At the same time, the electrification of multiple end-use sectors – including transport, heating, and industry – together with the rapid proliferation of diverse Distributed Energy Resources (DERs), is fundamentally reshaping the way power systems are planned, operated, and controlled (ENTSO-E, 2021).

These structural changes pose significant challenges for System Operators (SOs). The inherent variability and limited predictability of RES generation increase operational uncertainty, place greater stress on system balancing, and substantially raise flexibility requirements. In response, recent European policy and regulatory frameworks emphasize the growing role of both final consumers and Distribution System Operators (DSOs) in supporting system operation through the provision of Ancillary Services (ASs). Within this evolving operational paradigm, DERs are expected to actively contribute to system security and efficiency across all voltage levels. This shift requires enhanced coordination between transmission and distribution systems and, more broadly, a redefinition of interaction mechanisms among SOs (Hatziargyriou et al., 2017).

The efficient mobilization of DERs offers substantial system-wide benefits. It can reduce reliance on conventional generation for the provision of ASs, defer or mitigate network reinforcement investments through improved utilization of existing infrastructure, and enhance overall asset efficiency. Ultimately, these advances support the cost-effective integration of RES, strengthen system reliability, and enable the transition toward a more sustainable, flexible, and consumer-centric energy sector (Liu et al., 2020; Nikoobakht et al., 2020). Achieving these objectives, however, requires the development of advanced optimization frameworks and robust coordination mechanisms capable of managing the increasing complexity, uncertainty, and dynamism of modern electric power systems.

1.1 Motivation

Energy is a fundamental driver of modern economies and, consequently, of human prosperity and well-being. At the same time, the energy sector accounts for nearly three-quarters of global Greenhouse Gas (GHG) emissions, making it the primary contributor to climate change. Achieving a transition toward low-carbon energy systems is therefore essential to mitigate emissions and meet the internationally agreed targets established under the Paris Agreement (UNFCCC, 2015). At the European level, the European Climate Law establishes a target of reducing net GHG emissions by at least 55% by 2030 relative to 1990 levels (European Parliament and Council of the European Union, 2021). In parallel, the revised Renewable Energy Directive raises the binding EU-wide share of renewable energy in gross final energy consumption to at least 42.5%, with a collective endeavour to reach 45% (European Parliament and Council of the European Union, 2023). These targets are expected to deliver multiple societal and economic benefits, including reduced dependence on energy imports, enhanced security of supply, improved affordability for consumers, and significant environmental and public health gains. Achieving them, however, requires a profound transformation of how electricity is produced, transmitted, distributed, and consumed (IEA, 2023e).

While the large-scale deployment of RESs is indispensable for decarbonization, it simultaneously introduces significant operational challenges. Conventional synchronous generators have historically provided most of the ASs required to ensure system security and stability. As these units are progressively displaced, equivalent services must increasingly be supplied by alternative sources of flexibility. The electrification of end-use sectors and the rapid growth of DERs – including Energy Storage Systems (ESSs), Electric Vehicles (EVs), and Flexible Loads (FLs) – offer promising substitutes. Nevertheless, despite their technical potential, these resources remain largely underutilized from a system-wide operational perspective. In practice, the proliferation of DERs has significantly increased the complexity of power system operation. DSOs are increasingly required to actively manage their networks and coordinate a growing number of heterogeneous resources. This evolution induces power exchanges at the Transmission Network (TN)–DN interface that are more variable, less predictable, and subject to greater uncertainty. As a result, Transmission System Operators (TSOs) face mounting challenges in maintaining system balance and ensuring adequate flexibility availability, often leading to increased procurement of ASs.

Despite the growing relevance of distributed flexibility, coordination mechanisms between TSOs and DSOs remain limited and fragmented. The absence of well-defined operational frameworks and market mechanisms constrains the efficient integration of DERs and restricts their participation in system balancing and ASs provision. Addressing this gap is therefore critical to unlocking the full value of distributed flexibility and enabling the secure, reliable, and cost-effective operation of future power systems.

1.1.1 Energy Supply, GHG Emissions, and GDP

Economic development, energy consumption, and GHG emissions are inherently interdependent. Historically, growth in Gross Domestic Product (GDP) has been strongly correlated with increases in energy demand, which in turn have driven higher levels of energy-related GHG emissions (Topolewski, 2021; Danish and Ulucak, 2021). Although the progressive decarbonization of the energy sector and the large-scale deployment of RESs are beginning to weaken this relationship in some regions, the structural dependence of economic activity on energy supply – and its associated environmental impacts – remains evident at the global level. Figure 1.1 illustrates the evolution of energy-related GHG emissions and Total Energy Supply (TES), both normalized to 1990 levels, across different regions: the world, the Organisation for Economic Co-operation and Development (OECD), non-OECD, and OECD Europe (IEA, 2024a).

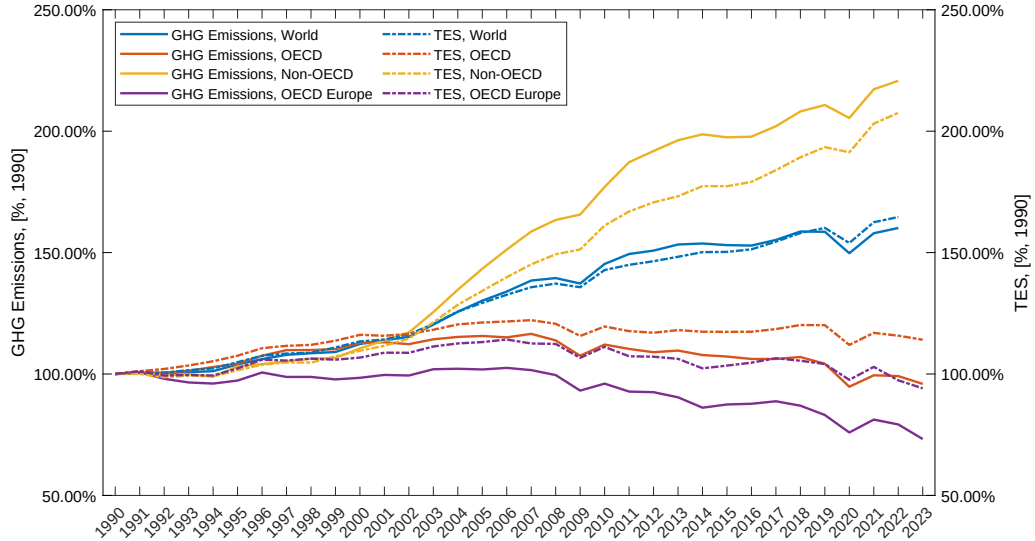


Figure 1.1: Energy-related GHG emissions and TES (1990–2023), normalized to 1990 values. Comparison between world, OECD, non-OECD, and OECD Europe regions. Data source: IEA (2024a).

As shown in Figure 1.1, TES and energy-related GHG emissions have followed closely aligned trajectories over the past three decades, highlighting the persistent coupling between energy use and environmental impact. Nevertheless, marked regional differences can be observed. In OECD countries, both energy consumption and emissions have stabilized – or even declined – in recent years. This trend is largely attributable to improvements in energy efficiency, structural shifts toward less energy-intensive economic activities, and increased penetration of RESs. By contrast, non-OECD regions continue to experience sustained growth in both energy consumption and emissions, reflecting ongoing industrialization, urbanization, and population growth. These divergent trends underscore the uneven pace of energy transition across regions and the continued challenge of decoupling economic growth from emissions at the global scale.

Additional insight into the evolving relationship between energy consumption and economic output is provided in Figure 1.2, which depicts energy intensity – defined as the ratio of TES to GDP – from 1990 to 2023 (IEA, 2024a). The consistent downward trend observed across all regions indicates substantial improvements in economic energy efficiency over time. OECD economies exhibit a smooth and sustained decline in energy intensity, driven by technological innovation and efficiency-oriented policies. Non-OECD countries, while maintaining higher absolute levels of energy intensity, have achieved faster relative reductions, partly due to modernization of industrial processes and infrastructure. However, these gains are often constrained by continued reliance on carbon-intensive fuels and rapidly growing energy demand.

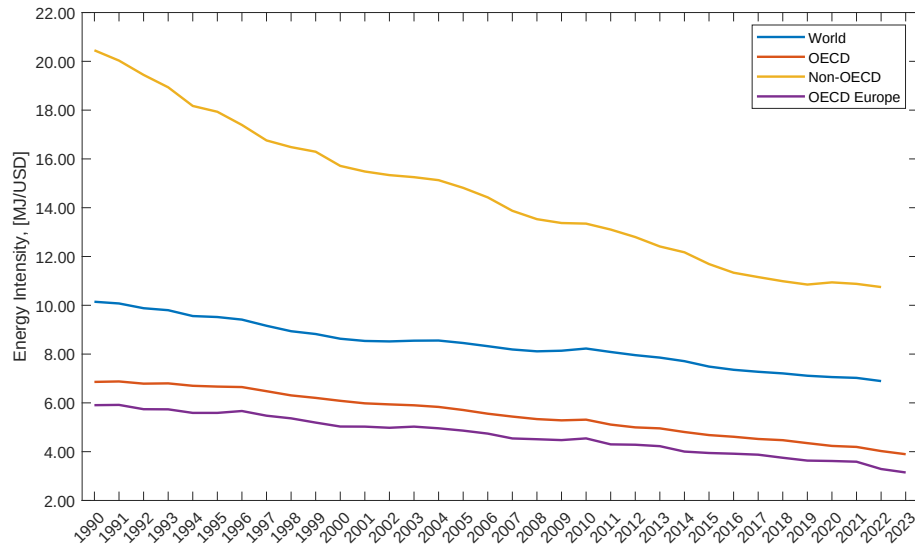


Figure 1.2: Energy intensity (1990-2023). Comparison between world, OECD, non-OECD, and OECD Europe regions. Exchange rates based on 2015 USD. Data source: IEA (2024a).

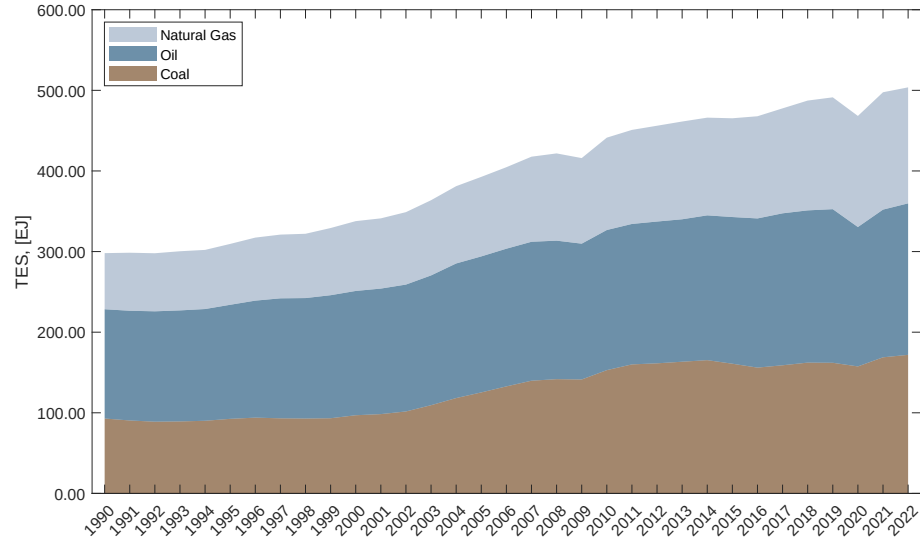
Despite these improvements, the central role of energy as an enabler of economic development implies that fully decarbonizing the energy sector remains a major and unresolved challenge. Achieving this objective will require sustained advances in energy efficiency, accelerated deployment of low-carbon technologies, and deep, system-wide transformations in energy production, transmission, distribution, and end-use (IEA, 2024a).

1.1.2 Evolution of the Generation Mix

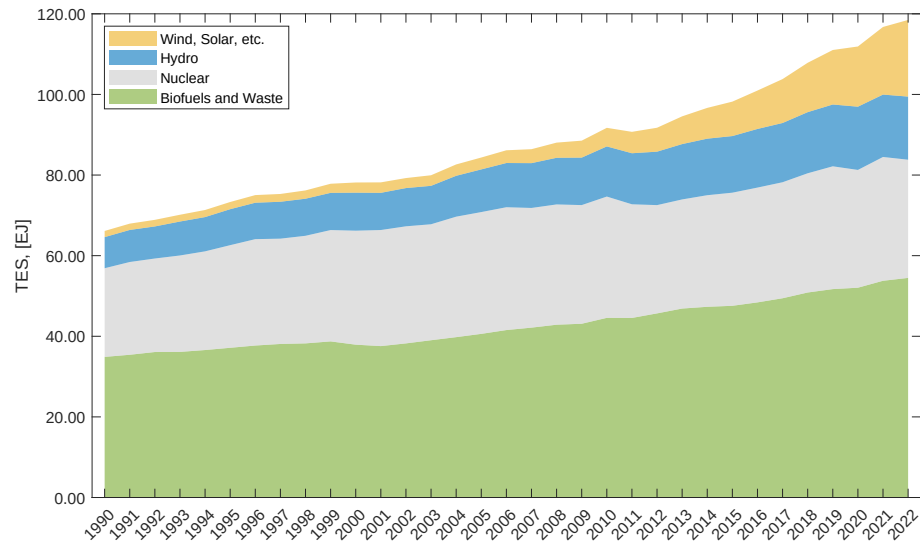
Despite substantial progress in the deployment of clean energy technologies¹, fossil fuels continue to dominate the global energy system. As of 2022, fossil-based sources accounted for approximately 80% of TES, only marginally lower than the 82% share observed in 1990. This persistence highlights both the scale of the decarbonization challenge and the inertia inherent in existing energy infrastructures.

¹As defined by the International Energy Agency (IEA), including wind and solar Photovoltaic (PV), hydropower, nuclear, and bioenergy.

Figure 1.3 illustrates the evolution of global TES between 1990 and 2022, disaggregated into fossil fuels and clean energy technologies.



(a) Fossil fuels.



(b) Clean technologies.

Figure 1.3: Global TES by fossil fuels and clean energy technologies (1990–2022). Data source: IEA (2024a).

According to the IEA, consumption of all major fossil fuels – coal, oil, and natural gas – is projected to peak before 2030 under current policy trajectories (IEA, 2023a). In advanced economies, fossil-fueled power plants are progressively transitioning from their traditional role as providers of bulk energy toward suppliers of flexibility and reliability services. At the same time, clean energy technologies are expanding at an unprecedented pace. Renewables are expected to account for approximately 80% of new power generation capacity additions by 2030, with solar PV alone representing more than half of this growth.

The large-scale deployment of variable RESs introduces significant operational challenges. As inverter-based generation increasingly displaces conventional synchronous units, concerns arise regarding the provision of essential ASs, including frequency and voltage control, rotational inertia, short-circuit current contribution, and black-start capability. Moreover, the inherent variability of RESs increases the need for additional ASs, such as fast-ramping flexibility, enhanced reserve products, and more sophisticated balancing mechanisms. These challenges underscore the necessity of new operational paradigms, adapted market mechanisms, and advanced optimization frameworks capable of ensuring secure and efficient system operation in high-RES environments.

1.1.3 DER Deployment

The rapid proliferation of DERs is fundamentally reshaping how electricity is generated, traded, delivered, and consumed. While these resources offer significant opportunities to enhance system flexibility, resilience, and efficiency, their large-scale integration also introduces substantial operational and regulatory challenges (IEA, 2022a).

In many jurisdictions, the understanding of DERs – including their operational behavior, system impacts, and potential contribution to grid services – remains limited. By contrast, regions with more mature experience demonstrate that, under appropriate technological, regulatory, and market conditions, DERs can substantially improve system reliability and reduce operational costs (IEA, 2022a). The increasing diversity of DER technologies is also enabling consumers to evolve from passive electricity users into active market participants, while facilitating the emergence of new actors, such as aggregators, that consolidate small-scale resources and enable their participation in wholesale markets and the provision of ASs. Despite significant technological progress, many SOs still lack sufficient visibility and controllability over DERs, limiting their ability to fully exploit available distributed flexibility. Figure 1.4 illustrates this paradigm shift, highlighting how the integration of DERs is reshaping traditional power system operational philosophies.

Moreover, because many DERs are privately owned, their operation is often driven by individual economic incentives rather than system-wide objectives. This misalignment can hinder their effective contribution to grid reliability and flexibility. In addition, many DNs still lack the monitoring, communication, and automation infrastructure required to observe real-time DER behavior or to coordinate their activation for system services. This limited situational awareness constrains the ability of SOs to effectively leverage distributed flexibility, particularly when coordinated action across voltage levels is required. Addressing these challenges requires the formal recognition of DER-based services within regulatory and market frameworks. Close coordination between policymakers, regulators, and SOs is essential to establish mechanisms that enable the fair, efficient, and secure participation of DERs in system operation and flexibility markets (ENTSO-E, 2021).

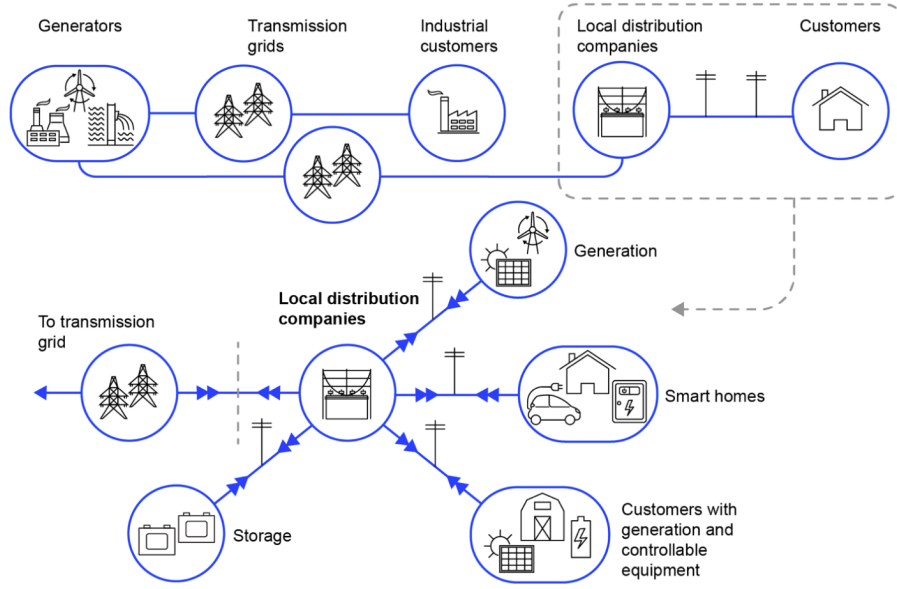


Figure 1.4: The power systems of the past and future. Source: IEA (2022a).

1.1.4 TSO-DSO Coordination

The large-scale integration of **DERs** is progressively blurring the traditional operational boundary between the **TN** and the **DN**. Historically, **DSOs** were responsible for operating largely passive **DNs**, while **TSOs** managed the bulk power system and procured **ASs** primarily from large, centralized generators. With the rapid deployment of **DERs**, however, **DNs** are evolving into active systems capable of providing flexibility services beyond their local boundaries. This transformation creates opportunities to enhance system efficiency, resilience, and sustainability, but it also introduces new layers of operational complexity.

As responsibilities and control actions increasingly overlap across voltage levels, effective **TSO-DSO** coordination has become a central concern for regulators, policymakers, and **SOs** themselves. Enhanced coordination is essential to unlock the value of distributed flexibility while maintaining secure and stable operation under growing uncertainty and decentralization (ENTSO-E, 2021). Although numerous coordination architectures have been proposed in the literature (e.g., Gerard et al., 2018), their large-scale practical implementation remains limited. Key barriers include regulatory constraints, limited data interoperability, fragmented market designs, and insufficient standardization of operational processes (Kerin et al., 2025). Distributed flexibility must therefore be mobilized not only to address local **DN**-level constraints, but also to *actively support transmission system operation*. Achieving this objective requires coordination frameworks that enable transparent and privacy-preserving information exchange, harmonized decision-making across **SOs**, and efficient activation of flexibility across all voltage levels. Such frameworks are indispensable for integrating higher shares of variable **RESs**, preserving system stability, and ensuring that **DERs** contribute effectively to both local and system-wide objectives.

1.2 Objectives and Research Questions

The overarching objective of this thesis is to conceptualize, develop, and validate a set of methodological and computational tools that enable effective coordination between **TSOs** and **DSOs**. By doing so, the thesis aims to facilitate the secure, efficient, and system-wide participation of **DERs** in electric power system operation.

To achieve this overarching goal, the thesis pursues the following specific objectives:

- Design a coordination framework that clearly defines the roles, responsibilities, and interaction mechanisms of **TSOs** and **DSOs**, enabling the secure and efficient exploitation of **DER** flexibility across voltage levels.
- Develop a coordinated operational planning tool that operationalizes the proposed coordination framework, explicitly accounting for shared resources located at the **TN-DN** interfaces, whose operation is coordinated between the participating **SOs**.
- Formulate a planning methodology to determine the optimal siting, sizing, and investment strategies for shared resources located at **TN-DN** interface nodes, ensuring their effective integration into both transmission- and distribution-level operation.
- Quantify the system-wide impacts of coordinated operation by assessing its economic, environmental, and operational benefits, including cost reduction, enhanced renewable integration, and improved overall system efficiency.

Guided by these objectives, the research addresses the following key questions:

- How can the flexibility of **DERs** be effectively mobilized to support power system operation across voltage levels, and how can **TSO-DSO** coordination be implemented in practice to outperform existing coordination approaches?
- Which models, methodologies, and optimization frameworks are required to accurately capture the system-wide value of distributed flexibility while respecting institutional separation and data privacy constraints?
- What are the expected economic, environmental, and operational impacts of coordinated **TSO-DSO** operation, and how do these outcomes compare with current operational practices?

Overall, this thesis seeks to advance the state-of-the-art in **TSO-DSO** coordination by delivering both conceptual insights and optimization-based tools that translate coordination principles into actionable and scalable procedures suitable for real-world power system applications.

1.3 Contributions of the Thesis

This thesis advances the state-of-the-art in **TSO–DSO** coordination by proposing a novel coordination paradigm, a set of optimization-based operational tools, and complementary planning models that collectively enable the secure and efficient integration of **DERs** into power system operation. Beyond methodological development, the thesis also provides a systematic assessment of the economic and environmental value of coordinated operation.

1.3.1 Research and Innovation

The research conducted within this thesis has resulted in multiple peer-reviewed publications, has been implemented in several Research, Development, and Innovation (**R&D&I**) projects at INESC TEC, and has been disseminated through public technical webinars.

The scientific contributions of this thesis are supported by the following peer-reviewed publications:

- International Journals:
 - **M. Simões**, A. Madureira, F. Soares, J. P. Lopes, “Degradation-Aware Planning of Shared Battery Energy Storage Systems for Coordinated Transmission and Distribution System Operation,” *Journal of Energy Storage*, 2026, *In Press*.
 - C. Oliveira, **M. Simões**, L. Bitencourt, T. Soares, M. A. Matos, “Distributed Network-Constrained P2P Community-Based Market for Distribution Networks,” *Energies*, vol. 16, no. 3, p. 1520, 2023.
 - D. Pereira, D. Reis, **M. Simões**, T. Soares, “Nonlinear Programming-Based Multi-Period Approach for Security Constrained Optimal Power Flow,” *Smart Grids and Sustainable Energy*, 2026.
 - I. Ponomarev, T. Soares, A. Carrillo-Galvez, **M. Simões**, “Technical Grid Operating Tool for Application at the Port of Sines,” in *Digital and Green Transition in Maritime Ports: Trends and Challenges*, 2025.
- International Conferences:
 - **M. Simões**, A. Madureira, J. P. Lopes, “A Comparison Between Hierarchical and Distributed Coordination Mechanisms for TSO-DSO Coordination,” in *Proc. IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*, 2025, pp. 1–5.
 - **M. Simões**, A. Madureira, F. Soares, J. P. Lopes, “TSO-DSO Coordinated Operational Planning in the Presence of Shared Resources,” in *Proc. IEEE Belgrade PowerTech*, 2023, pp. 1–8.
 - C. Oliveira, **M. Simões**, T. Soares, M. A. Matos, L. Bitencourt, “Fully Distributed P2P Market and Distribution Network Operation Based on ADMM:

Testing and Evaluation,” in *Proc. 19th International Conference on the European Energy Market (EEM)*, 2023, pp. 1–6.

- **M. Simões**, J. P. Lopes, F. Soares, “Degradation-Aware Planning of Shared Energy Storage Systems for TSO–DSO Coordinated Operation,” in *Proc. IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*, 2026, *Accepted*.
- D. Reis, **M. Simões**, T. Soares, J. P. Lopes, “Security-Constrained Multi-Period Optimal Power Flow With Stochastic Uncertainty Modelled Through Chance Constraints,” in *Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion (MEDPOWER)*, 2026, *In Press*.
- **M. Simões**, R. Rocha, A. Camanho, “Benchmarking Smart Grid Research & Development Engagement by European Distribution System Operators,” in *Proc. Congress of the Portuguese Association of Operational Research*, 2019, pp. 155–170.

- White Papers:

- **M. Simões**, R. Portelinha, E. Alves, J. Pereira, C. Gouveia, R. Bessa, “Transmission Network Congestion Management through Zonal Autonomous Control,” White Paper, GE Vernova, 2024.

1.3.2 R&D&I Projects

The methodologies and tools developed in this thesis have been implemented, tested, and further validated within several European, national, and industrial **R&D&I** projects. These projects include:

- ATTEST: European research project funded under the Horizon 2020 programme (Grant Agreement No. 864298). Available at: <https://attest-project.eu/>
- GridNode: Industrial **R&D&I** consultancy project developed for GE Vernova.
- ATE: Portuguese project funded by IAPMEI and co-financed under Component 5 – Capitalization and Business Innovation – within the Resilience Dimension of the Recovery and Resilience Plan, part of the EU’s Next Generation initiative (2021–2026). Available at: <https://recuperarportugal.gov.pt/>
- GPDER: Portuguese project funded by the European Regional Development Fund (ERDF) through the COMPETE 2020 Operational Programme for Competitiveness and Internationalisation (Project Ref. POCI-01-0247-FEDER-039892).

In addition, the methodologies developed in this thesis have been adopted in other **R&D&I** initiatives at INESC TEC beyond the direct involvement of the author, demonstrating their maturity and transferability.

1.3.3 Webinars

The results and methodologies developed in this thesis have also been disseminated to a broader technical audience through the following public webinars:

- Webinar “Open-source tools for TSO-DSO coordination”, hosted by INESC TEC. Title of the presentation: “Planning of TSO-DSO Shared Technologies”, 2023. Available at: <https://attest-project.eu/>
- Webinar “Navigating TSO-DSO Operational and Institutional Challenges”, hosted by INESC TEC. Title of the presentation: “TSO-DSO Coordination: Fostering Demand Side Flexibility for Optimal Operation of the Overall Power System”, 2025. Available at: <https://energywebinars.inesctec.pt/>

1.4 Structure of the Thesis

This thesis is organized into eight chapters, structured as follows:

- Chapter 1 introduces the research context and motivation, defines the scientific problem addressed, and outlines the objectives and main contributions of the thesis.
- Chapter 2 presents a comprehensive review of the relevant scientific literature, with emphasis on TSO-DSO coordination mechanisms, operational and expansion planning approaches, ESS planning methodologies, and Optimal Power Flow (OPF) models.
- Chapter 3 introduces the proposed TSO-DSO coordination mechanism, discusses its main features, advantages, and limitations, and positions it relative to state-of-the-art approaches.
- Chapter 4 presents the Stochastic Multi-period Optimal Power Flow (SMOPF) model developed in this work, which constitutes the analytical foundation of the proposed operational planning tools and represents a significant advancement over existing Nonlinear Programming (NLP)-based OPF formulations.
- Chapter 5 details the coordinated operational planning tool that operationalizes the proposed coordination framework, including the mathematical decomposition strategy adopted to preserve data privacy while ensuring computational tractability.
- Chapter 6 presents the planning framework for shared resources installed at TN-DN interface nodes, describing the stochastic multi-year formulation, decomposition techniques, and the integrated battery ESS degradation model.
- Chapter 7 reports the simulation studies conducted to evaluate the performance of the proposed methodologies under representative operating conditions.

- Chapter 8 summarizes the main findings and contributions of the thesis and outlines directions for future research.

The proposed coordination framework and optimization models constitute the methodological core of the work, while the simulation and Hardware-In-the-Loop (HIL)-based validation demonstrate their practical relevance and applicability. Taken together, the contributions of this thesis to coordinated TSO–DSO operation span multiple timeframes – from long-term investment decisions, to operational planning, and real-time control – representing a significant contribution to both the current state-of-the-art and the operation of power systems with high penetration of DERs.

Chapter 2

Literature Review

Energy constitutes a fundamental pillar of modern industrial economies, underpinning economic growth, social welfare, and technological progress. Empirical evidence consistently points to a strong positive relationship between **GDP** and access to reliable and affordable electricity, highlighting the central role of the energy sector in fostering prosperity and improving quality of life (**World Bank, 2023**).

As economies pursue deep decarbonization, a critical challenge emerges: *how to accelerate the transition toward low-carbon electricity generation technologies without undermining economic development or compromising the security of energy supply*. The increasing penetration of **RESs** and **DERs** is profoundly reshaping both the structure and operation of power systems. While these decentralized and variable resources introduce new sources of uncertainty and operational complexity, they also offer significant potential to provide flexibility and **ASs** to the wider grid. Fully realizing this potential requires a fundamental rethinking of transmission and distribution system operation, as well as the coordination mechanisms among **TSOs**, **DSOs**, and prosumers, to ensure secure, resilient, and sustainable power system operation.

This chapter begins by reviewing the empirical relationships between energy consumption, **GHG** emissions, and economic growth, alongside current trends in the deployment of **DERs**. The chapter then surveys the main coordination mechanisms and interaction frameworks proposed for **TSO-DSO** coordination, with particular emphasis on optimization-based approaches that enable their practical implementation. Subsequently, the chapter reviews the state-of-the-art in **OPF** modeling, which forms the computational backbone of modern power system operation. Particular attention is given to the trade-offs between modeling accuracy, and computational tractability and scalability. Finally, the chapter concludes with a critical assessment of the surveyed coordination frameworks, optimization methodologies, and modeling techniques. Their respective strengths and limitations are discussed, and key research gaps are identified, thereby motivating the methodological developments and contributions presented in the subsequent chapters.

2.1 Context

The energy sector plays a central role in the transition toward a low-carbon economy and is pivotal to achieving the objectives established under the *European Climate Law* (European Commission, 2020). While the reduction of GHG emissions remains a primary policy driver, it is no longer the sole motivation underpinning this transformation. Clean energy technologies have reached unprecedented levels of technological maturity and cost competitiveness, while concerns related to energy security have intensified in recent years due to geopolitical tensions, supply chain disruptions, and market volatility (IEA, 2023f).

Within this evolving landscape, the effective mobilization of flexibility from DERs has emerged as a critical enabler of secure, efficient, and resilient power system operation (Mayorga Gonzalez et al., 2018). At the European level, policymakers increasingly emphasize the need for enhanced coordination between TSOs and DSOs as a prerequisite for unlocking this flexibility. However, owing to the historical separation of transmission and distribution responsibilities, practical coordination mechanisms remain limited. As a result, flexibility from DERs is often confined to the distribution level, restricting its contribution to system-wide balancing, congestion management, and the provision of ASs (AEMO, 2017; Wang et al., 2020).

2.1.1 Distributed Energy Resources

Historically, power systems were designed around centralized architectures in which consumers acted as passive electricity users. Wholesale markets primarily facilitated transactions between large-scale generators and retailers, with generation assets typically connected at the TN-level and operated under the supervision of the TSO. DNs were largely passive, with DSOs mainly focused on ensuring reliable power delivery.

The increasing penetration of DERs is fundamentally transforming power system structure and operation. Electricity markets are evolving from centralized systems dominated by large generators toward more decentralized architectures with heterogeneous participants. At the same time, large-scale DER integration introduces significant technical, operational, and regulatory challenges, particularly where grid infrastructures, operational practices, and market designs have not yet adapted to their distributed and dynamic nature (IEA, 2022a). These challenges are especially pronounced at the TN–DN interface, where insufficient coordination between SOs can lead to conflicting control actions, limited situational awareness, and inefficient use of distributed flexibility.

The extent and maturity of DER integration vary considerably across regions. In many jurisdictions, SOs and regulators still have limited visibility into the real-time behavior of DERs, and their impacts are not systematically integrated into operational planning or system-wide decision-making. Nevertheless, more mature markets – such as those in Europe, North America, and Australia – are gaining practical experience in leveraging DERs to support system operation.

2.1.1.1 Energy Storage Systems

Historically, energy storage has played a fundamental role in providing system flexibility, most notably through reservoir-based hydropower, which for decades has offered large-scale, dispatchable storage capacity. In recent years, a broader portfolio of storage technologies – including compressed air energy storage, flywheels, thermal storage, and battery-based **ESSs** – has gained increasing relevance. Among these options, battery **ESSs** have emerged as the most versatile and rapidly deployable solution. Sustained cost reductions, together with advances in efficiency and performance, have positioned batteries as economically competitive providers of short-term flexibility services (IEA, 2024b).

Unlike traditional storage assets, battery **ESSs** are capable of delivering a wide range of services across multiple time scales and system levels. Their modular design enhances scalability and enables deployment at the transmission, distribution, and “behind-the-meter” levels, thereby supporting both centralized and decentralized operational strategies (IEA, 2024b). Table 2.1 summarizes the main services provided by battery **ESSs** across different domains of power system operation.

Table 2.1: Battery ESS services in power systems. Adapted from IEA (2024b).

	Generation	Network	Consumption
Short-term flexibility	- Wholesale arbitrage - RES integration (via energy shifting)	- Congestion relief	- Increased self-consumption - Fixed charge reduction - Variable charge reduction
Ancillary Services	- Black-start - RES generation smoothing	- Frequency regulation - Voltage support - Inertia services - Contingency reserve - Ramping reserve	- Grid support - Power quality - Power recovery following outage - Backup power
Infrastructure planning		- TN investment deferral - DN investment deferral	
System adequacy	- Peak capacity - RES firming		

Beyond energy shifting, large-scale battery **ESS** installations are increasingly regarded as critical infrastructure for maintaining grid reliability. They can provide a broad range of **ASs**, including frequency and voltage regulation, synthetic inertia, Fast Frequency Response (**FFR**), short-circuit current support, capacity adequacy, and black-start capability. At the distribution level, consumer-owned behind-the-meter storage systems contribute to localized flexibility through voltage control and congestion management. When appropriately aggregated, these distributed assets can also support system-wide balancing and **ASs** provision (IEA, 2024b).

The rapid expansion and diversification of battery storage applications is reflected in global deployment trends. Figure 2.1 illustrates worldwide utility-scale battery capacity additions by application type between 2018 and 2023 (IEA, 2024b).

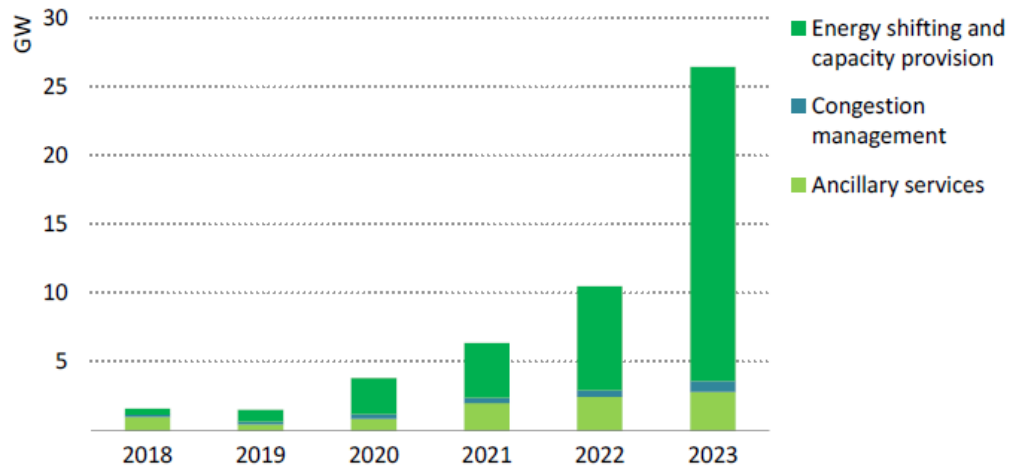


Figure 2.1: Utility-scale battery storage capacity additions by application (2018-2023). Source: IEA (2024b).

Governmental support for battery deployment is increasing worldwide through financial incentives and regulatory reforms. Within the European Union (EU), member states have collectively committed to approximately 45 GW of storage capacity by 2030. Several countries – including Sweden, Spain, Italy, and Germany – have implemented targeted measures such as the removal of double taxation and grid tariffs, while Greece and Italy have introduced long-term remuneration schemes to enhance investment certainty (IEA, 2024b). Despite these advances, battery storage investments remain capital-intensive and are often hindered by regulatory complexity and grid connection delays (Lawrence Berkeley National Laboratory, 2023).

Lithium-ion technology continues to dominate the global battery storage market due to its high efficiency and fast response. However, its limitations for long-duration storage have accelerated research into alternative chemistries, including redox flow, iron-air, and solid-state batteries. For seasonal or multi-day storage requirements, mechanical (e.g., pumped hydro, compressed air) and chemical (e.g., hydrogen-based) solutions are currently considered more suitable (Afreh et al., 2025).

Finally, geopolitical and supply-chain dependencies remain key concerns. The production and processing of critical minerals such as lithium, cobalt, and nickel are highly geographically concentrated – particularly in China – creating strategic vulnerabilities. To mitigate these risks, diversification of battery chemistries, improved recycling technologies, and circular-economy strategies are being actively pursued (McKinsey & Company, 2023). Recent European policy initiatives, including the *Critical Raw Materials Act* and the *Net Zero Industry Act*, exemplify efforts to strengthen supply-chain resilience for clean energy technologies (IEA, 2024b, 2025b,a).

2.1.1.2 Electric Vehicles

EVs have become central to both transport decarbonization and the provision of distributed flexibility services. Initially driven by policy incentives such as purchase subsidies and tax reductions, global EV adoption has expanded rapidly – from 4% of new car sales in 2020 to 18% in 2023 – largely propelled by growth in China and other advanced economies (IEA, 2024b). Figure 2.2 illustrates the evolution of global EV sales between 2010 and 2023 (IEA, 2024b).

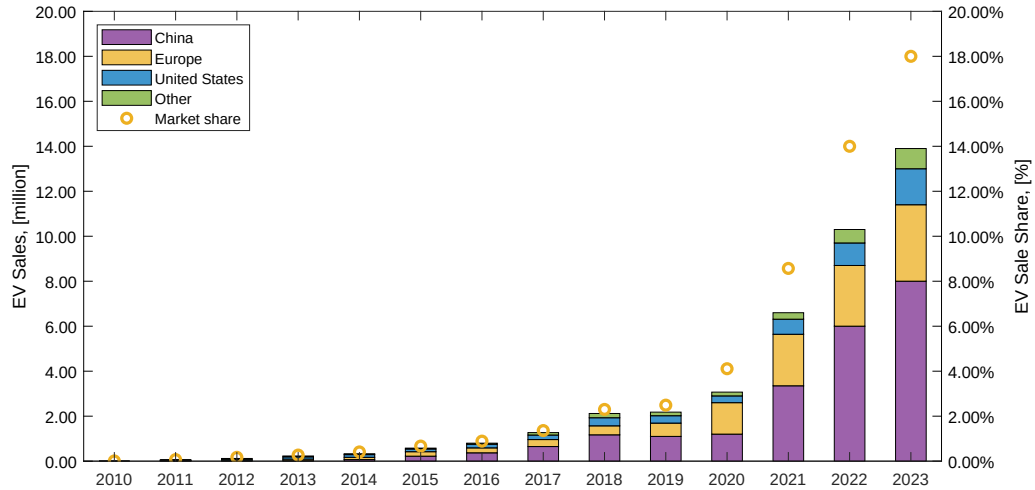


Figure 2.2: EV global sales, shown as total sales (left) and share of new vehicle sales (right) between 2010 and 2023. Source: IEA (2023a,d).

As markets mature, policy focus is increasingly shifting from demand stimulation toward strengthening the broader EV value chain. Emerging measures emphasize domestic manufacturing, battery recycling and second-life applications, and secure access to critical raw materials. These strategies aim not only to enhance industrial competitiveness, but also to improve supply-chain resilience and reduce dependence on a limited number of global suppliers (IEA, 2023f).

Although EVs currently account for less than 1% of global electricity demand, their increasing penetration is expected to have a significant impact on power system operation. Uncoordinated charging at scale can exacerbate local congestion and increase peak demand, potentially requiring costly network reinforcements. Conversely, when enabled by appropriate control technologies and market incentives, EVs can function as flexible and responsive loads, providing Demand Response (DR) services and enhancing overall system efficiency (IEA, 2025b). This duality has accelerated the deployment of smart charging solutions that enable controlled charging schedules and load shifting. Policy initiatives are reinforcing this trend: since 2022, the United Kingdom (UK) has mandated smart functionality in all new residential chargers, while the EU's *Alternative Fuels Infrastructure Regulation* requires all chargers installed or refurbished after April 2024 to support smart charging (IEA, 2025a).

Beyond smart charging, bidirectional charging allows EVs to discharge energy back to homes, buildings, or the grid, effectively functioning as mobile ESSs. This Vehicle-to-Grid (V2G) capability substantially expands their potential as flexible resources for both consumers and SOs. However, large-scale deployment remains uneven and highly dependent on regulatory clarity, market access, and suitable remuneration mechanisms. Aggregators are expected to play a pivotal role by pooling individual EVs and enabling their participation in energy and ASs markets. Table 2.2 summarizes the regulatory and technological measures adopted across major regions to support smart charging and V2G development (IEA, 2025b).

Table 2.2: Measures to enable smart charging and V2G across different world regions. Adapted from IEA (2025b).

Country	Market access and legal frameworks					Technology availability	
	Differentiated tariffs	Aggregators	Ancillary Services	Local flexibility	Standards and legal definitions	Smart charging deployment	V2G model availability
Brazil	✓	×	✓	×	⊗	✓	✓
Chile	⊗	⊗	×	×	⊗	⊗	✓
China	✓	⊗	✓	⊗	⊗	⊗	✓
Denmark	✓	⊗	⊗	×	⊗	✓	✓
Finland	✓	⊗	✓	✓	⊗	✓	✓
France	✓	⊗	×	✓	✓	✓	✓
Indonesia	✓	×	×	×	⊗	⊗	✓
Italy	✓	✓	×	×	✓	⊗	✓
Japan	✓	✓	⊗	×	✓	⊗	✓
Korea	✓	⊗	×	✓	⊗	⊗	✓
Netherlands	✓	✓	✓	✓	✓	✓	✓
South Africa	✓	✓	✓	×	⊗	✓	✓
United Kingdom	✓	✓	✓	✓	✓	✓	✓
United States	✓	⊗	⊗	⊗	⊗	⊗	✓
Thailand	✓	×	×	×	⊗	⊗	✓

✓ – Measures in place
 ⊗ – Field test/pilot phase, or measures announced
 × – No framework

Interoperability between EVs and charging infrastructure is essential for the widespread adoption of bidirectional charging. The CHAdeMO standard was among the first to introduce V2G communication protocols in 2010, setting an early benchmark for subsequent developments. Parallel standardization efforts are ongoing: the IEA’s *Electric Vehicle Technology Collaboration Programme Task 53* promotes global harmonization, while the International Electrotechnical Commission (IEC) has published detailed use cases describing the role of EVs as DERs. In parallel, automakers are forming strategic alliances – such as the ChargeScape initiative – to develop interoperable V2G solutions (IEA, 2025b).

From an operational perspective, battery degradation remains a key constraint for large-scale V2G deployment. Empirical studies indicate that frequent bidirectional cycling can accelerate battery aging, potentially reducing lifetime and undermining economic viability. Sustainable integration therefore requires control and market mechanisms that balance grid support with user value. Promising approaches include degradation-aware charging strategies, market designs that internalize battery aging costs, and incentive schemes that compensate users for additional wear (IEA, 2022a).

2.1.1.3 Heat Pumps

Battery-based ESSs, including EVs, are highly versatile and controllable sources of power system flexibility. However, their relatively high capital costs have stimulated growing interest in alternative, lower-cost forms of energy storage. One such option is the use of smart electric storage water heaters, which can effectively operate as *thermal batteries*. By heating water during off-peak periods and storing it for later use, these devices enable load shifting without compromising user comfort. With modest investments in digital control and communication capabilities, such appliances can be converted into DR resources, providing flexibility services at a fraction of the cost of electrochemical storage.

Heat pumps extend this concept while relying on fundamentally different thermodynamic principles. Rather than directly converting electricity into heat, as resistance heaters do, heat pumps transfer thermal energy from ambient sources (air, water, or ground), typically achieving efficiencies two to four times higher. This coupling with environmental heat enables both superior energy efficiency and direct decarbonization when powered by renewable electricity. Moreover, heat pumps are commonly integrated into broader Heating, Ventilation, and Air-Conditioning (HVAC) systems, providing combined space and water heating services that further increase their flexibility potential. Owing to their longer operating cycles and inherent thermal inertia, heat pumps are particularly well suited for load-shifting and peak-shaving applications. Nevertheless, technical limitations remain: compressor-based operation constrains their ability to deliver fast-response services, limiting their suitability for applications such as frequency regulation (IEA, 2022a).

Despite their efficiency and operational flexibility, several barriers continue to hinder the large-scale deployment of heat pumps. In many mature markets, extensive natural gas infrastructure for space and water heating reduces the economic attractiveness of retrofitting existing buildings, as heat pump installation often requires substantial modifications to heating systems. Upfront equipment and installation costs also remain relatively high compared with conventional gas or resistance-based solutions, particularly in older and less energy-efficient buildings. By contrast, new constructions provide more favorable conditions, as heat pump systems can be optimally designed for low-temperature operation and high overall efficiency (IEA, 2022b).

Policy frameworks and incentive schemes are increasingly addressing these barriers through financial support for retrofits, minimum performance standards, and requirements for renewable-based heating in new buildings. With continued technological progress, cost reductions, and growing regulatory and consumer support, heat pumps are progressively being recognized as cost-effective and sustainable solutions for decarbonizing end-use energy demand while simultaneously enhancing system-level flexibility (IEA, 2022b).

2.1.1.4 Electrolyzers

While battery-based ESSs are expected to play a central role in meeting short-term flexibility requirements, they are less suited for providing long-duration and seasonal energy storage. In this context, hydrogen and hydrogen-derived fuels have emerged as promising complementary solutions for addressing deep decarbonization and long-term system balancing needs.

Electrolyzers convert electricity into hydrogen through water electrolysis, enabling the storage of electrical energy in chemical form. The produced hydrogen can be stored over long periods and either re-electrified via fuel cells or directly utilized as a clean energy carrier across multiple sectors. Beyond direct applications in industry and transport, hydrogen also serves as a feedstock for synthetic fuels such as ammonia and methanol, which are increasingly explored for marine and aviation uses. When combined with fuel cells, electrolyzers enable a complete power-to-gas-to-power cycle that offers long-duration storage alongside operational flexibility. Electrolyzers are inherently well suited to operate as controllable loads, as they can rapidly change their electricity consumption in response to renewable generation variability, electricity market signals, or system needs. As such, they can contribute not only to seasonal energy balancing but also to fast-response ASs provision under appropriate market and control frameworks (IEA, 2025a).

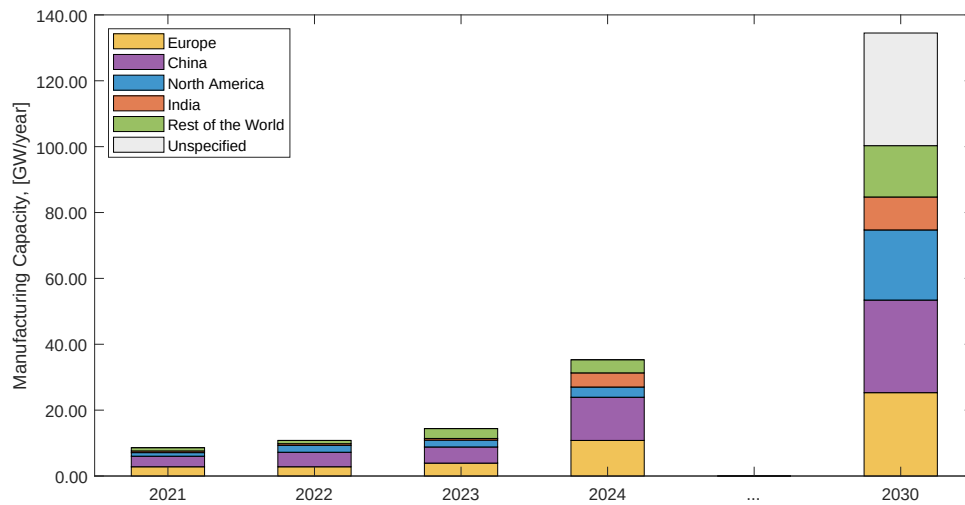


Figure 2.3: Electrolyzer manufacturing capacity by region. Source: IEA (2023a).

Several large-scale hydrogen projects have recently entered demonstration or early commercial phases. In May 2024, Fortescue’s *Green Pioneer* became the first vessel to operate using ammonia as a marine fuel, while major engine manufacturers – including Wärtsilä, WinGD, and Hyundai – have introduced ammonia-compatible propulsion systems. In parallel, innovative hydrogen production pathways are being explored: the Australian start-up Hazer commissioned the world’s first thermo-catalytic methane pyrolysis demonstration plant in 2024, with a capacity of 100 tonnes per year, and Finland’s Hycamite is developing a commercial-scale facility targeting 2 000 tonnes per year.

Despite this rapid progress, significant challenges remain. Electrolyzers remain capital-intensive, and their economic viability is strongly dependent on access to low-cost electricity, supportive regulatory frameworks, and stable long-term investment signals. Moreover, realizing the full system-level value of hydrogen-based flexibility requires coordinated development of the broader hydrogen value chain, including storage infrastructure, transport networks, and end-use applications (IEA, 2025a).

2.1.1.5 DER Aggregation

A key barrier to the large-scale deployment of **DR** is the voluntary nature of participation, combined with regulatory and market-access constraints that limit the ability of individual prosumers to provide flexibility services at scale. These limitations include minimum bid sizes, communication requirements, and transaction costs that are prohibitive for small-scale resources acting independently (Nezhad, 2025; Home-Ortiz et al., 2022; Gough et al., 2020). In this context, the aggregation of **DERs** has emerged as a key enabler for unlocking their full flexibility potential. By pooling heterogeneous assets – such as **ESSs**, **EVs**, heat pumps, and variable **RES** – aggregators can transform dispersed, small-scale resources into predictable and reliable sources of flexibility (IEA, 2022a).

A particularly prominent form of aggregation is the Virtual Power Plant (**VPP**), which enables heterogeneous **DERs** to operate collectively as a single dispatchable entity, analogous to a conventional power plant. In addition to providing **SOs** with services such as balancing, congestion management, and **ASs**, **VPPs** create economic value for **DER** owners by unlocking new revenue streams and cost-saving opportunities that often exceed those achievable through self-consumption alone. Aggregators play a pivotal role in this ecosystem, coordinating portfolios of distributed assets, optimizing their dispatch, and facilitating participation in wholesale and **ASs** markets (IEA, 2024b). Practical implementations of **DER** aggregation are emerging across multiple regions. In Australia, the Australian Energy Market Operator (**AEMO**) launched a **VPP** demonstration project in 2019 to assess the provision of balancing services and local voltage support from aggregated residential resources. In the United States of America (**USA**), Arizona Public Service has deployed a large-scale incentive program involving more than 50 000 smart thermostats and heat pumps, enabling peak shaving and load shifting. In Germany, a pioneering **VPP** integrates an electrolyzer that converts surplus wind generation into hydrogen, which is later re-electrified to support system balancing (IEA, 2022a).

Despite their considerable potential, **VPPs** and aggregation-based solutions continue to face barriers to widespread adoption. In many jurisdictions, regulatory frameworks and market rules remain misaligned with the operational characteristics of **DERs**, while remuneration mechanisms often favor self-consumption over the provision of system services. Fully realizing the value of **VPPs** will therefore require not only continued technological innovation, but also targeted reforms in market design and regulation (IEA, 2022a).

2.1.1.6 Interoperability

As increasing numbers of small and heterogeneous DERs participate in electricity markets and system operation, seamless and reliable data exchange among stakeholders becomes essential. TSOs, DSOs, DER owners, retailers, and aggregators must be able to exchange information in a standardized, interoperable, and interpretable manner to support coordinated decision-making, enhance transparency, and ensure fair and efficient market participation (EC, 2022).

Achieving interoperability, however, remains particularly challenging at the DER level due to the diversity of devices, communication protocols, and control architectures. Historically, many manufacturers have relied on proprietary technologies with limited consideration for standardization or cross-platform compatibility, resulting in fragmented communication ecosystems. This lack of harmonization has emerged as a major barrier to the large-scale integration of DERs, constraining their aggregation, control, and effective participation in electricity markets. In response, the EU has introduced a series of regulatory initiatives aimed at improving interoperability across the energy value chain. These measures promote standardized communication interfaces between DERs and higher-level control systems – such as Home Energy Management Systems (HEMSs) and Building Energy Management Systems (BEMSs) – and encourage the adoption of open communication protocols and common data models (EU, 2019a,b).

At the SO level, interoperability extends beyond device-level interfaces to the integration of operational and information technology systems supporting grid and market processes. This requires common data models and standardized, secure interfaces through which TSOs, DSOs, aggregators, and DER management platforms can exchange operationally relevant information across organizational boundaries (Valverde et al., 2027). These system-level requirements are discussed further in Section 2.6.

2.1.1.7 Data Privacy and Cybersecurity

As digitalization deepens and DERs become increasingly integrated into electricity markets and system operation, ensuring robust data privacy and cybersecurity has become a critical priority. Cyberattacks targeting power system infrastructure can have severe consequences, ranging from widespread service disruptions and financial losses to broader risks for national security. At the same time, the growing volume and granularity of consumer and operational data exchanged across the electricity value chain significantly increase exposure to data breaches and misuse. Vulnerabilities may arise at multiple points in the data ecosystem, including third-party service providers, retailers, aggregators, and SOs. To mitigate these risks, clear and enforceable rules governing data access, processing, and governance are essential (EC, 2023).

Despite the acknowledged importance of data protection, regulatory frameworks in many jurisdictions remain fragmented or ambiguous. In particular, it is often unclear

which categories of smart meter data may be accessed without explicit consumer consent, even by regulated **SOs** for essential grid operation and planning functions. Addressing this gap requires regulators to clearly define data ownership, access rights, and accountability structures, thereby enabling secure and transparent data sharing (EC, 2023). As emerging technologies – such as smart appliances, **EVs**, and **VPP** platforms – become increasingly integrated into power systems, new cyber and data-related vulnerabilities are expected to arise. Proactive and collaborative approaches involving regulators, **SOs**, technology providers, and cybersecurity experts are therefore essential to anticipate and mitigate evolving threats, ensuring the long-term security, reliability, and resilience of increasingly digitalized and decentralized energy systems (IEA, 2022a).

In this context, federated information architectures and distributed coordination schemes are particularly relevant, as they can limit exchanges to aggregated or boundary information, thereby preserving the operational autonomy of **TSOs**, **DSOs**, and market participants while reducing the disclosure of sensitive network, cost, and operational data (Valverde et al., 2027).

2.1.1.8 Compensation Mechanisms

Historically, wholesale energy and **AS** markets were designed around large, transmission-connected power plants. Unlocking the full flexibility potential of **DERs** therefore requires the development of appropriate compensation mechanisms that enable their effective and economically viable participation in system operation. Fair and transparent remuneration schemes are essential to align the operational behavior of **DER** owners with system needs, thereby strengthening grid reliability while improving the business case for distributed flexibility (IEA, 2022a).

Regulatory frameworks play a central role in enabling such mechanisms. For instance, updated Network Codes (**NCs**) can establish minimum performance, observability, and interoperability requirements for **DERs**, ensuring that their participation does not compromise system security. However, fully capturing the value of distributed flexibility requires broader regulatory and market reforms (IEA, 2022a), including:

- Revised retail pricing and distribution tariffs: Tariff structures that reflect the temporal and locational value of flexibility, providing appropriate price signals and fair compensation for **DER**-based services.
- Local flexibility markets: Market platforms that enable the transparent trading of **DER** services, allowing remuneration mechanisms to adapt to local network constraints and operational requirements.
- Integration of **DERs** into system planning: Explicit recognition of **DERs** as viable *non-wire alternatives* to conventional grid reinforcements, enabling investment decisions that account for their contribution to system adequacy, resilience, and cost efficiency.

Behind-the-meter resources typically monetize their flexibility through tariff-based incentives, aggregator-mediated participation models, or local flexibility markets. In contrast, utility-scale Flexibility Service Providers (**FSPs**) – such as large renewable plants or grid-connected storage systems – generally participate directly in wholesale markets, where they are remunerated for energy, balancing, and **ASs** provision. In the absence of well-designed compensation schemes, prosumers often prioritize self-consumption, leaving a significant share of flexibility underutilized. Coherent regulatory and market arrangements are therefore essential to ensure that both consumer-owned and utility-scale **DERs** are deployed and operated in a manner that maximizes their value – not only for individual participants, but for the electricity system as a whole (**IEA, 2022a**).

2.1.2 Energy Security and Resilience

Recent global events – including the Covid-19 pandemic, Russia’s invasion of Ukraine, the 2022–2023 global energy crisis, and ongoing geopolitical instability in the Middle East – have exposed critical vulnerabilities in the global energy system. These shocks have underscored the strong interdependence between energy security, geopolitical stability, supply chain resilience, and the reliability of electricity networks. In response, governments have accelerated efforts to strengthen energy security through large-scale investments in **RESs**, domestic clean technology supply chains, and grid modernization (**IEA, 2023c**).

In this evolving context, the traditional “energy trilemma” of *sustainability*, *security*, and *affordability* is evolving to encompass broader priorities such as *climate resilience*, *technological sovereignty*, and *geopolitical stability*. This evolution reflects the growing recognition that the clean energy transition must not only reduce emissions but also withstand shocks arising from conflicts, pandemics, supply disruptions, and climate-induced extreme events. Meanwhile, as global demand for energy services continues to rise, resource-rich countries seek to maximize the value of their natural resources, while energy-importing nations must safeguard affordable and resilient supply chains. In this context, diversification of both energy sources and technology supply chains – particularly in manufacturing capacity and access to critical minerals – has become a cornerstone of modern energy security strategies (**IEA, 2023c**).

Battery-based **ESSs** are expected to play a central role in future power systems, yet their large-scale deployment depends on secure access to critical minerals such as lithium, nickel, cobalt, and graphite. The extraction, refining, and processing of these materials are highly geographically concentrated, creating significant vulnerabilities in global supply chains. While mining activities are dominated by a limited number of countries, refining capacity is even more concentrated, with China controlling the majority of global processing for most battery-relevant minerals. This concentration amplifies exposure to geopolitical risks and trade disruptions, making supply security a key concern for the clean energy transition. Figure 2.4 illustrates the share of the top three countries in the extraction and refining of critical minerals for battery **ESSs** in 2023 (**IEA, 2024b**).

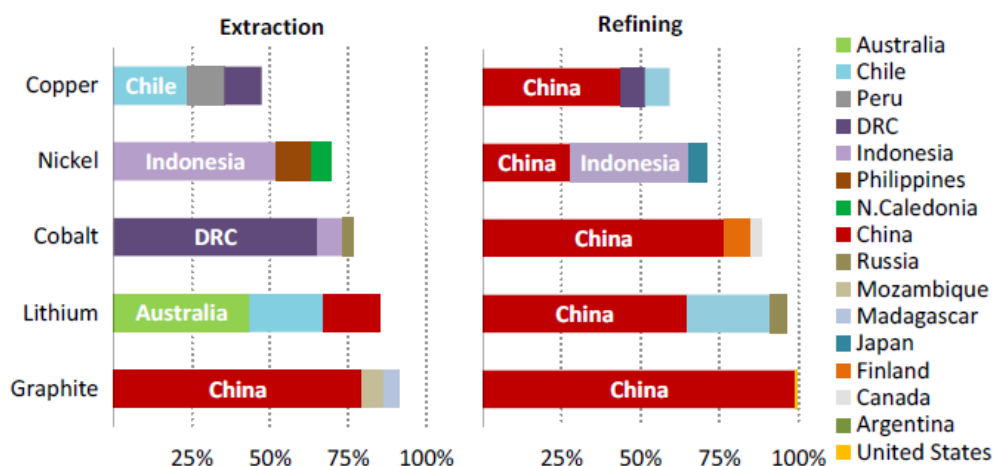


Figure 2.4: Share of the top-three countries in extraction and refining of critical minerals for battery ESS in 2023 (IEA, 2024b).

This dependency is unlikely to diminish in the near term: approximately 70–75% of projected growth in refined lithium, nickel, and cobalt production until 2030 is expected to originate from today’s top three producers. Addressing this structural vulnerability will therefore require coordinated global action, including: (i) accelerated development of alternative battery chemistries and clean technologies; (ii) expanded recycling and circular-economy infrastructures to reduce reliance on primary raw materials; and (iii) the establishment of strategic reserves and regional partnerships to mitigate supply disruptions. Together, these measures are essential not only for securing access to clean technologies, but also for strengthening the resilience and stability of the global energy system amid rising geopolitical uncertainty (IEA, 2025a, 2023c).

Beyond supply chain risks, regulatory and financial barriers remain major obstacles to the large-scale deployment of clean energy technologies. These challenges arise both directly – through restrictive or fragmented regulation – and indirectly, by limiting viable business models and investment incentives. The absence of consistent, long-term policy signals increases investor uncertainty, while abrupt regulatory changes or the withdrawal of support schemes can destabilize emerging markets. In addition, lengthy permitting and certification procedures frequently delay project development and increase upfront costs, further undermining investor confidence. These challenges have been exacerbated by recent macroeconomic conditions. Rising global interest rates have significantly increased the cost of capital, with particularly severe impacts in emerging and developing economies, where electrification progress depends critically on affordable financing. Table 2.3 summarizes the relative risk profiles associated with the deployment of major clean energy technologies (IEA, 2023b).

Minimizing risks across these dimensions is essential to achieving a secure, affordable, and timely energy transition. Governments and industry stakeholders play a pivotal role in de-risking clean energy deployment through coordinated action across policy, markets, and

Table 2.3: Primary risks associated with clean technologies. Adapted from IEA (2023b).

	Wind Power	Solar PV	Nuclear Power	Battery Storage	Demand Response	Electric Grids	Electric Vehicles	Heat Pumps
Regulatory and Policy								
Regulatory Frameworks	Medium	Low	Medium	Medium	High	Medium	Medium	Medium
Policy Support	Low	Low	Medium	Low	High	Low	Low	Low
Permitting and Certification	Medium	Medium	High	Low	Low	High	Medium	Low
Supply Chain								
Critical Minerals	High	Medium	Low	High	Low	Medium	High	Low
Manufacturing	High	Low	Medium	Medium	Low	Low	Low	Medium
Skilled Labor	Medium	Medium	High	Low	Low	High	Low	Medium
Financial								
Costs of financing	High	Medium	High	Medium	Low	High	Medium	Medium
Revenue and Savings Predictability	Medium	Low	Low	Medium	Medium	Low	Low	Low
Overall	High	Low	Medium	Medium	Medium	High	Low	Medium

value chains. This includes providing long-term regulatory stability, enabling transparent and predictable market frameworks, diversifying clean technology supply chains, and improving access to affordable financing. Progress across all domains is critical: weaknesses in regulation, infrastructure, or capital availability can quickly become systemic bottlenecks. By adopting an integrated and forward-looking approach, policymakers and industry leaders can ensure that clean energy technologies contribute effectively to a resilient, secure, and cost-efficient energy system capable of withstanding both economic shocks and geopolitical uncertainty (IEA, 2023b).

2.1.3 Policy Progress

The energy sector remains a cornerstone of national and international innovation strategies. To accelerate the clean energy transition, governments are deploying a broad portfolio of policy instruments tailored to different stages of technology readiness, market maturity, and regional development. These frameworks typically combine financial support, regulatory facilitation, and market-based incentives to reduce investment risk, lower entry barriers, and mobilize private-sector investments (IEA, 2025a).

Public intervention is particularly critical at the R&D&I stage, where early experimentation and technology validation are characterized by high uncertainty, long development cycles, and limited commercial attractiveness. To address these challenges, governments rely on targeted instruments such as research grants, tax incentives, and funding for academic-industrial collaboration, as well as access to specialized testing and demonstration infrastructures. Such measures are essential to support innovation by Small and Medium-sized Enterprises (SMEs) and emerging technology providers. At the European level, this approach is reflected in flagship initiatives including the *European Innovation Council Trusted Investors Network* and the *InvestEU Advisory Hub* (IEA, 2025a).

The effectiveness of these innovation ecosystems ultimately depends on strong coordination among researchers, policymakers, investors, and end-users. Public policy plays a central role in fostering this coordination by facilitating knowledge transfer and ensuring that research outcomes are translated into scalable commercial solutions. In parallel, governments must address cross-cutting barriers – such as skills shortages, labor market mismatches, and public acceptance of emerging technologies – that can otherwise hinder deployment. By aligning financial, regulatory, and societal instruments, policy frameworks can accelerate the scaling of clean energy technologies while strengthening competitiveness, inclusiveness, and long-term system resilience (IEA, 2025a).

2.2 TSO-DSO Coordination

In response to the operational challenges introduced by the energy transition, policymakers and regulators are increasingly emphasizing the need for stronger coordination between TSOs and DSOs. European regulatory frameworks and strategic initiatives explicitly call for coordinated operational schemes that better align transmission and distribution system management (Council of European Union, 2017). The overarching objective is to ensure the efficient use of system resources, facilitate the large-scale integration of RESs, and maintain secure and reliable power system operation under conditions of growing decentralization, uncertainty, and variability.

Despite these ambitions, practical TSO–DSO cooperation remains limited. Historically, transmission and distribution networks have been operated largely independently, with minimal real-time interaction and clearly delineated responsibilities. TSOs have traditionally focused on bulk system operation and security, while DSOs were primarily tasked with ensuring reliable electricity delivery at the distribution level. This separation, while effective in centralized systems, is increasingly misaligned with the operational realities of modern power systems. The transition toward decarbonized, decentralized, and digitalized electricity systems is fundamentally reshaping this long-standing division of roles. As prosumers and DERs become active participants in energy and ASs markets, DSOs are evolving from passive network operators into active system managers and key intermediaries between DERs and TSOs. In this expanded role, DSOs are expected to enable the mobilization of distribution-level flexibility in support of both local network constraints and system-wide reliability objectives (D’Adamo et al., 2019).

Within this evolving landscape, effective TSO–DSO coordination has become indispensable. Coordinated operational schemes provide the means to align local and system-level decision-making, avoid conflicting control actions, and unlock the full value of distributed flexibility. As such, TSO–DSO coordination is not merely a technical enhancement, but a foundational pillar for the secure, efficient, and resilient operation of future power systems.

2.2.1 Coordination Mechanisms

Coordination mechanisms between **TSOs** and **DSOs** can be broadly distinguished according to how decision-making authority, market clearing, and information exchange are organized across network levels. In centralized schemes, the coordination problem is cleared by a single entity, such as the **TSO** or an independent Market Operator (**MO**), using information from the participating transmission- and distribution-level systems. Such arrangements can provide high economic efficiency, but may require extensive information exchange and detailed representation of multiple networks, raising concerns regarding scalability, data confidentiality, computational burden, and institutional feasibility.

In decentralized or distributed schemes, operational and market decisions remain separated among the participating **SOs**. Coordination may be achieved through sequential market clearing, exchange of interface quantities, prequalification procedures, or iterative distributed optimization. These arrangements preserve greater operational autonomy and limit information disclosure, although their efficiency depends strongly on the adopted coordination rules, market sequence, and representation of cross-network interactions.

Gerard et al. (2018), within the framework of the SmartNet project, established five **TSO–DSO** coordination mechanisms that have since become a widely used reference framework and benchmark for subsequent studies in this field:

1. Centralized **AS** market model (centralized scheme): A single market exists for **FSPs** connected at both **TN** and **DN** levels. The **TSO** is solely responsible for system and market operation, procuring services directly from all **FSPs**. **DSOs** do not participate in flexibility procurement or market operation.
2. Local **AS** market model (decentralized scheme): Separate markets operate for **TN**- and **DN**-connected resources. **DERs** first participate in local markets operated by **DSOs**. Any non-procured flexibility is then aggregated and offered into the global market operated by the **TSO**.
3. Shared balancing responsibility model (decentralized scheme): **DSOs** are fully responsible for balancing their local grids, relying solely on local **DERs**. They adhere to pre-defined schedules at the **TN–DN** interface, without sharing **DERs** services with the **TSO**.
4. Common **TSO–DSO AS** market model:
 - (a) Centralized variant: All bids from **FSPs** are submitted to a single market session. Unlike the centralized **AS** market model, **DSOs** also procure flexibility services within the same clearing process as the **TSO**.
 - (b) Decentralized variant: Local markets, operated by **DSOs**, are cleared first, and results are passed on to the **TSO**. However, unlike the local **AS** market model, **DSOs** do not have priority in using local **DERs**.

5. Integrated flexibility market model (centralized scheme): A common market is established for both **TN**- and **DN**-connected resources. Its distinguishing feature is the inclusion of commercial market participants, who can procure flexibility services alongside **TSOs** and **DSOs**, broadening market participation.

These five mechanisms constitute the original SmartNet reference framework and remain useful for describing the fundamental allocation of roles among **TSOs**, **DSOs**, **MOs**, and flexibility providers. However, they should be understood as foundational archetypes rather than as the current definitive taxonomy of **TSO-DSO** coordinated flexibility markets. Their design was subsequently refined through the CoordiNet and OneNet projects, with increasing emphasis on flexibility sharing across voltage levels, sequential market clearing, grid-safety assessment, bid forwarding, and practical implementation (Valverde et al., 2027).

Givisiez et al. (2020) sought to simplify these approaches into three fundamental models. This reclassification aims to provide a clearer conceptual structure, emphasizing the roles and responsibilities of **TSOs** and **DSOs** in managing distributed flexibility:

1. **TSO**-managed model: centralized coordination scheme. **TSO**, or an Independent Market Operator (**IMO**), is responsible for dispatching **FSPs** at both **TN** and **DN** levels, explicitly accounting for **DN** constraints. The role of **DSOs** is mainly supportive, providing real-time operational data from their networks.
2. **TSO-DSO** hybrid-managed model: also a centralized scheme, where the **TSO** dispatches all **FSPs** but does not explicitly model **DN** constraints. Instead, **DSOs** validate **DER** bids before they enter the market, ensuring that flexibility provision does not compromise **DN** operation.
3. **DSO**-managed model: two variants are proposed, centralized and decentralized. In the centralized version, a single market exists where the **TSO** dispatches **TN**-connected and aggregated **DN**-connected resources. In the decentralized version, local markets are established and operated directly by **DSOs**, who validate bids and forward them to the **TSO**, acting as central coordinators of **DERs**.

The CoordiNet project further advanced the development of collaboration schemes by placing stronger emphasis on real-world demonstrators, regulatory feasibility, and the operational deployment of flexibility markets – particularly for congestion management purposes. Building upon the coordination mechanisms established in the SmartNet project, CoordiNet proposed a total of seven **TSO-DSO** coordination models (CoordiNet, 2021):

1. Local market model: A single market designed exclusively to address local flexibility needs. Unlike SmartNet’s local **AS** model, no interaction with a central market is assumed, and no market-based coordination between **TSO** and **DSO** is envisioned.

2. Central market model: Flexibility is procured solely for central system needs, with the **TSO** acting as the sole buyer. The **DSO** has no explicit market role, making this model closely aligned with SmartNet’s centralized **AS** market.
3. Common market model: Both **SOs** procure flexibility through a single common market that simultaneously addresses **TN**- and **DN**-level needs. In contrast to the previous models, **DSOs** actively participate in securing flexibility for local operation.
4. Integrated market model: Similar to SmartNet’s integrated flexibility market, this scheme extends the common market by allowing commercial market participants to procure flexibility alongside the **TSO** and **DSOs** on a unified platform.
5. Multi-level market model: A layered structure combining local and central markets. The **DSO** first procures flexibility locally, and any uncontracted bids are subsequently forwarded to the central market operated by the **TSO**. This resembles SmartNet’s local **AS** model, with a stronger emphasis on hierarchical coordination.
6. Fragmented market model: Also featuring separate local and central markets, but the **TSO** cannot access **DERs**. This configuration is conceptually aligned with SmartNet’s shared balancing responsibility model.
7. Distributed market model: Introduces a fully decentralized Peer-to-Peer (**P2P**) market architecture in which participants act as both buyers and providers of flexibility, establishing bilateral exchanges without centralized market clearing.

The distributed market model represents a distinctive extension of the more conventional centralized and sequential market structures considered in CoordiNet. By leveraging **P2P** trading architectures, it challenges traditional centralized and hierarchical market designs. However, realizing such a paradigm would require a fundamental redesign of regulatory frameworks, market architectures, and data exchange protocols to ensure interoperability, transparency, and system security. While **P2P** markets are beginning to emerge within local energy communities, their scalability, integration with wholesale markets, and long-term role in future power systems remain open research and regulatory questions (CoordiNet, 2021).

More recent work has consolidated these developments into four main market structures: disjoint, common, multilevel, and fragmented markets (Valverde et al., 2027). In the disjoint model, each **SO** procures flexibility solely from resources connected to its own network, without either direct or indirect flexibility sharing across voltage levels. At the opposite end of the spectrum, the common market jointly clears the needs of all participating **SOs** using a common pool of flexibility resources while accounting for the constraints of all networks involved. The multilevel and fragmented models adopt sequential clearing structures. In the multilevel model, unused distribution-level bids are forwarded to the transmission-level market, allowing the **TSO** to access distribution-connected flexibility

directly. In addition, distribution-level procurement may modify the power exchanged at the TSO–DSO interface, resulting in indirect flexibility sharing. In the fragmented model, unused distribution-level bids are not forwarded, and the TSO therefore has no direct access to distribution-connected flexibility. Coordination occurs only indirectly, as changes in interface exchanges resulting from local procurement are subsequently handled at the transmission level. This classification therefore refines the earlier SmartNet framework by explicitly distinguishing the form of flexibility sharing and the interaction between market layers.

Other EU projects have also proposed TSO–DSO coordination mechanisms, often targeting specific market products or operational functions, for example:

- FutureFlow introduced a scheme to open balancing, redispatch, and reserve markets to new flexibility sources. A central aggregation platform was developed to allow Distributed Generation (DG) and commercial or industrial consumers to participate in DR markets, consistent with the common TSO–DSO AS market model (FutureFlow, 2019).
- EU-SysFlex examined two procurement approaches: a regulated model requiring specific resources to provide ASs, and a market-based model enabling broader participation by FSPs. It also compared two organizational structures – a centralized market aligned with SmartNet’s centralized common model, and a decentralized market similar to SmartNet’s local AS market model (EU-SysFlex, 2020).
- evolvDSO proposed dual markets, with TSOs operating for transmission-connected resources and DSOs for distribution-connected ones, reflecting SmartNet’s local AS market model (evolvDSO, 2015).
- GOFLEX established separate transmission and distribution markets. In this framework, TSOs procure flexibility through reserve markets, while DSOs act as sole buyers in local markets responsible for congestion management and local balancing, consistent with SmartNet’s shared balancing responsibility model (GOFLEX, 2019).

Centralized coordination mechanisms are widely recognized as difficult to deploy in real-world power systems due to several regulatory and privacy constraints. These include scale and complexity of electricity networks, limited observability of distributed resources, and the high computational burden of jointly managing TN and DN operations (Gerard et al., 2018). As a result, such schemes have largely remained theoretical benchmarks, used primarily for comparative analysis rather than operational implementation. To alleviate these limitations, several mitigation strategies have been proposed, including bid pre-qualification by DSOs (Le Cadre et al., 2019), decomposition-based solution techniques (Neuhoff et al., 2018), and simplified or relaxed Power Flow (PF) formulations (Le Cadre et al., 2019; Najibi et al., 2021).

As a result, most recent research has shifted toward decentralized coordination approaches, which are generally regarded as more practical for implementation. Nonetheless, these models introduce their own challenges that must be addressed to ensure reliable and efficient operation:

- **Data management:** information exchange among multiple agents (e.g., **TSO**, **DSOs**, aggregators, and **FSPs**) raises concerns related to data privacy, cybersecurity, and data governance. Robust and reliable Information and Communication Technologies (**ICT**) infrastructure is essential to ensure effective and secure data sharing.
- **Computational requirements:** while decentralization alleviates the computational burden on individual **SOs**, the overall framework must still ensure scalability and real-time performance when coordinating large numbers of participants. Algorithmic efficiency and interoperability remain key design criteria.
- **Operational efficiency:** decentralized coordination must deliver near-optimal system outcomes – minimizing operating costs, mitigating congestion, and facilitating higher **RES** integration – while promoting the active participation of **DERs** across both local and system-wide markets.

In summary, while centralized coordination offers theoretical optimality, its practical limitations significantly constrain real-world adoption. Decentralized approaches, by contrast, provide greater scalability, modularity, and regulatory compatibility; however, their successful deployment depends on the careful design of data exchange mechanisms, computational architectures, and coordination strategies capable of ensuring secure, scalable, and economically efficient system operation.

2.2.2 Demonstration Pilots

Real-world demonstration pilots play a critical role in translating conceptual **TSO–DSO** coordination frameworks into operational practice. While numerous coordination models have been proposed in the literature, their practical feasibility depends on validation under real network conditions, where technical, regulatory, and market complexities interact.

The SmartNet project represented a major step toward testing the practical implementation of **TSO–DSO** coordination. Three pilot demonstrations were carried out, each focusing on different coordination mechanisms ([Gerard et al., 2018](#)):

- **Centralized AS market model (Italy):** Hydroelectric power plants, acting as distributed **FSPs**, provided reactive power for voltage regulation at the **TN** level. The pilot successfully demonstrated the capability of the **TSO** to directly harness distributed resources for system-wide voltage control.
- **Common TSO–DSO AS market model (Denmark):** The pilot targeted **DSO** congestion management and **TSO** frequency control, using water pumps in swimming pools

as **FSPs**. Both direct operator control and indirect price-based signals were tested. Results showed that coordinated operation can reduce operational costs and **GHG** emissions while enabling **DERs** to provide multiple services.

- Shared balancing responsibility model (Spain): **TSO** and **DSO** jointly coordinated power flows using the flexibility of **ESSs** to mitigate congestion, demonstrating the potential of shared responsibility schemes.

From these pilots, two critical success factors for effective coordination were identified. First, robust and reliable **ICT** infrastructures are indispensable to meet the stringent operational and reliability requirements of **TSOs**. Second, appropriate compensation mechanisms for **DERs** are essential to secure active prosumer participation and ensure that flexibility is mobilized efficiently and sustainably (Andren et al., 2019).

Building on these findings, the CoordiNet project further advanced the practical implementation of **TSO-DSO** coordination through extensive field demonstrations across multiple European countries. Its primary objective was to evaluate the performance of different coordination models under real-world conditions, with particular emphasis on flexibility procurement for congestion management (CoordiNet, 2020):

- Common market model (Spain): A centralized congestion management market was tested, starting with the estimation of flexibility needs from both **TSOs** and **DSOs**, followed by identification of available **DERs**. Through a centralized platform, **SOs** and **FSPs** could openly publish flexibility needs and offers, promoting efficient resource allocation and market transparency (Utrilla et al., 2020).
- Fragmented market model (Sweden): Local and regional flexibility was procured by **DSOs** to control power flows at multiple grid interfaces (local-regional **DN** and regional **DN-TN**). The mechanism aimed at preventing interface power flows from exceeding predefined subscription limits, ensuring secure operation under high **DER** penetration (Gürses-Tran et al., 2020).
- Multi-level market model (Greece): A layered market scheme was tested. First, the local **DSO**-level market was cleared to ensure subscription limits at the local-regional interface were respected. Remaining flexibility bids were then forwarded to the regional market, where they could be used to manage interactions between the regional **DSO** and the **TSO** (Savvopoulos et al., 2021).

The CoordiNet demonstrations provided valuable insights into the operational feasibility of different **TSO-DSO** coordination schemes, illustrating how market structures can be adapted to diverse regulatory frameworks and system conditions. In addition to the SmartNet and CoordiNet projects, other European initiatives have tested **TSO-DSO** coordination mechanisms through real-world pilots. EU-SysFlex demonstrated a local **AS** market model in Germany, where the **DSO** MITNETZ STROM assessed active and reactive

power flexibility within the **DN** and communicated the results to the **TSO** 50Hertz through Active-Reactive power (**PQ**) maps. The **TSO** then leveraged this flexibility for congestion management and voltage control. To support this process, a software platform based on Common Information Model (**CIM**)-Common Grid Model Exchange Standard (**CGMES**) standards was deployed (Staudt et al., 2019).

2.3 TSO-DSO Coordinated Operation Tools

A broad range of operational tools has been proposed to support **TSO-DSO** coordination across planning and real-time operation horizons. These tools aim to enhance decision-making, improve system reliability, and enable the efficient integration of **DERs** into power system operation. While early approaches largely relied on rule-based or heuristic strategies, most contemporary coordination frameworks are formulated as optimization problems, with **OPF**-based models serving as their computational backbone.

The design of effective coordination tools requires careful consideration of several interrelated aspects that determine their practical applicability and long-term value:

- Coordination effectiveness and efficiency: Coordination mechanisms must deliver tangible operational benefits – such as cost reduction, congestion relief, and increased **RES** integration – while limiting procedural complexity and computational burden.
- Data exchange and sensitivity: Effective coordination depends on extensive information sharing among multiple agents, including **TSOs**, **DSOs**, and **FSPs**. Data privacy, cybersecurity, and governance critically influence what data can be exchanged, at what level of detail, and under which institutional arrangements.
- Network modeling and scalability trade-offs: The level of detail adopted in representing **TN** and **DN** components directly affects both model accuracy and computational tractability. Detailed network representations provide higher fidelity but can be computationally intensive, whereas simplified formulations improve scalability at the potential cost of overlooking critical operational constraints.

Overall, effective **TSO-DSO** coordination tools must strike a careful balance between optimization accuracy, data protection, and computational scalability. Achieving this balance requires the integration of advanced optimization techniques with secure and efficient data exchange protocols, supported by appropriate modeling abstractions.

The choice of solution techniques for implementing a coordination model depends strongly on the characteristics of the underlying coordination framework. A method well-suited for one approach may not be directly transferable to another without significant adaptation. In practice, these techniques are implemented using different optimization paradigms, which can be broadly categorized as follows (Givisiez et al., 2020):

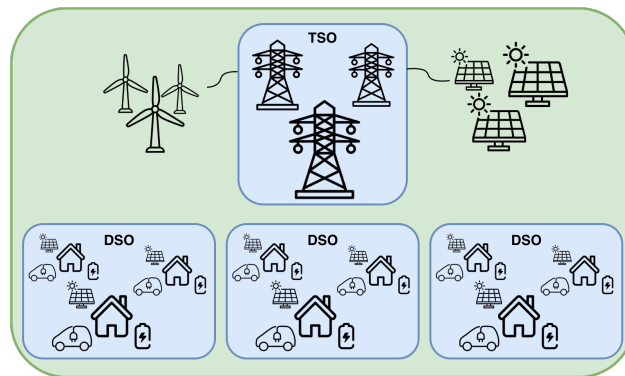
- Centralized optimization: The coordination problem is formulated and solved as a single large-scale optimization model, encompassing all system variables and constraints within a unified framework.
- Hierarchical optimization: The problem is decomposed into subproblems organized in a hierarchical (leader–follower) structure, where each subproblem is locally solved, and the optimization outcomes are communicated to higher-level decision layers.
- Distributed optimization: the problem is decomposed into subproblems that operate on local copies of shared (coupling) variables (e.g., power flows, voltages). Through iterative exchanges of these variables, subproblems converge to a consensus solution.

Although, in theory, these optimization paradigms can be applied to all TSO–DSO coordination models, their practical implementation must account for factors such as computational tractability, data privacy, regulatory compliance, and the capabilities of the underlying ICT infrastructure. In practice, centralized optimization is most often applied in studies of centralized market structures, such as SmartNet’s centralized AS market model or the TSO-managed model proposed by [Givisiez et al. \(2020\)](#). Hierarchical optimization, by contrast, is typically adopted in local market-based schemes that follow a leader–follower structure, as seen in SmartNet’s local AS market model or in hybrid TSO–DSO coordination arrangements. Distributed optimization is particularly relevant to fully decentralized designs, where no hierarchical control is assumed, as exemplified by the distributed market model developed within the CoordiNet project ([CoordiNet, 2021](#)). Comparative analyses by [Zhao et al. \(2019a\)](#) and [Le Cadre et al. \(2019\)](#) indicate that decentralized strategies are generally more promising for real-world implementation, offering superior scalability, stronger protection of sensitive data, and greater adaptability to diverse regulatory environments. Figure 2.5 provides a conceptual overview of the three optimization paradigms commonly used to implement TSO–DSO coordination frameworks.

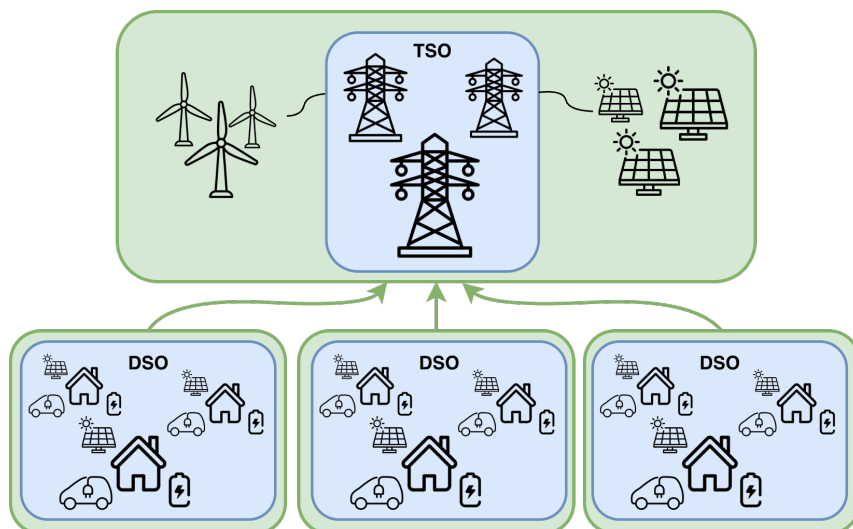
2.3.1 Centralized Frameworks

Centralized frameworks constitute some of the earliest approaches to TSO–DSO coordination. They are typically formulated as co-optimization problems in which an IMO centrally dispatches flexibility resources connected to both the TN and the DN. Such formulations assume full system observability, including complete knowledge of network topology, operational constraints, and resource characteristics. As a result, centralized models are predominantly used as benchmark references against which decentralized coordination schemes are evaluated.

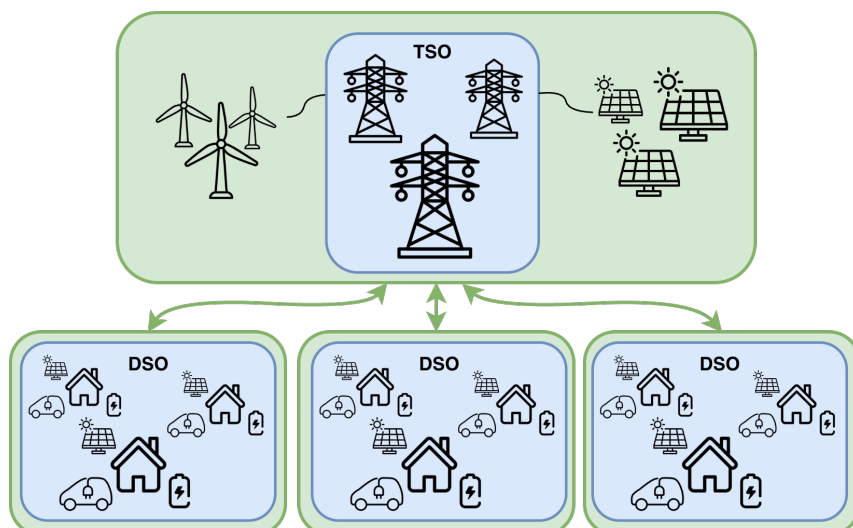
[Le Cadre et al. \(2019\)](#) introduce a centralized co-optimization framework based on the common AS market model. To mitigate scalability challenges, their approach relies on a linearized PF formulation for the TN and a Second-Order Cone Programming (SOCP)



(a) Centralized optimization.



(b) Hierarchical optimization.



(c) Distributed optimization.

Figure 2.5: TSO-DSO coordinated operation. Illustration of solution techniques.

relaxation for the **DN**. Similarly, [Chang and Moser \(2020\)](#) develop a centralized benchmark using linearized network representations derived from Sensitivity Coefficients (**SCs**). Centralized coordination has also been extended to multi-objective settings to reconcile potentially conflicting **TSO** and **DSO** objectives. [Najibi et al. \(2021\)](#) propose a formulation in which the **TSO** minimizes system operating costs while **DSOs** prioritize voltage deviation mitigation and activation cost reduction. The problem is solved using a weighted-sum approach, employing a Direct Current (**DC**)-**PF** approximation for the **TN** and an **SOCP** relaxation for the **DN**. A related multi-objective formulation based on Mixed-Integer Linear Programming (**MILP**) is presented by [Grøttum et al. \(2019\)](#).

Despite these methodological advances, centralized coordination approaches remain largely confined to theoretical analysis and benchmarking studies. Even when linear approximations or convex relaxations are employed, their computational burden becomes prohibitive for large-scale systems. More importantly, many centralized formulations omit critical features required for realistic operation and planning, including explicit treatment of uncertainty in load and **RES** forecasts, multi-period dynamics essential for modeling energy storage and flexible resources, and security considerations such as $N - 1$ criteria. Collectively, these limitations substantially restrict the practical applicability of centralized frameworks, reinforcing their role as conceptual reference models rather than deployable solutions for real-world power system coordination.

2.3.2 Hierarchical Frameworks

Centralized optimization approaches rapidly become computationally intractable as the number of controllable assets, **DERs**, and network buses increase. This limitation has driven growing interest in hierarchical frameworks, which structure **TSO-DSO** interaction through layered decision-making processes. By decomposing responsibilities across system levels, these frameworks preserve the operational autonomy and data privacy of each **SO** and offer improved scalability compared to fully centralized models.

[Le Cadre et al. \(2019\)](#) propose two hierarchical coordination schemes based on the shared balancing responsibility and local **AS** market models, formulated as a simultaneous non-cooperative game and a Stackelberg game, respectively. Both approaches adopt linearized **PF** models at the **TN** level and **SOCP** relaxations at the **DN** level. Although these schemes are less efficient than a fully centralized benchmark, the shared balancing responsibility model achieves performance close to the centralized solution, highlighting its potential as a scalable alternative. Building on this work, [Capitanescu \(2018a,c, 2024\)](#) extends hierarchical coordination to short-term operational planning by introducing **PQ** capability maps to characterize Active Distribution Network (**ADN**) flexibility at the **TN-DN** interface. **PQ** maps provide a compact and computationally tractable representation of **DN**-level flexibility and have been widely applied in decision-making problems such as congestion management, security assessment, and voltage control ([Schwerdfeger et al.,](#)

2016; Contreras et al., 2021; Stock et al., 2018; Stanković et al., 2021). Their primary limitation lies in their inability to capture inter-temporal dynamics of ESSs and FLs, which reduces their suitability for multi-period coordination contexts. A detailed discussion of the PQ map methodology is provided in Subsection 2.3.4.

Several studies extend hierarchical schemes into multi-stage coordination frameworks. Alizadeh et al. (2022) propose a three-step process for active power procurement comprising: (i) DSOs' flexibility characterization at the TN–DN interface, (ii) centralized TSO procurement of ASs, and (iii) DSOs' local redispatch of ADNs. This approach was later extended to reactive power provision (Alizadeh et al., 2023) and joint active–reactive power flexibility under uncertainty (Usman et al., 2023). Other examples include dual-horizon rolling OPF scheduling (Saint-Pierre and Mancarella, 2017) and coordinated Unit Commitment (UC) (Dzikowski, 2020). In a related contribution, Hinnners et al. (2019b,a) introduce a framework based on shared balancing responsibility and Smart Power Cells (SPCs) concept, partitioning the network into semi-autonomous areas to reduce coordination complexity while preserving operational independence. Uncertainty has been addressed through Robust Optimization (RO) for reactive power support (Li et al., 2019b), Stochastic Programming (SP) for congestion management (Soares et al., 2020), and Chance-Constrained Optimization (CCO) for OPF (Tang et al., 2021). More recent work explores data-driven approaches: Morales et al. (2022) infer ADN flexibility from historical Locational Marginal Prices (LMPs), while Wang et al. (2024b) apply multi-agent Reinforcement Learning (RL) to enable EV-based voltage and frequency support. Despite their promise, these methods raise concerns regarding data privacy and governance.

Hierarchical frameworks currently dominate the literature as the most practical approach for coordinating TSO–DSO operations. However, further advances are required to accurately represent ADNs in coordinated operational settings (Pozo, 2025). Key challenges include the development of secure and standardized data exchange mechanisms, the protection of sensitive information, and the faithful representation of the dynamic flexibility of DERs – particularly ESSs and FLs.

2.3.3 Distributed Schemes

Distributed coordination schemes decentralize system operation by allowing both TSO and DSOs to retain control over their respective networks. These frameworks rely on iterative information exchange and local decision-making, minimizing the need for centralized oversight. As a result, they offer distinct advantages in terms of scalability, data privacy, and compatibility with existing regulatory requirements (Gerard et al., 2018).

Most distributed coordination approaches in the literature rely on mathematical decomposition techniques. Mohammadi et al. (2019) propose an Analytical Target Cascading (ATC)-based framework to solve a coordinated Alternating Current (AC)-OPF, using interface voltages as coupling variables. The TSO problem is solved at the upper level and

DSOs' problems are solved at the lower level, applying both Diagonal Quadratic Approximation (DQA) and truncated DQA methods. Building on this work, Li et al. (2018a) introduce a Heterogeneous Decomposition (HGD) algorithm, later enhanced with LMP sensitivities to improve convergence and reduce communication overhead (Li et al., 2018d). The HGD framework has since been extended to voltage stability assessment (Li et al., 2018c) and coordinated Economic Dispatch (ED) (Li et al., 2018b). Price-based coordination has also been widely explored. Li et al. (2019a) propose a bi-level model in which DSOs submit generalized bid functions to an Independent System Operator (ISO), solved using a Generalized Master-Slave Splitting (GMSS) method. Similarly, Najibi et al. (2021) adopt LMPs as coupling variables within a DC-OPF/SOCP framework. More recently, Nezhad (2025) applies an LMP-based approach to coordinated congestion management, although the extensive data exchange required raises concerns regarding data privacy and regulatory compliance.

Several studies extend distributed frameworks to multi-period settings. Lin et al. (2017) propose a coordinated multi-period ED solved using a multi-parametric Quadratic Programming (QP) algorithm. Arpanahi et al. (2021) enhance this approach by explicitly modeling inter-temporal DER constraints and RES uncertainty through an accelerated augmented Lagrangian Relaxation (LR) method. Related work by Arpanahi and Golshan (2020) formulates decentralized Volt-VAr optimization as a non-cooperative game. Zhao et al. (2019b) and Rousis et al. (2021) also address the reactive power management problem, with the latter demonstrating practical feasibility through HIL testing. Distributed formulations have further been applied to UC and restoration problems. Bragin et al. (2018); Bragin and Dvorkin (2022) introduce mixed-integer linear frameworks solved via Surrogate Lagrangian Relaxation (SLR) and proximal penalty methods, respectively. Papalexopoulos et al. (2020) develop a day-ahead and real-time market model integrating DERs while accounting for unbalanced three-phase AC-PF at the DN level. Coordinated system restoration is addressed by Zhao et al. (2019a) using ATC-based decomposition and by Roofegari Nejad et al. (2019) through an Alternating Direction Method of Multipliers (ADMM)-based approach.

Aramahy et al. (2025) extend the coordination scope to integrate Microgrids (MGs) into a three-level architecture combining P2P trading at the microgrid level; hierarchical coordination between DSOs and Microgrid Operators (MGOs); and system-level interaction between TSOs and DSOs. While conceptually innovative, this approach introduces significant operational complexity, raising concerns regarding scalability and practical deployment. Distributed coordination has also been tailored to specific services. For example, Gorostiza and Gonzalez-Longatt (2020) propose a framework for FFR provision based on VPPs, enabling the aggregation of DERs for fast-response ASs.

Distributed schemes have emerged as a promising pathway for scalable and privacy-preserving TSO-DSO coordination. Their decentralized nature aligns well with the increasing complexity and heterogeneity of modern power systems, allowing each SO to

retain operational autonomy while contributing to system-wide efficiency. Nevertheless, several challenges remain. These include ensuring the stability and convergence of iterative decomposition algorithms, achieving sufficiently accurate network and DER representations, and establishing secure, low-overhead data exchange mechanisms. Equally critical is the evolution of regulatory frameworks to support distributed architectures.

2.3.4 Representation of DNs Through Equivalent Models

The use of equivalent models to represent ADNs has gained prominence as an effective strategy for reducing the procedural and computational complexity of coordinated TSO–DSO operations. By abstracting the detailed dynamics of DNs into simplified yet representative forms, these models allow their straightforward integration into transmission-level decision-making tools, striking a balance between modeling accuracy and computational tractability (Capitanescu, 2018a).

2.3.4.1 PQ Flexibility Maps

Among the various DN equivalent models, PQ flexibility maps (also referred to as PQ capability curves) have received particular attention in the literature. These maps characterize the Feasible Operating Region (FOR) of an ADN, describing the admissible combinations of active and reactive power that the DN can inject or absorb at the TSO–DSO interface without violating operational constraints.

Two main approaches have been proposed for constructing PQ maps:

- Sampling-based methods: rely on large sets of PF simulations under varying operating scenarios. While conceptually simple and parallelizable, they are computationally expensive and often fail to capture the extreme boundaries of the FOR.
- Optimization-based methods: typically employ OPF formulations to systematically trace the FOR boundary. Starting from extreme values of active and reactive power, intermediate points are determined through additional OPF runs, with convex hulls or interpolation used to form the final map (Prasad et al., 2025).

A seminal contribution by Heleno et al. (2015) applied random sampling to generate PQ maps of ADNs, producing feasible operating points through multiple PF simulations of randomly generated DER scenarios (Figure 2.6). While conceptually straightforward, the method is computationally demanding and prone to underestimating extreme flexibility points, limiting its usefulness for TSO decision-making.

To overcome these drawbacks, Silva et al. (2018a) introduced the Interval-Constrained Power Flow (ICPF) approach, which solves a sequence of nonlinear AC-OPFs to trace the FOR boundary. A similar formulation was developed independently by Capitanescu (2018b), while Rossi et al. (2017) tested three reconstruction methods – radial, fixed tangents, and points-and-slopes – each refining different aspects of the FOR boundary.

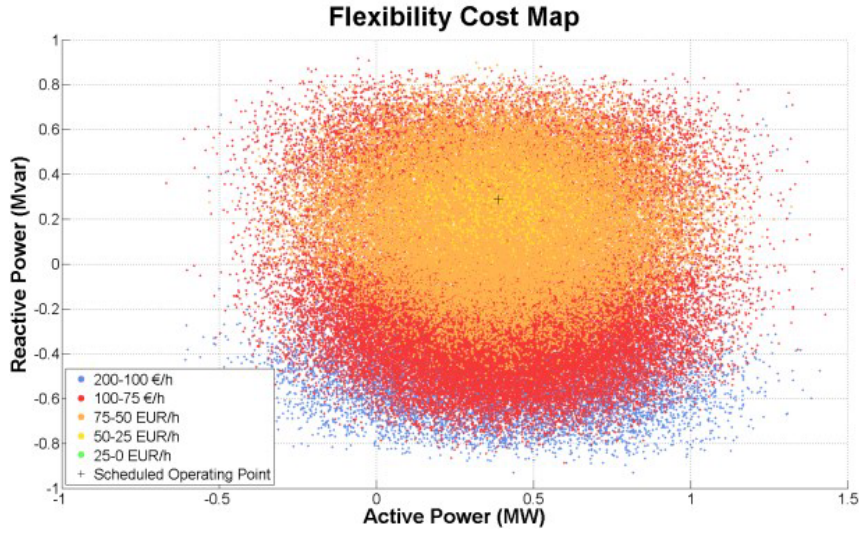


Figure 2.6: FOR obtained through random sampling. Source: [Heleno et al. \(2015\)](#).

Later, [Silva et al. \(2018b\)](#) extended ICPF to incorporate resources with discrete controls, such as On-Load Tap Changer (OLTC) transformers and Capacitor Banks (CBs), that were shown to fragment the FOR, yielding disjoint PQ areas (Figure 2.7).

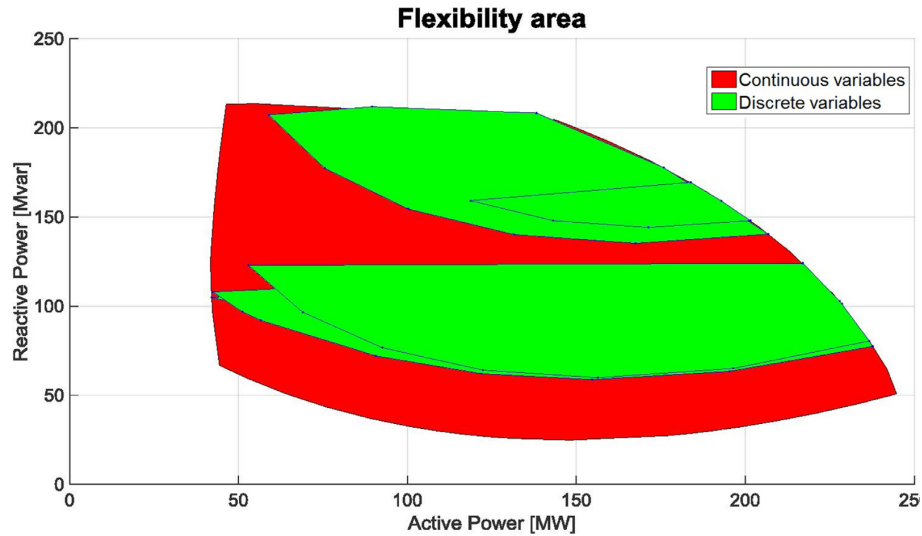


Figure 2.7: PQ flexibility map obtained through ICPF. Impact of discrete control variables in the flexibility map. Source: [Silva et al. \(2018b\)](#).

Dynamic extensions of PQ maps have also been explored. [Mayorga Gonzalez et al. \(2018\)](#) incorporated multi-period dynamics and forecast uncertainty using Monte Carlo simulations, enabling a more realistic temporal characterization of distribution flexibility, albeit at significant computational cost. In a follow-up work, the same authors applied this methodology in a cross-voltage-level coordination framework ([Mayorga Gonzalez et al., 2020](#)). [Contreras and Rudion \(2019\)](#) apply multi-period PQ maps to the congestion management under a local AS market model. Figure 2.8 shows an illustrative example of a

multi-period PQ map.

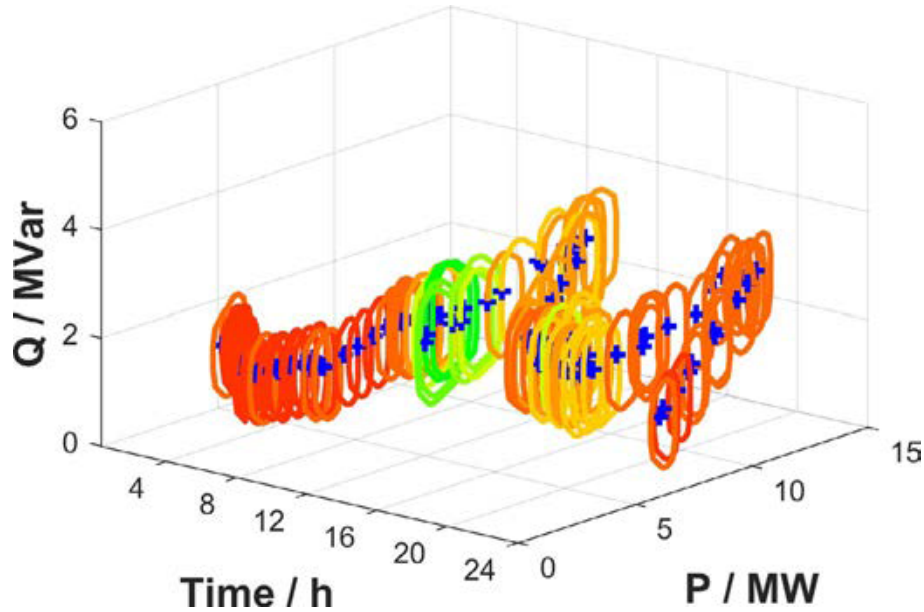


Figure 2.8: Multi-period PQ map. Source: Contreras and Rudion (2019).

Riaz and Mancarella (2019) proposed the distinction between a *feasibility space* – encompassing all technically achievable operating points – and a *flexibility space*, which accounts for the time required to transition between points. This temporal dimension is especially relevant for fast-response ASs, such as frequency regulation, where dynamic capability is as important as static feasibility. Subsequent works further broadened the PQ map methodology. Stanković et al. (2021) introduced *capability* and *desirability surfaces* to align DSO flexibility with TSO needs. Prasad et al. (2025) explicitly modeled unbalanced ADNs, and Tan et al. (2020) incorporated uncertainty through *robust capability curves*, based on RO-OPF, offering TSOs *guaranteed* feasible regions.

While PQ maps offer clear advantages for short-term operational planning and real-time applications – where rapid decision-making is essential and detailed modeling of individual DERs is often impractical – their accuracy decreases in multi-period contexts. Resources with strong inter-temporal dependencies, such as ESSs and deferrable loads, are particularly challenging because their flexibility depends not only on the present state but also on past (and future) operating conditions. Since standard PQ maps are inherently static, they often fail to adequately capture this temporal dimension, often leading to oversimplified or inaccurate representations of dynamic flexibility.

2.3.4.2 Virtual Power Plants

The concept of the VPP was first introduced by Awerbuch and Preston (1997) under the term *virtual utility*, describing a “collaborative network of independent entities delivering energy services without owning physical assets”. It has since evolved into a recognized

paradigm for aggregating and coordinating DERs, enabling their participation in wholesale and ASs markets. By pooling heterogeneous and geographically dispersed resources, VPPs enhance flexibility, mitigate variability, and provide predictable, dispatchable services (Richter et al., 2017). From a financial standpoint, aggregated operation through VPPs has been shown to yield higher revenues than individual DER market participation (Loßner et al., 2017; Othman et al., 2017).

Numerous strategies have been proposed to optimize VPP participation in electricity markets. Liang et al. (2019) introduce a two-stage SP framework to mitigate price volatility in day-ahead and real-time markets, while Giuntoli and Poli (2013) investigate the coordinated scheduling of thermal loads and ESSs. Bi-level SP formulations by Kardakos et al. (2016) and Baringo and Baringo (2017) explicitly capture the trade-off between maximizing day-ahead profits and minimizing imbalance risks, while Wang et al. (2016) adopt game theory approaches to analyze competitive VPPs bidding strategies. While much of the literature has focused on day-ahead energy markets, several works extend the scope to co-optimized participation in both energy and ASs markets. Qiu et al. (2017a) develop a transactive energy framework for scheduling DERs across multiple markets to maximize aggregated profit, while Mashhour and Moghaddas-Tafreshi (2011) propose a UC model that enables simultaneous participation in energy and spinning reserve markets. Complementary contributions include the risk-averse joint energy-reserve model of Dabbagh and Sheikh-El-Eslami (2016) and the two-stage SP bidding strategy for energy and secondary reserves by Iria et al. (2019). Broader techno-economic perspectives are offered by Wang et al. (2020), who propose a framework for urban VPPs, validated through a real-world pilot at the University of Melbourne’s campus. Their results demonstrate the ability of VPPs to participate effectively in energy, frequency control ASs, and DR markets.

In the context of TSO-DSO coordination, VPPs can serve as practical intermediaries between SOs and DERs. By aggregating DER flexibility, they can provide localized services to DSOs – such as voltage regulation, congestion management, and loss minimization – while simultaneously offering system-level services to TSOs, including frequency control, reserve provision, and balancing services. Baracé et al. (2024) propose an aggregated model for ADNs using virtual synchronous machines to enhance frequency support, demonstrating how aggregation reduces computational complexity while preserving data privacy. Similarly, Zhao et al. (2017) represent thermostatically controlled loads through a “virtual battery” model to provide regulation services to the TSO. More recently, Wang et al. (2024a) highlighted the potential of Artificial Intelligence (AI), applying RL to improve coordinated real-time frequency- and voltage control.

2.3.4.3 Machine Learning and Data-Driven Approaches

The computational complexity of solving large-scale coordination problems has spurred growing interest in Machine Learning (ML) and data-driven techniques (Yang et al., 2023). Instead of explicitly solving optimization problems at every decision step, these approaches

aim to approximate or replace them with surrogate models trained on historical data or simulation outputs. By doing so, they enable faster decision-making and real-time applicability while maintaining acceptable levels of accuracy. Beyond efficiency, learning-based methods can also capture nonlinearities and “hidden” patterns that are difficult to model analytically, offering new opportunities for enhancing coordination and flexibility management in complex power system environments.

Escobar et al. (2025) propose a data-driven framework that enables ADNs with high DER penetration to actively participate in TN voltage support. Their method leverages historical and real-time operational data to estimate a sensitivity matrix, which is integrated into the TSO’s voltage control scheme to optimize reactive power exchange at the TN-DN interface. To ensure feasibility in online operation, the capabilities of each ADN are periodically updated within the optimization routine, reflecting DER availability. Dindar et al. (2025) introduce an ML-based framework in which distribution-level technical constraints are embedded into trained surrogate models. These models allow the TSO to solve a single-round OPF that directly determines DER dispatch, eliminating the need for a disaggregation step. Their approach explicitly incorporates PQ characteristics of DGs and the influence of TN–DN interface voltages, offering a more faithful representation of ADN’s flexibility. Expanding to demand-side resources, Wang et al. (2024b) address the integration of EV-based flexibility into coordinated TSO–DSO operation. They propose a two-stage framework where, in the first stage, EVs participate in the day-ahead reserve market, while the second stage focuses on real-time dispatch of the DNs, ensuring reserve provision while maintaining local voltage security. A decentralized dispatch scheme is adopted, complemented by a multi-agent RL algorithm designed to improve scalability and reduce communication overhead during training.

ML and data-driven methods represent a promising complement to optimization-based coordination tools, offering scalability, faster decision-making, and adaptability to real-time conditions. However, their deployment is still constrained by challenges such as data quality, model robustness, feasibility guarantees, and regulatory acceptance. While these approaches open new avenues for integrating advanced analytics into TSO–DSO coordination, further progress in explainability, interpretability as well as in the development of privacy-preserving and resilient models is needed before they can be fully established as reliable operational tools.

2.4 TSO-DSO Coordinated Planning Tools

Traditionally, Transmission Expansion Planning (TEP) and Distribution Expansion Planning (DEP) have been addressed separately, both in academic research and industry practice. However, the increasing penetration of DERs is disrupting conventional power flow patterns between TN and DNs, challenging the adequacy of established planning approaches. This evolution calls for a fundamental revision of existing frameworks, as

investment decisions at one network level can have direct implications for the other. Consequently, coordinated planning between TSOs and DSOs is increasingly recognized as essential – not only to optimize system-wide efficiency, but also to unlock the full flexibility potential of DERs (El-Meligy et al., 2021).

Kiani Rad and Moravej (2017) propose a unified expansion planning framework that simultaneously considers distribution, sub-transmission, and transmission levels, formulated as a centralized optimization problem and solved using a genetic algorithm. Along the same line, Liu et al. (2018) present an integrated TN–DN planning approach, highlighting two main challenges of joint TEP–DEP: data privacy, given regulatory unbundling, and computational tractability due to problem size. To mitigate these issues, the same authors later introduce a hierarchical framework in which TEP is modeled at the upper level while DN operation is modeled at the lower level (Liu et al., 2020). Although more scalable, this formulation does not explicitly incorporate distribution-level investment decisions. Expanding the scope, Ferreira et al. (2025) propose a joint transmission and Generation Expansion Planning (GEP) model that accounts for TSO–DSO interconnections. Similarly to Liu et al. (2020), DEP is not explicitly considered. The objective is to minimize total system costs, including transmission and generation investments, operation, and flexibility requirements. Uncertainty from load and RES generation is modeled through a data-driven Distributionally Robust Optimization (DRO) approach, solved using a column-and-constraint generation algorithm. The formulation employs a linear AC-OPF model with reactive power considerations.

Böttcher et al. (2024) extend the FOR concept to the planning stage by introducing Flexible Planning Regions (FPRs). These regions define the admissible solution space for DEP within system-level planning frameworks, characterizing feasible interface power flows at substations as a function of expansion cost. Conceptually, an FPR is a series of FORs aligned along a cost dimension, where each layer represents a different DEP level. Lower-cost expansions typically provide limited flexibility, while higher-cost configurations enable broader feasible exchanges with the transmission grid. This hierarchical representation allows DNs to be integrated into TEP models while preserving unbundled operation and explicitly capturing the trade-offs between investment cost and flexibility provision. Figure 2.9 illustrates an FPR, showing how the active and reactive power ranges at the Point of Common Coupling (PCC) evolve across successive expansion stages, each associated with a specific investment level.

El-Meligy et al. (2021) propose a tri-level hierarchical framework for coordinated expansion planning of TN and DN. The first level addresses the TSO’s planning problem, the second models each DSO’s planning problem, and the third represents the optimal ED solved by an ISO. The ED stage is reformulated using a primal–dual representation, reducing the overall problem to a bi-level multi-follower MILP. This formulation is solved via multi-parametric programming, which decomposes the planning task into independent single-level optimization problems. As with distributed operational planning approaches

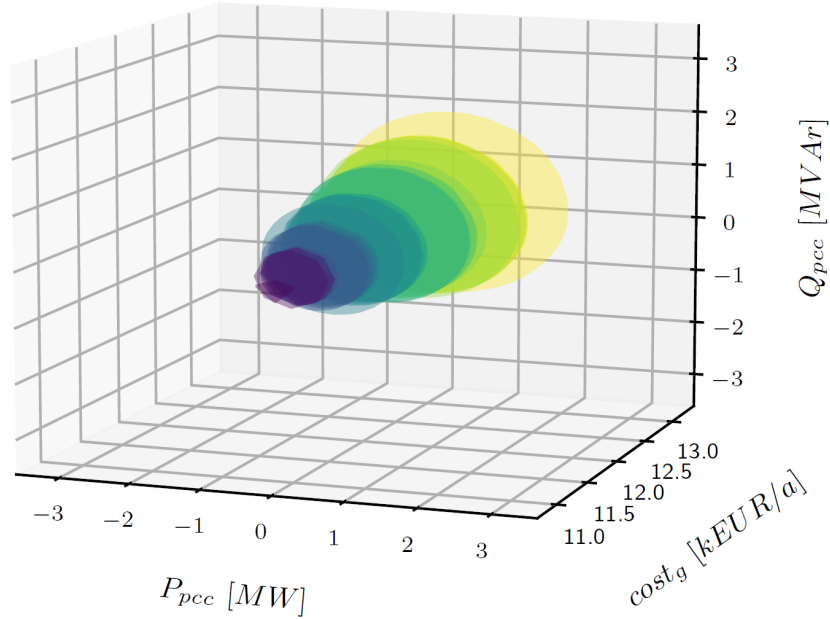


Figure 2.9: Example of an FPR. Representation of an ADN's active (P_{PCC}) and reactive power (Q_{PCC}) capability chart, for each DN expansion level and associated investment cost ($cost_g$). Source: Böttcher et al. (2024).

(Subsection 2.3.3), the key limitation lies in the information requirements: a single coordinating entity must access both TSO and DSO planning data, raising concerns regarding data confidentiality and regulatory unbundling, therefore limiting the method's applicability in practice. Building on similar concepts, Ma et al. (2025) introduce a tri-level coordinated planning model for TN and DN that jointly considers normal operating conditions and severe fault scenarios. The upper level minimizes investment and operational costs under normal conditions, while the middle and lower levels minimize expected operating costs under fault conditions in the TN and DNs, respectively. Unlike the centralized approach of El-Meligy et al. (2021), this framework adopts a decentralized structure: the TSO provides interface node voltages and angles to the DSOs, who in turn feedback active and reactive power flows. The overall problem is solved using the HGD method, which supports scalability by enabling distributed computation while respecting information boundaries between SOs.

Nikoobakht et al. (2020) present a coordinated TSO–DSO expansion planning framework based on a hybrid RO–SP formulation, where RO is applied at the transmission level and SP at the distribution level. The model adopts a hierarchical coordination structure, with the TSO's RO problem solved via Benders' decomposition. In a later work, Nikoobakht et al. (2022) extend this approach to a four-level hierarchical optimization model, incorporating security constraints into the TEP subproblem. Along similar lines, Liu et al. (2022) propose a hybrid RO–SP formulation within a distributed decision-making framework, where coordination between TN and DN is enforced through deviation penal-

ties on interface PFs, resembling an augmented LR method. In their model, the TSO's RO problem is reformulated as a two-stage MILP. A key limitation, however, is its single-period scope, which may yield unrepresentative system states and neglect the inherently dynamic behavior of ADNs.

In summary, coordinated expansion planning of TN and DN remains an open research challenge, with the main difficulty lying in balancing computational tractability with realistic system representation. Tractability is often pursued through convex relaxations or approximations of the AC-PF equations, which reduce computational effort but typically yield solutions that are not strictly AC-feasible, limiting their practical deployment. For example, Heide et al. (2021) propose a convex polar second-order Taylor expansion that improves approximation accuracy for TEP, yet still overlooks critical flexible resources such as ESSs. Future approaches must bridge this gap by integrating distribution-level investment decisions, explicitly modeling DERs, and capturing the uncertainty of demand and RES generation. Developing scalable, AC-feasible, and flexibility-aware planning models will be essential to support the reliable and cost-effective evolution of integrated transmission–distribution systems.

2.5 Energy Storage Planning

ESSs are increasingly recognized as critical assets for enhancing the flexibility, reliability, and efficiency of modern power systems. Among available technologies, batteries stand out for their rapid response, modular scalability, and ability to deliver both energy and ASs across multiple timescales. Their deployment supports key functions such as frequency regulation, congestion management, peak shaving, and RES integration, making them indispensable in RES-dominated grids. However, the investment case for battery ESSs remains highly sensitive to planning and operational decisions. Despite substantial cost reductions in recent years, capital expenditure is still significant, and long-term profitability depends on optimal siting, sizing, and control strategies. Consequently, ESS planning represents not only a technical optimization problem but also an economic and regulatory challenge – one that requires coordinated approaches aligning market incentives, grid needs, and investor expectations.

Formulating and solving a comprehensive ESS planning model that spans long-term horizons remains computationally challenging. The growing penetration of RESs and the increasing participation of active prosumers amplify system variability, making uncertainty a critical factor in planning. Although incorporating a larger number of scenarios can enhance solution robustness, it also substantially increases computational burden. Another important yet often overlooked dimension of ESS planning is *modularity*. Most existing approaches assume a one-time investment in a fixed-size unit (e.g., Pandzic et al., 2015; Liu et al., 2016; Li et al., 2015; Bayram et al., 2017; Zhang et al., 2013a; Hedayati et al., 2014; Konstantelos and Strbac, 2015), disregarding the technical and economic advantages of

staged or incremental capacity additions at the same location. Moreover, long-term planning must account for short-term operational effects – particularly battery degradation from cycling – which directly influence lifetime performance and economic viability. However, explicit degradation modeling remains relatively uncommon. To balance accuracy and computational tractability, most existing methods employ PF approximations (e.g., Fortenbacher et al., 2016; Nick et al., 2018; Zhao et al., 2023), heuristic approaches (e.g., Pandzic et al., 2015; Motaleb et al., 2016; Celli et al., 2018), or mathematical decomposition techniques (e.g., Nasrolahpour et al., 2016; Feng et al., 2025).

Hedayati et al. (2014) and Konstantelos and Strbac (2015) propose multi-stage planning models for optimal ESS siting, assuming pre-defined unit sizes and using a DC-PF formulation. A distinctive feature of Konstantelos and Strbac (2015) is the explicit inclusion of $N - 1$ security criteria and long-term wind capacity uncertainty. Nasrolahpour et al. (2016) and Xu et al. (2017) extend the analysis to joint siting and sizing through bi-level formulations, though with different emphases. Nasrolahpour et al. (2016) develop a bi-level SP model, reformulated as a Mathematical Programming with Equilibrium Constraints (MPEC) and solved with Benders' decomposition, but notably omit PF equations. In contrast, Xu et al. (2017) employ a DC-PF representation. Their model determines investment decisions in the upper level and daily operational schedules in the lower level, solved via primal decomposition and a subgradient-based cutting-plane method. Building on this line of research, Abdeltawab and Mohamed (2019) investigate the planning of *mobile* ESSs, which can be relocated across substations to provide services at multiple locations over time. Their bi-level framework identifies rated power and station locations at the upper level, then optimizes capacity allocation and operation at the lower level. The second stage is formulated as an MILP with linearized PF equations.

In a novel conceptual approach, Zhao et al. (2023) propose an SP model that incorporates the spatial-temporal correlations of wind generation and generator outages. To represent RES uncertainty, the authors adopt a scenario generation technique based on *random field theory*, which captures both the spatial and temporal evolution of wind speed profiles. The ESS sizing problem is formulated as a MILP and solved using an SLR-based method. However, this framework omits PF equations, which limits its ability to fully capture network operational constraints in the sizing process.

Battery degradation has been largely overlooked in the scientific literature on planning models. Qiu et al. (2017b) address this gap by proposing a stochastic, multi-stage planning framework that jointly considers TEP and battery ESS deployment, explicitly incorporating storage capacity degradation under different RES generation and load growth scenarios. The results show that co-planning transmission lines and storage capacity significantly reduces the need for new line construction. However, a key limitation of the model is its simplified assumption of a flat degradation rate, which disregards the impact of actual ESS utilization on capacity loss.

Research on ESS planning across multiple voltage levels – spanning both TN and DN

– and enabling services to both **TSOs** and **DSOs** remains relatively scarce. One of the earliest contributions is by **Motalleb et al. (2016)**, who propose a heuristic siting and sizing approach where **ESSs** are centrally managed by an **ISO** to smooth **RES** output at the distribution level while providing frequency support and contingency reserves at the transmission level. Building on this idea, **Massucco et al. (2021)** develop a more detailed optimization framework to determine the location, energy capacity, and power rating of battery **ESSs** across multiple voltage levels. Their **SC**-based linearized model captures losses, reactive power effects, and **OLTC** behavior, though **SCs**’ dependence on the current operating point may reduce accuracy (**Capitanescu, 2016**). In a similar line of research, **Hassan and Dvorkin (2018)** propose a hierarchical formulation where **DNs** are modeled through a **SOCP**-based **OPF** and the **TN** through a **DC-PF**. Here, **DSOs** maximize local revenues while the **TSO** seeks to minimize system-wide operational costs. More recently, **Feng et al. (2025)** introduce a distributed planning framework that integrates long-term hydrogen-based **ESSs** with short-term electrochemical storage. The **TN** is represented with a **DC-PF** model and the **DN** with a branch-flow method. Their approach captures seasonal balancing and short-term uncertainty mitigation, while preserving privacy between **SOs** through a distributed robust **ADMM** algorithm – pointing toward a scalable and privacy-aware solution for multi-level planning.

Recent research increasingly highlights the role of **ESSs** in supporting both **TSOs** and **DSOs**. Yet, persistent challenges remain in accurately modeling network and resource behavior, handling uncertainty, and ensuring scalability without compromising data privacy. Future directions point toward distributed coordination methods as the most promising path to deliver tractable, reliable, and flexibility-aware planning tools.

2.6 Data Exchange and Communication

While most of the reviewed literature focuses on the design of **TSO–DSO** coordination mechanisms, comparatively less attention has been devoted to the underlying data exchange processes and associated privacy considerations (**Miah et al., 2024**). Yet, the efficiency, scalability, and security of these mechanisms are strongly dependent on the robustness of the information exchange infrastructure.

Although information exchange between **TSOs** and **DSOs** has long been standard practice – particularly for network planning (**Alves et al., 2015**) – recent developments in European regulatory frameworks have reinforced the need for interoperable and standardized data exchange solutions (**Bytyqi et al., 2022**). This shift is driven by the increasing operational complexity of power systems, the expanding number of market and grid participants, and the growing need for near-real-time situational awareness in **DER**-rich networks. In this context, **Al-Saadi et al. (2019)** conducted a comprehensive survey of European **SOs** and market stakeholders to identify the main barriers and priorities for enhanced coordination. The study highlighted three key challenges: (i) the integration of heterogeneous

platforms, such as planning tools and real-time monitoring systems; (ii) the facilitation and streamlining of information flows among stakeholders; and (iii) the adoption of common standards and protocols for data exchange.

Beyond interoperability, data security and privacy remain pressing concerns. Malicious exploitation of operational data could threaten system integrity, while excessive visibility into **DN** assets may conflict with unbundling regulations and confidentiality requirements (Jeong, 2023). Moreover, as coordination shifts from periodic planning exchanges to continuous, operation-oriented interactions, the required data volume and granularity increase significantly. This evolution requires resilient **ICT** infrastructures capable of high-frequency, high-volume exchanges without compromising performance. Recent research trends emphasize the adoption of common European **NCs** for data exchange, **CIM**-based standards, and secure Application Programming Interfaces (**APIs**) for interoperability. Privacy-enhancing approaches, including federated learning and distributed ledger technologies, are also being investigated for selected data-sharing and market applications (Miglani et al., 2020; Wang et al., 2021; Diaz Valdivia, 2023). However, their suitability for time-critical operational coordination remains application-dependent and requires careful assessment of latency, scalability, governance, and cybersecurity.

More broadly, interoperability in **TSO–DSO** coordination extends beyond device-level communication to the integration of operational-technology systems used for grid control and information-technology systems supporting market and enterprise processes. Valverde et al. (2027) emphasize that effective coordination requires secure and interoperable data exchange between these environments, subject to strict latency, reliability, scalability, and cybersecurity requirements. Standardized communication protocols and data models, combined with edge and distributed computing, can support the timely exchange of high-quality operational information. In parallel, coordination architectures based on aggregated or boundary information can reduce the need for participating entities to disclose complete network models, cost functions, or other sensitive internal data.

In summary, robust and standardized data exchange frameworks are pivotal for the deployment of **TSO–DSO** coordination models. While progress in interoperability standards has been made, outstanding challenges remain in cybersecurity, privacy protection, and scalability. Future directions will likely center on standardized communication interfaces and privacy-preserving methods to ensure secure, efficient, and resilient coordination.

2.7 Optimal Power Flow

The family of optimization problems collectively known as *Optimal Power Flow* constitutes one of the most influential and extensively studied areas in power system engineering. Originally introduced by Carpentier (1962), the **OPF** was conceived as an extension of the classical optimal **ED** formulation, used to schedule generation resources at minimum cost. Carpentier’s seminal contribution was the explicit incorporation of the **PF** equations into

the **ED** framework, thereby coupling economic objectives with the physical laws governing power system operation. This innovation ensured that optimized operating points would not only minimize costs but also remain physically feasible with respect to the network's topology, electrical parameters, and operational limits (Frank and Rebennack, 2016).

Over the past six decades, **OPF** has evolved into a benchmark problem for testing some of the most influential algorithms in nonlinear optimization, with its development unfolding across several phases:

- 1960s–1970s: Early computationally viable solutions emerged with gradient-based methods (Dommel and Tinney, 1968), followed by Newton-type methods that improved convergence (Peschon et al., 1972). Around the same time, Sequential Linear Programming (**SLP**) enabled the scaling of **OPF** to larger networks (Stott and Hobson, 1978a,b).
- 1980s: Sequential Quadratic Programming (**SQP**) gained traction, offering better accuracy in handling nonlinear constraints (Burchett et al., 1982).
- 1990s: The introduction of linear and nonlinear Interior Point Methods (**IPMs**) revolutionized the field by providing significant improvements in scalability and computational speed (Granville, 1994; Torres and Quintana, 1998).
- 2000s: The scope of **OPF** expanded into Security-Constrained Optimal Power Flow (**SCOPF**), incorporating contingency analysis and becoming a cornerstone of day-ahead and real-time electricity market operations (Capitanescu et al., 2011; Stott and Alsac, 2012).
- 2010s: Convex relaxations of the **PF** equations were introduced to improve tractability, most notably Semi-Definite Programming (**SDP**) (Lavari and Low, 2012) and **SOCP** (Low, 2014a,b).
- 2020s: Research focus shifted to distributed, stochastic, and real-time **OPF** formulations. Decentralized methods were developed for inter-area and **TSO-DSO** coordination, with tractability and data privacy as key priorities. In parallel, stochastic frameworks such as **SP**, **RO**, and **DRO** gained prominence to address uncertainty from load and **RES** variability. More recently, **ML**-based approaches have emerged, aiming to accelerate real-time decision-making and complement traditional optimization techniques.

The evolution of **OPF** reflects the broader trajectory of power system optimization: from early centralized formulations to today's distributed, stochastic, and learning-based approaches. Despite these advances, key challenges persist in ensuring scalability, robustness under uncertainty, and real-time implementability. Overcoming these barriers will be essential for establishing **OPF** as a core enabler of secure and efficient operation in

increasingly complex, DER-rich power systems. The following subsections review recent advances in OPF modeling that address these emerging challenges.

2.7.1 Primer on Optimal Power Flow

In OPF formulations, the PF equations form the core equality constraints and are the primary source of non-convexity, ensuring that solutions remain physically feasible. Two main paradigms are widely used to model network power flows:

- Bus injection model: The most widely adopted in both research and practice. It provides a compact formulation with fewer variables and constraints, and its structure closely mirrors conventional PF analysis, allowing existing algorithms to be readily adapted to OPF. However, branch power flow limits must be enforced indirectly, often requiring additional constraints or post-processing.
- Branch flow model: Explicitly represents power flows along network branches, making it easier to integrate branch capacity and thermal limits. Moreover, its structure naturally lends itself to certain convex relaxation techniques, such as SOCP, which can improve tractability.

The bus injection model is generally more compact and efficient for large-scale meshed transmission systems, while the branch flow model offers a more transparent treatment of line power flows and is well suited to radial distribution systems.

A central modeling choice in the bus injection formulation is the representation of voltage in polar or rectangular coordinates. Polar coordinates simplify the enforcement of voltage magnitude limits, while rectangular coordinates remove trigonometric functions, offering several computational advantages (Torres and Quintana, 1998):

- Faster evaluation: the absence of trigonometric terms speeds up equation evaluation.
- Exact Taylor expansion: for quadratic functions, the second-order Taylor series expansion is exact, improving efficiency in higher-order IPM algorithms for OPF.
- Constant Hessian: the Hessian of a quadratic function is constant and only needs to be computed once, simplifying the application of Newton methods to the Karush-Kuhn-Tucker (KKT) conditions of the OPF problem.
- QP form: if all constraints and objective function are quadratic, the OPF becomes a Quadratically Constrained Quadratic Program (QCQP), albeit non-convex, enabling the use of specialized solvers.

Traditionally, both modeling paradigms assume a fixed network admittance matrix, omitting controllable elements such as OLTCs and phase-shifting transformers. Recent advances in OPF formulations, however, increasingly treat these resources as decision variables, thereby improving model accuracy but substantially increasing computational complexity (Farivar and Low, 2013a,b).

2.7.2 Approximations of the Power Flow Equations

Modern optimization solvers – whether general-purpose or specifically tailored for OPF – have achieved remarkable maturity, enabling efficient solutions for many large-scale problems. Nonetheless, the inherently nonlinear and non-convex nature of the AC-PF equations continues to pose a fundamental challenge to mathematical solvers. Local NLP-based methods, while fast in practice, are vulnerable to convergence failures, particularly under stressed network conditions or near-infeasible operating points. These limitations have motivated the development of alternative OPF formulations that replace or approximate the AC-PF equations. Such approaches span a spectrum from simplified linear and quadratic models, which enhance tractability at the expense of accuracy, to convex relaxation techniques that aim to preserve feasibility guarantees while improving computational robustness (Capitanescu and Wehenkel, 2013a).

2.7.2.1 DC Power Flow

To simplify the representation of electrical networks, a widely used linearized approximation of the PF is the DC-PF (Dommel and Tinney, 1968). This formulation neglects reactive power flows, earning its name from the fact that its equations structurally resemble current flow in purely resistive DC circuits (Frank and Rebennack, 2016).

By removing nonlinearities associated with voltage magnitudes, reactive power, and trigonometric terms, the DC-PF delivers substantial computational gains, making it especially attractive for large-scale OPF and long-term planning applications where speed and robustness are critical. Its validity, however, depends on restrictive assumptions: (i) small voltage angle differences between buses, (ii) lossless transmission lines, and (iii) negligible voltage magnitude variations. These conditions are generally satisfied in high-voltage TNs under normal operating states, which explains the model’s widespread adoption in TN analysis and commercial software. Nevertheless, the DC-PF has well-recognized limitations. Under stressed system conditions – such as large voltage deviations, high resistance-to-reactance ratios, or significant reactive power flows – it can introduce large errors or even infeasible solutions (Rau, 2003; Stott et al., 2009; Zhu, 2009). Moreover, in modern grids with high RES penetration, the neglect of reactive power effects makes it poorly suited for capturing critical operational constraints – such as voltage magnitude limits.

The DC-PF offers unmatched computational efficiency but at the expense of physical fidelity. It remains highly useful for applications such as market clearing, long-term planning, and other contexts where tractability is prioritized over precision. However, for real-time operation, security-critical tasks, or scenarios requiring accurate representation of network physics, its limitations become pronounced. To address these shortcomings, more advanced approximation methods – such as decoupled formulations and enhanced linear approximations – have been proposed in the literature (Rider et al., 2007; Bent et al., 2014).

2.7.2.2 Decoupled Power Flow

In **TNs**, where transmission lines typically exhibit low resistance-to-reactance ratios, active power injections are strongly coupled with voltage angles, while reactive power injections are strongly coupled with voltage magnitudes. By contrast, the dependence of active power on voltage magnitudes and of reactive power on voltage angles is comparatively weak. These structural characteristics motivated the development of decoupled solution methods for the **PF** equations, which exploit these strong couplings to simplify computations and enhance scalability (Glover et al., 2017; Zhu, 2009).

Building on this principle, decoupled **OPF** algorithms decompose the problem into two subproblems: active power–voltage angle and reactive power–voltage magnitude optimization problems (Sun et al., 1984; Contaxis et al., 1986). Each subproblem is solved independently under the assumption that their results remain consistent when combined. This decomposition significantly reduces computational burden, allowing much faster solutions for large-scale networks compared to exact formulations. However, the validity of the approach depends on the accuracy of the decoupling assumptions. In grids with advanced control devices, high resistance-to-reactance ratios, or under stressed operating conditions, the cross-coupling between active and reactive power can become non-negligible. In such cases, decoupled solutions may deviate considerably from the true optimum, limiting their reliability for security-critical applications (Zhang, 2010).

2.7.2.3 Linearization of AC Power Flows

A variety of methods have been proposed to linearize the **AC-PF** equations, broadly classified into iterative approaches (Thukaram et al., 1984; Stott and Alsac, 1974) and convex approximations (Wang et al., 1996; Lavaei and Low, 2012; Koster and Lemkens, 2011). Iterative methods, such as the fast-decoupled load flow (Stott and Alsac, 1974), achieve significant computational savings and sufficient accuracy for many applications, but they are not easily integrated into decision-support or market-clearing tools.

An alternative line of research explores piecewise linearization. For instance, Zhang et al. (2013b) proposed a method based on first-order Taylor expansions that retains reactive power, power losses, and non-nominal voltage magnitudes. Similarly, Coffrin and Van Hentenryck (2014) introduced a convex approximation using piecewise-linear representations of trigonometric terms, later extended by Sepetanc and Pandzic (2021), who proposed a second-order Taylor approximation with selective substitution of problematic relaxed constraints by linear equalities to improve accuracy. Another widely used technique relies on **SCs**, which represent bus voltage sensitivities with respect to active and reactive power injections. This enables a linear approximation of the **PF** equations that is computationally attractive. However, since **SCs** are typically obtained from a single **PF** solution, their validity is strongly dependent on the chosen operating point, which can reduce accuracy in dynamic or stressed conditions.

2.7.3 Convex Relaxations of the OPF Problem

Convex relaxations of the **AC-OPF** problem have gained considerable traction in recent years. Since **OPF** is a Nondeterministic Polynomial time (**NP**)-hard problem, such relaxations are particularly valuable when conditions can be identified under which they yield exact solutions (**Capitanescu, 2016**).

Pioneering work by **Bai et al. (2008)** and **Lavaei and Low (2012)** initiated an active line of research by exploring convex formulations that, in many practical case studies, have been shown to produce tight solutions. These relaxation techniques offer several theoretical and practical benefits, including: (i) providing a lower bound on the objective function value of the original **NLP** problem, allowing the degree of suboptimality of local solutions to be quantified; (ii) guaranteeing global optimality when the duality gap is zero; and (iii) the ability to certify infeasibility of the original problem.

Most convex relaxations build upon the fact that the **AC-OPF** problem can be formulated as a **QCQP**. The **QCQP** formulation of the **AC-OPF** can be written as follows (**Coffrin et al., 2016**):

$$\min \sum_{g \in G} c^G(P_g^G) \quad (2.1a)$$

$$\text{s.t. } V_i^{\min} \leq |V_i| \leq V_i^{\max}, \quad \forall i \in N \quad (2.1b)$$

$$S_g^{G,\min} \leq S_g^G \leq S_g^{G,\max}, \quad \forall g \in G \quad (2.1c)$$

$$|S_{ij}^B| \leq S_{ij}^{B,\max}, \quad \forall (i,j) \in B \quad (2.1d)$$

$$S_i^G - S_i^L = \sum_{(i,j) \in B} S_{ij}^B, \quad \forall i \in N \quad (2.1e)$$

$$S_{ij}^B = Y_{ij}^* V_i V_i^* - Y_{ij}^* V_i V_j^*, \quad \forall (i,j) \in B \quad (2.1f)$$

$$-\theta_{ij}^{\max} \leq \angle(V_i V_j^*) \leq \theta_{ij}^{\max}, \quad \forall (i,j) \in B \quad (2.1g)$$

where N , B , and G are the sets of network nodes, branches (lines, transformers), and generators, respectively; $c^G(\cdot)$ is the generation cost function; P_g^G is the active power output of generator $g \in G$; S_g^G is the apparent power generated by generator $g \in G$, with bounds $S_g^{G,\min}$ and $S_g^{G,\max}$; S_{ij}^B is the apparent power flow in branch $(i,j) \in B$, with limit $S_{ij}^{B,\max}$; S_i^G and S_i^L denote the total apparent power generation and load at bus $i \in N$, respectively; V_i is the complex voltage at bus $i \in N$; Y is the network admittance matrix; and $\theta_{ij}^{\max}$ is the maximum phase angle difference between buses $i \in N$ and $j \in N$.

Admitting a constant Y , the non-convexity in Model (2.1) arises exclusively from the bilinear voltage products $V_i V_j^*$. Most convex relaxation techniques exploit this property by introducing lifted variables $W_{ij} = V_i V_j^*$, $\forall (i,j) \in N$. The reformulated **QCQP AC-OPF** problem in the W -domain is therefore given by:

$$\min \sum_{g \in G} c^G(P_g^G) \quad (2.2a)$$

$$\text{s.t. } W_{ij} = V_i V_j^*, \quad \forall i, j \in N \quad (2.2b)$$

$$(V_i^{\min})^2 \leq W_{ii} \leq (V_i^{\max})^2, \quad \forall i \in N \quad (2.2c)$$

$$S_g^{G,\min} \leq S_g^G \leq S_g^{G,\max}, \quad \forall g \in G \quad (2.2d)$$

$$|S_{ij}^B| \leq S_{ij}^{B,\max}, \quad \forall (i, j) \in B \quad (2.2e)$$

$$S_i^G - S_i^L = \sum_{(i,j) \in B} S_{ij}^B, \quad \forall i \in N \quad (2.2f)$$

$$S_{ij}^B = Y_{ij}^* W_{ii} - Y_{ij}^* W_{ij}, \quad \forall (i, j) \in B \quad (2.2g)$$

$$S_{ji}^B = Y_{ij}^* W_{jj} - Y_{ij}^* W_{ij}^*, \quad \forall (i, j) \in B \quad (2.2h)$$

$$\tan(-\theta_{ij}^{\max}) \leq \frac{\Im(W_{ij})}{\Re(W_{ij})} \leq \tan(\theta_{ij}^{\max}), \quad \forall (i, j) \in B \quad (2.2i)$$

The advantage of this reformulation lies in its ability to isolate non-convexity into a single structural requirement: the constraint that W must equal the outer product of the voltage vector with itself. This translates into two conditions: (i) W must be positive semidefinite, ensuring physical feasibility, and (ii) W must have rank one, guaranteeing that it corresponds to a realizable set of voltages:

$$W_{ij} = V_i V_j^*, \quad \forall i, j \in N \Leftrightarrow W \succeq 0 \wedge \text{rank}(W) = 1 \quad (2.3)$$

By relaxing or approximating the rank constraint, the problem can be transformed into a convex program. These relaxations are computationally attractive because they allow the use of efficient convex solvers (Lavai and Low, 2012).

2.7.3.1 Semidefinite Programming and Moment Relaxations

Recognizing that a **QCQP** is a special case of polynomial optimization (i.e., optimization problems with polynomial objectives and constraints), tools from polynomial optimization theory can be applied to broaden the range of tractable **QCQP** problems (Bai et al., 2008).

As discussed earlier, unlike Model (2.1), which is quadratic in V , the reformulated Model (2.2) is convex in W except for the non-convex constraint (2.2b). Since enforcing the rank-1 condition is non-convex and computationally intractable, the standard **SDP** relaxation removes this requirement while retaining positive semidefiniteness. The result is a convex problem that can be efficiently solved with “off-the-shelf” **SDP** solvers. The relaxed formulation of the **AC-OPF** can therefore be written as (Bai et al., 2008):

$$\min \sum_{g \in G} c^G(P_g^G) \quad (2.4a)$$

$$\text{s.t. } (V_i^{\min})^2 \leq W_{ii} \leq (V_i^{\max})^2, \quad \forall i \in N \quad (2.4b)$$

$$S_g^{G,\min} \leq S_g^G \leq S_g^{G,\max}, \quad \forall g \in G \quad (2.4c)$$

$$|S_{ij}^B| \leq S_{ij}^{B,\max}, \quad \forall (i,j) \in B \quad (2.4d)$$

$$S_i^G - S_i^L = \sum_{(i,j) \in B} S_{ij}^B, \quad \forall i \in N \quad (2.4e)$$

$$S_{ij}^B = Y_{ij}^* W_{ii} - Y_{ij}^* W_{ij}, \quad \forall (i,j) \in B \quad (2.4f)$$

$$S_{ji}^B = Y_{ij}^* W_{jj} - Y_{ij}^* W_{ij}^*, \quad \forall (i,j) \in B \quad (2.4g)$$

$$\tan(-\theta_{ij}^{\max}) \leq \frac{\Im(W_{ij})}{\Re(W_{ij})} \leq \tan(\theta_{ij}^{\max}), \quad \forall (i,j) \in B \quad (2.4h)$$

$$W \succeq 0 \quad (2.4i)$$

When the **SDP** relaxation is exact (i.e., when the optimal W is rank-1), the solution corresponds to the global optimum of the original problem. Even when inexact, the method provides valuable insights into feasibility and optimality gaps (Sojoudi and Lavaei, 2012).

Moment relaxations generalize the **SDP** approach by exploiting the connection between polynomial optimization and the Lasserre hierarchy (Lasserre, 2001). In this hierarchy, the standard **SDP** corresponds to the first-order relaxation. Higher-order relaxations introduce additional constraints that progressively tighten the feasible region (Molzahn and Hiskens, 2015). Although computationally expensive, second- and third-order moment relaxations have been demonstrated to yield exact solutions in benchmark cases (Josz et al., 2015).

2.7.3.2 Second-Order Cone Programming

The **SOCP** relaxation provides an alternative convexification strategy to the **SDP** approach by relaxing each bilinear voltage product in (2.2b) separately, rather than enforcing them jointly through a global rank-1 constraint (Jabr, 2006). Starting from the bilinear identity:

$$W_{ij} W_{ij}^* = V_i V_j^* V_i^* V_j, \quad (2.5a)$$

$$|W_{ij}|^2 = W_{ii} W_{jj}, \quad (2.5b)$$

$$|W_{ij}|^2 \leq W_{ii} W_{jj}, \quad (2.5c)$$

the exact equality (2.5b) is replaced by the inequality (2.5c), which is a rotated Second-Order Cone (**SOC**) constraint. **SOC** constraints are natively supported by modern optimization solvers and scale much more efficiently than semidefinite matrix constraints (Cofrin et al., 2016).

The complete **SOCP** relaxation of the **AC-OPF** can be written as:

$$\min \sum_{g \in G} c^G(P_g^G) \quad (2.6a)$$

$$\text{s.t. } (V_i^{\min})^2 \leq W_{ii} \leq (V_i^{\max})^2, \quad \forall i \in N, \quad (2.6b)$$

$$S_g^{G,\min} \leq S_g^G \leq S_g^{G,\max}, \quad \forall g \in G, \quad (2.6c)$$

$$|S_{ij}^B| \leq S_{ij}^{B,\max}, \quad \forall (i, j) \in B, \quad (2.6d)$$

$$S_i^G - S_i^L = \sum_{(i,j) \in B} S_{ij}^B, \quad \forall i \in N, \quad (2.6e)$$

$$S_{ij}^B = Y_{ij}^* W_{ii} - Y_{ij}^* W_{ij}, \quad \forall (i, j) \in B, \quad (2.6f)$$

$$S_{ji}^B = Y_{ij}^* W_{jj} - Y_{ij}^* W_{ij}, \quad \forall (i, j) \in B, \quad (2.6g)$$

$$\tan(-\theta_{ij}^{\max}) \leq \frac{\Im(W_{ij})}{\Re(W_{ij})} \leq \tan(\theta_{ij}^{\max}), \quad \forall (i, j) \in B, \quad (2.6h)$$

$$|W_{ij}|^2 \leq W_{ii} W_{jj}, \quad \forall (i, j) \in B. \quad (2.6i)$$

Compared to the **SDP** relaxation, the **SOCP** formulation introduces fewer variables and avoids the computationally intensive requirement of enforcing positive semidefiniteness on large dense matrices. Instead, it leverages localized **SOC** constraints, which are more memory-efficient and take advantage of the sparsity inherent in electrical networks. This makes **SOCP** particularly attractive for large-scale systems where **SDP** quickly becomes intractable. However, this computational efficiency comes at the cost of tightness. While **SDP** relaxations are often exact in practice, **SOCP** relaxations are weaker: they may leave non-negligible duality gaps and fail to capture global feasibility under stressed operating conditions. Nevertheless, for large-scale planning and real-time operational contexts where solution speed is paramount, **SOCP** relaxations can offer a good balance between accuracy and scalability.

2.7.3.3 Quadratic Convex Relaxation

The Quadratic Convex (**QC**) relaxation proposed by Coffrin et al. (2016) leverages convex envelopes in the polar representation of the **AC-OPF** problem to relax the dependencies among voltage variables. Unlike the **SDP** and **SOCP** relaxations, the **QC** formulation imposes additional constraints that preserve stronger coupling between voltage magnitudes and phase angles, resulting in a tighter approximation.

In the **QC** relaxation, the non-convex constraint (2.2b) is removed, and explicit variables are introduced for bus voltages, $v_i \angle \theta_i \ \forall i \in N$, and squared branch current magnitudes, $l_{ij} \ \forall (i, j) \in B$:

$$W_{ii} = \left\langle v_i^2 \right\rangle^T, \quad \forall i \in N, \quad (2.7a)$$

$$\Re(W_{ij}) = \left\langle \langle v_i v_j \rangle^M \langle \cos(\theta_i - \theta_j) \rangle^C \right\rangle^M, \quad \forall (i, j) \in B, \quad (2.7b)$$

$$\Im(W_{ij}) = \left\langle \langle v_i v_j \rangle^M \langle \sin(\theta_i - \theta_j) \rangle^S \right\rangle^M, \quad \forall (i, j) \in B, \quad (2.7c)$$

$$S_{ij} + S_{ji} = Z_{ij} l_{ij}, \quad \forall (i, j) \in B, \quad (2.7d)$$

$$|S_{ij}|^2 \leq W_{ii} l_{ij}, \quad \forall (i, j) \in B. \quad (2.7e)$$

where superscripts T , M , C , and S denote convex envelopes for the square, bilinear product, cosine, and sine functions, respectively; and Z_{ij} is the branch impedance.

The complete **QC** model for the **AC-OPF** is:

$$\min \quad \sum_{g \in G} c^G (P_g^G) \quad (2.8a)$$

$$\text{s.t.} \quad (V_i^{\min})^2 \leq W_{ii} \leq (V_i^{\max})^2, \quad \forall i \in N, \quad (2.8b)$$

$$S_g^{G, \min} \leq S_g^G \leq S_g^{G, \max}, \quad \forall g \in G, \quad (2.8c)$$

$$|S_{ij}^B| \leq S_{ij}^{B, \max}, \quad \forall (i, j) \in B, \quad (2.8d)$$

$$S_i^G - S_i^L = \sum_{(i, j) \in B} S_{ij}^B, \quad \forall i \in N, \quad (2.8e)$$

$$S_{ij}^B = Y_{ij}^* W_{ii} - Y_{ij}^* W_{ij}, \quad \forall (i, j) \in B, \quad (2.8f)$$

$$S_{ji}^B = Y_{ij}^* W_{jj} - Y_{ij}^* W_{ij}^*, \quad \forall (i, j) \in B, \quad (2.8g)$$

$$\tan(-\theta_{ij}^{\max}) \leq \frac{\Im(W_{ij})}{\Re(W_{ij})} \leq \tan(\theta_{ij}^{\max}), \quad \forall (i, j) \in B, \quad (2.8h)$$

$$W_{ii} = \left\langle v_i^2 \right\rangle^T, \quad \forall i \in N, \quad (2.8i)$$

$$\Re(W_{ij}) = \left\langle \langle v_i v_j \rangle^M \langle \cos(\theta_i - \theta_j) \rangle^C \right\rangle^M, \quad \forall (i, j) \in B, \quad (2.8j)$$

$$\Im(W_{ij}) = \left\langle \langle v_i v_j \rangle^M \langle \sin(\theta_i - \theta_j) \rangle^S \right\rangle^M, \quad \forall (i, j) \in B, \quad (2.8k)$$

$$S_{ij} + S_{ji} = Z_{ij} l_{ij}, \quad \forall (i, j) \in B, \quad (2.8l)$$

$$|S_{ij}|^2 \leq W_{ii} l_{ij}, \quad \forall (i, j) \in B. \quad (2.8m)$$

The **QC** relaxation typically dominates **SOCP** in terms of tightness at similar computational complexity, and is particularly effective in meshed **TNs** with tight phase angle limits. [Coffrin et al. \(2016\)](#) provide both theoretical and computational evidence that: (i) the **QC** relaxation is strictly stronger than **SOCP**; (ii) it is neither strictly stronger nor weaker than **SDP**; and (iii) it often achieves near-**SDP** accuracy at much lower computational cost. Moreover, both **QC** and **SOCP** relaxations are significantly faster and more scalable than **SDP** given the current mathematical solver technology.

2.7.3.4 Other Convex Relaxation Techniques

Beyond SDP, SOCP, and QC relaxations, other convex relaxation approaches for the AC-OPF problem have been explored in the literature. A notable example is the *Branch Flow Model* introduced by Farivar and Low (2013a,b), which can be applied to both radial and meshed networks. This formulation proceeds through two main relaxation steps: (i) elimination of voltage and current angle variables, resulting in a reduced problem formulation; and (ii) approximation of the resulting problem by a conic program, which can be solved efficiently using off-the-shelf convex optimization solvers. For radial networks, the authors prove that both relaxation steps are exact under the assumption that no upper bounds are imposed on loads. In meshed networks, the conic relaxation remains exact, but the angle relaxation may fail. In such cases, they propose a test to verify whether the relaxed solution is globally optimal. Despite the appealing theoretical guarantees, the underlying assumptions are often unrealistic in practical settings. In particular, convex relaxations of the branch flow model, while advantageous for tractability, may yield solutions that are not physically meaningful for the original OPF problem under tight operational constraints. Further potential shortcomings include inaccuracies in representing voltage magnitudes in systems with unbalanced conditions or low resistance-to-reactance ratios, and reduced applicability in meshed TNs. As a result, the method is most commonly applied to radial DNs, with adaptations required for realistic meshed grids (Farivar and Low, 2013b).

Other research lines seek to alleviate the substantial computational burden of solving large-scale AC-OPF relaxations by exploiting network sparsity and selectively applying tighter relaxations. Molzahn and Hiskens (2015) proposed the application of chordal extension theory to identify a sparse structure in the network's admittance matrix, combined with the detection of the subset of buses where the relaxed solution induces significant power mismatches, thus restricting higher-order relaxations to only these buses. Jabr (2012) proposed an approach that employs maximal clique decomposition using matrix completion theorems, which aim to reduce the problem's dimensionality and improve tractability without sacrificing accuracy. In parallel, alternative NLP algorithms have been explored. For example, trust-region methods – originally developed for unconstrained optimization problems – have been adapted to the AC-OPF. Sousa et al. (2011) investigate such an approach and demonstrate that, while the method is globally convergent and robust to poor problem initializations, it is approximately six times slower than state-of-the-art IPMs.

2.7.4 Decomposition Techniques

Solving large-scale instances of the AC-OPF often becomes intractable due to memory limitations and/or prohibitive computation times. As a result, mathematical decomposition techniques have emerged as a promising research direction to enhance tractability.

Phan and Kalagnanam (2014) propose an exact branch-and-bound framework that exploits the quadratic structure of the OPF problem in rectangular voltage coordinates. Two decomposition strategies are adopted: Benders' decomposition and ADMM, applied to the SCOPF problem. Results show that the proposed approach not only accelerates computation for large problem instances, but also often produces solutions with smaller objective function values than conventional methods. Oliveira et al. (2023a,b) also adopt ADMM to solve the AC-OPF problem of an energy community, considering P2P energy trading. The authors propose the application of a residual balancing technique, to improve the convergence characteristic of the proposed algorithm. Sharma et al. (2024) address a hierarchically coordinated TSO–DSO OPF problem through a mixed interior–exterior penalty approach. In their framework, DSOs' subproblems are reformulated as Mathematical Program with Complementary Constraints (MPCC) using first-order KKT conditions, enabling a coordinated yet decomposed solution process that respects the autonomy of each SO. Velloso et al. (2021) focus on large-scale SCOPF problems in the presence of primary frequency response constraints. The problem is modeled as a MILP and solved with a column-and-constraint generation algorithm.

2.7.5 Machine Learning and Data-Driven Approaches

ML and data-driven approaches have also received some interest from the OPF research community. Several approaches for PF approximation have shown promising results, through the application of Neural Networks (NNs) (e.g., Khodayar et al., 2021; Tiwari et al., 2024). Hu et al. (2021) use an encoder/decoder with regularization to build a physics-guided Deep Neural Network (DNN)-PF solver; Yang et al. (2020) propose a probabilistic PF model incorporating the branch flow equations into the loss function of a DNN to improve solution feasibility; and Hansen et al. (2023) utilize Graph Neural Networks (GNNs) representing distribution feeders as branch graphs to locally estimate power balance considering topology changes. Despite their strong empirical performance, deep learning-based methods typically require large training datasets and frequent re-training to remain accurate under evolving system conditions – requirements that may be difficult to satisfy in operational settings. Moreover, such models remain less interpretable to SOs and are often perceived as black-box solutions, limiting their acceptance in safety-critical applications. To address some of these limitations, Glover et al. (2025) introduce a data-driven PF approach based on *Gaussian processes*, a Bayesian learning framework, to approximate three-phase unbalanced PFs by mapping net load injections to nodal voltages. The authors report accuracy comparable to DNN-based methods, while requiring significantly less training data and offering improved uncertainty quantification.

Mezghani et al. (2020) propose a data-driven framework for stochastic AC-OPF based on an iterative scenario generation strategy. The key innovation lies in combining information on constraint violations observed during optimization with data-driven sparse regression to adaptively refine the uncertainty representation. Compared to conventional

approaches relying on random scenario sampling, the proposed method achieves feasible operating points for realistic power systems with significantly fewer scenarios.

Recent works have studied the potential of **AI** Foundation Models (**FMs**), particularly those leveraging **GNNs**, to address the data scarcity and computational challenges of grid analysis. Puech et al. (2024) propose an architecture for a self-supervised **FM** trained to learn **PF** dynamics from limited data, for application in operational and planning tools. Similarly, Hamann et al. (2024) introduce the concept of *GridFMs*, **FMs** trained on diverse grid topologies and operating conditions, for application in **OPF**, contingency analysis, forecasting, and stability assessment tools.

2.7.6 Discrete Controls

A significant number of controls in electrical grids are inherently discrete, e.g., network switches, switched capacitor and reactor banks, and tap-changers on transformers (Panciatici et al., 2014). Despite the significant progress in mathematical solvers, a rigorous solution of the **OPF** problem by means of classical Mixed-Integer Nonlinear Programming (**MINLP**) methods (e.g., branch and bound, outer approximation) remains intractable for large systems (Leyffer et al., 2009; Capitanescu and Wehenkel, 2010).

The efficient handling of discrete variables in the **OPF** has received significant attention since the late 1980s (Stott et al., 1987; Tinney et al., 1988; Papalexopoulos et al., 1989). Since then, a large number of heuristic approaches have been proposed to deal with discrete variables. The simplest approach for handling discrete variables is based on the round-off strategy (Tinney et al., 1988; Papalexopoulos et al., 1989). In this technique, an **OPF** relaxation is first solved by treating all variables as continuous. Next, at the optimal solution, the discrete variables are rounded-off and fixed to their nearest discrete value, and the continuous variables are determined by re-solving the **NLP OPF**. To mitigate the abrupt effects of simultaneously rounding all discrete variables, Karoui et al. (2008) propose a progressive rounding strategy. In this approach, only a subset of discrete variables that are sufficiently close to admissible discrete values is rounded at each iteration. The treatment of discrete variables by means of penalty terms has been proposed in the context of the active-set method (Liu et al., 1992), and **IPM** (Liu et al., 2002). The latter approach provides results comparable with the performances of **IPM** solution of **OPF** relaxation. However, it uses very small steps for shunt banks, whereas in real-life, these steps are often significantly large. An approach using ordinal optimization theory is proposed by Lin et al. (2004). This approach reduces the search space of discrete variables by keeping only the two closest discrete values to the continuous **OPF** solution. Next, the **OPF** is solved only for some combinations of discrete values, selected by means of ordinal optimization theory according to their estimated impact on the objective function. Global optimization methods have also been applied to the **MINLP OPF**, e.g. genetic algorithms (Bakirtzis et al., 2002); simulated annealing (Chen et al., 1997); or hybrid approaches coupling genetic algorithms and local **NLP** solvers (Yan et al., 2006).

Capitanescu and Wehenkel (2010) propose and compare three heuristic approaches for handling discrete variables in large-scale MINLP OPF problems. The first two approaches are based on the sensitivities of the objective and inequality constraints with respect to discrete variables. They set the discrete variables values either by solving a MILP problem or by using a simple procedure based on a merit function, respectively. The third approach is an iterative approach, that relies on the use of Lagrange multipliers corresponding to the discrete variables bound constraints of the OPF solution, to determine a subset of discrete variables to fix. Heid et al. (2025) propose an “iterative deflation” approach for solving the MINLP AC-OPF problem. In each iteration, a continuously relaxed version of the AC-OPF problem is solved and one candidate integer value is systematically eliminated, based on the evaluation of a PF result. The computational complexity of the proposed algorithm grows linearly with the number of integer optimization variables, ensuring scalability.

2.7.7 Uncertainty Handling

The increasing penetration of RESs, the widespread deployment of DERs, and the growing complexity of electricity markets have made uncertainty a central challenge in modern OPF formulations. Unlike traditional power systems dominated by fully controllable generation, contemporary power systems must operate under substantial variability in generation, demand, and network conditions. Uncertainty arises from multiple sources, including fluctuations in RES output and electricity demand, as well as market-driven phenomena such as price volatility. When systems operate close to their technical limits, these uncertainties can significantly affect both operational reliability and economic efficiency (Roald et al., 2023).

2.7.7.1 Stochastic Optimization

Stochastic optimization (or SP) has emerged as one of the most widely adopted frameworks for explicitly addressing uncertainty in OPF problems, particularly in systems with high penetrations of variable RESs and DERs. The core idea is to generate representative scenarios of uncertain parameters and minimize an *expected* objective function across them. The quality of the resulting solutions, however, is highly dependent on the scenario selection (Dvorkin et al., 2014). Unlike deterministic formulations, which rely on a single forecasted trajectory of system conditions, SP explicitly incorporates multiple realizations of uncertain parameters allowing decision-makers to produce control strategies that remain effective under a wide range of possible operating conditions.

SP has been successfully applied to a wide variety of power system problems, including UC (Dvorkin et al., 2014; Antenucci and Sansavini, 2018), OPF (Perninge and Hamon, 2013; Nasri et al., 2014; Summers et al., 2015; Isuru et al., 2020; Usman and Capitanescu, 2023), SCOPF (Murillo-Sánchez et al., 2013), TEP (Qiu et al., 2017b), ASs procurement (Khoshjahan et al., 2021), and P2P energy markets (Hou et al., 2023; Lin

et al., 2021). In the specific context of TSO–DSO coordination, applications include voltage support (Alizadeh et al., 2023), UC (Bjerland et al., 2024), ED (Jiang et al., 2022), OPF (Mohandes et al., 2025), SCOPF (Alizadeh et al., 2023), expansion planning (Liu et al., 2023a; Kabiri-Renani et al., 2019), ESS planning (Massucco et al., 2021), and DN flexibility characterization (Savvopoulos and Hatziaargyriou, 2023).

The key advantage of stochastic OPF lies in its ability to balance economic efficiency and operational security, avoiding the excessive conservatism of RO while still explicitly hedging against uncertainty. However, these benefits come at the cost of significant computational challenges. The optimization problem size grows rapidly with the number of scenarios required to approximate probability distributions accurately, leading to scalability issues in large-scale systems. Consequently, much of the ongoing research focuses on advanced scenario generation and reduction techniques, decomposition methods, and hybrid formulations that preserve the benefits of stochastic modeling while improving computational tractability (Roald et al., 2023).

2.7.7.2 Chance-Constrained Optimization

Many optimization problems under uncertainty aim to determine solutions that explicitly limit the risk of constraint violations. These methods are often referred to as *risk-averse*, with CCO representing one of the most prominent approaches in this category, particularly in power system applications (Roald et al., 2023). Unlike SP, which typically considers a large number of explicit scenarios, the core idea of CCO is to minimize an objective function subject to constraints that are required to hold with a specified probability. In this formulation, feasibility is no longer deterministic but probabilistic: operational limits must be satisfied with sufficiently high confidence, while allowing for rare violations below a predefined tolerance. This makes CCO especially relevant when enforcing all constraints under every possible realization of uncertainty would be either infeasible or excessively conservative (Panciatichi et al., 2014).

Two main classes of chance constraints are often distinguished:

- Single chance constraints: where the probability of violation is individually bounded for each constraint;
- Joint chance constraints: where the joint probability that *any* constraint is violated is bounded by a given threshold, providing stronger guarantees for overall system reliability.

In the context of power system operations, chance constraints are widely employed to capture risks associated with uncertain inputs such as RES generation, load fluctuations, or component outages. For instance, in OPF formulations, they allow the SO to explicitly quantify and control the risk of network limit violations (e.g., line overloads or voltage violations). This approach provides a compromise between purely deterministic formulations, which may underestimate operational risks, and RO methods, which often lead to

overly conservative and costly solutions. By directly bounding the probability of insecure operation, chance-constrained **OPF** enables the design of preventive control actions that balance operational security and economic efficiency.

Roald et al. (2013) apply **CCO** to the **SCOPF** problem, using single chance constraints to enforce line **PF** limits under uncertainty. Building on this, the same authors later introduced a probabilistically robust randomized optimization method, which reduces the number of scenarios required compared to the classical scenario approach, while still maintaining similar probabilistic guarantees (Roald et al., 2015). Hamon et al. (2013) address the chance-constrained **OPF** problem by approximating chance constraints through derivative-based estimation techniques, whereas Qin et al. (2022) and Bienstock et al. (2014) adopt formulations based on joint chance constraints to ensure system-wide security guarantees. Beyond **OPF**, chance constraints have also been applied to related problems such as day-ahead congestion management (Guha Thakurta et al., 2015) and voltage control under uncertainty (Vrakopoulou et al., 2013).

Despite these advances, the main drawback of the **CCO** framework is its insensitivity to the severity of constraint violations. In practice, even rare but large violations can have disproportionate consequences for system reliability and security. Thus, while **CCO** provides a compelling balance between economic efficiency and robustness – less conservative than **RO** and more risk-aware than deterministic formulations – its application in real-world systems must be carefully assessed, especially in safety-critical contexts (Roald et al., 2023).

2.7.7.3 Robust Optimization

In many practical situations, detailed probabilistic information about uncertain parameters may not be available, either due to insufficient data or because the uncertainty stems from rare, high-impact events. Moreover, there are contexts where even low-probability outcomes cannot be ignored, as their consequences may be catastrophic (e.g., major black-outs). In such cases, it is desirable to adopt a conservative decision-making framework that safeguards against the worst possible realizations of uncertainty, rather than optimizing for expected or likely scenarios. **RO** provides such a framework by formulating the problem as a *min-max* optimization problem: first-stage decisions are chosen to minimize the objective function, while the second-stage is evaluated under the worst-case realization of uncertainty within a predefined set (Roald et al., 2023).

Panciatichi et al. (2010) proposed an **RO** framework for operation planning under uncertainty, spanning time horizons from day-ahead to intraday. Their formulation adopts the **DC** approximation of the **PF** equations and reformulates the problem as a **MILP**. Focusing specifically on the **SCOPF** problem, Fliscounakis et al. (2013) also rely on the **DC** model, but employ a fixed-point algorithm combined with several **MILP OPF** formulations. In contrast, Capitanescu and Wehenkel (2013b) consider a full **AC** network model for the **SCOPF** problem and propose a heuristic decomposition approach to reduce

the problem's computational complexity. While this method proves effective for large systems, the authors note that solving the resulting nonlinear bi-level optimization problem remains a significant challenge, requiring further research. Beyond these studies, RO has also been applied to a wide range of other power system problems, including UC (Alizadeh et al., 2018; Amjady et al., 2017; Ye and Li, 2016), single-period OPF (Lee et al., 2021; Attarha et al., 2018; Zeng et al., 2022; Louca and Bitar, 2019; Yang et al., 2021), multi-period OPF (Soares et al., 2018; Lorca and Sun, 2018), and the characterization of ADN capability curves (Savvopoulos et al., 2024).

RO provides a powerful framework for safeguarding power system operation against the worst-case realization of uncertainty, ensuring guaranteed feasibility without relying on probabilistic assumptions. Its strength lies in its ability to deliver conservative and reliable solutions, making it particularly attractive in sensitive operational contexts. However, this conservatism often comes at the expense of economic efficiency, as solutions must remain feasible across all scenarios in the uncertainty set, including highly unlikely extremes. Consequently, while RO is well suited for problems where security and resilience dominate, ongoing research has increasingly turned to hybrid approaches, such as DRO, which seek to balance the guarantees of RO with the efficiency gains of probabilistic frameworks.

2.7.7.4 Distributionally Robust Optimization

Both SP and CCO require specifying the probability distribution of uncertain parameters, which is often unknown or only partially available in practice. By contrast, RO does not rely on distributional knowledge but tends to be overly conservative (Roald et al., 2023). To bridge this gap, DRO has emerged as a middle ground: it optimizes decisions against the worst-case distribution within an *ambiguity set*, i.e., a family of probability distributions consistent with available data or forecasts (Arrigo et al., 2023). This allows DRO to capture uncertainty more realistically than purely robust methods, while avoiding the strong reliance on exact probability distributions required by stochastic approaches.

Early DRO-OPF formulations focused on moment information. Lubin et al. (2016) introduce a cutting-plane method to handle ambiguity in the first and second moments of uncertain variables. Similarly, Zhang et al. (2016) propose a moment-based DRO-OPF that captures uncertainty from RES generation and FLs, reformulated as either an SDP or SOCP. Extending this work to distribution grids, Mieth and Dvorkin (2018) design a DRO-OPF model for radial systems considering uncertain DER injections.

Another active research strand leverages Wasserstein ambiguity sets, which quantify the distance between probability distributions. Duan et al. (2018) introduce a Wasserstein-DRO for uncertain RES generation, while Wang et al. (2018) combine moment-based and Wasserstein sets. Joint chance constraints under a Wasserstein-DRO framework are investigated by Ordoudis et al. (2021). More recent work enriches these formulations: Arrigo et al. (2022) propose an exact reformulation, later extended to capture spatial dependencies of wind generation in both meshed TN and radial DN settings (Arrigo et al., 2023).

Building on this, [Yu et al. \(2025\)](#) integrate spatio-temporal correlations of RESs using Copula functions and Markov chains, reformulating the problem as an SOCP solved via column-and-constraint generation. Similarly, [Yang et al. \(2025\)](#) design Wasserstein-based joint chance constraints that explicitly address frequency security under wind generation uncertainty.

Other contributions explore adaptive and multi-stage robust settings. [Attarha et al. \(2018\)](#) propose a tri-level adaptive robust AC-OPF with bounded polyhedral uncertainty sets, solved via primal-dual decomposition. [Guo et al. \(2019\)](#) extend Wasserstein-DRO to multi-stage problems, while [Akbari and Sansavini \(2023\)](#) consider correlated polytopic uncertainty for intra-hour injections, using SOCP relaxation and sequential convex programming to recover AC feasibility. [Zheng et al. \(2021\)](#) adapt DRO to three-phase unbalanced DN reconfiguration. Finally, [Huang et al. \(2025\)](#) propose a DRO-SCOPF with modified copula-based ambiguity sets to capture dependencies among wind farms, deriving tractable reformulations and introducing sensitivity indexes to reduce complexity.

Despite these advances, most DRO-OPF formulations continue to rely on linear approximations or convex relaxations of the PF equations to preserve tractability ([Guo et al., 2019](#)). This reliance underscores a persistent trade-off: while DRO offers stronger distributional guarantees than SP, and avoids the excessive conservatism of RO, its tractable reformulations often come at the expense of accurately capturing nonlinear grid physics. Recent contributions aimed at reducing ambiguity sets (e.g., [Esteban-Pérez and Morales, 2023](#)) represent important steps toward alleviating this conservatism, and signal progress toward reconciling model fidelity with computational scalability.

2.8 Concluding Remarks

Nowadays, TSOs and DSOs already cooperate and exchange information to a limited extent. However, with the rising penetration of variable RES and DERs, alongside growing concerns over energy security, such cooperation must evolve into more sophisticated and structured mechanisms. Enhanced coordination is critical to ensure the efficient use of distributed resources while safeguarding overall system reliability. In practice, this requires TSOs and DSOs to jointly address both operational and planning challenges, particularly regarding DER flexibility provision. The implementation of the NCs and the ongoing development of the *European Balancing Platforms* represent important regulatory and technical steps in this direction ([ENTSO-E, 2019](#)). Yet, national market rules often remain misaligned, creating barriers to effective coordination. Efforts to harmonize these frameworks are underway but remain uneven across jurisdictions.

Despite these advances, large-scale demonstration projects are still scarce. Comprehensive pilots exploring the wide spectrum of services that DERs can provide to system operation are limited, and real-world deployments of coordination mechanisms are virtually absent. A further challenge lies in the methodologies themselves: many coordination

frameworks proposed in the literature rely on oversimplified representations of **ADN** flexibility, raising security and reliability concerns that make **TSOs** understandably cautious. Ensuring system security will remain the primary concern for **TSOs**, which means that any proposed coordination framework must convincingly demonstrate both robustness and reliability. Moreover, before tackling the complexities of large-scale coordination, significant challenges related to the **AC-OPF** problem must be resolved. Ensuring computational tractability in the presence of uncertainty remains a key bottleneck, and progress in scalable algorithms and accurate formulations is still required.

To address the identified research gaps, this thesis advances the state-of-the-art through the following main contributions:

- (i) **TSO-DSO** coordination mechanism: a novel coordination framework, developed within the European project ATTEST, that accurately captures **DER** flexibility and introduces the innovative concept of shared resources whose operation is coordinated between **TSOs** and **DSOs**. The mechanism was co-developed in close collaboration with the Croatian **TSO** HOPS and the Croatian **DSO** HEP ODS. The proposed **TSO-DSO** coordination mechanism is presented in detail in Chapter 3.
- (ii) Stochastic Multi-Period **AC-OPF**: a full **AC**-based optimization model that explicitly captures **DER** behavior and multiple sources of uncertainty, including **RES** generation, load, and market price forecasts. The model has been validated in a laboratory environment and currently underpins a joint project with GE Vernova and National Grid. The proposed **SMOPF** formulation is presented in Chapter 4.
- (iii) **TSO-DSO** operational planning tool: built upon the proposed coordination mechanism and the **SMOPF** framework, this tool is implemented using a consensus-based, residual-balanced **ADMM** algorithm, enabling secure, privacy-preserving, and scalable distributed optimization between **SOs**. The proposed **TSO-DSO** operational planning tool is presented in Chapter 5.
- (iv) **TSO-DSO** shared resource planning tool: a two-layer decomposition planning framework developed to optimize system-wide investment decisions concerning shared **ESS** deployment. Battery degradation is explicitly modeled at the subproblem level of the two-level formulation, ensuring scalability to large-scale systems. The proposed **TSO-DSO** shared resource planning tool is described in Chapter 6.

In the following chapter, the proposed **TSO-DSO** coordination framework is introduced. This framework constitutes the conceptual and methodological foundation upon which the operational and planning tools developed throughout this thesis are built.

Chapter 3

TSO-DSO Coordination

TN and DNs have traditionally been planned and operated as largely independent domains, managed separately by TSOs and DSOs. This separation was well aligned with conventional power systems dominated by large, centralized generation, where limited information exchange and simplified representations of the counterpart grid were sufficient (Yuan and Hesamzadeh, 2017). This paradigm is no longer adequate. The rapid penetration of RESs and DERs is displacing conventional synchronous generation and fundamentally reshaping power flows across all voltage levels. Ensuring the secure, reliable, and cost-efficient integration of these resources – while enabling their participation in appropriate market arrangements for ASs procurement – requires substantially closer coordination between TSOs and DSOs (Council of European Union, 2019).

This chapter examines the evolving need for coordinated TSO–DSO operation and introduces the distributed coordination mechanism developed in this thesis. The chapter begins by reviewing the regulatory framework and current operational practices, highlighting the key institutional and technical barriers that limit effective coordination. It then surveys the most relevant coordination approaches proposed in the literature and, building on their strengths and limitations, presents the coordination framework proposed in this work. The chapter is structured as follows:

- Section 3.1 outlines the regulatory framework for TSO–DSO interaction.
- Section 3.2 reviews existing practices and identifies barriers to coordinated operation.
- Section 3.3 defines the roles and responsibilities of TSOs and DSOs, and explores anticipated developments.
- Section 3.4 discusses ASs markets and the potential for DER participation.
- Section 3.5 surveys the main coordination mechanisms proposed in the literature.
- Section 3.6 details the mechanism proposed in this thesis.
- Section 3.7 summarizes key insights and outlines directions for future research.

3.1 Regulatory Framework

The ongoing energy transition poses significant challenges to the operation of electric power systems, requiring regulatory frameworks that can accommodate increasing decentralization, variability, and cross-border integration. In response, the EU has established a comprehensive set of regulatory instruments aimed at enhancing system efficiency, reliability, and market integration. Two pillars are particularly relevant in this context: the *Network Codes and Guidelines* (ENTSO-E, 2019) and the *Clean Energy Package* (European Commission, 2019). Together, these instruments harmonize technical and market rules across Member States, supporting secure system operation, competitive electricity markets, and the effective integration of DERs.

The *Clean Energy Package* places strong emphasis on flexibility, consumer empowerment, and market-based solutions, with the objective of fostering a more sustainable, resilient, and participatory electricity system. It clarifies the roles and responsibilities of TSOs and DSOs, while providing the regulatory foundation for enhanced coordination between them. In parallel, the NCs define detailed technical and operational standards to ensure interoperability and coordinated operation across the European power system. These objectives are further reinforced by the *Energy Roadmap 2050*, which places decarbonization at the core of European energy policy while explicitly safeguarding security of supply and economic competitiveness (European Commission, 2012).

Despite this progress, several regulatory barriers persist. Challenges related to data sharing, operational protocols, and market design continue to limit large-scale RES integration and constrain the deployment of innovative flexibility and coordination mechanisms (Degefa et al., 2023; Miah et al., 2024). While some degree of TSO–DSO interaction is already embedded in current operational practices, the growing complexity and interdependence of TN and DN operations demand substantially closer mutual awareness and coordination. Decisions taken at one voltage level increasingly affect system performance at others, underscoring the need for more integrated regulatory and operational approaches (Alves et al., 2015).

3.1.1 Clean Energy Package

The *Clean Energy Package* constitutes the most comprehensive EU legislative initiative to date aimed at accelerating the decarbonization of the energy system. It promotes sustainability, consumer empowerment, and more efficient and competitive electricity markets, while explicitly addressing the challenges posed by increasing decentralization. In the context of TSO–DSO coordination, two legislative acts are of particular relevance: the *Electricity Regulation* (European Union, 2019b) and the *Electricity Directive* (European Union, 2019a). Together, these instruments formally recognize the growing role of DERs in system operation and establish the legal basis for enhanced cooperation and information exchange between SOs.

3.1.1.1 Electricity Regulation

Article 53 of the *Electricity Regulation* explicitly addresses TSO–DSO coordination, establishing two core requirements (European Union, 2019b): (i) enhanced and timely data exchange between SOs for both operational and planning purposes; and (ii) the creation of mechanisms that enable DERs to provide services to both TSOs and DSOs.

The regulation reflects the evolving role of DSOs, emphasizing their responsibility to actively facilitate the integration of DERs into electricity and AS markets. To support this transition, the regulation highlights the need for appropriate regulatory incentives, including the deployment of Active Network Management (ANM). A further institutional milestone introduced by the regulation is the establishment of the *EU DSO Entity*, a formal body representing DSOs at the European level, complementing the role of European Network of Transmission System Operators for Electricity (ENTSO-E) for TSOs.

3.1.1.2 Electricity Directive

Complementing the *Electricity Regulation*, the *Electricity Directive* (European Union, 2019a) further strengthens the integration of DERs into electricity and AS markets. In particular, it requires that DSOs be both enabled and appropriately incentivized to procure local flexibility through transparent, non-discriminatory, and market-based mechanisms. The directive frames this mandate around three core objectives:

1. Optimal resource utilization: ensuring efficient mobilization of all available flexibility.
2. Secure and efficient operation: improving reliability while minimizing system costs.
3. Market development facilitation: enabling competitive and accessible markets with fair opportunities for DERs.

Together, the *Electricity Regulation* and the *Electricity Directive* establish the legislative foundation for enhanced TSO–DSO cooperation and for the systematic participation of DERs in European electricity and AS markets (European Union, 2019b,a).

3.1.2 Network Codes and Guidelines

The *Network Codes and Guidelines* constitute a complementary set of binding European rules, developed by ENTSO-E in cooperation with the Agency for the Cooperation of Energy Regulators (ACER), with the objective of harmonizing technical and market practices across Member States and fostering efficient, integrated electricity markets (ENTSO-E, 2019). Both instruments carry equal legal force; however, they differ in their mode of implementation. While NCs are directly applicable upon adoption, Guidelines (GLs) require European or regional TSOs to develop detailed implementation methodologies, which are subsequently subject to regulatory approval.

The *Network Codes and Guidelines* are grouped into three families – connection, operation, and market – each directly referencing TSO–DSO coordination:

- Connection Codes: The *Demand Connection Code* sets requirements for demand units capable of providing DR services and introduces the concept of Closed DSOs,¹ which may contribute to grid management and market participation.
- Operation Codes: The *Transmission System Operation Code* establishes rules for coordination and data exchange between TSOs, DSOs, and Significant Grid Users (SGUs),² covering both planning and near real-time operation.
- Market Codes: The *Electricity Balancing Code* promotes competition in balancing markets, requiring rules that ensure fair competition between participants, including aggregators and FSPs connected at the distribution level.

Collectively, these instruments recognize the critical role of DERs in future power systems and emphasize the importance of DSO adoption of ANM practices. Their effective implementation ultimately depends on national regulatory authorities, who must adapt and enforce them to ensure effective TSO–DSO coordination.

3.2 Current Practices and Challenges

Over the past two decades, strategic developments in the European power sector have been driven by two overarching objectives: decarbonizing electricity generation and fostering competitive electricity markets. More recently, concerns over security of supply – intensified by geopolitical instability – have elevated system resilience to an equally central priority. Together, these drivers have accelerated the deployment of DERs, supported by rapid cost reductions and continued technological progress.

As the penetration of DERs increases, their potential to provide system flexibility has become increasingly valuable to both TSOs and DSOs. At the same time, large-scale DER integration introduces new operational challenges. Most FSPs are connected at the distribution level and remain neither directly observable nor controllable by the TSO, leading to two key implications:

1. Increased reliance on active distribution management: secure TN operation increasingly depends on the behavior and control of ADNs.
2. Reduced controllability for the TSO: the displacement of conventional dispatchable generation by variable RESs weakens traditional system-balancing levers.

Addressing these challenges requires much closer cooperation between TSOs and DSOs, spanning both operational practices and long-term planning (Usman et al., 2023).

¹A Closed DSO is a natural or legal entity responsible for operating, maintaining, and, if necessary, developing a Closed Distribution System in line with Article 28 of Directive 2009/72/EC.

²An SGU is a generating or demand facility designated by the TSO as significant due to its potential impact on transmission system security, including the provision of ASs.

3.2.1 Network Operation

In recent years, TSOs have steadily increased procurement of ASs from distribution-connected resources, while DSO procurement – especially from low-voltage DERs – remains limited. Many distribution grids are still operated under the assumption that they can passively absorb resulting flows without significant constraints, but this assumption is becoming untenable as DER penetration grows (Givisiez et al., 2020).

Without proper coordination, several risks emerge:

- “Hidden” congestion: Direct TSO activation of DERs can create bottlenecks in the distribution grid that the TSO cannot directly observe.
- Limited DSO tools: Many DSOs lack advanced network management capabilities, forcing costly reinforcements instead of leveraging flexibility.

The CoordiNet project surveyed the European landscape of DER-based services and found wide variations in what TSOs and DSOs currently procure (Table 3.1) (CoordiNet, 2019). Despite the ambition of the *Clean Energy Package*, several barriers remain:

- Economic disincentives: Reinforcement is often cheaper for DSOs than procuring services from DERs.
- Restrictive participation rules: Strict eligibility criteria, minimum bid size requirements, and the exclusion of certain resources (e.g., DR from balancing markets) can limit participation (CoordiNet, 2019).

Table 3.1: Current state of DERs capable of providing services to TSO and DSO, by country. Adapted from CoordiNet (2019).

Country	Consumers (DR)		Prosumers (DR + DG)		Generators (DG)		Storage Facilities (incl. batteries)	
	TSO	DSO	TSO	DSO	TSO	DSO	TSO	DSO
Germany	✓	✓	✓		✓	✓	✓	✓
Austria					✓		✓	
Czech Republic				✓	✓			
Cyprus	✓		✓		✓	✓	✓	
Italy			✓				✓	
Netherlands	✓	✓	✓	✓	✓	✓	✓	✓
Belgium	✓		✓		✓		✓	

Unlocking the potential of DERs requires the design of market products tailored to their characteristics, supported by trading platforms that allow participation either directly or through aggregators (Damisa et al., 2018).

3.2.2 Network Planning

Investment in transmission and distribution grids involves long lead times and large capital investments, making coordinated planning essential. Effective planning requires that reinforcement strategies account for the mutual impacts between **TN** and **DN**s, ensuring cost-efficient and synergistic solutions (Alves et al., 2015).

The FlexPlan project reviewed existing European practices, engaging two **TSOs** and four **DSOs** across six countries (FlexPlan, 2020). The study found that:

- In most cases, coordination is limited to exchanging development plans or interface measurement data.
- In some countries, there is no systematic information exchange at all.

These findings suggest that coordinated planning is still the exception rather than the rule, despite its importance for enabling **DERs** to participate reliably and cost-effectively in **AS** markets. Regulatory frameworks must evolve to make joint **TSO-DSO** planning a standard requirement.

3.2.3 Data Exchange and Trading Mechanisms

The increasing reliance on distribution-connected services requires robust, standardized data exchange between **TSOs** and **DSOs**. European regulation highlights the importance of interoperability, and standards such as the **CIM** and its extension **CGMES** are emerging as the foundation for efficient data sharing (Bytyqi et al., 2022; Marten et al., 2019). Originally developed for transmission applications, **CGMES** has shown strong potential to support coordination at the **TN-DN** interface (Gietz and Rogowski, 2019).

Beyond interoperability standards, digital trading platforms are reshaping flexibility markets. Blockchain offers tamper-proof, transparent validation of transactions, reducing information asymmetry and enabling decentralized trading (Gao et al., 2018; Khajeh et al., 2019). However, scalability and regulatory acceptance remain barriers. Data spaces are emerging as a complementary paradigm, enabling secure, federated access to operational datasets for forecasting, market participation, and system operation (European Commission, 2023; Otto et al., 2021). In combination, these approaches could provide the governance (data spaces) and transaction validation (blockchain) needed for next-generation flexibility markets.

3.3 Roles and Responsibilities

The secure and efficient operation of the power system has always been the core responsibility of **SOs**. At the transmission level, **TSOs** safeguard overall system security, reliability, and efficiency, primarily through the procurement and deployment of **ASs** such as

frequency control, voltage support, and operating reserves. **DSOs**, by contrast, have traditionally ensured reliable supply at the distribution level, focusing on long-term planning and largely passive network operation. Historically, **DSOs** did not procure local services for congestion or voltage management. Instead, operational challenges were addressed at the planning stage through grid reinforcement – a solution considered both technically straightforward and, under prevailing regulatory incentives, more cost-effective than flexibility procurement (**ENTSO-E, 2015**).

The rapid rise of **DERs** has disrupted this paradigm. With growing shares of variable **RES**, prosumers, and **FLs**, distribution grids are becoming active participants in balancing and market operations. To enable large-scale **DER** participation in energy and **AS** markets, the roles of both **TSOs** and **DSOs** must be revised and clearly delineated (**ENTSO-E, 2021**). Key priorities include:

- Aggregation and market access: Establishing rules and products that allow small-scale resources and aggregators to compete fairly.
- Operational coordination: Defining planning, real-time control, and data exchange procedures to prevent conflicting actions between **SOs**.
- Consumer participation: Explicitly promoting end-user and prosumer involvement in energy and flexibility markets.

Achieving this will require not only regulatory clarity but also robust interoperability standards and transparent settlement mechanisms, ensuring trust in both technical operation and financial transactions.

The most profound transformation is expected at the distribution level. **DSOs** must transition from passive operators into active system managers, technological enablers, and data stewards (**SGTC, 2015**). This evolution implies that **DSOs** will increasingly:

- Operate local flexibility markets to manage congestion and voltage;
- Act as neutral **MOs**, guaranteeing fair, non-discriminatory access to services; and
- Coordinate directly with **TSOs** to contribute to system security and **AS** provision (**Cedec et al., 2015; Givisiez et al., 2020**).

Finally, the shift toward active distribution operation also brings new responsibilities in data governance. Flexibility markets depend on accurate, timely information, making it essential for **DSOs** to implement secure and standardized data exchange platforms. Close collaboration with regulators will be required to define rules on data privacy, access rights, and cybersecurity, thereby ensuring that market integration does not compromise security.

3.4 Ancillary Services

A power system is continuously exposed to stresses as demand and RES generation fluctuate, and components remain vulnerable to faults. These dynamics cause ongoing variations in voltage, frequency, power flows, and power losses. To maintain secure and optimal operation, SOs must constantly monitor network conditions and deploy corrective actions whenever necessary (Mayorga Gonzalez et al., 2020).

Historically, conventional synchronous power plants have been the backbone of ASs, providing the capabilities that underpin system stability and reliability (ENTSO-E, 2019; Machowski et al., 2020; Kundur and Malik, 2022). Their key contributions include:

- Inertial response: Rotor kinetic energy is released instantly during load or fault events, stabilizing short-term frequency.
- Governor response: Turbine governors restore system frequency after disturbances by adjusting mechanical torque.
- Voltage control: Automatic Voltage Regulators (AVRs) adjust reactive power to maintain voltage stability locally and system-wide.
- Redispatch flexibility: Active and reactive power outputs can be directly controlled to manage congestion, balance demand, and support cross-border flows.

As conventional power plants are decommissioned and displaced by inverter-based RES, these essential resources must be replaced. DERs are therefore expected to deliver capabilities such as fault ride-through, local voltage control, and frequency-sensitive power regulation, alongside the broader range of ASs historically provided by large synchronous units (Mayorga Gonzalez et al., 2020). This shift makes DSOs pivotal: they must enable and coordinate DER participation so that distributed resources contribute effectively to secure system operation (Alves et al., 2015).

3.4.1 Frequency Regulation

Maintaining frequency close to the nominal value requires continuous balance between active power generation and demand. Deviations caused by load changes, generator outages, or faults must be corrected quickly.

The main frequency-related ASs are (ENTSO-E, 2022):

- Frequency Containment Reserve (FCR) – Primary control: The first response activated to counteract a sudden frequency deviation. FCR is activated locally and autonomously throughout the synchronous area, typically beginning within seconds and reaching full output within 30 s of the disturbance.
- Frequency Restoration Reserve (FRR) – Secondary control. An automated, centrally dispatched response initiated by the TSO to correct sustained frequency deviations

and balance inter-area power flows. **FRR** acts within 30 s to 15 min after the disturbance and includes both automatic Frequency Restoration Reserve (**aFRR**) and manual Frequency Restoration Reserve (**mFRR**).

- Replacement Reserve (**RR**) – Tertiary control. A manually activated measure used to restore or reinforce system security and economic efficiency. **RR** is generally deployed 15 min after the initial imbalance and can remain active for several hours.

Under suitable coordination frameworks, **DERs** can contribute to all these services. Inverter-based technologies such as wind, **PV**, and batteries can provide synthetic inertia and fast active power adjustments, complementing the declining contribution of synchronous machines.

3.4.2 Non-Frequency Regulation

Non-frequency services ensure reliable operation during both normal and contingency conditions. They include voltage regulation, congestion management, black-start capability, islanding support, and short-circuit current provision.

3.4.2.1 Voltage Regulation and Reactive Power Supply

Voltage stability requires local injection or absorption of reactive power, traditionally delivered by **AVRs**, **OLTC** transformers, and dedicated devices such as synchronous condensers or Static VAr Compensators (**SVCs**). Within a coordinated **TSO–DSO** framework, **ADNs** can provide voltage support at interface nodes. For this to scale, connection codes must define technical requirements and markets must reward reactive power as a distinct product (**IRENA, 2019**).

3.4.2.2 System Restoration (Black Start)

Black start capability, once the domain of hydro or diesel generators, can increasingly be supplied by battery **ESSs**. Advantages include fast response, low maintenance, and no reliance on fuel logistics, making them especially valuable in remote or constrained areas (**IEA, 2024b**). Coordinated restoration planning between **TSOs** and **DSOs** is essential to fully leverage **DER** capabilities and ensure resilient recovery.

3.4.2.3 Islanded Operation

Unintentional islanding is unsafe and generally prevented by anti-islanding protection. However, intentional islanding can be deployed to contain blackouts and is a cornerstone of **MG** operation. Here, **DERs**, supported by **DR** and **ESSs**, can maintain supply-demand balance and stabilize isolated networks (**IEA, 2024b**).

3.4.2.4 Short-Circuit Current

System protection relies on short-circuit current contributions. Inverter-based resources supply far lower fault currents than synchronous machines, challenging protection coordination. Solutions include controlled **ESSs** contributions or coordinated short-circuit forecasts at **TN–DN** interfaces (Lacerda et al., 2023). Despite its importance, short-circuit support has received limited attention in **TSO–DSO** coordination research.

3.4.3 Innovative Services

Future low-inertia, **RES**-dominated systems will require new services beyond today’s **ASs** definitions. Innovative **ASs** are emerging services not yet widely integrated into existing **ASs** markets but increasingly recognized as essential for the future operation of power systems. Two notable examples are (IRENA, 2019):

- Fast Ramping Services (**FRSs**): Steep ramping to balance sharp demand or **RES** fluctuations. As **RES** penetration grows, such rapid changes occur more frequently, driving up market prices and disadvantaging participants that cannot respond quickly. To address this challenge, some **SOs** have begun to define **FRSs** as a dedicated **AS** product (Khajeh et al., 2019).
- Synthetic Inertia: Inverter-based resources – such as wind turbines, solar **PV**, and battery **ESSs** – can emulate the inertial response of synchronous generators by dynamically adjusting active power output during frequency disturbances.

Unlocking the potential of **DERs** to supply the aforementioned services could significantly enhance system stability in low-inertia, **RES**-dominated grids. This prospect highlights the need for effective **TSO–DSO** coordination to enable their large-scale deployment and reliable integration in system-wide operations (IRENA, 2019).

3.5 Coordination Mechanisms

The design of coordination mechanisms between **TSO** and **DSOs** lies at the heart of ongoing debates about the future of electricity markets and system operation. These mechanisms determine not only the formal roles and responsibilities of **TSOs** and **DSOs**, but also the extent to which flexibility from distributed resources can be mobilized to support system security and efficiency (Rivero et al., 2015).

Broadly, coordination models can be classified into:

- Centralized schemes: place responsibility for procurement and activation of services primarily in the hands of the **TSO** (or **ISO**), who clears a single market covering resources across all voltage levels.

- Decentralized schemes: distributed responsibility. DSOs procure services locally while TSOs retain control of transmission-level resources, and the two interact through structured information exchange and market coupling.

While centralized designs are often conceptually simpler, they may be difficult to reconcile with institutional separation and unbundling principles, particularly when the TSO is expected to operate the market and access detailed DN information. For this reason, most European research and demonstration projects, including SmartNet, have focused on decentralized or hybrid approaches (Gerard et al., 2018).

The SmartNet project has become a cornerstone reference in this field, identifying five representative coordination mechanisms that span the design space between full centralization and highly decentralized, market-integrated arrangements. Each of these mechanisms is discussed in detail below, followed by critical analysis and comparison with more recent contributions from ATTEST and other initiatives. Although these five SmartNet mechanisms are retained here as the historical and analytical basis for comparison, subsequent projects and studies have re-expressed the market-based coordination design space in terms of disjoint, common, multilevel, and fragmented market structures (Valverde et al., 2027). The SmartNet terminology is retained in this chapter because it provides the reference framework against which the proposed coordination mechanism was originally developed and assessed. The evolution toward the more recent market-structure classification is discussed in Section 2.2.1.

3.5.1 Centralized AS Market Model

In the centralized AS market model, a single market session is operated by the TSO, who simultaneously acts as both SO and MO. In this arrangement, the TSO directly contracts resources connected at both transmission and distribution levels, while the DSO plays only a residual role. At most, DSOs may be involved in a prequalification process to verify that contracted resources do not compromise distribution-level operation. An illustrative diagram of the centralized AS market model is shown in Figure 3.1.

The appeal of this approach lies in its simplicity: with a single buyer and a single clearing process, transaction costs are minimized, and implementation is largely compatible with the current regulatory framework. However, the limitations are equally clear. The DSO has no active role in managing local congestion or voltage, which can lead to hidden congestion problems that the DSO cannot observe. Operationally, coordination under the centralized AS market model is limited to a one-directional process of bid validation, which is insufficient to capture the dynamic and adaptive characteristics of networks with significant DER penetration.

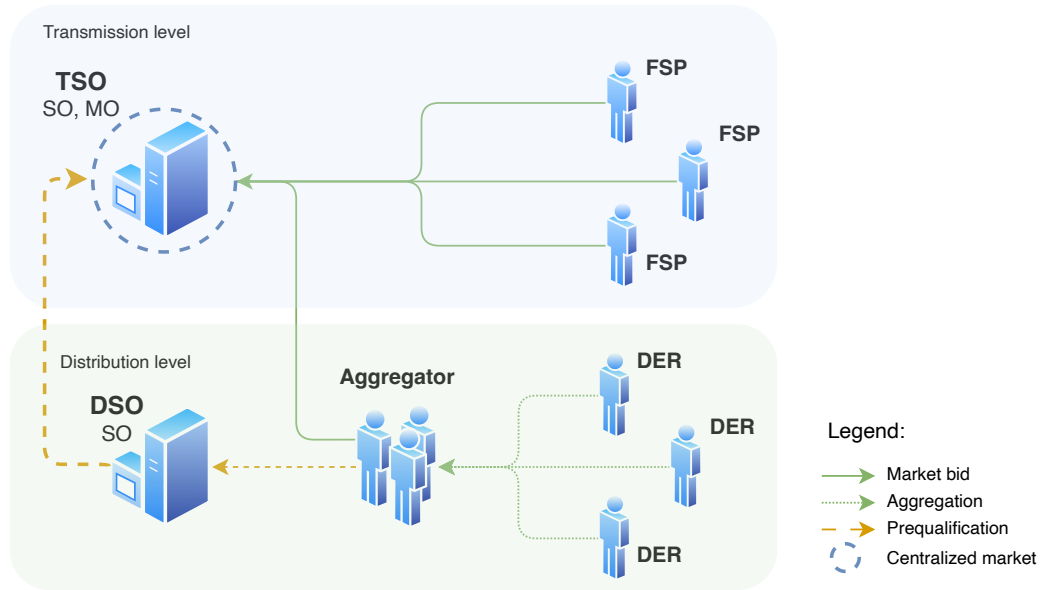


Figure 3.1: Centralized AS market model. Adapted from: Gerard et al. (2018).

3.5.2 Local AS Market Model

The local market model addresses the shortcomings of the centralized AS market model by granting DSOs priority access to flexibility within their networks. Here, DSOs operate local markets to procure services from DERs for congestion management or voltage support. Only bids that remain unused locally are aggregated and forwarded to the TSO, who then clears a central market for transmission-level needs. An illustrative diagram of the local AS market model is shown in Figure 3.2.

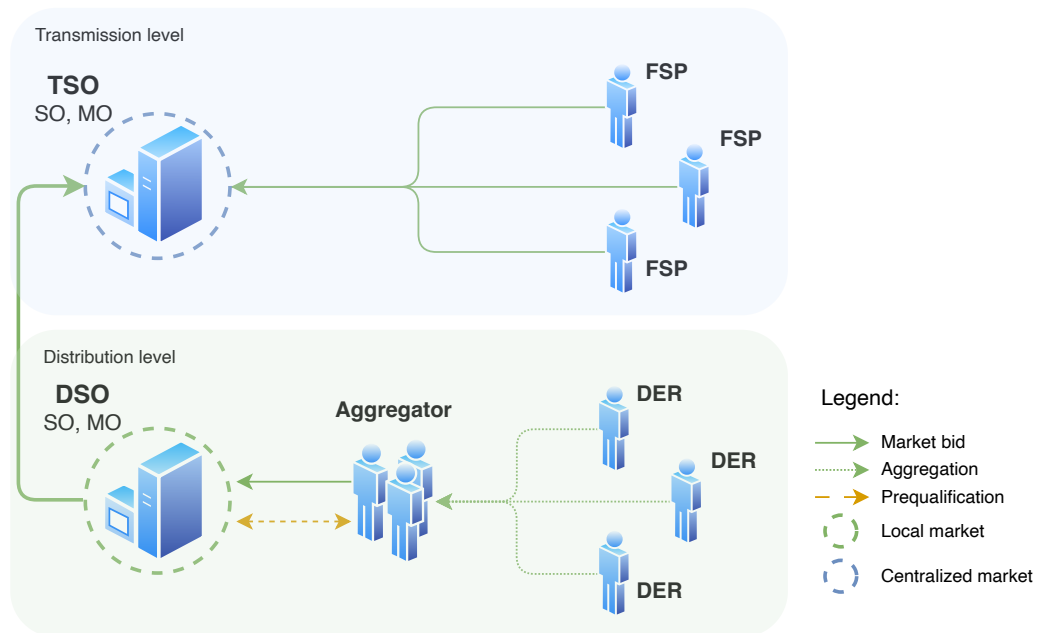


Figure 3.2: Local AS market model. Adapted from: Gerard et al. (2018).

This design creates a more active role for **DSOs** while still enabling resources to contribute to system-wide balancing. Importantly, it ensures that local operational limits are respected before flexibility is exported upward, to the global market operated by the **TSO**. However, sequential clearing introduces inefficiencies: **TSOs** may face restricted access to resources that could have been used more effectively at the system level, and liquidity in local markets may be low, especially in smaller networks.

3.5.3 Shared Balancing Responsibility Model

The shared balancing responsibility model extends the logic of the local market approach by introducing a fundamental change in the **DSO's** role. In this arrangement, the **DSO** is not only responsible for congestion management but also for ensuring that its network remains balanced against a pre-agreed schedule with the **TSO**. An illustrative diagram of the shared balancing responsibility model is shown in Figure 3.3.

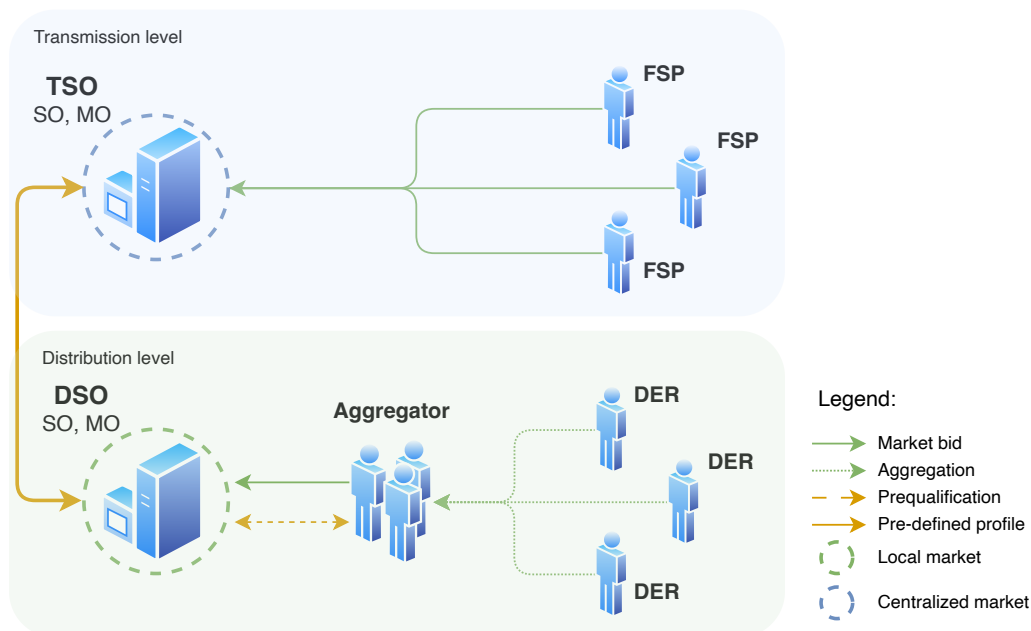


Figure 3.3: Shared balancing responsibility model. Adapted from: Gerard et al. (2018).

In practice, this requires **DSOs** to procure sufficient flexibility to offset imbalances within their own areas, effectively transforming them into *active balancing entities*. While this strengthens the autonomy of **DSOs** and reduces the balancing burden on **TSOs**, it also exposes **DSOs** to significant risks. Insufficient flexibility may force costly redispatches, **RES** curtailment, or even load shedding.

The economic viability of the shared balancing responsibility market model is especially questionable in areas with limited **DER** penetration, where liquidity constraints may undermine competition and inflate flexibility and **AS** prices.

3.5.4 Common TSO-DSO AS Market Model

A more integrated vision is provided by the common market model, in which **TSOs** and **DSOs** jointly procure flexibility within a unified marketplace. Resources are allocated to the **SO** with the highest need, with the explicit aim of minimizing overall system costs rather than prioritizing either transmission or distribution concerns. An illustrative diagram of the common **TSO-DSO AS** market model is shown in Figure 3.4.

Implementation of the common market can follow two main variants:

- Centralized variant: All bids are submitted and cleared in a single optimization problem, simultaneously accounting for both **TN** and **DN** constraints.
- Decentralized variant: A two-stage process is employed. First, **DSOs** clear local markets, and their results are then communicated to the **TSO**, who runs a system-level clearing stage. The final allocation of resources is determined in the second stage and subsequently communicated back to the local market participants.

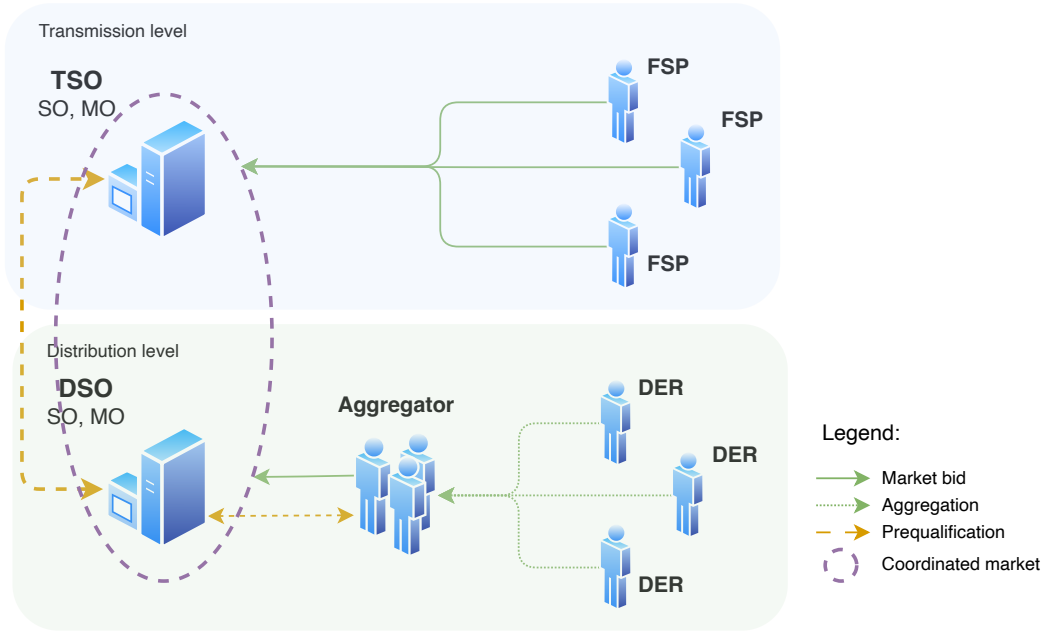


Figure 3.4: Common TSO-DSO AS market model. Adapted from: Gerard et al. (2018).

The model's strength is its global efficiency: it allows for the optimal use of resources across the whole system. Yet the practical challenges are considerable. Centralized clearing is computationally demanding, particularly for large-scale systems. Moreover, the absence of agreed cost-sharing frameworks between **TSOs** and **DSOs** raises concerns about how to allocate expenditures and benefits.

3.5.5 Integrated Flexibility Market Model

The integrated flexibility market model takes one step further by extending participation to non-regulated actors, such as aggregators and retailers. All parties compete on equal terms in a single market platform, with flexibility allocated to those who value it most. An illustrative diagram of the integrated flexibility market model is shown in Figure 3.5.

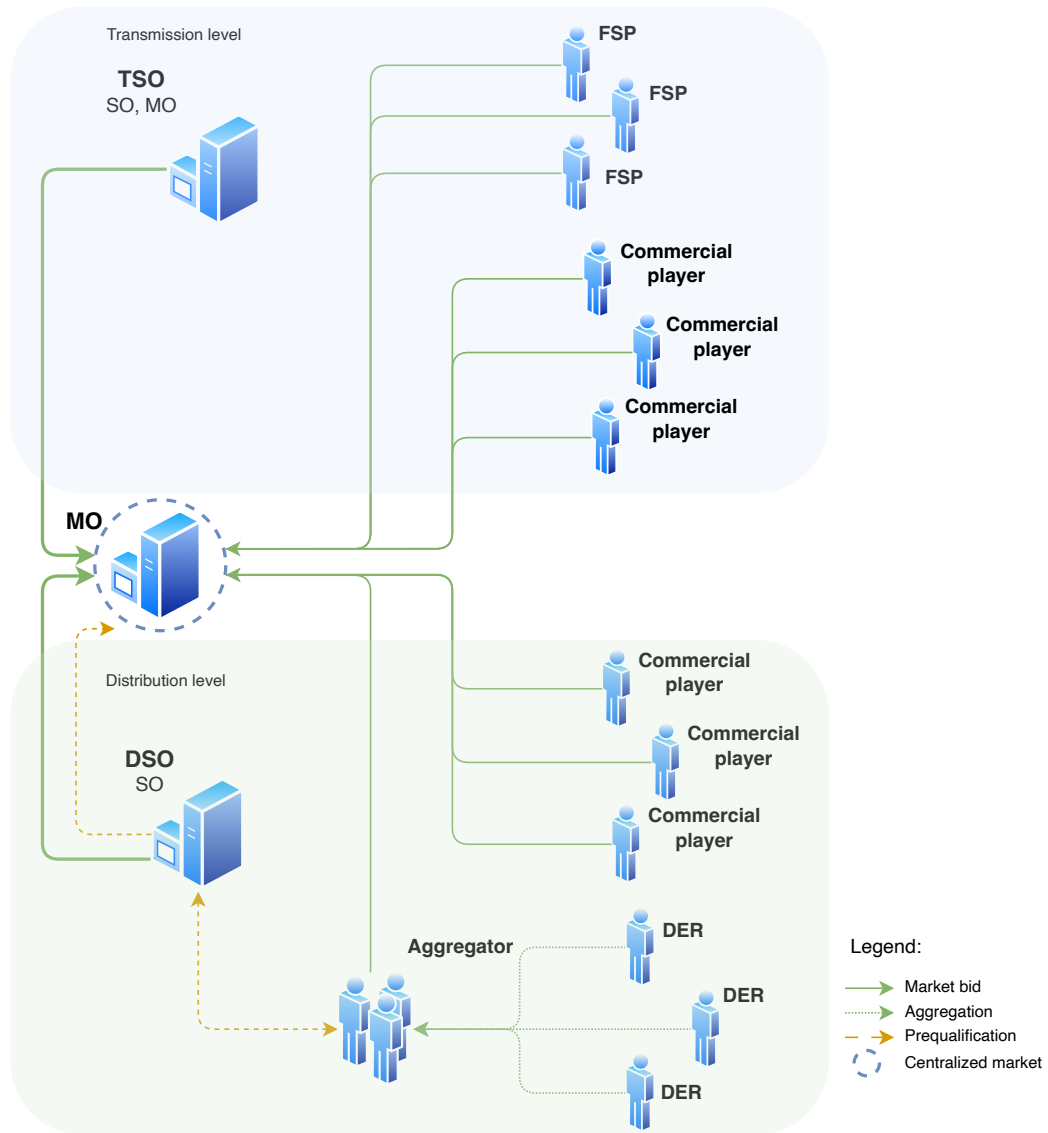


Figure 3.5: Integrated flexibility market model. Adapted from: Gerard et al. (2018).

The main advantage of this model is that all flexibility services are procured through a single market platform. The inclusion of commercial actors enhances liquidity and typically lowers prices. To preserve neutrality when both regulated and non-regulated entities compete, however, the presence of an IMO is essential. Despite these strengths, notable limitations persist: it is computationally burdensome, and TSOs may still need to procure supplementary ASs outside the market to ensure secure operation. Competition for the

same resources can drive up prices, while simultaneous activation by TSOs and DSOs in opposing directions may create operational problems. Speculative trading represents an additional concern, as it may introduce risks of inefficiency or manipulation. Clear and robust regulatory safeguards are therefore required to preserve both fairness and efficiency in the integrated flexibility market model.

3.5.6 Summary and Analysis of SmartNet’s Coordination Mechanisms

SmartNet proposed a set of benchmark TSO–DSO coordination mechanisms that differ significantly in scope, complexity, and regulatory feasibility. These mechanisms illustrate the diverse ways in which flexibility resources located in DNs can be mobilized for system services at both transmission and distribution levels. Their main points of differentiation lie in: (i) the types of ASs that can be procured and allocated, (ii) the extent of DSO involvement in market processes, (iii) the presence of regulatory and institutional barriers, and (iv) the computational complexity associated with real-world implementation.

This subsection provides a critical analysis of the SmartNet mechanisms, focusing first on their capacity to deliver specific ASs, then on the regulatory hurdles that constrain their adoption, and finally on the broader trade-offs each mechanism entails.

3.5.6.1 Types of Services

The feasibility of three essential services – congestion management, frequency control, and voltage control – varies considerably across the coordination mechanisms proposed by the SmartNet project. Table 3.2 summarizes their service coverage.

Table 3.2: Feasibility of each AS in the coordination mechanisms analyzed.

Coordination Mechanism	Congestion Management	Frequency Control	Voltage Control
Centralized AS market model	✓	✓	
Local AS market model	✓		✓
Shared balancing responsibility market model	✓		✓
Common TSO-DSO AS market model	✓	✓	✓
Integrated flexibility market model	✓		

All models enable congestion management, though not always at both levels. In the centralized market model, for example, the DSO cannot actively resolve distribution-level constraints. Although pre-qualification of bids offers some protection against local violations, the DSO plays only a passive role. By contrast, the local and shared balancing responsibility models empower DSOs to use local flexibility for congestion management or balancing, but these frameworks exclude distribution resources from providing frequency regulation services. The common TSO–DSO market model stands out as the only

mechanism that fully covers all three services, but this comes at the cost of high computational requirements, particularly in its centralized form. Frequency control, in particular, remains the most challenging service to coordinate due to its stringent time-response requirements. In practice, only the centralized and common market models can reliably guarantee frequency support, since these preserve a central role for the TSO in system balancing.

3.5.6.2 Regulatory Barriers

Beyond technical feasibility, each mechanism encounters legal and institutional barriers that shape its practical applicability. Most notably:

- Centralized AS market model: Current legislation does not define procedures for the prequalification process or active blocking of flexibility bids by DSOs.
- Local AS market model: DSOs receive no remuneration for contracting flexibility and are not permitted to act as aggregators on behalf of the TSO.
- Shared balancing responsibility model: Would require a redefinition of the balancing mandate, currently held exclusively by TSOs, and compensation structures for DSOs.
- Common TSO-DSO AS market model: Faces the absence of a cost-sharing framework and no current legal basis for DSOs to act as flexibility providers or aggregators.
- Integrated flexibility market model: Encounters the most regulatory gaps, including undefined participation rights for commercial actors, no remuneration schemes for DSOs, and no framework for secondary (speculative) trading safeguards.

Among these, the centralized model faces the fewest explicit regulatory restrictions but is operationally fragile, since the TSO lacks visibility of distribution constraints. Conversely, models that more fully empower DSOs require significant legal reforms before real-world deployment is possible.

3.5.6.3 Summary

Table 3.3 summarizes the key benefits and challenges of the five TSO-DSO coordination schemes proposed by SmartNet.

A recurring theme across all models is the expansion of the DSO role. Moving beyond their traditional passive role, DSOs must evolve into active flexibility managers, procuring services not only for local needs but also on behalf of the TSO. This shift is particularly central to the local and common market models, where the effectiveness of coordination depends critically on active and empowered DSO participation.

In summary, SmartNet provides a comprehensive framework of reference models, each reflecting a distinct balance of centralization, regulatory feasibility, and service coverage.

Table 3.3: Summary of the benefits and challenges of the five TSO-DSO coordination schemes proposed by SmartNet. Adapted from [Morch et al. \(2019\)](#).

Coordination Scheme	Benefits	Challenges
Centralized AS market model	- Efficient scheme when the TSO is the only buyer of the service - Having only one market reduces operational costs and supports standardized processes - Closest to current regulatory framework	- No real involvement of DSO - DSO grid constraints not always respected
Local AS market model	- DSO has priority in using local flexibility - DSO actively supports AS procurement	- TSO and DSO markets are cleared sequentially - Local markets may suffer from low liquidity - High communication requirements
Shared balancing responsibility model	- TSO procures fewer ASs - Local markets reduce entry barriers for small-scale DERs	- Overall AS volumes may increase - Higher costs for balancing - Local markets may lack sufficient liquidity to meet DSO needs
Common TSO-DSO AS market model	- Total AS costs minimized at system level - Optimal use of resources by both SOs	- Individual costs for TSO/DSO may increase - Cost allocation between SOs is difficult
Integrated flexibility market model	- Broader possibilities for SOs to solve imbalances - High liquidity and lower prices due to more buyers and sellers	- Independent MO required - Risk of undermining intraday market liquidity - Need for extensive data sharing with independent MO

All coordination mechanisms present drawbacks: those that maximize service scope are often computationally or institutionally complex, while those with fewer barriers often restrict the **DSO** to a limited role. This trade-off underscores the broader challenge of designing coordination frameworks that are both technically robust and institutionally viable for real-world power systems.

3.5.7 Coordination Mechanism Proposed in the ATTEST Project

ATTEST was an **EU** Horizon 2020 project whose primary objective was to develop an open-source suite of tools to support the coordinated operation, maintenance, and planning of future energy systems. Building on the coordination models introduced by SmartNet, ATTEST proposed a hybrid mechanism that integrates features of both the local **AS** market model and the shared balancing responsibility model.

The distinctive feature of the ATTEST framework is its two-stage provision of services from the **DSO** to the **TSO**: first for active power, and subsequently for reactive power. This staged approach ensures that flexibility originating within the **DN** is offered to the **TSO** via the **DSO**, safeguarding compliance with local operational constraints. The process is further organized into two sequential timeframes: a day-ahead capacity reservation stage and a real-time reserve activation stage. Figure 3.6 illustrates the day-ahead **AS** reservation process (ATTEST, 2019).

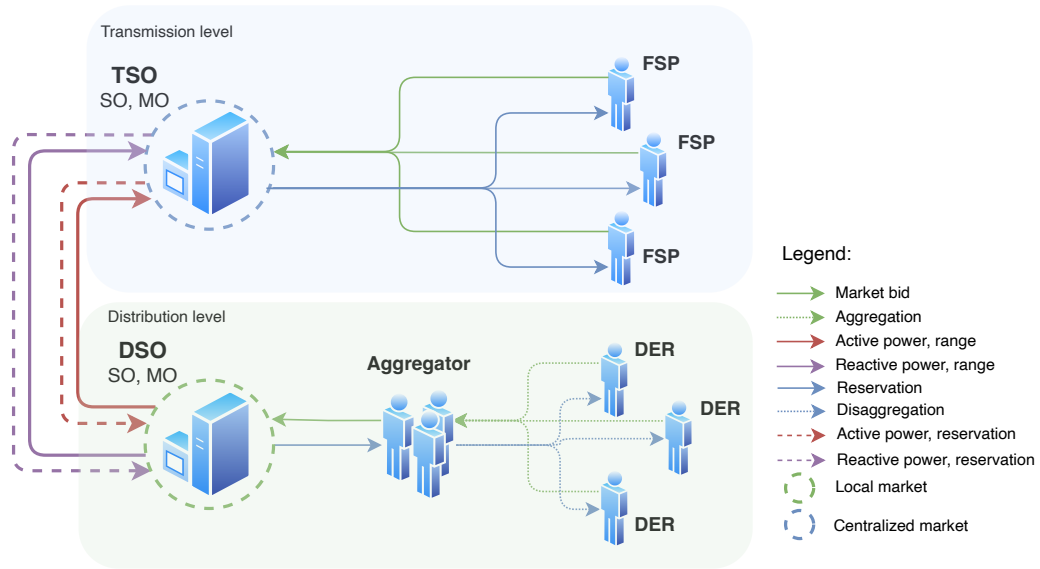


Figure 3.6: ATTEST's TSO-DSO coordination mechanism. Reservation of **AS**s in day-ahead operational planning. Adapted from: ATTEST (2019).

In the day-ahead stage, **FSP**s connected to the **DN** first submit their bids to the **DSO**. The **DSO** then evaluates the safe operating range of active and reactive power that can be transferred to the **TSO** without jeopardizing local network reliability. This assessment is performed in two sequential steps: (i) active power exchanges are initially determined and

fixed, and (ii) reactive power capabilities are subsequently evaluated based on the agreed active power schedule. Once the global market has cleared, the TSO communicates its day-ahead capacity reservations to TN-connected resources, while the DSO conducts a local market settlement to satisfy distribution-level needs, ensuring consistency with the agreed interface power flow profiles.

In real-time operation, the TSO runs an OPF to determine the activation of reserved capacities and communicates activation requests to the DSO. The DSO then runs its own real-time OPF, incorporating these requests while clearing the local market, thus ensuring that DN constraints remain respected. A key limitation of the ATTEST mechanism is its sensitivity to deviations between day-ahead schedules and real-time conditions. Unexpected variations may require redispatch actions, RES curtailment, and even load shedding if not enough flexibility is available. These vulnerabilities are comparable to those observed in SmartNet’s shared balancing responsibility model, highlighting the operational risks associated with shifting balancing duties toward DSOs.

3.5.8 Other Coordination Mechanisms Proposed in the Literature

Research on TSO–DSO coordination has expanded significantly, producing a wide range of conceptual and practical frameworks, many of which extend, refine, or hybridize elements of SmartNet’s coordination mechanisms portfolio.

Three of the SmartNet mechanisms fall under a centralized paradigm: the centralized AS market model, the centralized variant of the common TSO–DSO market model, and the integrated flexibility market model (Gerard et al., 2018). Analogous frameworks are found in the literature under different designations, such as the *joint market model* (Roos, 2017), *total TSO model* (Kristov et al., 2016), or *enhanced bulk balancing authority model* (Burger et al., 2018). Similarly, the centralized common model resembles the *second coordination enhancement* of CAISO et al. (2017) and the *centralized TSO–DSO design* of Najibi et al. (2021). The integrated flexibility market, in turn, parallels the *fully integrated market-clearing model* of Neuhoff et al. (2018).

Three other SmartNet mechanisms embody a hierarchical approach: the local AS market model, the shared balancing responsibility model, and the decentralized common market model. These designs are echoed in several European initiatives. The *separated TSO–DSO congestion management framework* of CEDEC et al. (2019) and the model proposed by Dzikowski (2020) both resemble SmartNet’s local AS market model. The TDX-ASSIST project (TDX-ASSIST, 2018) proposed a mechanism similar to the shared balancing responsibility model, where DSOs procure local flexibility and pre-disclose expected power flows to the TSO. Other hybrid variants, such as the *common market model* of CoordiNet (2020) and the *hybrid scheme* of Burger et al. (2018), are conceptually aligned with SmartNet’s decentralized common AS market model. Several studies have also explored fully distributed coordination – a paradigm not explicitly addressed in SmartNet. Notable contributions include the distributed TSO–DSO ED proposed by

Yuan and Hesamzadeh (2017), the iterative price-based coordination framework of Najibi et al. (2021), and the power flow exchange method introduced by Zhao et al. (2019a).

While these approaches show significant promise, they remain largely at the conceptual or small-scale validation stage and have not yet been demonstrated at the scale of major European research projects. Their relevance lies not merely in assigning a more active role to DSOs, but in enabling both TSOs and DSOs to retain operational autonomy while coordinating decisions that affect both network levels. Compared with sequential hierarchical schemes, distributed coordination can reduce information loss, limit the disclosure of detailed internal models, and better reconcile local network security with system-wide efficiency. These potential benefits motivate the development of alternative coordination mechanisms, including the distributed framework introduced in the following section.

3.6 Proposed TSO-DSO Coordination Mechanism

This chapter proposes a novel TSO-DSO coordination mechanism that builds upon the conceptual foundations of both the SmartNet and ATTEST frameworks while addressing several of their key limitations. Existing coordination models have demonstrated the importance of balancing local network security with system-level efficiency, yet they often rely on hierarchical or centralized designs in which active and reactive power decisions are determined sequentially, only partially capturing their interaction and the intertemporal flexibility of DERs. Such simplifications can result in suboptimal utilization of flexibility, limiting the effectiveness of coordination.

The mechanism introduced here adopts an integrated distributed approach that enables a more precise representation of DER operational constraints, while also expanding the range of ASs that distribution-level resources can reliably provide. In doing so, it contributes both a methodological innovation – through the use of distributed optimization – and a structural innovation – through the deployment of shared resources at the transmission–distribution interface.

3.6.1 Coordination Mechanism

In the proposed framework, the DSO assumes a dual role. As in the ATTEST scheme, it acts simultaneously as a local SO and as an aggregator representing distribution-connected resources in negotiations with the TSO. Voltage magnitude and active and reactive power exchanges at the transmission–distribution interface are thus determined jointly by both SOs, with the explicit requirement that all distribution-level constraints are respected. Two central innovations distinguish this mechanism from existing approaches:

1. From sequential to distributed optimization: Unlike ATTEST’s standard coordination mechanism, which determines active and reactive power exchanges through a two-stage hierarchical process, the proposed mechanism integrates both decisions

within an iterative distributed optimization procedure. This enables a more accurate representation of DER behavior, particularly for deferrable loads and storage technologies whose flexibility is inherently time-dependent.

2. Introduction of shared interface resources: A new category of resources – such as interface-located ESSs – is introduced at the transmission–distribution boundary whose operation is coordinated between TSO and participating DSOs. These shared assets provide additional flexibility where operational responsibilities of TSO and DSO overlap, allowing both SOs to directly coordinate their utilization.

Through iterative exchanges of interface quantities (voltage magnitudes, active and reactive power flows) and shared resource schedules, the mechanism converges to a mutually acceptable solution. This process captures the evolving flexibility of DERs more effectively than hierarchical models, which provide only static feasibility regions. Figure 3.6 illustrates the proposed TSO-DSO coordination mechanism.

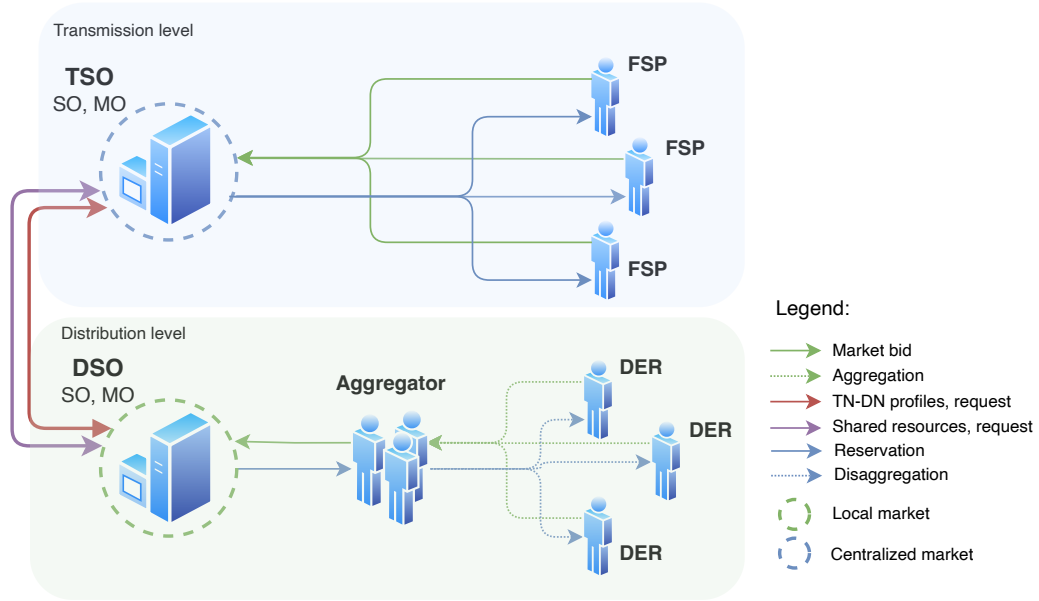


Figure 3.7: Proposed TSO-DSO coordination mechanism: day-ahead reservation of ASs.

3.6.2 Analysis of the Proposed Coordination Framework

Although the proposed mechanism introduces additional procedural and computational complexity, it also delivers clear advantages over existing coordination frameworks.

The most significant advancement of the proposed coordination mechanism lies in its capacity to broaden the portfolio of ASs that distribution-level resources can provide to support system-wide operation. Beyond congestion management and voltage control – already enabled by SmartNet’s local, common, and shared balancing responsibility models as well as by the ATTEST mechanism – the proposed framework is also able to provide

frequency regulation **ASs**. This extension is made possible through the integration of shared interface resources, whose operation is coordinated between **TSO** and **DSOs**. In contrast, earlier schemes largely excluded **DN**-level resources from frequency-related services, with the exception of fully centralized models such as the centralized **AS** market and the common **TSO-DSO** market model. Table 3.4 extends the comparative assessment presented in Table 3.2 to include ATTEST’s mechanism and the novel coordination framework proposed in this thesis.

Table 3.4: Feasibility of different **ASs** across SmartNet’s, ATTEST’s, and the proposed coordination mechanisms.

Coordination Mechanism	Congestion Management	Frequency Control	Voltage Control
Centralized AS market model	✓	✓	
Local AS market model	✓		✓
Shared balancing responsibility market model	✓		✓
Common TSO-DSO AS market model	✓	✓	✓
Integrated flexibility market model	✓		
ATTEST coordination mechanism	✓		✓
Proposed coordination mechanism	✓	✓	✓

The proposed mechanism is among the few frameworks capable of enabling the full range of services – congestion management, voltage control, and frequency regulation – while preserving the unbundled operation of **TN** and **DNs**. This dual achievement – broadening the scope of services accessible from distribution-level resources while respecting the distinct responsibilities of **TSOs** and **DSOs** – positions the proposed framework as an important advancement in the evolution of **TSO-DSO** coordination.

3.7 Summary, Research Directions and Recommendations

European regulations already acknowledge the pivotal role of **DERs** in the operation of modern power systems. Yet, despite this recognition, national market frameworks remain fragmented, and progress toward a harmonized European framework has been uneven (ENTSO-E, 2019). This lack of alignment continues to limit the seamless integration of **DERs** into system operation and **ASs** markets.

3.7.1 Current Challenges

Despite significant academic progress, several practical challenges in **TSO-DSO** coordination remain insufficiently addressed:

- Limited large-scale demonstrations. Most projects remain confined to simulations or small pilots. Only a handful of field trials have tested the full range of services that

DERs can provide, and widespread real-world deployment of coordination mechanisms is still missing.

- Oversimplified modeling of ADNs. Many frameworks fail to capture the true complexity and temporal dynamics of ADN flexibility, leading to concerns about robustness and security from the perspective of TSOs. Because security of supply remains a non-negotiable priority, mechanisms must demonstrate reliability and resilience before implementation.
- Critical enablers of successful implementation. Lessons from SmartNet and CoordiNet underscore the importance of two enabling conditions (Andren et al., 2019; CoordiNet, 2020):
 1. A secure and standardized ICT infrastructure, capable of high-frequency, low-latency data exchange that satisfies the operational requirements of TSOs.
 2. Transparent and equitable remuneration frameworks that ensure sustained participation from prosumers and other flexibility providers.

In summary, while the strategic value of distributed flexibility is widely recognized, regulatory fragmentation, insufficient real-world validation, and inadequate modeling of DNs continue to pose obstacles. Overcoming these barriers will require harmonized policy frameworks, resilient digital infrastructures, and fair market mechanisms that translate academic advances into reliable operational practice.

3.7.2 Contributions of this Thesis

This thesis advances the state-of-the-art in TSO-DSO coordination by proposing a distributed coordination framework that addresses several of the gaps identified in the available scientific literature:

- Comprehensive modeling of flexibility. The mechanism explicitly captures the intertemporal behavior of DERs, while introducing the novel concept of shared resources installed at the TN-DN interface whose operation is coordinated between both SOs.
- Enhanced provision of services. By embedding these shared resources into a distributed negotiation process, the framework expands the range of ASs available from distribution-level resources and improves the efficiency of system-wide operation.
- Industry-informed design and validation. The mechanism was co-developed with the Croatian TSO (HOPS) and the main DSO (HEP ODS), ensuring that operational requirements, institutional roles, and practical constraints from both SOs were incorporated and validated.

3.7.3 Concluding Remarks and Future Research Directions

The proposed distributed coordination mechanism represents a substantial departure from current operational practice. Existing information exchange between SOs is limited, whereas the proposed framework relies on an iterative process with frequent data sharing. This increased procedural complexity poses a significant barrier to real-world implementation and would require corresponding adaptations in regulatory frameworks to define new roles, responsibilities, and compensation mechanisms. In this context, hierarchical coordination may act as a pragmatic intermediate solution, enabling incremental improvements in coordination efficiency while maintaining relatively modest information exchange requirements.

Looking ahead, several research directions deserve further attention:

- **Advanced distributed algorithms:** The continued development of scalable, privacy-preserving distributed optimization methods is essential to accommodate system heterogeneity while safeguarding the operational autonomy of individual SOs.
- **Integration of AI:** The application of ML techniques – including emerging FMs – holds the potential to address data scarcity, accelerate computations, and support predictive or real-time decision-making under uncertainty (Puech et al., 2024; Hamann et al., 2024), enhancing the responsiveness and robustness of TSO–DSO coordinated operation.
- **Field-scale demonstrations and market harmonization:** Large-scale pilot projects, complemented by harmonized European market rules, will be critical to validate the technical robustness, economic efficiency, and institutional feasibility of distributed coordination mechanisms. Regulatory sandboxes could play a key role in bridging the gap between research and deployment.

In conclusion, advancing distributed TSO–DSO coordination will require a combination of methodological innovation, supportive regulation, and collaborative field validation. With sustained research and policy alignment, the flexibility of DERs can be fully harnessed to ensure a secure, efficient, and low-carbon European power system.

Beyond its technical contributions, the TSO–DSO coordination framework proposed in this thesis should be understood as part of a broader academic and institutional trajectory. Academic research on TSO–DSO coordination has progressed rapidly over the past decade, moving from conceptual discussions toward increasingly sophisticated models and pilot projects. Yet the full potential of distributed coordination remains largely unrealized in practice, constrained by regulatory inertia, institutional boundaries, and infrastructural limitations. The mechanism proposed in this work does not claim to offer a definitive solution to these complex challenges. Rather, it should be viewed as a step toward bridging the gap between theoretical advances and operational feasibility.

Chapter 4

Stochastic Multi-Period Optimal Power Flow

At the core of the decision-support tools developed in this thesis lies the operational planning framework used by SOs. Their operational planning tasks are formulated as SMOPF problems, explicitly accounting for uncertainty from multiple data sources, making the formulation sufficiently general to address both short-term operational planning and long-term planning applications.

This chapter introduces the SMOPF module, which combines three interdependent components: (i) a stochastic scenario generation module, responsible for generating representative realizations of uncertain variables; (ii) the core SMOPF formulation, which determines optimal operating strategies under uncertainty; and (iii) a real-time redispatch OPF, designed to refine planning decisions in response to realized system conditions.

The remainder of this chapter is organized as follows:

- Section 4.1 introduces the overall architecture of the SMOPF module.
- Section 4.2 details the stochastic scenario generation module.
- Section 4.3 presents the SMOPF’s mathematical formulation, discussing modeling assumptions and positioning the proposed approach relative to existing formulations.
- Section 4.4 addresses the treatment of discrete decision variables within the optimization framework.
- Section 4.5 describes the real-time redispatch module and the HIL setup used for validation experiments.
- Section 4.6 outlines extensions and applications of the proposed SMOPF.
- Section 4.7 concludes the chapter, highlighting the main findings and identifying opportunities for future research.

4.1 Introduction

The family of optimization problems collectively referred to as **OPF** represents one of the most important and extensively studied topics in both power systems engineering and constrained nonlinear optimization (Frank and Rebennack, 2016). The concept was first introduced by Carpentier (1962) as an extension of the classical **ED** problem, with its defining innovation being the explicit inclusion of network power flow equations in the optimization framework. Over the decades, **OPF** has become indispensable for modern power system operation and planning, underpinning day-ahead scheduling, congestion management, voltage regulation, and other essential operational processes.

In its conventional form, the **AC-OPF** is formulated as a large-scale, non-convex **MINLP**. The inherent nonlinearity of power flow equations, combined with discrete decision variables and stringent network constraints, makes these problems computationally challenging to solve within the time limits imposed by real-time operation, even when using state-of-the-art solvers. As a result, much of the research in recent decades has focused on improving the tractability of **OPF** formulations – through convex relaxations, decomposition techniques, or algorithmic approximations – often at the expense of fully capturing the underlying network physics (Capitanescu, 2016).

In this thesis, an exact **SMOPF** formulation is proposed. Its primary objective is to provide a rigorous and transparent framework for evaluating the impact of **DERs** not only within **DNs** but also across the entire power system. The framework is composed of three submodules: (i) a stochastic scenario generation module; (ii) the core **SMOPF** optimization engine; and (iii) a real-time **OPF** redispatch algorithm. The overall architecture of the proposed framework is shown in Figure 4.1.

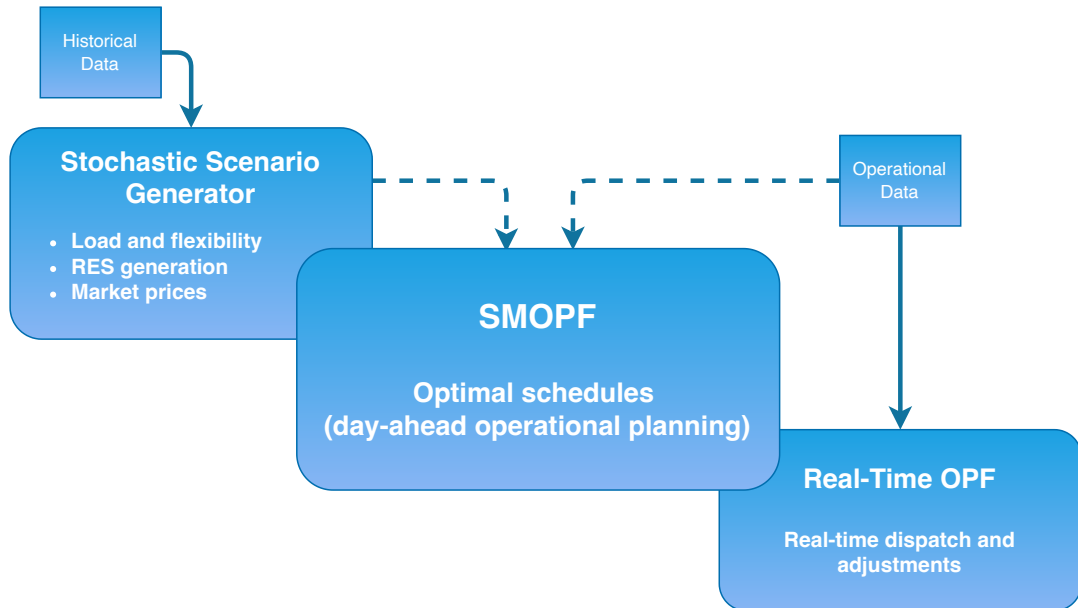


Figure 4.1: Architecture of the proposed SMOPF module.

The proposed **SMOPF** framework is both comprehensive and flexible, enabling the explicit modeling of uncertainty from multiple sources – including load, renewable generation, and market prices – while accounting for a broad portfolio of controllable resources. It is sufficiently general to be applied to both the **TN** and **DN**s, supporting applications that range from short-term operational planning to long-term system development studies. The remainder of this chapter details the implementation of each component of the framework. The chapter concludes with a discussion of possible extensions and directions for future research. The framework has been implemented and tested in a laboratory environment using a **HIL** platform – presented in Case Study 4 of Chapter 7 – validating its feasibility for real-time operation.

4.2 Stochastic Scenario Generation

The *stochastic scenario generator* module relies on historical observations of load, flexibility resources, **RES** generation, and market prices to produce representative stochastic realizations of uncertainty. These scenarios serve as inputs to the **SMOPF**, enabling operational plans that remain robust across a diverse range of possible conditions.

In many applications, scenarios can be directly derived from historical data or probabilistic forecasts. When treated as *independent and identically distributed (i.i.d.)* samples, each scenario represents a distinct realization of the uncertain parameters, all assumed to have equal probability of occurrence. This purely data-driven approach avoids restrictive assumptions about the underlying probability distributions. However, it also entails certain limitations: accurately approximating multivariate distributions may require a large number of scenarios, increasing computational burden; different sample sets can lead to variability in the resulting solutions; and the *i.i.d.* assumption is often violated in practice, since time-series data such as load and **RES** exhibit strong temporal dependencies.

4.2.1 Methodology

To jointly model correlated sources of uncertainty, a Gaussian copula with non-parametric marginals is employed. This approach allows for flexible modeling of nonlinear dependencies while preserving the empirical distributions of each variable. Three multivariate models are trained independently for different uncertainty classes:

- Load: active and reactive power base profiles, and their associated upward and downward flexibility margins;
- **RES** generation: solar **PV** and wind power, for both active and reactive power;
- Market prices: wholesale energy and flexibility market prices.

Each class is modeled using a Gaussian copula, with marginal distributions estimated non-parametrically via Kernel Density Estimation (**KDE**).

4.2.1.1 Model Specification

Let $\mathbf{X} = (X_1, \dots, X_d)$ denote the variables within one class. We assume a Gaussian copula C_Σ with correlation matrix Σ and continuous marginal Cumulative Distribution Functions (CDFs) F_j , defined as (Silverman, 2018):

$$F_{\mathbf{X}}(\mathbf{x}) = C_\Sigma(F_1(x_1), \dots, F_d(x_d)) \quad (4.1)$$

$$C_\Sigma(\mathbf{u}) = \Phi_\Sigma(\Phi^{-1}(u_1), \dots, \Phi^{-1}(u_d)) \quad (4.2)$$

where Φ_Σ is the multivariate standard normal CDF with correlation Σ . The marginals F_j are learned from data via KDE with bandwidth h .

4.2.1.2 Estimation and Sampling Workflow

The estimation and sampling procedure proceeds as follows:

1. Data preparation: Historical time series are cleaned, temporally aligned, and checked for missing or inconsistent values (e.g., mismatched active and reactive power profiles). Missing entries are conservatively imputed to preserve data integrity.
2. Scaling: For numerical stability, data are normalized using either min-max scaling or standardization, depending on the variable type. Power-related quantities are scaled to $[0, 1]$, while market prices are standardized to zero mean and unit variance.
3. Model fitting: A GaussianMultivariate copula with KDE-based marginals is fitted to the scaled data (Virtanen et al., 2020). The copula captures inter-variable statistical dependencies, while the marginals reproduce each variable's empirical distribution.
4. Scenario generation: A user-specified number of joint samples are drawn, preserving the learned cross-variable dependence structure. These samples are then mapped back to the original physical units using inverse transformations.
5. Post-processing: Physics-informed bounds are enforced (e.g., generator capacity limits, zero PV output during nighttime) to ensure realistic and operationally feasible scenario realizations.

The Gaussian copula effectively captures *cross-sectional* dependencies among variables but does not account for temporal autocorrelation. To recover temporal structure, a block bootstrap approach is employed: contiguous historical segments (e.g., 24-hour profiles) are sampled and perturbed with copula-generated noise. This hybrid procedure allows the resulting scenarios to preserve both realistic intra-day dynamics and inter-variable correlations (Bashtannyk and Hyndman, 2001).

4.3 SMOPF Formulation

The **SMOPF** algorithm developed in this work is built upon the exact **AC-PF** equations and explicitly incorporates uncertainty arising from both operational forecasts (load and **RES** generation) and market price variability. Unlike many formulations in the literature – which often rely on simplified approximations of the power flow equations or restrict the range of controllable resources – the proposed approach preserves the full nonlinearity of power flow equations and extends the modeling scope to capture the multi-dimensional flexibility of modern power systems. The formulation considers several key aspects, summarized as follows:

- **Exact network representation:** The full **AC-PF** model is expressed in Cartesian voltage coordinates and solved as an **NLP** problem, ensuring physically consistent results across all operating conditions.
- **Integrated uncertainty modeling:** Stochastic variations in load, renewable generation, and market prices are jointly represented, enabling a unified techno-economic assessment that accounts for both physical and market-driven uncertainties.
- **Advanced modeling of energy storage:** **ESSs** are modeled with full four-quadrant capability, allowing simultaneous active and reactive power control.
- **Reactive support from renewables:** **RES** units are equipped with power factor control, enabling reactive power compensation.

In addition, the proposed **SMOPF** formulation captures the operational flexibility of a broad portfolio of controllable assets, including **OLTC** transformers, curtailable loads and **RES** units, **ESSs**, **FLs**, and **CBs**. By integrating these diverse resources within a unified **SO** framework, the model establishes a rigorous foundation for analyzing the coordinated operation of **TN** and **DN** under uncertainty. The following subsections detail the mathematical formulation of the proposed **SMOPF** model.

4.3.1 Objective Functions

Four types of objective functions are implemented, designed to capture the distinct operational goals and responsibilities of **TSOs** and **DSOs**: (i) cost minimization, (ii) congestion management, (iii) power loss minimization, and (iv) **RES** curtailment minimization.

By definition, the **TSO** objective is formulated as a cost minimization problem, seeking to minimize total system operating costs while ensuring compliance with voltage and branch flow limits. In contrast, the **DSO** objective by definition focuses on congestion management – aiming to mitigate local network violations and reduce the need for load or **RES** curtailment. The framework is deliberately designed to remain flexible, allowing users to select objective functions in accordance with specific operational roles, regulatory frameworks, or market settings.

4.3.1.1 Cost Minimization

The *cost minimization* objective aims to minimize the total system operating cost while penalizing violations of operational constraints (e.g., voltage deviations, branch overloads) and limiting the need for load or **RES** curtailment:

$$\min \sum_{m \in \Omega_m} \sum_{o \in \Omega_o} \sum_{t \in T} \omega_m \omega_o \left(\text{GC} + \text{FC} + \text{LCC} + \text{GCC} + \text{NVV} + \text{NVO} + \text{NEV} \right) \quad (4.3)$$

where:

- Ω_m is the set of market scenarios, with probability ω_m ;
- Ω_o is the set of operational scenarios, with probability ω_o ; and
- T is the set of discrete time instants in the optimization horizon.

The cost components comprising the objective function are defined as:

- GC: Generation cost – conventional generation;
- FC: Flexibility cost – flexibility activation cost;
- LCC: Load curtailment penalty;
- GCC: Renewable generation curtailment cost;
- NVV: Voltage feasibility-restoration penalty;
- NVO: Penalty for branch overloads; and
- NEV: Penalty for infeasibility in **ESS** complementarity constraints.

Generation cost: Represents the cost of active power produced by conventional generators participating in the wholesale energy market:

$$\text{GC} = \sum_{g \in G^C} c_{m,t}^G P_{g,m,o,t}^G \quad (4.4)$$

where:

- $G^C \subseteq G$ is the subset of conventional generators, with G denoting the full set of generators;
- $c_{m,t}^G$ denotes the wholesale energy price in market scenario $m \in \Omega_m$ and time period $t \in T$; and
- $P_{g,m,o,t}^G$ represents the active power output of generator $g \in G^C$ under market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$.

Flexibility cost: Accounts for the activation of active and reactive power flexibility provided by **FLs** participating in the flexibility market:

$$\text{FC} = \sum_{f \in L^F} \left(c_{m,t}^{F,P} P_{f,m,o,t}^{L,\text{Down}} + c_{m,t}^{F,Q} Q_{f,m,o,t}^{L,\text{Down}} \right) \quad (4.5)$$

where:

- $L^F \subseteq L$ is the subset of flexible loads, with L denoting the set of all loads;
- $c_{m,t}^{F,P}$ and $c_{m,t}^{F,Q}$ are the unit costs of downward active and reactive power flexibility, respectively, in market scenario $m \in \Omega_m$ and time instant $t \in T$;
- $P_{f,m,o,t}^{L,\text{Down}}$ represents the downward active power flexibility provided by **FL** $f \in L^F$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$; and
- $Q_{f,m,o,t}^{L,\text{Down}}$ represents the downward reactive power flexibility provided by **FL** $f \in L^F$, under the same market scenario, operational scenario, and time instant.

In this formulation, an **FL** does not necessarily correspond to an individual consumer or exclusively to an industrial load. Depending on the voltage level considered, it may also represent the aggregated power exchange of a downstream network.

Active and reactive power flexibility are represented separately since they may be provided by different resources within the underlying network. This representation does not imply complete physical independence between active and reactive power, but provides a tractable approximation of the flexibility available at the connection point. The corresponding limits are assumed to reflect the operational capabilities of the represented load or network.

Load curtailment cost: Penalizes load curtailment, applied to both active and reactive power components:

$$\text{LCC} = \sum_{l \in L^C} c_l^{LC} \left(P_{l,m,o,t}^{L,\text{Curt},\text{Up}} + P_{l,m,o,t}^{L,\text{Curt},\text{Down}} + Q_{l,m,o,t}^{L,\text{Curt},\text{Up}} + Q_{l,m,o,t}^{L,\text{Curt},\text{Down}} \right) \quad (4.6)$$

where:

- $L^C \subseteq L$ is the subset of curtailable loads;
- c_l^{LC} is the penalty cost associated with curtailing load $l \in L^C$;
- $P_{l,m,o,t}^{L,\text{Curt},\text{Up}}$ and $P_{l,m,o,t}^{L,\text{Curt},\text{Down}}$ represent the upward and downward active power curtailment of load $l \in L^C$; and
- $Q_{l,m,o,t}^{L,\text{Curt},\text{Up}}$ and $Q_{l,m,o,t}^{L,\text{Curt},\text{Down}}$ represent the corresponding upward and downward reactive power curtailment.

High penalty coefficients ensure that curtailment is used only as a last-resort action. These coefficients may also be differentiated across loads to establish priority levels and preserve critical demand.

Depending on the voltage level considered, a curtailable load may also represent the aggregated power exchange of a downstream network. Active and reactive power curtailment are therefore represented separately. In addition to preserving feasibility under stressed conditions, this representation helps identify whether corrective action is primarily required in the active or reactive power balance. Curtailment is disabled by default in standard operational studies. Further modeling details are provided in Subsection 4.3.6.4.

Renewable generation curtailment cost: Penalizes curtailments of renewable generation output:

$$\text{GCC} = \sum_{g \in G^R} c_g^{GC} S_{g,m,o,t}^{G,\text{Curt}} \quad (4.7)$$

where:

- $G^R \subseteq G$ is the subset of **RES** generators;
- c_g^{GC} is the penalty cost associated with curtailing generator $g \in G^R$; and
- $S_{g,m,o,t}^{G,\text{Curt}}$ represents the apparent power curtailed from generator $g \in G^R$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$.

Since renewable generators operate under power factor control, curtailment applies to apparent rather than active power. Penalty factors may vary per unit, enabling strategic curtailment prioritization. Further details on the modeling of renewable generators are provided in Subsection 4.3.6.

Voltage feasibility-restoration penalty: Ensures feasibility under stressed conditions by penalizing auxiliary adjustments to the Cartesian voltage components:

$$\text{NVV} = \sum_{i \in N} c^V \left(e_{i,m,o,t}^{\text{Up}} + f_{i,m,o,t}^{\text{Up}} + e_{i,m,o,t}^{\text{Down}} + f_{i,m,o,t}^{\text{Down}} \right) \quad (4.8)$$

where:

- N is the set of buses;
- c^V is the penalty coefficient associated with voltage feasibility-restoration;
- $e_{i,m,o,t}^{\text{Up}}$ and $e_{i,m,o,t}^{\text{Down}}$ are the upward and downward slack variables for the real component of bus $i \in N$'s voltage in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time period $t \in T$, respectively; and

- $f_{i,m,o,t}^{\text{Up}}$ and $f_{i,m,o,t}^{\text{Down}}$ are the upward and downward slack variables for the imaginary component of bus $i \in N$'s voltage in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time period $t \in T$, respectively.

The component-wise slack variables do not directly quantify voltage magnitude violations. Instead, they constitute auxiliary Cartesian adjustments introduced to preserve feasibility of the nonlinear power flow equations under stressed operating conditions. The admissible voltage magnitude constraints on the non-slacked variables remain defined by (4.30). Consequently, the corresponding objective function term should be interpreted as a numerical feasibility-restoration cost rather than as a measure of the voltage magnitude limit violation.

The penalty coefficient c^V is intentionally set to a high value to discourage activation of the feasibility-restoration variables, allowing such adjustments only when strictly necessary to preserve feasibility. Further details on the modeling of voltage magnitude constraints are provided in Subsection 4.3.2.

Branch overload penalty: Accounts for violations of thermal or flow limits in network branches (lines, transformers):

$$\text{NVO} = \sum_{ij \in B} c^I F_{ij,m,o,t}^{S^2} \quad (4.9)$$

where:

- B is the set of branches;
- c^I is the penalty coefficient associated with branch overloads;
- $F_{ij,m,o,t}^{S^2}$ is the slack variable representing the violation of the branch $ij \in B$ power flow limit in market scenario $m \in \Omega_m$, operation scenario $o \in \Omega_o$, and time instant $t \in T$.

The user may select whether branch flow limits are enforced in terms of apparent power or current magnitude. As with voltage penalties, the coefficient c^I is assigned a sufficiently high value to discourage violations while preserving overall feasibility. Further implementation details on branch flow constraint modeling are provided in Section 4.3.5.

ESS complementarity violation penalty: Maintains feasibility when the complementarity constraints of ESSs are relaxed by penalizing non-physical storage behavior (i.e., simultaneous charging and discharging):

$$\text{NEV} = \sum_{e \in E} c^E S_{e,m,o,t}^{S,E} \quad (4.10)$$

where:

- E is the set of ESSs;
- c^E is the penalty coefficient associated with violations of ESSs' complementarity constraints; and
- $S_{e,m,o,t}^{S,E}$ represent the slack variables indicating the degree of infeasibility for storage unit $e \in E$, in market scenario $m \in \Omega_m$, operation scenario $o \in \Omega_o$, and time instant $t \in T$.

The penalty coefficient c^E is deliberately set to a high value to ensure that such violations occur only when strictly necessary to preserve overall feasibility. Further details on the modeling of ESSs – including the various storage models analyzed and implemented – are provided in Subsection 4.3.6.

4.3.1.2 Congestion Management

The *congestion management* objective focuses on minimizing network constraint violations and curtailments rather than operating costs. Specifically, it penalizes Cartesian voltage feasibility-restoration adjustments, branch overloads, and the curtailment of load and RES generation. Its formulation is given by:

$$\min \sum_{m \in \Omega_m} \sum_{o \in \Omega_o} \sum_{t \in T} \omega_m \omega_o (\text{LCC} + \text{GCC} + \text{NVV} + \text{NVO} + \text{NEV}) \quad (4.11)$$

where the terms LCC, GCC, NVV, NVO, and NEV retain their previous definitions, representing the load curtailment cost, renewable generation curtailment cost, and the penalty terms associated with Cartesian voltage feasibility-restoration adjustments, branch overloads, and ESS complementarity violations, respectively.

In practice, this formulation reflects the traditional responsibilities of DSOs, whose primary objective is to ensure reliable energy supply within their networks. Conversely, TSOs typically adopt the *cost minimization* formulation presented in (4.3), in line with their overarching goal of achieving system-wide operational efficiency (ENTSO-E, 2022).

4.3.1.3 Power Losses Minimization

The *power loss minimization* objective seeks to minimize the total active power losses while explicitly penalizing operational constraint violations and the curtailment of load and RES generation:

$$\min \sum_{m \in \Omega_m} \sum_{o \in \Omega_o} \sum_{t \in T} \omega_m \omega_o \left(\sum_{(i,j) \in B} P_{ij,m,o,t}^{\text{loss}} + \text{LCC} + \text{GCC} + \text{NVV} + \text{NVO} + \text{NEV} \right) \quad (4.12)$$

where the active power losses on branch $(i, j) \in B$, $P_{ij,m,o,t}^{\text{loss}}$, are defined as:

$$P_{ij,m,o,t}^{\text{loss}} := P_{ij,m,o,t} + P_{ji,m,o,t} \quad (4.13)$$

and $P_{ij,m,o,t}$ and $P_{ji,m,o,t}$ denote the active power flows in the “from” and “to” directions of branch $(i, j) \in B$, under market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$, respectively.

4.3.1.4 RES Curtailment Minimization

The *RES curtailment minimization* objective seeks to minimize renewable generation curtailment while penalizing operational constraint violations and unnecessary load curtailment. It is defined as:

$$\min \sum_{m \in \Omega_m} \sum_{o \in \Omega_o} \sum_{t \in T} \omega_m \omega_o (\text{GCC} + \text{LCC} + \text{NVV} + \text{NVO} + \text{NEV}) \quad (4.14)$$

Since *RES* units may provide reactive power support, renewable generation curtailment is expressed in terms of apparent power. The corresponding generator model is detailed in Subsection 4.3.6.1.

4.3.2 Node Voltage in Cartesian Coordinates

In this work, bus voltages are expressed in the *Cartesian* (rectangular) coordinate system rather than in the conventional polar form. While the polar representation is more intuitive from an electrical engineering perspective, it introduces trigonometric terms into the power flow equations, which substantially increase their nonlinearity and complicate numerical solution by interior-point-based *NLP* solvers. In practice, many commercial solvers replace these trigonometric expressions with internal approximations, potentially compromising numerical accuracy and convergence reliability. By contrast, the Cartesian representation eliminates trigonometric functions altogether, yielding polynomial power flow equations that are more amenable to solve. This formulation typically improves both the conditioning of the Jacobian matrix and the robustness of convergence, particularly in large-scale or ill-conditioned systems (Torres and Quintana, 1998).

Formally, the voltage at bus $i \in N$ in Cartesian coordinates is defined as ($\forall i \in N$, $\forall m \in \Omega_m$, $\forall o \in \Omega_o$, $\forall t \in T$):

$$V_{i,m,o,t} = e_{i,m,o,t} + j f_{i,m,o,t} \quad (4.15)$$

where $V_{i,m,o,t}$ denotes the complex voltage at bus $i \in N$, under market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$; and $e_{i,m,o,t}$ and $f_{i,m,o,t}$ represent, respectively, the real and imaginary components of that voltage.

The real and imaginary components of the bus voltage are bounded, respectively, by the following limits ($\forall i \in N, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$-V_i^{\max} \leq e_{i,m,o,t} \leq V_i^{\max} \quad (4.16)$$

$$-V_i^{\max} \leq f_{i,m,o,t} \leq V_i^{\max} \quad (4.17)$$

Here, $V_i^{\max}$ denotes the upper admissible voltage magnitude at bus $i \in N$. Equations (4.16) and (4.17) are numerical box bounds on the Cartesian voltage components and do not constitute physical voltage magnitude limits. Although they are implied by the upper voltage magnitude constraint, retaining them as explicit variable bounds can improve numerical conditioning. The admissible voltage magnitude is enforced through the quadratic constraint presented in Section 4.3.5.

To preserve feasibility under stressed operating conditions, auxiliary adjustments are introduced in the Cartesian voltage components used in the power flow equations. In the Cartesian formulation, the bus voltage including these slack terms is expressed as ($\forall i \in N, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$\tilde{V}_{i,m,o,t} = \tilde{e}_{i,m,o,t} + j\tilde{f}_{i,m,o,t} \quad (4.18)$$

where $\tilde{V}_{i,m,o,t}$ denotes the voltage at bus $i \in N$ including the effects of slack variables, and $\tilde{e}_{i,m,o,t}$ and $\tilde{f}_{i,m,o,t}$ represent its real and imaginary components, respectively, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$.

The real and imaginary components of the bus voltage, extended to include slack variables, are defined as ($\forall i \in N, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$\tilde{e}_{i,m,o,t} = e_{i,m,o,t} + e_{i,m,o,t}^{\text{Up}} - e_{i,m,o,t}^{\text{Down}} \quad (4.19)$$

$$\tilde{f}_{i,m,o,t} = f_{i,m,o,t} + f_{i,m,o,t}^{\text{Up}} - f_{i,m,o,t}^{\text{Down}} \quad (4.20)$$

where $e_{i,m,o,t}$ and $f_{i,m,o,t}$ denote the bounded real and imaginary components of the bus voltage at node $i \in N$, respectively. The slack variables $e_{i,m,o,t}^{\text{Up}}$, $e_{i,m,o,t}^{\text{Down}}$, $f_{i,m,o,t}^{\text{Up}}$, and $f_{i,m,o,t}^{\text{Down}}$ represent positive and negative adjustments to the real and imaginary voltage components used in the power flow equations, respectively. These auxiliary variables are included in the objective function with large penalty coefficients, ensuring that they are activated only when strictly necessary to preserve the overall feasibility of the optimization problem.

The slack variables associated with the real and imaginary components of the bus voltage are strictly non-negative and constrained within the following bounds ($\forall i \in N, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$0 \leq e_{i,m,o,t}^{\text{Up}} \leq V_i^{\max} \phi^V \quad (4.21)$$

$$0 \leq e_{i,m,o,t}^{\text{Down}} \leq V_i^{\max} \phi^V \quad (4.22)$$

$$0 \leq f_{i,m,o,t}^{\text{Up}} \leq V_i^{\max} \phi^V \quad (4.23)$$

$$0 \leq f_{i,m,o,t}^{\text{Down}} \leq V_i^{\max} \phi^V \quad (4.24)$$

Here, ϕ^V is a tuning parameter that bounds each Cartesian adjustment as a fraction of $V_i^{\max}$, thereby preventing unbounded growth of the feasibility-restoration variables. These bounds enhance the numerical stability of the **NLP** solver. In practice, ϕ^V should be selected large enough to accommodate the maximum adjustment required under the stressed operating conditions considered. The inclusion of these slack variables provides a generic feasibility-restoration mechanism for the Cartesian-voltage power flow formulation; however, this comes at a computational cost. Specifically, four additional variables are introduced per network bus, operational scenario, market scenario, and time instant, increasing the size and nonlinearity of the power flow and branch-flow expressions. Their inclusion is optional and may be avoided in studies where feasibility restoration is not required.

Finally, the reference bus $i^{\text{ref}} \in N$ defines the voltage angle reference. Since the power flow equations are formulated using the slack-adjusted Cartesian voltage components, the imaginary component of the reference bus voltage is fixed as $(\forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$\tilde{f}_{i^{\text{ref}},m,o,t} = 0 \quad (4.25)$$

thereby setting the voltage angle at the reference bus to zero. When the voltage feasibility-restoration variables are disabled, Equation (4.25) reduces to $f_{i^{\text{ref}},m,o,t} = 0$.

4.3.3 Power Flow Equations

As previously discussed, this work employs the exact **AC-PF** equations to model network operation. In contrast to many recent studies that adopt linearized approximations or convex relaxations of the power flow equations, the present formulation deliberately prioritizes physical accuracy over computational simplicity. This choice enables a faithful representation of system behavior under realistic operating conditions and allows for a rigorous assessment of the proposed coordination framework.

The active and reactive nodal power balance equations, formulated in Cartesian voltage coordinates and extended to incorporate **OLTC** transformer tap ratios, are expressed as follows $(\forall i \in N, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$\begin{aligned}
P_{i,m,o,t}^{\text{Net}} = & g_i \left(\tilde{e}_{i,m,o,t}^2 + \tilde{f}_{i,m,o,t}^2 \right) + \sum_{j \in N} g_{ij} \left(\tilde{e}_{i,m,o,t}^2 + \tilde{f}_{i,m,o,t}^2 \right) r_{ij,m,o,t}^2 \\
& - \sum_{j \in N} r_{ij,m,o,t} \left(g_{ij} \left(\tilde{e}_{i,m,o,t} \tilde{e}_{j,m,o,t} + \tilde{f}_{i,m,o,t} \tilde{f}_{j,m,o,t} \right) \right. \\
& \left. + b_{ij} \left(\tilde{f}_{i,m,o,t} \tilde{e}_{j,m,o,t} - \tilde{e}_{i,m,o,t} \tilde{f}_{j,m,o,t} \right) \right) \quad (4.26)
\end{aligned}$$

$$\begin{aligned}
Q_{i,m,o,t}^{\text{Net}} = & -b_i \left(\tilde{e}_{i,m,o,t}^2 + \tilde{f}_{i,m,o,t}^2 \right) - \sum_{j \in N} \left(b_{ij} + b_{ij}^{\text{Sh}} \right) \left(\tilde{e}_{i,m,o,t}^2 + \tilde{f}_{i,m,o,t}^2 \right) \\
& + \sum_{j \in N} r_{ij,m,o,t} \left(b_{ij} \left(\tilde{e}_{i,m,o,t} \tilde{e}_{j,m,o,t} + \tilde{f}_{i,m,o,t} \tilde{f}_{j,m,o,t} \right) \right. \\
& \left. - g_{ij} \left(\tilde{f}_{i,m,o,t} \tilde{e}_{j,m,o,t} - \tilde{e}_{i,m,o,t} \tilde{f}_{j,m,o,t} \right) \right) \quad (4.27)
\end{aligned}$$

where:

- $\tilde{e}_{i,m,o,t}$ and $\tilde{f}_{i,m,o,t}$ denote the real and imaginary components of the bus voltage at node $i \in N$ considering slack variables, as defined in Section 4.3.2;
- $P_{i,m,o,t}^{\text{Net}}$ and $Q_{i,m,o,t}^{\text{Net}}$ represent the net active and reactive power injections at node $i \in N$, market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$;
- g_{ij} and b_{ij} are the series conductance and susceptance of branch $(i, j) \in B$;
- b_{ij}^{Sh} is the half-line shunt susceptance of branch $(i, j) \in B$, modeled using the standard Π -equivalent representation;
- $r_{ij,m,o,t}$ denotes the tap ratio of an **OLTC** transformer $(i, j) \in B^T$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$, with $B^T \subseteq B$ representing the subset of controllable transformers.¹

The exact nonlinear **AC-PF** formulation adopted in this work ensures consistent applicability across both **TNs** and **DNs**, enhances the fidelity of results under stressed or uncertain operating conditions, and directly supports the overarching objectives of this thesis: capturing uncertainty, accurately modeling the dynamic flexibility of **DERs**, and rigorously evaluating the effectiveness and potential benefits of **TSO-DSO** coordination.

4.3.4 Node Power Balance

The nodal active and reactive power balance equations ensure that, at every bus $i \in N$, the total net injections equal the algebraic sum of all connected generation and consumption

¹For standard lines or transformers without **OLTC** capability, the tap ratio is fixed at $r_{ij,m,o,t} = 1$.

terms. Accordingly, the net active and reactive power injections at bus $i \in N$ are expressed as follows ($\forall i \in N, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$P_{i,m,o,t}^{\text{Net}} = \sum_{g \in G \cap i} P_{g,m,o,t}^G - \sum_{l \in L \cap i} P_{l,m,o,t}^L - \sum_{l \in L^F \cap i} P_{l,m,o,t}^{L,\text{Flex}} + \sum_{l \in L^C \cap i} P_{l,m,o,t}^{L,\text{Curt}} - \sum_{e \in E \cap i} P_{e,m,o,t}^E \quad (4.28)$$

$$Q_{i,m,o,t}^{\text{Net}} = \sum_{g \in G \cap i} Q_{g,m,o,t}^G + \sum_{c \in C \cap i} Q_{c,m,o,t}^C - \sum_{l \in L \cap i} Q_{l,m,o,t}^L - \sum_{l \in L^F \cap i} Q_{l,m,o,t}^{L,\text{Flex}} + \sum_{l \in L^C \cap i} Q_{l,m,o,t}^{L,\text{Curt}} - \sum_{e \in E \cap i} Q_{e,m,o,t}^E \quad (4.29)$$

where:

- $P_{l,m,o,t}^L$ and $Q_{l,m,o,t}^L$ denote the active and reactive power demand of load $l \in L$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$;
- $P_{l,m,o,t}^{L,\text{Curt}}$ and $Q_{l,m,o,t}^{L,\text{Curt}}$ represent the net corrective active and reactive power adjustments associated with resource $l \in L^C$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$;
- $P_{l,m,o,t}^{L,\text{Flex}}$ and $Q_{l,m,o,t}^{L,\text{Flex}}$ correspond to the active and reactive flexibility provided by **FL** $l \in L^F$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and instant $t \in T$;
- $P_{e,m,o,t}^E$ and $Q_{e,m,o,t}^E$ denote the active and reactive power output of **ESS** $e \in E$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$;
- $Q_{g,m,o,t}^G$ is the reactive power output of generator $g \in G$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$; and
- $Q_{c,m,o,t}^C$ represents the reactive power injection from **CB** $c \in C$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$, with C denoting the set of **CBs**.

Further details on the modeling of individual controllable resources are provided in Subsection 4.3.6. The decomposition into directional components provides a unified mathematical representation of controllable adjustments. The admissible directions and limits remain resource-dependent: conventional loads are restricted to physically meaningful curtailment, while aggregated net-demand equivalents may be parameterized to represent a broader range of interface-level adjustments. Full four-quadrant operation is modeled explicitly only for resources whose physical capabilities support it, such as **ESSs**.

4.3.5 Operational Constraints

This subsection presents the network operational constraints that govern bus voltage magnitudes and branch power flow limits. As discussed previously, the framework allows users to specify whether Cartesian voltage feasibility-restoration variables are included in the optimization model. Separately, slack variables may be introduced in the branch flow constraints to permit controlled overloads, and users can select the limiting metric applied to branches, choosing between *current magnitude* and *apparent power flow*.

The inclusion of these optional slack variables enhances the model's capacity to represent stressed or near-infeasible operating conditions, providing greater robustness in contingency or stress-testing studies. However, it also increases the dimensionality of the problem, potentially extending solver runtimes and raising computational complexity. Consequently, the framework offers flexibility to tailor the formulation according to study requirements, enabling users to balance model fidelity, numerical tractability, and computational performance.

4.3.5.1 Bus Voltage Magnitude

Bus voltage magnitude constraints ensure that the voltage at each network bus remains within its permissible range. The admissible voltage limits are defined as $(\forall i \in N, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$(V_i^{\min})^2 \leq e_{i,m,o,t}^2 + f_{i,m,o,t}^2 \leq (V_i^{\max})^2 \quad (4.30)$$

where $V_i^{\max}$ and $V_i^{\min}$ denote, respectively, the upper and lower admissible voltage magnitudes for bus $i \in N$.

For PV buses – where the voltage magnitude is fixed at a specified set-point – the constraint becomes $(\forall i \in N^{\text{PV}}, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$e_{i,m,o,t}^2 + f_{i,m,o,t}^2 = (V_{i,t}^{\text{S}})^2 \quad (4.31)$$

where $N^{\text{PV}} \subseteq N$ denotes the subset of PV buses, and $V_{i,t}^{\text{S}}$ represents the specified voltage magnitude set-point for bus $i \in N^{\text{PV}}$ at time period $t \in T$.

4.3.5.2 Branch Power Flow Limits

Branch flow limits can be enforced on either the branch current magnitude or the apparent power flow, depending on the user's chosen formulation.

Generically, branch flow constraints are defined as $(\forall ij \in B, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$F_{ij,m,o,t}^2 \leq (F_{ij}^{\text{Rated}})^2 + F_{ij,m,o,t}^{\text{S}^2} \quad (4.32)$$

where:

- $F_{ij,m,o,t}$ generically denotes the branch flow – either current magnitude or apparent power – on branch $(i,j) \in B$, under market scenario $m \in \Omega_m$, operation scenario $o \in \Omega_o$, and time instant $t \in T$;
- F_{ij}^{Rated} represents the thermal rating of branch $(i,j) \in B$; and
- $F_{ij,m,o,t}^{S^2}$ is an optional slack variable capturing any violation of the flow limit on branch $(i,j) \in B$, under market scenario $m \in \Omega_m$, operation scenario $o \in \Omega_o$, and instant $t \in T$.

If congestion is chosen to be strictly not permitted, slack variables $F_{ij,m,o,t}^{S^2}$ are omitted from the formulation, thereby reducing the dimensionality of the problem.

Current-Based Limits: Current-based line flow limits can be formulated either by considering only the longitudinal branch current or by accounting for the total current magnitude, including shunt admittances and the effects of **OLTC** transformers.

The *longitudinal current magnitude* of branch $(i,j) \in B$ is given by $(\forall(i,j) \in B, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$I_{ij,m,o,t}^2 = (g_{ij}^2 + b_{ij}^2) \left((\tilde{e}_{i,m,o,t} - \tilde{e}_{j,m,o,t})^2 + (\tilde{f}_{i,m,o,t} - \tilde{f}_{j,m,o,t})^2 \right) \quad (4.33)$$

where $I_{ij,m,o,t}$ denotes the current magnitude in branch $(i,j) \in B$, under market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$. Equation (4.33) provides a simple – and often sufficiently accurate – approximation of the full current magnitude expression, particularly when shunt admittances are negligible or branch loading remains well below thermal limits.

When shunt admittances and **OLTC** tap ratios are explicitly modeled, the squared current magnitude is expressed as $(\forall(i,j) \in B, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$\begin{aligned} I_{ij,m,o,t}^2 = & b_{ij}^{\text{Sh}} \left(\tilde{e}_{i,m,o,t}^2 + \tilde{f}_{i,m,o,t}^2 \right) \\ & + (g_{ij}^2 + b_{ij}^2) \left[(r_{ij,m,o,t}^2 \tilde{e}_{i,m,o,t} - r_{ij,m,o,t} \tilde{e}_{j,m,o,t})^2 \right. \\ & \quad \left. + (r_{ij,m,o,t}^2 \tilde{f}_{i,m,o,t} - r_{ij,m,o,t} \tilde{f}_{j,m,o,t})^2 \right] \\ & + 2g_{ij}b_{ij}^{\text{Sh}} \left[(r_{ij,m,o,t}^2 \tilde{f}_{i,m,o,t} - r_{ij,m,o,t} \tilde{f}_{j,m,o,t}) \tilde{e}_{i,m,o,t} \right. \\ & \quad \left. - (r_{ij,m,o,t}^2 \tilde{e}_{i,m,o,t} - r_{ij,m,o,t} \tilde{e}_{j,m,o,t}) \tilde{f}_{i,m,o,t} \right] \\ & + 2b_{ij}b_{ij}^{\text{Sh}} \left[(r_{ij,m,o,t}^2 \tilde{e}_{i,m,o,t} - r_{ij,m,o,t} \tilde{e}_{j,m,o,t}) \tilde{e}_{i,m,o,t} \right. \\ & \quad \left. - (r_{ij,m,o,t}^2 \tilde{f}_{i,m,o,t} - r_{ij,m,o,t} \tilde{f}_{j,m,o,t}) \tilde{f}_{i,m,o,t} \right] \end{aligned} \quad (4.34)$$

The choice of current-limit formulation is user-configurable, allowing the model to be adapted to specific network characteristics, modeling fidelity requirements, or study objectives.

Apparent Power-Based Limits: Alternatively, branch flow limits can be enforced using apparent power constraints ($\forall (i, j) \in B, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$S_{ij,m,o,t}^2 = P_{ij,m,o,t}^2 + Q_{ij,m,o,t}^2 \quad (4.35)$$

where $S_{ij,m,o,t}$, $P_{ij,m,o,t}$, and $Q_{ij,m,o,t}$ denote the apparent, active, and reactive power flows on branch $(i, j) \in B$, respectively, under market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$.

The active and reactive power flows on branch $(i, j) \in B$, explicitly accounting for **OLTC** transformer tap ratios, are given by ($\forall (i, j) \in B, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$\begin{aligned} P_{ij,m,o,t} = & g_{ij} \left(\tilde{e}_{i,m,o,t}^2 + \tilde{f}_{i,m,o,t}^2 \right) r_{ij,m,o,t} \\ & - g_{ij} \left(\tilde{e}_{i,m,o,t} \tilde{e}_{j,m,o,t} + \tilde{f}_{i,m,o,t} \tilde{f}_{j,m,o,t} \right) r_{ij,m,o,t} \\ & - b_{ij} \left(\tilde{f}_{i,m,o,t} \tilde{e}_{j,m,o,t} - \tilde{e}_{i,m,o,t} \tilde{f}_{j,m,o,t} \right) r_{ij,m,o,t} \end{aligned} \quad (4.36)$$

$$\begin{aligned} Q_{ij,m,o,t} = & - \left(g_{ij} + b_{ij}^{\text{Sh}} \right) \left(\tilde{e}_{i,m,o,t}^2 + \tilde{f}_{i,m,o,t}^2 \right) r_{ij,m,o,t} \\ & - g_{ij} \left(\tilde{e}_{i,m,o,t} \tilde{e}_{j,m,o,t} + \tilde{f}_{i,m,o,t} \tilde{f}_{j,m,o,t} \right) r_{ij,m,o,t} \\ & - b_{ij} \left(\tilde{f}_{i,m,o,t} \tilde{e}_{j,m,o,t} - \tilde{e}_{i,m,o,t} \tilde{f}_{j,m,o,t} \right) r_{ij,m,o,t} \end{aligned} \quad (4.37)$$

These expressions enable a precise evaluation of branch thermal limits when apparent power is the binding criterion. To manage the additional nonlinearity introduced by these expressions, numerical enhancements and solver strategies are discussed in Section 4.3.7.

4.3.6 Controllable Resources

This subsection describes the controllable resources modeled within the proposed **SMOPF** framework. The formulation includes detailed representations of both network assets and **FLs** participating in grid operation through **DR** programs. It also explicitly models **RESS** generators with power-factor control and **ESSs** capable of full four-quadrant operation.

All controllable elements are formulated using **NLP** models to accurately capture their physical behavior, operational limits, and dynamic flexibility.

4.3.6.1 Generators

Two main categories of generators are considered in this work: (i) conventional units, typically synchronous machines; and (ii) inverter-interfaced **RESSs**, such as solar **PV** and wind plants. All generators are constrained by their active and reactive power limits, defined as ($\forall g \in G, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$P_g^{G,\min} \leq P_{g,m,o,t}^G \leq P_g^{G,\max} \quad (4.38)$$

$$Q_g^{G,\min} \leq Q_{g,m,o,t}^G \leq Q_g^{G,\max} \quad (4.39)$$

where $P_g^{G,\min}$ and $P_g^{G,\max}$ denote the minimum and maximum active power outputs of generator $g \in G$, and $Q_g^{G,\min}$ and $Q_g^{G,\max}$ represent the corresponding reactive power limits.

Inverter-based **RES** generators' apparent power is further constrained by their inverter limits ($\forall g \in G^R, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$S_g^{G,\min} \leq S_{g,m,o,t}^G \leq S_g^{G,\max} \quad (4.40)$$

where $S_g^{G,\min}$ and $S_g^{G,\max}$ represent, respectively, the minimum and maximum apparent power capabilities of generator $g \in G^R$; and $S_{g,m,o,t}^G$ denotes the active power output of generator $g \in G^R$, under market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$, defined as ($\forall g \in G^R, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$\left(S_{g,m,o,t}^G\right)^2 = \left(P_{g,m,o,t}^G\right)^2 + \left(Q_{g,m,o,t}^G\right)^2 \quad (4.41)$$

As previously noted, **RES** generators are assumed to have power factor control capabilities. Since inverter hardware constrains the achievable power factor, the reactive power output of each **RES** unit depends on its active power generation ($\forall g \in G^R, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$P_{g,m,o,t}^G \tan(\varphi_g^{G,\min}) \leq Q_{g,m,o,t}^G \leq P_{g,m,o,t}^G \tan(\varphi_g^{G,\max}) \quad (4.42)$$

where $\varphi_g^{G,\min}$ and $\varphi_g^{G,\max}$ denote the minimum and maximum phase angle limits of the inverter associated with generator $g \in G^R$, respectively. In practice, most utility-scale **RES** inverters are designed to operate within a power factor range of $[-0.90, 0.90]$.

If the power factor control of a given **RES** unit is disabled, the unit operates at a fixed power factor ($\forall g \in G^R, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$Q_{g,m,o,t}^G = P_{g,m,o,t}^G \tan(\hat{\varphi}_{g,o,t}^G) \quad (4.43)$$

where $\hat{\varphi}_{g,o,t}^G$ denotes the initial forecasted phase angle of **RES** generator $g \in G^R$, in operational scenario $o \in \Omega_o$ and time instant $t \in T$.

Generation curtailment is modeled on the apparent power injected by each **RES** generator, expressed as ($\forall g \in G^R, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$S_{g,m,o,t}^{G,\text{Curt}} = \hat{S}_{g,o,t}^G - S_{g,m,o,t}^G \quad (4.44)$$

where $\hat{S}_{g,o,t}^G$ represents the forecasted apparent power output of generator $g \in G^R$, in operational scenario $o \in \Omega_o$ and time instant $t \in T$.

The forecasted apparent power is provided as an input to the **SMOPF** tool and inferred from the active and reactive power forecasts, according to $(\forall g \in G^R, \forall o \in \Omega_o, \forall t \in T)$:

$$\left(\hat{S}_{g,o,t}^G\right)^2 = \left(\hat{P}_{g,o,t}^G\right)^2 + \left(\hat{Q}_{g,o,t}^G\right)^2 \quad (4.45)$$

where $\hat{P}_{g,o,t}^G$ and $\hat{Q}_{g,o,t}^G$ denote, respectively, the forecasted active and reactive power of generator $g \in G^R$ in operational scenario $o \in \Omega_o$ and time instant $t \in T$.

This formulation allows **RES** generators to inject or absorb reactive power within their inverter limits, providing a realistic characterization of **RES** flexibility while meeting system operating requirements.

4.3.6.2 Energy Storage

ESSs are represented through a continuous **NLP** formulation, without binary charging or discharging state variables. Mutual exclusivity between the two operating modes is imposed through a nonlinear complementarity condition, which may be relaxed using a non-negative slack variable heavily penalized in the objective function.

The model represents the active and reactive power exchanged by the **ESS** in both charging and discharging modes, subject to the rated apparent power and inverter operating limits.

The apparent power associated with **ESS** charging and discharging processes is defined as $(\forall e \in E, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$\left(S_{e,m,o,t}^{E,\text{Ch}}\right)^2 = \left(P_{e,m,o,t}^{E,\text{Ch}}\right)^2 + \left(Q_{e,m,o,t}^{E,\text{Ch}}\right)^2 \quad (4.46)$$

$$\left(S_{e,m,o,t}^{E,\text{Dch}}\right)^2 = \left(P_{e,m,o,t}^{E,\text{Dch}}\right)^2 + \left(Q_{e,m,o,t}^{E,\text{Dch}}\right)^2 \quad (4.47)$$

where:

- $S_{e,m,o,t}^{E,\text{Ch}}$ and $S_{e,m,o,t}^{E,\text{Dch}}$ denote, respectively, the charging and discharging apparent power of storage unit $e \in E$ in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$;
- $P_{e,m,o,t}^{E,\text{Ch}}$ and $P_{e,m,o,t}^{E,\text{Dch}}$ represent the charging and discharging active power components of **ESS** $e \in E$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$; and
- $Q_{e,m,o,t}^{E,\text{Ch}}$ and $Q_{e,m,o,t}^{E,\text{Dch}}$ represent the charging and discharging reactive power components of **ESS** $e \in E$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$.

The apparent, active, and reactive charging and discharging powers of each **ESS** are constrained by $(\forall e \in E, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$0 \leq S_{e,m,o,t}^{E,\text{Ch}}, \quad S_{e,m,o,t}^{E,\text{Dch}} \leq S_e^{\text{Rated}} \quad (4.48)$$

$$0 \leq P_{e,m,o,t}^{E,\text{Ch}}, \quad P_{e,m,o,t}^{E,\text{Dch}} \leq S_e^{\text{Rated}} \quad (4.49)$$

$$-S_e^{\text{Rated}} \leq Q_{e,m,o,t}^{E,\text{Ch}}, \quad Q_{e,m,o,t}^{E,\text{Dch}} \leq S_e^{\text{Rated}} \quad (4.50)$$

where S_e^{Rated} denotes the rated apparent power of storage unit $e \in E$. The active power variables are constrained to non-negative values, while the reactive power variables are allowed to vary symmetrically within $\pm S_e^{\text{Rated}}$. The formulation enables operation in all four active–reactive power quadrants within the specified apparent power and power factor limits.

The *net* active and reactive power of each storage unit $e \in E$, denoted by $P_{e,m,o,t}^E$ and $Q_{e,m,o,t}^E$, respectively, are defined as ($\forall e \in E, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$P_{e,m,o,t}^E = P_{e,m,o,t}^{E,\text{Ch}} - P_{e,m,o,t}^{E,\text{Dch}} \quad (4.51)$$

$$Q_{e,m,o,t}^E = Q_{e,m,o,t}^{E,\text{Ch}} - Q_{e,m,o,t}^{E,\text{Dch}} \quad (4.52)$$

The inverters of **ESSs** are subject to power factor constraints that limit the reactive power exchange as a function of active power. These constraints are expressed as ($\forall e \in E, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$P_{e,m,o,t}^{E,\text{Ch}} \tan(\varphi_e^{E,\min}) \leq Q_{e,m,o,t}^{E,\text{Ch}} \leq P_{e,m,o,t}^{E,\text{Ch}} \tan(\varphi_e^{E,\max}) \quad (4.53)$$

$$P_{e,m,o,t}^{E,\text{Dch}} \tan(\varphi_e^{E,\min}) \leq Q_{e,m,o,t}^{E,\text{Dch}} \leq P_{e,m,o,t}^{E,\text{Dch}} \tan(\varphi_e^{E,\max}) \quad (4.54)$$

where $\varphi_e^{E,\min}$ and $\varphi_e^{E,\max}$ denote the minimum and maximum phase angle limits of the inverter associated with storage unit $e \in E$. In practice, utility-scale battery systems are commonly required to operate with a power factor magnitude of at least 0.90, in either the leading or lagging direction.

Charging and discharging are expressed in terms of apparent power. This provides a tractable aggregate representation of the conversion losses associated with both active and reactive power operation. Accordingly, the charging and discharging efficiencies are interpreted as aggregate conversion efficiencies.

The State-of-Charge (**SoC**) of each storage unit $e \in E$ is modeled as ($\forall e \in E, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$SoC_{e,m,o,t} - SoC_{e,m,o,t-1} = S_{e,m,o,t}^{E,\text{Ch}} \eta_e^{\text{Ch}} - \frac{S_{e,m,o,t}^{E,\text{Dch}}}{\eta_e^{\text{Dch}}} \quad (4.55)$$

where:

- $SoC_{e,m,o,t}$ represents the **SoC** of storage unit $e \in E$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$; and
- η_e^{Ch} and η_e^{Dch} denote the charging and discharging efficiencies, respectively.

The **SoC** admissible operating range is imposed by $(\forall e \in E, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$SoC_e^{\min} \leq SoC_{e,m,o,t} \leq SoC_e^{\max} \quad (4.56)$$

where $SoC_e^{\min}$ and $SoC_e^{\max}$ denote the minimum and maximum allowable **SoCs**.

The charging–discharging complementarity constraint ensures that an **ESS** cannot simultaneously charge and discharge. In its exact form, this constraint is formulated as $(\forall e \in E, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$S_{e,m,o,t}^{E,\text{Ch}} \times S_{e,m,o,t}^{E,\text{Dch}} = 0 \quad (4.57)$$

Although (4.57) eliminates the need for binary decision variables – allowing the **SMOPF** problem to remain a continuous **NLP** – such complementarity conditions are known to pose numerical challenges for **NLP** solvers (Capitanescu, 2016). To improve numerical robustness, (4.57) may be relaxed through $(\forall e \in E, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$S_{e,m,o,t}^{E,\text{Ch}} \times S_{e,m,o,t}^{E,\text{Dch}} \leq S_{e,m,o,t}^{E,S} \quad (4.58)$$

where $S_{e,m,o,t}^{E,S}$ is a non-negative slack variable representing any simultaneous charging and discharging of storage unit $e \in E$. This term is heavily penalized in the objective function (see Subsection 4.3.1), ensuring that violations of (4.57) occur only when strictly necessary to preserve the overall feasibility of the optimization problem. The charging and discharging efficiencies are interpreted as aggregate conversion efficiencies that account for the current-dependent losses associated with the corresponding apparent power exchange. A more detailed representation could employ explicit converter-loss and battery-current models as functions of active power, reactive power, voltage, and operating conditions.

The complementarity condition is imposed on the charging and discharging apparent powers because each variable represents a converter operating mode comprising both active and reactive power components. Consequently, the constraint prevents the simultaneous activation of opposing operating modes while retaining a continuous formulation and avoiding binary decision variables.

Finally, to ensure that each **ESS** begins the subsequent optimization horizon with an adequate amount of stored energy, the **SoC** at the final time step is constrained to return to its initial value through $(\forall e \in E, \forall m \in \Omega_m, \forall o \in \Omega_o)$:

$$SoC_{e,m,o,t_0} = SoC_{e,m,o,t_T} \quad (4.59)$$

where t_0 and t_T denote the first and last time instants of the optimization horizon, respectively. This condition enforces an energy-neutral operation across the optimization period, preventing the artificial depletion or overcharging of storage units to improve short-term performance.

4.3.6.3 Flexible Loads

FLs are modeled as controllable demand units capable of supporting network operation through upward and downward flexibility services, remunerated through the flexibility market described in Subsection 4.3.1.1. Within the optimization horizon, they may shift active power consumption while modulating reactive power, subject to their respective operational limits. Active power shifting preserves the total active energy consumption over the optimization period.

The *net* active and reactive power flexibility of each **FL** $l \in L^F$ are defined, respectively, as $(\forall l \in L^F, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$P_{l,m,o,t}^{L,\text{Flex}} = P_{l,m,o,t}^{L,\text{Up}} - P_{l,m,o,t}^{L,\text{Down}} \quad (4.60)$$

$$Q_{l,m,o,t}^{L,\text{Flex}} = Q_{l,m,o,t}^{L,\text{Up}} - Q_{l,m,o,t}^{L,\text{Down}} \quad (4.61)$$

where:

- $P_{l,m,o,t}^{L,\text{Up}}$ and $P_{l,m,o,t}^{L,\text{Down}}$ denote the upward and downward active power flexibility of load $l \in L^F$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$, respectively; and
- $Q_{l,m,o,t}^{L,\text{Up}}$ and $Q_{l,m,o,t}^{L,\text{Down}}$ represent the upward and downward reactive power flexibility of load $l \in L^F$, in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$.

The upward and downward active and reactive power flexibility variables are bounded as follows $(\forall l \in L^F, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$0 \leq P_{l,m,o,t}^{L,\text{Up}} \leq P_{l,o,t}^{L,\text{max}} \quad (4.62)$$

$$0 \leq P_{l,m,o,t}^{L,\text{Down}} \leq P_{l,o,t}^{L,\text{min}} \quad (4.63)$$

$$0 \leq Q_{l,m,o,t}^{L,\text{Up}} \leq Q_{l,o,t}^{L,\text{max}} \quad (4.64)$$

$$0 \leq Q_{l,m,o,t}^{L,\text{Down}} \leq Q_{l,o,t}^{L,\text{min}} \quad (4.65)$$

where:

- $P_{l,o,t}^{L,\max}$ and $P_{l,o,t}^{L,\min}$ denote the maximum upward and downward active power flexibility that **FL** $l \in L^F$ can provide in operational scenario $o \in \Omega_o$ and at time instant $t \in T$, respectively; and
- $Q_{l,o,t}^{L,\max}$ and $Q_{l,o,t}^{L,\min}$ denote the maximum upward and downward reactive power flexibility that **FL** $l \in L^F$ can provide in operational scenario $o \in \Omega_o$, and time instant $t \in T$.

These bounds define the admissible flexibility ranges of each **FL**, ensuring that its adjustments remain within the specified technical and contractual limits while allowing the simultaneous provision of active and reactive power flexibility.

The energy balance of each **FL** $l \in L^F$ is enforced through $(\forall l \in L^F, \forall m \in \Omega_m, \forall o \in \Omega_o)$:

$$\sum_{t \in T} P_{l,m,o,t}^{L,\text{Up}} = \sum_{t \in T} P_{l,m,o,t}^{L,\text{Down}} \quad (4.66)$$

Equation (4.66) ensures that, over the optimization horizon, the total upward active power flexibility provided by each **FL** equals its total downward active power flexibility. Since all time intervals have equal duration, the common time-step duration is omitted from the equation. The constraint therefore preserves active energy neutrality, allowing load-shifting actions to modify the temporal demand profile without changing the total active energy consumption.

In the proposed formulation, an **FL** generally represents the aggregated power exchange of a downstream network. Active and reactive power flexibility may therefore originate from different resources within the underlying network and are represented separately, subject to the corresponding operational limits. At this aggregation level, no fixed relationship between active and reactive power flexibility is imposed. No equivalent intertemporal balance is imposed on reactive power, since the aggregated response may include resources and devices, such as **CBs** and **OLTCs**, that do not require such a constraint. Participation of **FLs** in grid operation is optional: users may disable flexibility participation entirely or selectively specify the loads eligible to provide flexibility services.

4.3.6.4 Curtailable Loads

Curtailable loads correspond to loads whose consumption can be reduced or adjusted by the **SO** to relieve network constraints. Depending on the voltage level considered, these loads may also represent the aggregated power exchange of downstream networks. Unlike **FLs**, which provide scheduled flexibility through demand shifting, load curtailment is treated as a last-resort corrective action.

The active and reactive power curtailment variables are bounded as follows $(\forall l \in L^C, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$0 \leq P_{l,m,o,t}^{L,\text{Curt},\text{Up}} \leq P_{l,o,t}^{L,\text{Curt},\max} \quad (4.67)$$

$$0 \leq P_{l,m,o,t}^{L,\text{Curt,Down}} \leq P_{l,o,t}^{L,\text{Curt,min}} \quad (4.68)$$

$$0 \leq Q_{l,m,o,t}^{L,\text{Curt,Up}} \leq Q_{l,o,t}^{L,\text{Curt,max}} \quad (4.69)$$

$$0 \leq Q_{l,m,o,t}^{L,\text{Curt,Down}} \leq Q_{l,o,t}^{L,\text{Curt,min}} \quad (4.70)$$

where:

- $P_{l,o,t}^{L,\text{Curt,max}}$ and $P_{l,o,t}^{L,\text{Curt,min}}$ denote the maximum upward and downward active power curtailment limits of load $l \in L^C$ in operational scenario $o \in \Omega_o$ and time instant $t \in T$, respectively; and
- $Q_{l,o,t}^{L,\text{Curt,max}}$ and $Q_{l,o,t}^{L,\text{Curt,min}}$ denote the maximum upward and downward reactive power curtailment limits of load $l \in L^C$ in operational scenario $o \in \Omega_o$ and time instant $t \in T$, respectively.

The *net* active and reactive power curtailment of each curtailable load $l \in L^C$ are respectively defined as ($\forall l \in L^C, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$P_{l,m,o,t}^{L,\text{Curt}} = P_{l,m,o,t}^{L,\text{Curt,Up}} - P_{l,m,o,t}^{L,\text{Curt,Down}} \quad (4.71)$$

$$Q_{l,m,o,t}^{L,\text{Curt}} = Q_{l,m,o,t}^{L,\text{Curt,Up}} - Q_{l,m,o,t}^{L,\text{Curt,Down}} \quad (4.72)$$

The decomposition into upward and downward components provides a generic representation applicable to both individual loads and aggregated downstream networks. The admissible directions and limits are defined according to the characteristics of the represented load or network. Although active and reactive power are physically coupled, their separate representation provides a tractable approximation at the modeled voltage level. It also allows the active or reactive power component associated with infeasibility to be more clearly identified.

As with other controllable resources, the participation of curtailable loads in grid operation is user-configurable. Curtailment can be entirely disabled or selectively enabled for specific loads, depending on the study context or operational objectives. Moreover, the penalty coefficients can be specified on a *per-load* basis, allowing priority levels to be established so that critical demand is preserved. Since load curtailment is typically reserved for emergency conditions or for maintaining feasibility under stress, it is deactivated by default in standard operational studies.

4.3.6.5 Transformers

All network branches are modeled using a standard Π -equivalent representation that explicitly accounts for the tap ratio of voltage-regulating transformers. Lines are treated as a particular case of this generic formulation, in which the tap ratio is fixed to $r_{ij} = 1$. The adopted branch model is illustrated in Figure 4.2.

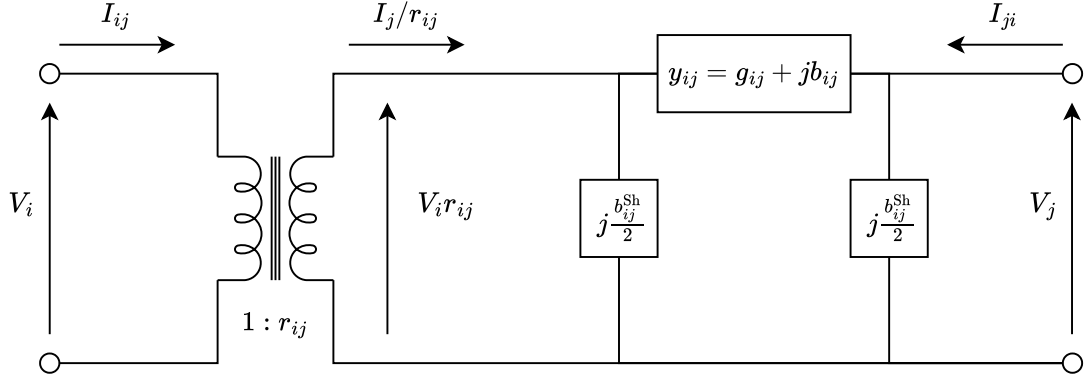


Figure 4.2: Branch model used in the SMOPF formulation.

The tap ratio of each voltage-regulating transformer $(i, j) \in B^T$ is bounded as follows ($\forall (i, j) \in B^T, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$r_{ij}^{\min} \leq r_{ij,m,o,t} \leq r_{ij}^{\max} \quad (4.73)$$

where $r_{ij}^{\min}$ and $r_{ij}^{\max}$ denote the minimum and maximum admissible tap ratios of transformer $(i, j) \in B^T$, respectively.

As with other controllable resources, the participation of **OLTC** transformers in grid operation is configurable by the user. Tap control can be fully disabled or selectively enabled for specific units, depending on the scope and objectives of the study. The approach adopted in this work to handle the discrete nature of **OLTC** controls is described in Section 4.4.

4.3.6.6 Capacitor Banks

CBs provide an additional source of operational flexibility that is often underrepresented in the literature, primarily due to their inherently discrete control characteristics. Typically composed of a few large switchable steps, **CBs** require discrete decision variables for accurate representation, which transforms the **AC-OPF** problem into a challenging **MINLP** formulation.

The reactive power injection of each **CB** $c \in C$ is constrained as follows ($\forall c \in C, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$0 \leq Q_{c,m,o,t}^C \leq Q_c^{C,\text{Nom}} \quad (4.74)$$

where $Q_c^{C,\text{Nom}}$ denotes the nominal reactive power rating of CB $c \in C$. The approach adopted in this work to handle the discrete nature of CBs is described in Section 4.4.

4.3.7 Modeling Refinements and Computational Considerations

This subsection outlines practical considerations and auxiliary features introduced to enhance the robustness, numerical stability, and computational efficiency of the proposed SMOPT algorithm. While the formulation retains the full AC-PF representation and detailed resource modeling, achieving tractable and reliable convergence in this nonlinear, multi-scenario framework required several refinements. Accordingly, the following discusses numerical conditioning strategies and solver-oriented improvements that ensure reliable performance without compromising model fidelity.

4.3.7.1 Numerical Stability and Computational Improvements

Although modern NLP solvers are generally robust, several modeling and initialization strategies were adopted to improve numerical performance:

- Auxiliary variables for nonlinear expressions: Auxiliary variables were introduced for selected squared and product terms, including:
 - the squared bus voltage magnitude, $\tilde{e}_{i,m,o,t}^2 + \tilde{f}_{i,m,o,t}^2$;
 - the squared tap ratio of controllable transformers, $r_{ij,m,o,t}^2$; and
 - products of voltage components, such as $\tilde{e}_{i,m,o,t}\tilde{f}_{i,m,o,t}$.

Although this substitution increases the number of variables and constraints, it avoids the repeated evaluation of selected nonlinear expressions and may improve the sparsity and numerical treatment of the resulting problem.

- Slack variables with calibrated penalties: Optional slack variables are introduced for Cartesian voltage feasibility restoration, branch flow limit violations, and ESS complementarity constraints. Their penalty coefficients are selected to discourage violations without introducing excessive numerical ill-conditioning.
- Primal warm starts: The decision variables are initialized using a solution obtained for a preceding optimization problem or a similar operating condition. Since consecutive problems generally exhibit limited changes, this solution-based initialization can improve convergence speed and numerical robustness.
- Temporal decomposition: Where applicable, multi-period problems may be decomposed into smaller subproblems to reduce computational burden and provide suitable initial solutions for the complete optimization problem.

These strategies improve the balance between model size, numerical robustness, and computational performance while preserving the physical fidelity of the power system representation.

4.4 Handling of Discrete Variables

The proposed **SMOPF** framework optionally incorporates discrete decision variables to represent the tap positions of **OLTC** transformers and the step settings of **CBs**.

Relaxing the **OLTC** transformer ratios r_{ij} has a minor impact on accuracy, as most transformers feature a large number of fine tap positions. By contrast, relaxing the discrete steps of **CBs** can have a more significant effect, since these devices typically have high reactive power ratings but only a few coarse switching stages. To efficiently account for discrete control while maintaining tractability, a *round-off* strategy is adopted (Tinney et al., 1988; Papalexopoulos et al., 1989). First, a relaxed version of the **SMOPF** is solved with all decision variables treated as continuous. Next, the discrete variables – namely the **OLTC** transformer ratios and **CB** step positions – are fixed to their nearest feasible discrete values, and the problem is re-solved. Both stages remain continuous **NLP** problems, allowing the use of mature **IPM** solvers while accommodating practical discrete network controls. The following subsections detail the modeling of **CBs** and **OLTC** transformers under discrete control.

4.4.1 Transformers

When discrete control is enabled, the tap ratio of each voltage-regulating **OLTC** transformer $(i, j) \in B^T$ is expressed as $(\forall (i, j) \in B^T, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$r_{ij,m,o,t} = r_{ij}^{\min} + t_{ij,m,o,t}^B \times t_{ij}^{\Delta,B} \quad (4.75)$$

where $t_{ij,m,o,t}^B$ is the integer tap position of transformer $(i, j) \in B^T$ in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$; and $t_{ij}^{\Delta,B}$ is the incremental ratio change per tap of transformer $(i, j) \in B^T$, computed as $(\forall ij \in B^T)$:

$$t_{ij}^{\Delta,B} = \frac{r_{ij}^{\max} - r_{ij}^{\min}}{n_{ij}^B} \quad (4.76)$$

where n_{ij}^B is the total number of discrete tap positions of **OLTC** transformer $(i, j) \in B^T$.

OLTC transformers play a central role in voltage regulation and reactive power management, enabling **SOs** to maintain acceptable voltage profiles and improve overall system efficiency. By explicitly modeling their discrete tap positions, the proposed formulation captures the inherent stepwise nature of on-load tap changes while ensuring that computed operating points remain physically feasible and directly implementable in practice.

This approach achieves a balanced compromise between modeling fidelity, computational tractability, and optimality – without resorting to a full **MINLP** formulation.

4.4.2 Capacitor Banks

CBs are modeled using a constant-impedance model, whereby their reactive power injection varies with the square of the terminal voltage magnitude. This approach reflects the true physical behavior of shunt capacitors and avoids the inaccuracies associated with the constant-power approximation often used in the literature.

When discrete control is enabled, the reactive power provided by each **CB** $c \in C$ is defined as ($\forall c \in C, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T$):

$$Q_{c,m,o,t}^C = Q_c^{C,\text{Nom}} \frac{t_{c,m,o,t}^C}{n_c^C} \left(\left(\tilde{e}_{c,m,o,t} \right)^2 + \left(\tilde{f}_{c,m,o,t} \right)^2 \right) \quad (4.77)$$

where:

- $Q_c^{C,\text{Nom}}$ is the nominal reactive power rating of **CB** $c \in C$;
- $t_{c,m,o,t}^C$ is the integer tap position of **CB** c in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$;
- n_c^C is the total number of discrete steps of **CB** $c \in C$; and
- $\tilde{e}_{c,m,o,t}$ and $\tilde{f}_{c,m,o,t}$ are the real and imaginary voltage components at the bus where **CB** $c \in C$ is connected.

This formulation captures both the discrete switching nature of **CBs** and their voltage-dependent reactive power injection. By linking the reactive output directly to terminal voltage and discrete tap positions, the resulting operating points are physically realistic, field-implementable, and consistent with the nonlinear behavior of shunt **CBs** – without incurring the computational burden of an **MINLP** formulation.

4.5 Real-time Optimal Power Flow

Real-time **AC-OPF** remains one of the most challenging problems in modern power system operation. Despite decades of research, only a limited number of practical implementations have been reported, and many published studies provide insufficient detail to enable reproducibility or direct deployment in real-world environments. This work proposes a real-time **AC-OPF** framework that preserves a full physical representation of the network, explicitly models all controllable resources, and incorporates an operational strategy for deploying control setpoints while respecting network constraints.

4.5.1 Framework

Conventional real-time **AC-OPF** schemes typically focus on computing optimal operating points from a single system snapshot. The resulting setpoints are then dispatched simultaneously to controllable devices, without accounting for their sequential or incremental impact on network conditions. Such direct application can cause temporary constraint violations or trigger protection systems, particularly when the optimal steady-state solution deviates significantly from the current operating point. To mitigate these issues, we introduce an *online* real-time **AC-OPF** algorithm that not only identifies the optimal steady-state operating point but also computes an *optimal deployment trajectory* for the associated control actions. By progressively steering the system toward its optimal configuration while maintaining feasibility at every step, the proposed method ensures secure and reliable real-time implementation.

The real-time **OPF** builds directly upon the **SMOPF** formulation developed in this chapter, and is designed as an online function for integration within a Supervisory Control and Data Acquisition (**SCADA**) environment. Operating in closed loop with an Advanced Metering Infrastructure (**AMI**), the module continuously acquires field data – either from a physical grid or from a real-time simulation platform—through Remote Terminal Units (**RTUs**) and Phasor Measurement Units (**PMUs**).

The process comprises three main phases:

- **Data Acquisition and Analysis:** At periodic intervals, or when specific triggers occur – such as network constraint violations, significant deviations from the scheduled operating point, or external signals such as a Dynamic Line Rating (**DLR**) alerts – the real-time **OPF** is activated. Raw field measurements are first processed by a State Estimation (**SE**) algorithm to produce a noise- and error-filtered snapshot of the system’s state.
- **Control Action:** The validated snapshot is then passed to the online **AC-OPF**, which determines a *staged* control plan. Instead of issuing all setpoints simultaneously, the algorithm computes a sequence of incremental adjustments designed to steer the system gradually toward its optimal operating point.
- **Implementation Monitoring:** The staged control actions are applied sequentially, with intermediate system states continuously monitored to verify that each step maintains network feasibility and operational security.

The flowchart in Figure 4.3 illustrates these stages – data acquisition and analysis, control action determination, and implementation monitoring – along with the feedback loops governing trigger logic and stepwise deployment checks.

A key computational enhancement is the use of a primal warm start. At each control cycle, the decision variables are initialized using the solution obtained for the preceding optimization problem. Since consecutive problems typically differ only marginally, this

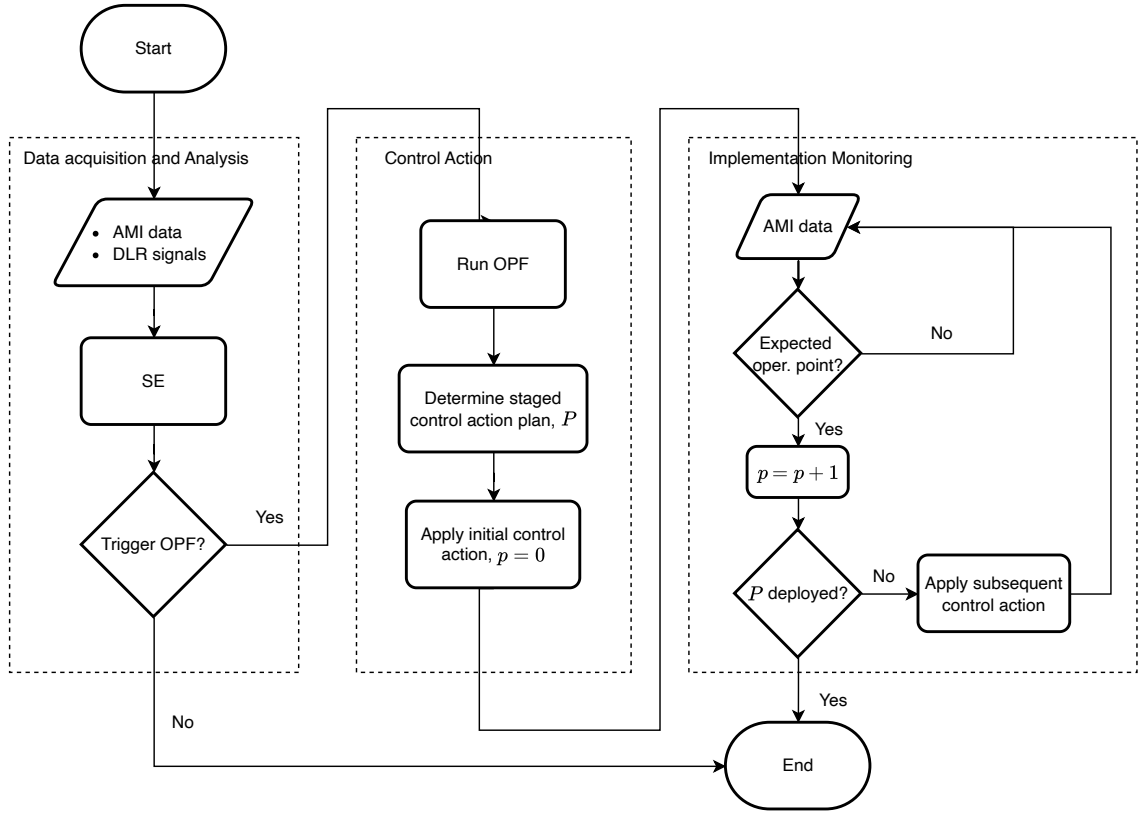


Figure 4.3: Flowchart of the proposed real-time OPF module.

solution-based initialization generally improves convergence speed and numerical robustness. This feature supports the computational efficiency required for continuous, closed-loop **OPF** operation.

4.5.2 Staged Control Action

A key innovation of the proposed real-time **AC-OPF** module is its *staged control-action* mechanism. Instead of applying all control setpoints in a single operation, the algorithm computes a sequence of intermediate operating points that progressively drive the system toward the desired optimum while continuously respecting security and operational limits.

The staged procedure unfolds as follows:

1. Compute the optimal operating point: A single-period **AC-OPF** is first solved to determine the optimal (target) network state according to the selected objective function. This formulation follows the methodology presented in Subsection 4.3, but with the market scenario set Ω_m , operational scenario set Ω_o , and time set T each containing a single element. The daily energy-balance constraints for **ESSs** (Constraint 4.59) and **FLs** (Constraint 4.66) are deactivated.
2. Determine the number of intermediate actions: The number of incremental control stages is computed based on the total discrete adjustments required – namely,

the number of **OLTC** and **CB** tap changes needed to reach the target state. The maximum allowable tap and step changes *per control stage* is a user-configurable parameter.

3. Generate intermediate setpoints: For each control stage, a new single-period **AC-OPF** is solved with an additional constraint: **OLTC** taps and **CB** steps may change by no more than the specified maximum number of discrete positions. This ensures that each successive operating point represents a secure, feasible transition toward the optimal steady-state solution.

This staged deployment strategy enables the network to progress smoothly toward its optimal operating point, preventing abrupt control changes that might otherwise violate operational limits or activate protection mechanisms. This gradual adjustment process not only enhances operational security but also provides a structured framework for implementing discrete control actions in real time.

4.5.2.1 Incremental Tap-Change Constraints

To formalize **OLTC** and **CB** tap and step transitions, additional constraints are introduced to limit the magnitude of each discrete adjustment – specifically, the maximum number of tap or step changes allowed between consecutive control stages.

The maximum number of **OLTC** tap changes per control stage is enforced as $(\forall (ij) \in B^T, \forall p \in P)$:

$$-t_{ij}^{B,\max} \leq t_{ij,p}^B - \hat{t}_{ij,p-1}^B \leq t_{ij}^{B,\max} \quad (4.78)$$

where:

- $\hat{t}_{ij,p}^B$ is the tap position of transformer $(i,j) \in B^T$ at control stage $p \in P$;
- $\hat{t}_{ij,p-1}^B$ is the tap position of transformer $(i,j) \in B^T$ in the previous stage; and
- $t_{ij}^{B,\max}$ is the maximum number of tap changes permitted per stage.

Similarly, the number of **CB** step changes per stage is limited by $(\forall c \in C, \forall p \in P)$:

$$-t_c^{C,\max} \leq t_{c,p}^C - \hat{t}_{c,p-1}^C \leq t_c^{C,\max} \quad (4.79)$$

where:

- $\hat{t}_{c,p}^C$ is the step position of **CB** $c \in C$ at control stage $p \in P$;
- $\hat{t}_{c,p-1}^C$ is the step position of **CB** $c \in C$ in the previous control stage; and
- $t_c^{C,\max}$ is the maximum number of step changes allowed per stage.

These box constraints guarantee that discrete control movements remain within user-specified bounds while preserving the numerical tractability of the optimization problem.

4.6 Extensions and Applications

The proposed **SMOPF** framework has been adopted in several Research and Development (**R&D**) projects at INESC TEC, demonstrating its adaptability and robustness beyond the scope of this thesis. Implemented in Python, using the Pyomo optimization modeling language (**Hart et al., 2017**), the framework is solver-agnostic and readily integrates with a wide range of optimization backends. A Python library has been developed within INESC TEC's *Center for Power and Energy Systems*, and future work will explore the feasibility of releasing it under an open source license to foster broader adoption in both academic and industrial contexts.

As part of a consultancy project with GE Vernova, the **SMOPF** engine was extended to support an inter-area coordination framework. This extension builds upon the *Coordinated Operational Planning* methodology introduced in Chapter 5, generalizing the concept of coordination – originally designed for **TSO–DSO** interaction – to enable cooperation among multiple **SOs**, each managing its own network and operational objectives. In parallel, a security-constrained variant of the **SMOPF** is under development. This forthcoming module is also intended to be distributed as an open-source Python package.

4.7 Concluding Remarks and Future Research

This chapter introduced the **SMOPF**, which constitutes the core operational framework for **SOs** developed and analyzed throughout this work. The framework integrates three complementary components, forming a unified platform for uncertainty-aware operational planning and real-time control:

- Stochastic scenario generator: produces representative operational and market price scenarios from historical data, defining the uncertainty sets used by the optimization model.
- Operational planning **SMOPF**, featuring:
 - An exact **AC-OPF** formulation, enabling accurate assessment of **DER** flexibility and performance, particularly under stressed network conditions.
 - Detailed yet computationally tractable models of controllable resources, allowing a realistic representation of network flexibility.
 - A comprehensive treatment of multi-source uncertainty, jointly capturing operational variability (load and **RES** generation) and market price uncertainty to support robust techno-economic analysis across operational and planning horizons.
- Real-time **OPF**: an online **AC-OPF** module, experimentally validated in a **HIL** environment, demonstrating the secure and staged deployment of optimal setpoints under dynamic grid conditions.

In the short term, the inter-area coordination tool will be demonstrated in collaboration with the UK's TSO, National Grid, while the development and deployment of the SCOPF module will be finalized.

Looking ahead, several research directions are envisioned to extend and enhance the SMOPF framework:

- (i) investigating data-driven and ML-based methods for improved ADN modeling;
- (ii) exploring convex relaxations and other tractable approximations of the power flow equations to improve scalability, with particular emphasis on methods for *tightening* such relaxations;
- (iii) developing mathematical decomposition techniques that exploit the temporal and spatial structure of the problem, enabling faster and more efficient solutions for large-scale optimization tasks; and
- (iv) exploring the application of emerging Graphics Processing Unit (GPU)-accelerated mathematical solvers to further enhance computational performance (Pacaud et al., 2024; Bynum and Nemhauser, 2023).

Overall, the SMOPF framework provides a robust foundation for future research in coordinated power system operation, and for the development of advanced OPF-based methods in particular. Nevertheless, several aspects warrant further investigation, most notably the development of network and resource models that achieve an effective balance between modeling accuracy and computational tractability. Continued advances in data-driven modeling, scalable optimization techniques, and hybrid control architectures are expected to further enhance the capabilities of this framework, enabling resilient, efficient, and intelligent operation of increasingly complex and decentralized electric power systems.

Chapter 5

TSO-DSO Coordinated Operational Planning

This chapter presents the coordinated operational planning tool developed in this thesis to enable effective **TSO-DSO** coordination. The proposed tool builds upon the coordination mechanism introduced in Chapter 3 and the **SMOPF** framework described in Chapter 4, integrating them into a unified and scalable operational decision-making framework.

Relative to the state-of-the-art, the proposed approach introduces two key methodological innovations. First, it explicitly incorporates *shared resources* located at **TN-DN** interface nodes, whose operation is coordinated between the **TSO** and participating **DSOs** to enhance operational efficiency and cross-level coordination. Second, the coordinated planning problem is solved using the **ADMM** algorithm, enabling a fully distributed optimization architecture that preserves data privacy among participating **SOs**, complies with regulatory unbundling requirements, and remains computationally tractable for large-scale systems. In addition, and in contrast to many existing coordination frameworks, the proposed tool explicitly models interface-node voltages and the dynamic flexibility of **ADNs**. This modeling detail is essential for accurately capturing the technical coupling between transmission and distribution systems, ensuring reliable **TN**-level operation, and fully representing the ability of **DERs** to provide system-wide ancillary and flexibility services.

The remainder of the chapter is organized as follows:

- Section 5.1 introduces the **TSO-DSO** coordinated operational planning concept.
- Section 5.2 presents the framework architecture and specifies the information exchanged between the **TSO** and **DSOs** during coordination.
- Section 5.3 details the distributed optimization formulation based on the **ADMM** algorithm, outlining its modeling assumptions and advantages over existing methods.
- Section 5.4 concludes the chapter and outlines directions for future research.

5.1 Introduction

This chapter presents a novel framework for the coordinated operational planning of **TN** and **DNs**. The proposed tool introduces the concept of *shared resources* located at **TN–DN** interface nodes, whose operation can be coordinated between the **TSO** and participating **DSOs** to support system-wide decision-making and improve cross-voltage-level operation. In this thesis, the term *shared* characterizes the coordinated operational use of an asset and does not imply a specific ownership or investment arrangement. Accordingly, the proposed framework is ownership-neutral and evaluates such resources from a system-wide techno-economic perspective. Potential governance, remuneration, and cost-recovery arrangements are discussed in Subsection 8.3.1. Uncertainty arising from both market prices and operational forecasts is explicitly modeled, enabling a realistic representation of system behavior under practical operating conditions.

To preserve the data privacy of participating **SOs** and ensure computational tractability at scale, the framework adopts a distributed optimization approach based on the **ADMM** algorithm. The proposed methodology is validated using modified Institute of Electrical and Electronics Engineers (**IEEE**) test systems, demonstrating that the coordination mechanism can effectively exploit demand-side flexibility to improve overall system efficiency while maintaining secure and reliable **DN** operation. The following section introduces the coordination framework in detail, describing the information exchange structure and the operational workflow between the **TSO** and **DSOs**.

5.2 Framework

As discussed in Chapter 3, the proposed **TSO–DSO** coordinated operational planning framework adopts a distributed architecture, in which the overall large-scale optimization problem is decomposed into separate subproblems for the **TSO** and each participating **DSO**. This structure enhances both scalability and data privacy by allowing each **SO** to optimize its own network independently, while exchanging only the minimal information required to ensure coordinated and system-consistent operation.

Within this framework:

- The **TSO** is responsible for ensuring system security, including congestion management at the **TN** level, voltage support, and the procurement and activation of appropriate **ASs**. This includes leveraging flexibility services offered by participating **ADNs**.
- Each **DSO** is responsible for the secure and efficient operation of its own **DN**, managing local congestion and ensuring that any flexibility services made available to the **TSO** do not jeopardize distribution-level security or reliability.

Figure 5.1 illustrates the proposed coordination mechanism and the information exchanged between the SOs. The notation used throughout this section is defined as follows:

- $N^I \subseteq N$: set of **TN-DN** interface nodes.
- $V_{i,t}^I$: expected voltage magnitude at interface node $i \in N^I$ and time instant $t \in T$; $\pi_{i,t}^{I,V}$ denotes the corresponding dual variable.
- $P_{i,t}^I, Q_{i,t}^I$: expected active and reactive power flows at interface node $i \in N^I$ and time instant $t \in T$; $\pi_{i,t}^{I,P}$ and $\pi_{i,t}^{I,Q}$ are the associated dual variables, respectively.
- $P_{i,t}^E, Q_{i,t}^E$: expected active and reactive power provided by the shared **ESS** at interface node $i \in N^I$ and time instant $t \in T$; $\pi_{i,t}^{E,P}$ and $\pi_{i,t}^{E,Q}$ denote the corresponding dual variables.

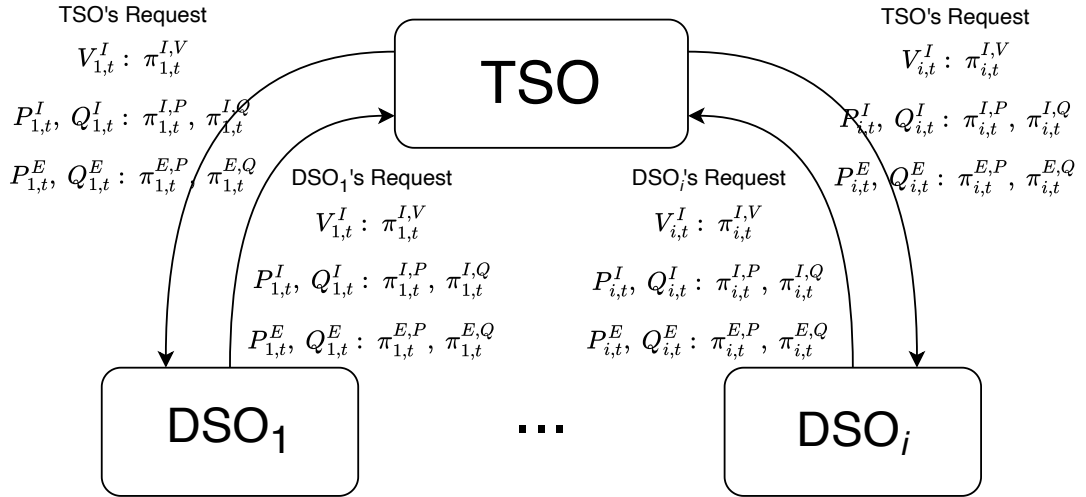


Figure 5.1: TSO-DSO coordination mechanism. Data exchanged between SOs.

As illustrated in Figure 5.1, the **TSO** and participating **DSOs** exchange information on voltage magnitudes, active and reactive power flows, and the active and reactive power contributions of shared **ESSs** located at each interface node $i \in N^I$ and time instant $t \in T$ of the optimization horizon. Within this architecture, each **SO** – namely the **TSO** and each participating **DSO** – solves an *independent* local optimization problem, subject to its own network constraints and operational objectives. Coordination across voltage levels is achieved exclusively through the exchange of a limited set of shared interface variables, which represent the physical coupling between the **TN** and the corresponding **DNs**.

During the coordination process, the **TSO** and participating **DSOs** iteratively update and exchange interface variables and their associated dual variables until convergence to a mutually consistent solution is achieved that balances the local objectives while satisfying the operational and consensus constraints of the participating parties. The **ADMM** algorithm enforces consistency among the shared interface variables by alternating between

local optimization steps and dual variable updates, progressively driving the coupled subproblems toward a coordinated consensus operating point. The following section presents the mathematical formulation of the proposed framework and details the iterative coordination procedure between the **TSO** and the **DSOs**.

5.3 Distributed Optimization Approach

The coordinated operational planning algorithm is implemented using the **ADMM**, a well-established decomposition technique for solving large-scale optimization problems (Boyd et al., 2011). Over the past decade, **ADMM** has been successfully applied to a broad range of power system optimization problems, including formulations with non-convex substructures and nonlinear network models (e.g., Iria et al., 2019).

In this framework, voltage magnitudes at interface nodes, active and reactive power exchanges, and the power profiles of shared **ESSs** are treated as coupling variables. This choice enables the otherwise monolithic optimization problem to be decomposed into smaller, independent subproblems for the **TSO** and each participating **DSO**. This decomposition offers two key advantages:

1. The large, computationally intensive system-wide problem is divided into smaller subproblems that can be solved independently using standard **AC-OPF** techniques. In particular, the **SMOPF** formulation introduced in Chapter 4 is adopted for both **SOs**, ensuring a consistent representation of network constraints, controllable resources, and uncertainty across voltage levels.
2. Data privacy and regulatory compliance: Each **SO** optimizes its local problem using only internal network data, exchanging solely a limited set of interface variables (i.e., voltage magnitudes, active and reactive power flows, and shared **ESS** schedules). This design preserves data confidentiality and complies with unbundling requirements, which restrict the direct sharing of detailed grid and market information between **SOs** involved in the coordination procedure.

More specifically, the **TSO-DSO** coordinated operational planning tool is implemented using a *consensus-based* **ADMM** algorithm. The procedure starts with a *cold start*, in which the **TSO** and the participating **DSOs** independently solve their local operational planning problems using forecasted interface power exchanges. Following this initialization, the core **ADMM** iterations proceed as follows:

1. **DSO-update**: Given the current **TSO**-proposed interface voltage magnitudes, active and reactive power exchanges, and shared **ESS** power profiles, each **DSO** solves its local optimization problem to meet these targets and returns its best-achievable interface quantities.

2. **TSO**-update: The **TSO** incorporates the updated **DSO** responses – namely the interface voltage magnitudes, power flows, and **ESS** schedules – into its own optimization problem and computes revised target values for the next iteration.

Before initiating the **ADMM** procedure, the **TSO** and each participating **DSO** independently solve their standalone operational planning problems. These initial solutions are used to initialize the coupling variables, provide the reference objective values used for normalization, and supply the starting point for the first **ADMM** iteration. In subsequent iterations, each local subproblem is initialized using the solution obtained in the preceding iteration, thereby providing a warm start to the **NLP** solver. This iterative exchange continues until the interface voltage magnitudes, active and reactive power exchanges, and shared **ESS** active and reactive power profiles converge within a predefined tolerance, thereby ensuring consensus across all coupling variables.

5.3.1 Mathematical Formulation

Each **TSO** and **DSO** subproblem within the consensus-based **ADMM** framework can be expressed in the following generic form:

$$\min \frac{f(X)}{|f^0|} + \sum_{i \in N^I} \sum_{t \in T} \mathcal{L}^{I,V} \left(V_{i,t}^{I,k}, \hat{V}_{i,t}^{I,k}, \pi_{i,t}^{I,V,k} \right) \quad (5.1a)$$

$$\begin{aligned} & + \sum_{i \in N^I} \sum_{t \in T} \mathcal{L}^{I,P} \left(P_{i,t}^{I,k}, \hat{P}_{i,t}^{I,k}, \pi_{i,t}^{I,P,k} \right) + \sum_{i \in N^I} \sum_{t \in T} \mathcal{L}^{I,Q} \left(Q_{i,t}^{I,k}, \hat{Q}_{i,t}^{I,k}, \pi_{i,t}^{I,Q,k} \right) \\ & + \sum_{e \in E^S} \sum_{t \in T} \mathcal{L}^{E,P} \left(P_{e,t}^{E,k}, \hat{P}_{e,t}^{E,k}, \pi_{e,t}^{E,P,k} \right) + \sum_{e \in E^S} \sum_{t \in T} \mathcal{L}^{E,Q} \left(Q_{e,t}^{E,k}, \hat{Q}_{e,t}^{E,k}, \pi_{e,t}^{E,Q,k} \right) \\ \text{s.t. } & h \left(X, V_{i,t}^{I,k}, P_{i,t}^{I,k}, Q_{i,t}^{I,k}, P_{e,t}^{E,k}, Q_{e,t}^{E,k} \right) \leq 0 \end{aligned} \quad (5.1b)$$

where:

- Sets and variables:
 - $N^I \subseteq N$: set of interface nodes with **ADNs** participating in the **TSO-DSO** coordination scheme.
 - $E^S \subseteq E$: set of shared **ESSs** installed at the interface nodes with **ADNs** participating in the **TSO-DSO** coordination scheme.
 - T : set of time periods.
 - X : set of local decision variables of the operator.
 - K : set of **ADMM** iterations.
- Objective function:
 - $f(X)$: local objective function of the **SO**;

- f^0 : value of the corresponding local objective evaluated at the initial standalone solution and used as a normalization factor.
- Augmented Lagrangian terms:
 - $\mathcal{L}^{I,V}$, $\mathcal{L}^{I,P}$, $\mathcal{L}^{I,Q}$: augmented Lagrangians associated with the interface node voltage magnitude and active/reactive power exchanges, respectively.
 - $\mathcal{L}^{E,P}$, $\mathcal{L}^{E,Q}$: augmented Lagrangians associated with the active and reactive power of shared **ESS**, respectively.
- Primal and dual variables:
 - $V_{i,t}^{I,k}$, $P_{i,t}^{I,k}$, $Q_{i,t}^{I,k}$: voltage magnitude and active/reactive power flows at interface node $i \in N^I$, at time instant $t \in T$ and iteration $k \in K$. $\hat{V}_{i,t}^{I,k}$, $\hat{P}_{i,t}^{I,k}$, and $\hat{Q}_{i,t}^{I,k}$ denote the corresponding local copies representing the target values received from the counterpart **SO**.
 - $\pi_{i,t}^{I,V,k}$, $\pi_{i,t}^{I,P,k}$, $\pi_{i,t}^{I,Q,k}$: dual variables associated with the voltage and power exchanges at interface node $i \in N^I$, time $t \in T$, and iteration $k \in K$, respectively.
 - $P_{e,t}^{E,k}$, $Q_{e,t}^{E,k}$: active and reactive power of shared **ESS** $e \in E^S$ at time $t \in T$ and iteration $k \in K$. $\hat{P}_{e,t}^{E,k}$ and $\hat{Q}_{e,t}^{E,k}$ denote the corresponding target values received from the counterpart **SO**.
 - $\pi_{e,t}^{E,P,k}$, $\pi_{e,t}^{E,Q,k}$: dual variables associated with the active and reactive power of shared **ESS** $e \in E^S$.
- Constraints:
 - $h(\cdot)$: generically represents the operator's internal **SMOPF** constraints, including network, resources, and operational limits.

Algorithm 5.1 summarizes the pseudo-code of the consensus-based **ADMM** implementation adopted for the proposed **TSO-DSO** coordinated operational planning framework.

Each participating **SO** retains its own local objective function, which may reflect operational priorities that differ from, or conflict with, those of the other operators. The coordinated problem therefore has an inherent multi-objective character. However, the proposed implementation does not explicitly construct a Pareto front. Instead, the consensus formulation can be interpreted as a scalarized coordination problem involving the normalized local objectives, the **SOs**' internal constraints, and the consensus constraints associated with the shared variables. Normalization reduces the influence of differences in the numerical scales of the local objectives. In the absence of additional **SO**-specific weights, the same explicit coefficient is assigned to each normalized objective, yielding a single compromise solution for the adopted scalarization. Alternative weights could be introduced to represent different coordination priorities and investigate other trade-offs among the **SOs**' objectives.

Algorithm 5.1: Coordinated operational planning. ADMM implementation.

```

1 for  $i \in N^I$  do
2   DSOi: Create local operational planning model
3   DSOi: Solve the standalone local operational planning model assuming
       $V_{i,t}^{I,0} = 1.0$  p.u. at the TN-DN interface
4   DSOi: Add consensus variables and augmented Lagrangian terms
5   DSOi: Initialize the ADMM model using the local solution
6 TSO: Create operational planning model
7 TSO: Solve the standalone operational planning model using forecasted values of
       $V_{i,t}^{I,0}$ ,  $P_{i,t}^{I,0}$ , and  $Q_{i,t}^{I,0}$ 
8 TSO: Add consensus variables and augmented Lagrangian terms
9 TSO: Initialize the ADMM model using the standalone solution
10 ADMM: Set  $k \leftarrow 1$  and converged  $\leftarrow$  false
11 while  $k \leq k^{\max}$  do
12   DSO updates:
13   for  $i \in N^I$  do
14     DSOi: Set  $\hat{V}_{i,t}^{I,k}$ ,  $\hat{P}_{i,t}^{I,k}$ ,  $\hat{Q}_{i,t}^{I,k}$ ,  $\hat{P}_{i,t}^{E,k}$ , and  $\hat{Q}_{i,t}^{E,k}$  to the targets received from
        the TSO
15     DSOi: Solve local operational planning problem
16     DSOi: Update dual variables  $\pi_{i,t}^{I,V,k}$ ,  $\pi_{i,t}^{I,P,k}$ ,  $\pi_{i,t}^{I,Q,k}$ ,  $\pi_{i,t}^{E,P,k}$ , and  $\pi_{i,t}^{E,Q,k}$ 
17   ADMM: Compute residuals and evaluate convergence criteria
18   if converged then
19     break
20   TSO update:
21   TSO: Set  $\hat{V}_{i,t}^{I,k}$ ,  $\hat{P}_{i,t}^{I,k}$ ,  $\hat{Q}_{i,t}^{I,k}$ ,  $\hat{P}_{i,t}^{E,k}$ , and  $\hat{Q}_{i,t}^{E,k}$  to the targets received from the
      DSOs
22   TSO: Solve operational planning problem
23   TSO: Update dual variables  $\pi_{i,t}^{I,V,k}$ ,  $\pi_{i,t}^{I,P,k}$ ,  $\pi_{i,t}^{I,Q,k}$ ,  $\pi_{i,t}^{E,P,k}$ , and  $\pi_{i,t}^{E,Q,k}$ 
24   ADMM: Compute residuals and evaluate convergence criteria
25   if converged then
26     break
27    $k \leftarrow k + 1$ 

```

Although global convergence of **ADMM** is formally guaranteed only for convex problems, empirical evidence indicates that the method can perform reliably in many non-convex settings (e.g., [Iria et al., 2019](#)). This motivates its adoption in the proposed coordinated operational planning framework, in which both the **TSO** and **DSO** subproblems are inherently non-convex. Nevertheless, global optimality and uniqueness of the coordinated solution cannot be guaranteed. Consequently, the initialization may influence the convergence trajectory and the stationary solution reached.

5.3.2 Augmented Lagrangian Terms

To promote stable convergence and balanced penalization, a *residual-balancing* strategy is employed to appropriately scale the original objective relative to the augmented Lagrangian penalty terms. This normalization compensates for differences in physical units and numerical magnitudes among interface variables, improving problem conditioning and enhancing the overall convergence behavior of the **ADMM** algorithm.

The following subsections describe the implementation of the residual-balanced augmented Lagrangian terms.

5.3.2.1 Voltage Magnitude

The augmented Lagrangian term enforcing consensus on the interface node voltage magnitude is defined as:

$$\mathcal{L}^{I,V} \left(V_{i,t}^{I,k}, \hat{V}_{i,t}^{I,k}, \pi_{i,t}^{I,V,k} \right) = \pi_{i,t}^{I,V,k} \left(\frac{V_{i,t}^{I,k} - \hat{V}_{i,t}^{I,k}}{V_i^{\text{Base}}} \right) + \frac{\rho^{I,V,k}}{2} \left\| \frac{V_{i,t}^{I,k} - \hat{V}_{i,t}^{I,k}}{V_i^{\text{Base}}} \right\|^2 \quad (5.2)$$

where:

- V_i^{Base} is the base voltage at interface node $i \in N^I$; and
- $\rho^{I,V,k}$ is the **ADMM** penalty parameter associated with the interface node voltage magnitude at iteration $k \in K$.

The *expected* interface node voltage magnitude, representing the stochastic mean over market and operational scenarios, is given by $(\forall i \in N^I, \forall t \in T)$:

$$V_{i,t}^I = \mathbb{E} \left(V_{i,m,o,t}^I \right) = \sum_{m \in \Omega_m} \sum_{o \in \Omega_o} \omega_m \omega_o V_{i,m,o,t}^I \quad (5.3)$$

where:

- $\mathbb{E}(\cdot)$ denotes the expectation operator;
- Ω_m is the set of market scenarios with probabilities ω_m ;
- Ω_o is the set of operational scenarios with probabilities ω_o ; and
- $V_{i,m,o,t}^I$ is the voltage magnitude at interface node $i \in N^I$ under market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$.

Each scenario-specific voltage magnitude is obtained from its rectangular components as $(\forall i \in N^I, \forall m \in \Omega_m, \forall o \in \Omega_o, \forall t \in T)$:

$$\left(V_{i,m,o,t}^I \right)^2 = \left(\tilde{e}_{i,m,o,t} \right)^2 + \left(\tilde{f}_{i,m,o,t} \right)^2 \quad (5.4)$$

where $\tilde{e}_{i,m,o,t}$ and $\tilde{f}_{i,m,o,t}$ are the real and imaginary voltage components at node $i \in N^I$, respectively, considering the associated slack variables, under market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$.

To limit the dispersion of voltage magnitudes across stochastic scenarios, the original **SMOPF** objective function is augmented with a regularization term that penalizes deviations from the expected value:

$$f(X) = f'(X) + \sum_{i \in N^I} \sum_{m \in \Omega_m} \sum_{o \in \Omega_o} \sum_{t \in T} c^{I,V} \left(V_{i,m,o,t}^I - V_{i,t}^I \right)^2 \quad (5.5)$$

where $f'(X)$ denotes the original **SMOPF** objective function, and $c^{I,V}$ is a weighting coefficient that discourages large deviations of scenario voltages from their expected values.

5.3.2.2 Active and Reactive Power Flows

The augmented Lagrangian terms enforcing consensus on the interface node active and reactive power flows are defined as:

$$\mathcal{L}^{I,P} \left(P_{i,t}^{I,k}, \hat{P}_{i,t}^{I,k}, \pi_{i,t}^{I,P,k} \right) = \pi_{i,t}^{I,P,k} \left(\frac{P_{i,t}^{I,k} - \hat{P}_{i,t}^{I,k}}{S_i^{\text{Rated}}} \right) + \frac{\rho^{I,P,k}}{2} \left\| \frac{P_{i,t}^{I,k} - \hat{P}_{i,t}^{I,k}}{S_i^{\text{Rated}}} \right\|^2 \quad (5.6)$$

$$\mathcal{L}^{I,Q} \left(Q_{i,t}^{I,k}, \hat{Q}_{i,t}^{I,k}, \pi_{i,t}^{I,Q,k} \right) = \pi_{i,t}^{I,Q,k} \left(\frac{Q_{i,t}^{I,k} - \hat{Q}_{i,t}^{I,k}}{S_i^{\text{Rated}}} \right) + \frac{\rho^{I,Q,k}}{2} \left\| \frac{Q_{i,t}^{I,k} - \hat{Q}_{i,t}^{I,k}}{S_i^{\text{Rated}}} \right\|^2 \quad (5.7)$$

where:

- S_i^{Rated} is the rated capacity of the branch connected to interface node $i \in N^I$; and
- $\rho^{I,P,k}$ and $\rho^{I,Q,k}$ are the **ADMM** penalty parameters for active and reactive power flows at iteration $k \in K$, respectively.

The *expected* interface node active and reactive power flows, representing their stochastic mean values across all market and operational scenarios, are given by $(\forall i \in N^I, \forall t \in T)$:

$$P_{i,t}^I = \mathbb{E} \left(P_{i,m,o,t}^I \right) = \sum_{m \in \Omega_m} \sum_{o \in \Omega_o} \omega_m \omega_o P_{i,m,o,t}^I \quad (5.8)$$

$$Q_{i,t}^I = \mathbb{E} \left(Q_{i,m,o,t}^I \right) = \sum_{m \in \Omega_m} \sum_{o \in \Omega_o} \omega_m \omega_o Q_{i,m,o,t}^I \quad (5.9)$$

where $P_{i,m,o,t}^I$ and $Q_{i,m,o,t}^I$ denote the active and reactive power flows at interface node $i \in N^I$ for market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and time instant $t \in T$.

To limit scenario-to-scenario variability – thereby ensuring consistent operation across stochastic realizations – the **SMOPF** objective function is augmented with a regularization term that penalizes deviations from the expected values:

$$f(X) = f'(X) + \sum_{i \in N^I} \sum_{m \in \Omega_m} \sum_{o \in \Omega_o} \sum_{t \in T} \left(c^{I,P} \left(P_{i,m,o,t}^I - P_{i,t}^I \right)^2 + c^{I,Q} \left(Q_{i,m,o,t}^I - Q_{i,t}^I \right)^2 \right) \quad (5.10)$$

where $c^{I,P}$ and $c^{I,Q}$ are weighting coefficients that discourage large deviations of the scenario-specific power flows from their expected (mean) values.

5.3.2.3 Shared ESS Active and Reactive Powers

The augmented Lagrangian terms enforcing consensus on the shared **ESSs** active and reactive powers are defined as:

$$\mathcal{L}^{E,P} \left(P_{e,t}^{E,k}, \hat{P}_{e,t}^{E,k}, \pi_{e,t}^{E,P,k} \right) = \pi_{e,t}^{E,P,k} \left(\frac{P_{e,t}^{E,k} - \hat{P}_{e,t}^{E,k}}{S_e^{\text{Rated}}} \right) + \frac{\rho^{E,P,k}}{2} \left\| \frac{P_{e,t}^{E,k} - \hat{P}_{e,t}^{E,k}}{S_e^{\text{Rated}}} \right\|^2 \quad (5.11)$$

$$\mathcal{L}^{E,Q} \left(Q_{e,t}^{E,k}, \hat{Q}_{e,t}^{E,k}, \pi_{e,t}^{E,Q,k} \right) = \pi_{e,t}^{E,Q,k} \left(\frac{Q_{e,t}^{E,k} - \hat{Q}_{e,t}^{E,k}}{S_e^{\text{Rated}}} \right) + \frac{\rho^{E,Q,k}}{2} \left\| \frac{Q_{e,t}^{E,k} - \hat{Q}_{e,t}^{E,k}}{S_e^{\text{Rated}}} \right\|^2 \quad (5.12)$$

where:

- S_e^{Rated} is the rated apparent power of shared **ESS** $e \in E^S$; and
- $\rho^{E,P,k}$ and $\rho^{E,Q,k}$ are the **ADMM** penalty parameters for the active and reactive power of shared **ESSs**, respectively, at iteration $k \in K$.

The *expected* shared **ESS** active and reactive powers, representing their stochastic mean across all market and operational scenarios, are given by ($\forall e \in E^S, \forall t \in T$):

$$P_{e,t}^E = \mathbb{E} \left(P_{e,m,o,t}^E \right) = \sum_{m \in \Omega_m} \sum_{o \in \Omega_o} \omega_m \omega_o P_{e,m,o,t}^E \quad (5.13)$$

$$Q_{e,t}^E = \mathbb{E} \left(Q_{e,m,o,t}^E \right) = \sum_{m \in \Omega_m} \sum_{o \in \Omega_o} \omega_m \omega_o Q_{e,m,o,t}^E \quad (5.14)$$

where $P_{e,m,o,t}^E$ and $Q_{e,m,o,t}^E$ denote the scenario-specific active and reactive powers of shared **ESS** $e \in E^S$ in market scenario $m \in \Omega_m$, operational scenario $o \in \Omega_o$, and instant $t \in T$.

To limit scenario-to-scenario variability – and thus ensure consistent behavior across stochastic realizations – the **SMOPF** objective function is augmented with a regularization term that penalizes active and reactive power deviations from the expected values:

$$f(X) = f'(X) + \sum_{e \in E^S} \sum_{m \in \Omega_m} \sum_{o \in \Omega_o} \sum_{t \in T} \left(c^{E,P} \left(P_{e,m,o,t}^E - P_{e,t}^E \right)^2 + c^{E,Q} \left(Q_{e,m,o,t}^E - Q_{e,t}^E \right)^2 \right) \quad (5.15)$$

where $c^{E,P}$ and $c^{E,Q}$ are weighting coefficients that discourage large deviations of the scenario-specific active and reactive powers from their expected means.

Balancing the original objective function with the augmented Lagrangian terms offers several key benefits: it enhances convergence robustness, mitigates numerical ill-conditioning, and improves overall algorithmic stability – an aspect that is particularly important given the non-convex nature of the SOs subproblems. In parallel, the inclusion of the regularization terms (5.5), (5.10), and (5.15) ensures that the flexibility services offered by participating ADN_s remain consistent across uncertainty realizations. This consistency allows the TSO to rely on DER_s as stable, predictable providers of system-level flexibility, even under volatile operational conditions.

5.3.3 Dual Variables Update

Within the ADMM framework, the dual variables act as Lagrange multipliers that guide the TSO and DSO_s subproblems toward consensus on the coupling variables – namely, the interface node voltage magnitudes, active and reactive power exchanges, and the power outputs of shared ESS_s. These multipliers can be interpreted as *price-like coordination signals* that penalize deviations between each SO's local solution and the evolving consensus values (Boyd et al., 2011).

To enhance numerical stability and convergence, the penalty parameters are progressively scaled during the iterative process rather than held constant. This adaptive mechanism balances the primal and dual residuals, reducing oscillatory behavior that commonly arises in non-convex settings and improving the robustness of the iterative process. Empirical evidence indicates that such adaptive strategies substantially improve convergence performance in large-scale, non-convex coordination problems, including power system operational planning applications (Liu et al., 2023b).

5.3.3.1 Voltage Magnitude

The dual variables associated with interface-node voltage magnitudes are updated at each iteration $k \in K$ as $(\forall i \in N^I, \forall t \in T)$:

$$\pi_{i,t}^{I,V,k} := \pi_{i,t}^{I,V,k-1} + \rho^{I,V,k} (V_{i,t}^{I,k} - \hat{V}_{i,t}^{I,k}) \quad (5.16)$$

where $\pi_{i,t}^{I,V,k}$ represents the price-like signal penalizing mismatches between the TSO and DSO interface voltages at iteration k . The corresponding penalty parameter is updated adaptively according to:

$$\rho^{I,V,k} := \rho^{I,V,k-1} (1 + r^{I,V}) \quad (5.17)$$

where $r^{I,V}$ is the update rate controlling the scaling of the voltage-related penalty term. This adaptive adjustment increases the weight of persistent discrepancies, improving convergence robustness and reducing oscillations across iterations.

5.3.3.2 Active and Reactive Power Flows

The dual variables associated with interface node active and reactive power flows are updated at each iteration $k \in K$ as $(\forall i \in N^I, \forall t \in T)$:

$$\pi_{i,t}^{I,P,k} := \pi_{i,t}^{I,P,k-1} + \rho^{I,P,k} (P_{i,t}^{I,k} - \hat{P}_{i,t}^{I,k}) \quad (5.18)$$

$$\pi_{i,t}^{I,Q,k} := \pi_{i,t}^{I,Q,k-1} + \rho^{I,Q,k} (Q_{i,t}^{I,k} - \hat{Q}_{i,t}^{I,k}) \quad (5.19)$$

where $\pi_{i,t}^{I,P,k}$ and $\pi_{i,t}^{I,Q,k}$ are the coordination signals (dual multipliers) penalizing mismatches between the **TSO** and **DSO** interface power exchanges. Their penalty parameters are updated adaptively as:

$$\rho^{I,P,k} := \rho^{I,P,k-1} (1 + r^{I,P}) \quad (5.20)$$

$$\rho^{I,Q,k} := \rho^{I,Q,k-1} (1 + r^{I,Q}) \quad (5.21)$$

where $r^{I,P}$ and $r^{I,Q}$ are the user-defined update rates for the active and reactive flow penalties, respectively. These adaptive adjustments progressively strengthen the penalization of persistent discrepancies in power-flow consensus, improving conditioning and accelerating convergence.

5.3.3.3 Shared ESS Active and Reactive Powers

The dual variables associated with the shared **ESSs** active and reactive power outputs are updated at each iteration $k \in K$ as $(\forall e \in E^S, \forall t \in T)$:

$$\pi_{e,t}^{E,P,k} := \pi_{e,t}^{E,P,k-1} + \rho^{E,P,k} (P_{e,t}^{E,k} - \hat{P}_{e,t}^{E,k}) \quad (5.22)$$

$$\pi_{e,t}^{E,Q,k} := \pi_{e,t}^{E,Q,k-1} + \rho^{E,Q,k} (Q_{e,t}^{E,k} - \hat{Q}_{e,t}^{E,k}) \quad (5.23)$$

where $\pi_{e,t}^{E,P,k}$ and $\pi_{e,t}^{E,Q,k}$ represent the coordination multipliers penalizing mismatches between the **TSO** and **DSO** estimates of shared **ESS** active and reactive power. The associated penalty parameters are updated adaptively according to:

$$\rho^{E,P,k} := \rho^{E,P,k-1} (1 + r^{E,P}) \quad (5.24)$$

$$\rho^{E,Q,k} := \rho^{E,Q,k-1} (1 + r^{E,Q}) \quad (5.25)$$

where $r^{E,P}$ and $r^{E,Q}$ are the user-defined update rates for the shared-ESSs' active and reactive power penalties. By dynamically scaling these penalties in response to residual discrepancies, the algorithm reinforces consensus on shared-resource operation, enhancing stability and accelerating convergence.

Collectively, the residual-balancing and adaptive penalty update mechanisms enhance the coordination process by promoting reliable and stable convergence in the presence of non-convex constraints, thereby reinforcing the robustness and scalability of the coordinated operational planning framework.

5.3.4 Convergence Criteria

In the ADMM framework, convergence is declared when the *primal* and *dual* residuals fall below user-defined tolerances, indicating that the coupling variables have reached consensus and that the dual variables have stabilized. These residual checks serve as practical numerical proxies for verifying the satisfaction of the KKT optimality conditions of the original problem:

- Primal residual (r^k): measures the violation of the consensus (coupling) constraints, corresponding to *primal feasibility* in the KKT system.
- Dual residual (s^k): measures the change in the dual variables – equivalently, the gradient of the augmented Lagrangian terms – between successive iterations, representing *dual feasibility and stationarity* conditions.

When both $\|r^k\|$ and $\|s^k\|$ fall below their respective tolerances, the ADMM iterates are considered approximately primal- and dual-feasible, indicating that the consensus and dual-update conditions are satisfied within the prescribed numerical accuracy. These tolerances are user-configurable and may be tightened to improve solution accuracy or relaxed to accelerate convergence, allowing for a flexible trade-off between computational efficiency and precision.

5.3.4.1 Primal Convergence

Since the formulation includes augmented Lagrangian terms with different physical units and scales, three separate primal convergence criteria are defined – covering interface voltage magnitudes, interface power flows, and shared ESSs power outputs – to ensure a balanced assessment of convergence across all coupling variables.

Primal convergence is achieved when the following conditions are simultaneously met:

$$\sum_{i \in N^I} \sum_{t \in T} \frac{|V_{i,t}^{I,k} - \hat{V}_{i,t}^{I,k}|}{V_i^{\text{Base}}} \leq \varepsilon^{I,V} n^{I,V} \quad (5.26)$$

$$\sum_{i \in N^I} \sum_{t \in T} \left(\frac{|P_{i,t}^{I,k} - \hat{P}_{i,t}^{I,k}|}{S_i^{\text{Rated}}} + \frac{|Q_{i,t}^{I,k} - \hat{Q}_{i,t}^{I,k}|}{S_i^{\text{Rated}}} \right) \leq \varepsilon^{I,PQ} n^{I,PQ} \quad (5.27)$$

$$\sum_{e \in E^S} \sum_{t \in T} \left(\frac{|P_{e,t}^{E,k} - \hat{P}_{e,t}^{E,k}|}{S_e^{\text{Rated}}} + \frac{|Q_{e,t}^{E,k} - \hat{Q}_{e,t}^{E,k}|}{S_e^{\text{Rated}}} \right) \leq \varepsilon^{E,PQ} n^{E,PQ} \quad (5.28)$$

where $\varepsilon^{I,V}$, $\varepsilon^{I,PQ}$, and $\varepsilon^{E,PQ}$ denote user-defined convergence tolerances, and $n^{I,V}$, $n^{I,PQ}$, and $n^{E,PQ}$ are the corresponding residual dimensions. Each residual is normalized by an appropriate base quantity – V_i^{Base} for voltage magnitudes, S_i^{Rated} for interface power flows, and S_e^{Rated} for shared **ESSs** – to ensure consistent scaling and a balanced assessment of convergence across all coupling variables.

5.3.4.2 Dual Convergence

Dual convergence assesses the stability of the Lagrange multipliers associated with the coupling variables. As with the primal residuals, dual residuals are normalized by the corresponding base quantities to ensure consistent scaling across different physical units.

Dual convergence is achieved when the following conditions simultaneously hold:

$$\sum_{i \in N^I} \sum_{t \in T} \rho^{I,V,k} \left(\frac{|V_{i,t}^{I,k} - \hat{V}_{i,t}^{I,k}|}{V_i^{\text{Base}}} \right) \leq \theta^{I,V} m^{I,V} \quad (5.29)$$

$$\sum_{i \in N^I} \sum_{t \in T} \left(\rho^{I,P,k} \left(\frac{|P_{i,t}^{I,k} - \hat{P}_{i,t}^{I,k}|}{S_i^{\text{Rated}}} \right) + \rho^{I,Q,k} \left(\frac{|Q_{i,t}^{I,k} - \hat{Q}_{i,t}^{I,k}|}{S_i^{\text{Rated}}} \right) \right) \leq \theta^{I,PQ} m^{I,PQ} \quad (5.30)$$

$$\sum_{e \in E^S} \sum_{t \in T} \left(\rho^{E,P,k} \left(\frac{|P_{e,t}^{E,k} - \hat{P}_{e,t}^{E,k}|}{S_e^{\text{Rated}}} \right) + \rho^{E,Q,k} \left(\frac{|Q_{e,t}^{E,k} - \hat{Q}_{e,t}^{E,k}|}{S_e^{\text{Rated}}} \right) \right) \leq \theta^{E,PQ} m^{E,PQ} \quad (5.31)$$

where $\theta^{I,V}$, $\theta^{I,PQ}$, and $\theta^{E,PQ}$ denote the tolerances for the dual residuals, and $m^{I,V}$, $m^{I,PQ}$, and $m^{E,PQ}$ are their respective dimensions.

Satisfying all three conditions ensures that the dual residuals lie within their prescribed tolerances, indicating dual feasibility and approximate stationarity of the coordination problem. When both the primal and dual convergence criteria are satisfied, the **ADMM** iterations are considered to have reached a stable consensus across all coupling variables, resulting in a coordinated system-wide operating plan that balances the objectives of the participating **SOs** while satisfying their operational constraints.

5.4 Conclusions and Future Work

This chapter presented a novel **TSO-DSO** coordinated operational planning framework aimed at addressing the increasing operational complexity of power systems with high penetration of **DERs**. Building on the coordination concepts introduced in Chapter 3 and the **SMOPF** formulation developed in Chapter 4, the proposed approach integrates transmission- and distribution-level operational planning within a unified, fully distributed decision-making framework.

From a methodological standpoint, the chapter introduced a consensus-based **ADMM** formulation that decomposes the coordinated operational planning problem into independent **TSO** and **DSO** subproblems. A key contribution of this work is the explicit modeling of *shared resources* located at **TN-DN** interface nodes. The resulting distributed architecture preserves data privacy, complies with regulatory unbundling requirements, and remains scalable to large systems with multiple participating **ADNs**. Furthermore, the adoption of adaptive penalty updates and residual-balancing strategies enhances numerical stability and convergence robustness, even in the presence of non-convex network constraints and stochastic representations of both market and operational uncertainty.

While the proposed framework represents a significant step toward practical and scalable **TSO-DSO** coordination, several important avenues for future research remain:

- (i) Although the **ADMM** algorithm demonstrated robust empirical performance (as shown in Chapter 7), further research is needed to investigate theoretical convergence guarantees and to develop acceleration techniques tailored to large-scale, highly non-convex power system models.
- (ii) Extending the framework to explicitly incorporate real-time activation layers – such as lower-voltage **DNs** or device-level control – would enable a more comprehensive assessment of the responsiveness and effectiveness of the coordination mechanism across voltage levels.
- (iii) Future work could extend the analysis to larger numbers of independently operated **DSOs**, particularly where their flexibility regions overlap or interact strongly, as well as to additional shared assets, including power-electronic-based power flow controllers.
- (iv) Finally, while the proposed approach has been validated using real-world network data and in a **HIL** environment, pilot-scale or field deployments would provide valuable insights into practical implementation challenges, including communication latency, forecasting errors, cybersecurity considerations, and regulatory constraints.

Addressing these challenges will be essential to translate coordinated operational planning frameworks from advanced research concepts into deployable tools capable of supporting the secure, efficient, and resilient operation of future power systems.

Chapter 6

TSO-DSO Shared Resources Planning

This chapter extends the operational coordination framework developed in the previous chapters by introducing a planning tool for the optimal deployment of shared **ESSs** at transmission–distribution interface nodes. The proposed approach builds directly on the coordination principles established in Chapter 3 and leverages the **TSO–DSO** coordinated operational planning framework presented in Chapter 5. In doing so, it ensures coherence between long-term investment decisions and short-term operational performance.

The **TSO–DSO** shared resources planning problem is formulated as a two-level optimization model and solved using a Benders’ decomposition approach. At the upper level, the master problem determines the optimal siting and sizing of shared **ESSs**, while the lower-level subproblem assesses their system-wide operational value through coordinated **TSO–DSO** operational planning. This hierarchical structure explicitly links long-term asset planning with operational simulation, ensuring that investment decisions are grounded in realistic, uncertainty-aware system operation and accurately reflect the value of flexibility across voltage levels.

The remainder of this chapter is organized as follows:

- Section 6.1 introduces the concept and motivation behind **TSO–DSO** shared resources planning.
- Section 6.2 presents the overall framework architecture and outlines the adopted mathematical decomposition strategy.
- Section 6.3 details the proposed Benders’ decomposition-based optimization methodology, highlighting key modeling assumptions and computational advantages.
- Section 6.4 summarizes the main findings and discusses directions for future research.

6.1 Introduction

Multi-stage planning problems in power systems are inherently large-scale and computationally demanding. Achieving a practical balance between modeling fidelity and computational tractability therefore requires carefully designed formulations and solution strategies (Qiu et al., 2017b). In this context, this chapter proposes a two-level optimization framework for planning shared ESSs installed at TN-DN interface nodes. These shared assets are deployed at interface points where DNs actively participate in the coordination scheme and whose operation is coordinated between the TSO and the corresponding DSOs, under the coordination mechanism introduced in Chapter 3. By providing additional active and reactive power flexibility at the interface level, shared ESSs enhance overall system efficiency and strengthen the effectiveness of coordinated TSO-DSO operation.

The proposed planning tool is formulated as a two-level optimization problem. At the upper level, the master problem determines the optimal siting and sizing of shared ESSs, explicitly accounting for uncertainty in investment cost projections. At the lower level, the subproblem evaluates the coordinated operational behavior of the system using the TSO-DSO operational planning framework developed in Chapter 5, resulting in a dual-decomposition structure. This subproblem captures coordinated system operation under uncertainty in load, RES generation, and market prices, and extends the operational model to explicitly account for battery capacity degradation induced by cycling. The adopted decomposition strategy effectively mitigates the computational burden of large-scale planning problems, particularly in the presence of nonlinear constraints arising from detailed ESS operation, degradation modeling, and exact network power flow representations.

Compared with existing approaches, the proposed planning framework introduces several key advances. To the best of the author's knowledge, this is the first TSO-DSO shared resource planning tool that simultaneously:

- incorporates an *exact* representation of network constraints, controllable assets, and flexibility-providing resources;
- models shared ESSs with full four-quadrant operational capability and explicit *capacity degradation* dynamics;
- accounts for uncertainty in ESS investment costs, operational forecasts (load and RES generation), and market prices (energy and flexibility); and
- preserves the data privacy of all agents involved in the coordination process.

The remainder of this chapter presents the proposed shared resources planning framework. Detailed simulation results are reported in Section 7.3.

6.2 Framework

The proposed planning tool adopts a two-level optimization framework for addressing the coordinated planning of shared resources in transmission and distribution systems. At the upper, or master, level, long-term investment decisions are determined, namely the rated converter power and energy capacity of the shared **ESSs** installed at each candidate **TN-DN** interface node over the planning horizon. At the lower, or subproblem, level, coordinated operational planning between the **TSO** and participating **DSOs** is evaluated, thereby quantifying the operational value of the candidate investments under the considered system conditions.

Figure 6.1 illustrates the overall architecture of the proposed framework.

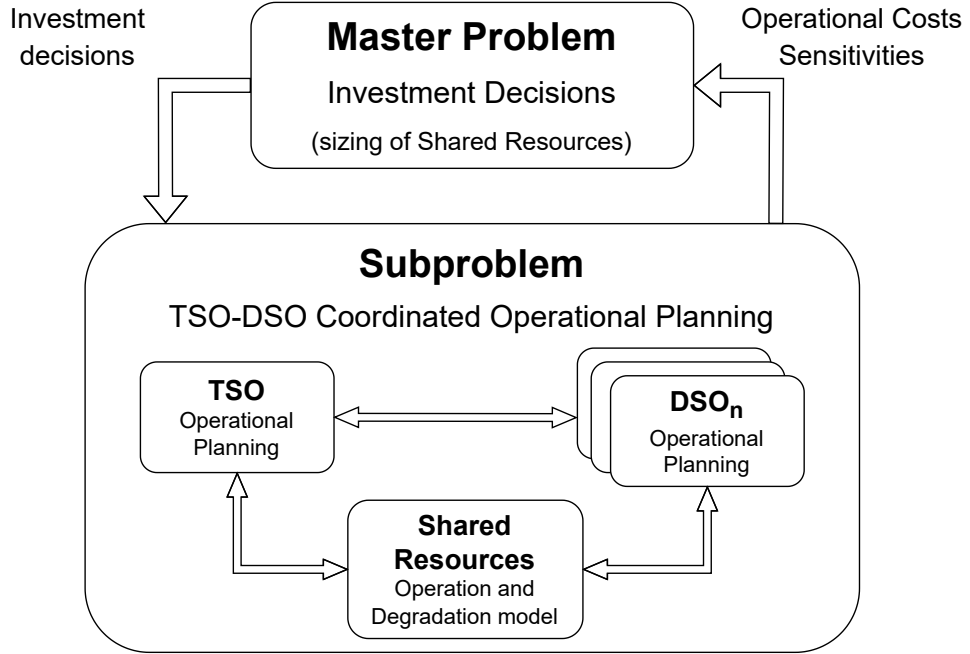


Figure 6.1: Diagram of the proposed two-level planning framework.

As previously discussed, the problem is solved using Benders decomposition. The coupling between the two levels is established through the investment variables, namely the rated converter power and energy capacity of each shared **ESS**, which represent system-wide investment decisions concerning their deployment. The solution procedure is iterative. At each iteration, the master problem determines candidate investments in shared **ESSs**, which are passed to the subproblem for evaluation through coordinated **TSO-DSO** operational planning. The subproblem returns the resulting system-wide operational cost and the corresponding sensitivities, which are used to construct Benders cuts and update the master problem. The procedure continues until the adopted stopping criterion is satisfied, i.e., when the difference between the upper- and lower-bound estimates falls below a predefined tolerance.

The proposed planning formulation involves only continuous decision variables; no binary or integer investment variables are introduced. The siting of shared ESSs is represented implicitly through their rated power and energy capacity variables, which may take a zero value at candidate interface nodes. Accordingly, the master problem remains continuous, while the operational subproblem is formulated as a non-convex NLP.

6.3 Methodology

The proposed planning problem integrates long-term investment decisions with short-term coordinated operation under uncertainty, while explicitly accounting for shared ESS degradation effects. Addressing this level of complexity requires a structured solution strategy capable of preserving modeling fidelity without compromising computational tractability. To this end, a two-layer decomposition strategy is adopted. The *outer* layer of the framework represents the long-term investment planning problem and is solved using Benders' decomposition (Conejo et al., 2006). The *inner* layer captures short-term system operation and is solved through the ADMM-based TSO-DSO coordination framework introduced in Chapter 5. This hierarchical structure enables the explicit coupling of planning and operation while maintaining scalability across multi-year horizons and large network instances.

As discussed earlier, the rated power and energy capacities of shared ESSs are optimized at the master level for each transmission-distribution interface node and planning year, while their operational value is evaluated through the coordinated TSO-DSO subproblem. This interaction follows a standard Benders' decomposition scheme, in which operational costs and sensitivity information are iteratively fed back to the master problem until convergence between investment and operational decisions is achieved. At the operational level, the framework is extended to explicitly capture multi-year dynamics and ESS capacity degradation. A dedicated optimization agent is introduced to model the evolution of the shared ESSs State-of-Health (SoH) and its impact on available capacity over time. This mechanism establishes a temporal link between representative years in the planning horizon, allowing the TSO and DSOs subproblems to remain decoupled by year while ensuring that degradation-driven capacity losses are consistently reflected in both operational feasibility and investment timing.

Unlike conventional ESS planning formulations, the proposed framework supports a *staged investment strategy*, whereby shared ESSs installed at the same interface node can be progressively expanded or upgraded over the planning horizon, leveraging the modular nature of battery-based storage technologies. In addition, uncertainty in investment costs is explicitly captured through scenario-based representations. This enables decision-makers to assess the timing, siting, and sizing of investments under multiple scenario realizations, while ensuring that the resulting operational strategies remain feasible and cost-effective across a wide range of system conditions.

Because the operational subproblem is non-convex, the classical convergence guarantees of Benders decomposition do not directly apply. Convergence is therefore assessed numerically using the adopted upper- and lower-bound estimates, while the empirical convergence behavior of the proposed methodology is evaluated in Chapter 7.

The following subsections present the master and subproblem formulations of the proposed two-level optimization framework and describe the extensions introduced to the TSO–DSO coordinated operational planning model to support multi-year operation and shared-ESS degradation in a computationally tractable manner.

6.3.1 Master Problem

At the master level, the optimization framework focuses on strategic investment decisions. It determines the configuration of shared ESSs across transmission–distribution interface nodes over the planning horizon, defining the capacity expansion pathways that underpin the coordinated operational analysis carried out at the lower level.

6.3.1.1 Objective Function

The objective of the master problem is to minimize the total discounted investment cost of the shared resources, defined as:

$$\min \sum_{e \in E^S} \sum_{y \in Y} \sum_{c \in \Omega_C} \left(\frac{\omega_c}{(1+r)^{y-y_0}} \left(c_{y,c}^{\text{Inv,S}} S_{e,y,c}^{\text{Inv}(l)} + c_{y,c}^{\text{Inv,E}} E_{e,y,c}^{\text{Inv}(l)} \right) \right) + \alpha^{(l)} \quad (6.1)$$

where:

- L^B : set of iterations of the Benders' algorithm;
- E^S : set of interface nodes where shared ESSs may be installed;
- Y : set of representative years in the planning horizon;
- Ω_C : set of investment cost scenarios, with ω_c denoting the associated probability;
- r : annual discount rate, with y_0 denoting the initial year of the planning horizon;
- $c_{y,c}^{\text{Inv,S}}, c_{y,c}^{\text{Inv,E}}$: unit investment costs for power converter rating and energy capacity, respectively, in year $y \in Y$ and scenario $c \in \Omega_C$;
- $S_{e,y,c}^{\text{Inv}(l)}, E_{e,y,c}^{\text{Inv}(l)}$: decision variables representing the installed rated power and energy capacity of shared ESS $e \in E^S$, in year $y \in Y$, scenario $c \in \Omega_C$, at iteration $l \in L^B$;
- $\alpha^{(l)}$: underestimator of the subproblem's objective function, providing the lower bound of the Benders' algorithm at iteration $l \in L^B$.

6.3.1.2 Total Rated Power and Energy Capacity

The *total* rated power and energy capacity of each shared **ESS** at interface node $e \in E^S$ are cumulative functions of the yearly investments made throughout the planning horizon. For each iteration $l \in L^B$, investment scenario $c \in \Omega_C$, and year $y \in Y$, the effective rated power and energy capacity are respectively given by:

$$S_{e,y,c}^{\text{Rated}(l)} = \sum_{y^{\text{Inv}}=\max(y-T_{e,y}^{\text{Cal}}, y_0)}^y S_{e,y^{\text{Inv}},c}^{\text{Inv}(l)} \quad (6.2)$$

$$E_{e,y,c}^{\text{Rated}(l)} = \sum_{y^{\text{Inv}}=\max(y-T_{e,y}^{\text{Cal}}, y_0)}^y E_{e,y^{\text{Inv}},c}^{\text{Inv}(l)} \quad (6.3)$$

where:

- $S_{e,y,c}^{\text{Rated}(l)}$ and $E_{e,y,c}^{\text{Rated}(l)}$ denote the total rated power and energy capacity available at node $e \in E^S$, in year $y \in Y$, under investment scenario $c \in \Omega_C$, at iteration $l \in L^B$;
- $S_{e,y,c}^{\text{Inv}(l)}$ and $E_{e,y,c}^{\text{Inv}(l)}$ represent the *incremental* yearly investments in rated power and energy capacity, respectively; and
- $T_{e,y}^{\text{cal}}$ is the calendar lifetime of the **ESS** installed at node e in year y , defining how long previous yearly investments remain active and contribute to total installed capacity.

6.3.1.3 Maximum Installable Capacity

Each shared **ESS** $e \in E^S$ is subject to an upper bound on installable capacity, reflecting physical, spatial, or technical limitations at the corresponding **TN-DN** interface substation. This constraint is enforced as follows ($\forall e \in E^S, \forall y \in Y, \forall c \in \Omega_C, \forall l \in L^B$):

$$E_{e,y,c}^{\text{Rated}(l)} \leq E_{e,y}^{\text{Max}} \quad (6.4)$$

where $E_{e,y}^{\text{Max}}$ denotes the maximum installable capacity for **ESS** $e \in E^S$ in year $y \in Y$.

6.3.1.4 Energy-to-Power Capacity Ratio

Battery-based **ESSs** are characterized by technology- and application-specific energy-to-power ratios. These relationships are explicitly enforced through the following constraint ($\forall e \in E^S, \forall y \in Y, \forall c \in \Omega_C, \forall l \in L^B$):

$$\phi_e^{\text{Min}} S_{e,y,c}^{\text{Inv}(l)} \leq E_{e,y,c}^{\text{Inv}(l)} \leq \phi_e^{\text{Max}} S_{e,y,c}^{\text{Inv}(l)} \quad (6.5)$$

where ϕ_e^{Min} and ϕ_e^{Max} denote the minimum and maximum admissible energy-to-power ratios for the shared **ESS** $e \in E^S$. These bounds constrain the storage duration (in hours) according to the selected technology and operational use case. Typical values for utility-scale lithium-ion batteries range from $\phi_e^{\text{Min}} = 2$ h to $\phi_e^{\text{Max}} = 10$ h (NREL, 2024).

6.3.1.5 Available Budget

The total discounted investment cost incurred over the planning horizon is constrained by the available budget, expressed by the following condition ($\forall l \in L^B$):

$$\sum_{e \in E^S} \sum_{y \in Y} \sum_{c \in \Omega_C} \frac{\omega_c}{(1+r)^{y-y_0}} \left(c_{y,c}^{\text{Inv},S} S_{e,y,c}^{\text{Inv}(l)} + c_{y,c}^{\text{Inv},E} E_{e,y,c}^{\text{Inv}(l)} \right) \leq c^{\text{Inv}} \quad (6.6)$$

where c^{Inv} denotes the total investment budget available for shared **ESSs**. This constraint ensures that, across all interface nodes, planning years, and scenarios, the discounted cost of new installations remains within the predefined financial limit.

6.3.1.6 Expected Rated Power and Energy Capacity

The *expected* rated power and energy capacities are defined as probability-weighted averages over all investment cost scenarios $c \in \Omega_C$ ($\forall e \in E^S, \forall y \in Y, \forall l \in L^B$):

$$S_{e,y}^{\text{Rated}(l)} = \sum_{c \in \Omega_C} \omega_c S_{e,y,c}^{\text{Rated}(l)} \quad (6.7)$$

$$E_{e,y}^{\text{Rated}(l)} = \sum_{c \in \Omega_C} \omega_c E_{e,y,c}^{\text{Rated}(l)} \quad (6.8)$$

Analogously, the expected investment decisions for rated power and energy capacity are given by ($\forall e \in E^S, \forall y \in Y, \forall l \in L^B$):

$$S_{e,y}^{\text{Inv}(l)} = \sum_{c \in \Omega_C} \omega_c S_{e,y,c}^{\text{Inv}(l)} \quad (6.9)$$

$$E_{e,y}^{\text{Inv}(l)} = \sum_{c \in \Omega_C} \omega_c E_{e,y,c}^{\text{Inv}(l)} \quad (6.10)$$

These expected investment variables form the set of variables coupling the master and subproblem in the Benders' decomposition framework. At each iteration $l \in L^B$, they are computed by the master problem and passed to the subproblem, where the multi-year **TSO-DSO** coordinated operational planning is simulated.

6.3.1.7 Benders' Cuts

In the proposed implementation of the Benders' decomposition algorithm, both *optimality* and *feasibility* cuts are employed to improve the convergence of the problem.

When the operational subproblem is feasible, an optimality cut is generated from the corresponding sensitivities with respect to the coupling variables ($\forall k = 1, \dots, l-1$):

$$\alpha^{(l)} \geq y^{(k)} + \sum_{e \in E^S} \sum_{y \in Y} \mu_{e,y}^{S(k)} \left(S_{e,y}^{\text{Inv}(l)} - S_{e,y}^{\text{Inv}(k)} \right) + \sum_{e \in E^S} \sum_{y \in Y} \mu_{e,y}^{E(k)} \left(E_{e,y}^{\text{Inv}(l)} - E_{e,y}^{\text{Inv}(k)} \right) \quad (6.11)$$

where:

- $y^{(k)}$ denotes the objective value of the subproblem at iteration k , corresponding to the upper bound in the Benders' algorithm;
- $\mu_{e,y}^{S(k)}$ and $\mu_{e,y}^{E(k)}$ are sensitivity coefficients associated with the rated power and energy capacity of shared **ESS** $e \in E^S$ in year $y \in Y$, obtained from the subproblem at iteration k , respectively.

If the subproblem is *infeasible*, a feasibility cut is introduced to exclude the corresponding investment solution from the feasible region of the master problem ($\forall k = 1, \dots, l-1$):

$$0 \geq -y^{(k)} + \sum_{e \in E^S} \sum_{y \in Y} \mu_{e,y}^{S(l)} (S_{e,y}^{\text{Inv}(l)} - S_{e,y}^{\text{Inv}(k)}) + \sum_{e \in E^S} \sum_{y \in Y} \mu_{e,y}^{E(l)} (E_{e,y}^{\text{Inv}(l)} - E_{e,y}^{\text{Inv}(k)}) \quad (6.12)$$

Finally, to prevent unboundedness during the initial iteration, the subproblem underestimator is constrained by:

$$\alpha^{(l)} \geq \alpha^{\text{Down}} \quad (6.13)$$

where α^{Down} is an adequately selected predefined lower bound introduced to ensure numerical stability during initialization.

6.3.2 Subproblem

As discussed previously, the subproblem is decomposed into three components: the **TSO** subproblem, the set of **DSOs** subproblems, and a dedicated shared **ESSs** operation subproblem responsible for modeling the **ESSs**' **SoH** and associated capacity degradation.

To manage the scale of the multi-year planning problem, the formulation is further decomposed across representative years (corresponding to investment stages) and representative days (capturing seasonal operating conditions). This temporal decomposition exploits the intrinsic structure of the problem, in which intertemporal coupling arises solely from the progressive degradation of shared **ESSs** capacity. To accommodate this structure, a new agent – the *shared **ESSs** operation subproblem* – is integrated into the coordinated operational planning framework introduced in Chapter 5. Its primary role is to ensure that operational requests issued by the **TSO** and participating **DSOs** remain jointly feasible, while enforcing minimum **SoH** requirements throughout the planning horizon. By isolating shared **ESSs** degradation dynamics from the **SOs** operational subproblems, the **TSO** and **DSOs** optimization problems can be solved independently for each representative year and day. Intertemporal consistency is handled exclusively through the shared **ESSs** operation subproblem. This design preserves tractability in large-scale settings, enhances scalability, and ensures data privacy, as each operator relies solely on local information without disclosing proprietary network or detailed operational data to counterpart agents.

6.3.2.1 Shared ESSs Operation Subproblem

As discussed earlier, the lower level of the proposed two-level optimization framework simulates multi-year **TSO-DSO** coordinated operational planning in the presence of shared **ESSs**, explicitly accounting for long-term battery capacity degradation. To capture these intertemporal effects within a distributed setting, the **ADMM**-based coordination framework introduced in Chapter 5 is extended with an additional agent – the *shared ESSs operation subproblem*.

This agent models the coupling between short-term operational decisions and long-term storage degradation by tracking the evolution of available capacity and **SoH** of the shared **ESSs** across the planning horizon. In doing so, it ensures that operational schedules proposed by the **TSO** and participating **DSOs** remain jointly feasible over time, while consistently reflecting degradation-driven capacity losses. Algorithm 6.1 presents the updated pseudo-code of the consensus-based **ADMM** implementation incorporating this additional agent into the **TSO-DSO** coordination process.

6.3.2.2 Shared ESSs Mathematical Formulation

Investment decisions regarding the rated power and energy capacity of the shared **ESSs**, as determined by the master problem, are treated as fixed parameters within the subproblem. These parameters are enforced through the following constraints ($\forall e \in E^S, \forall y \in Y$):

$$S_{e,y}^{\text{Inv}} = \hat{S}_{e,y}^{\text{Inv}} + S_{e,y}^{\text{S,Up}} - S_{e,y}^{\text{S,Down}} \quad (6.14)$$

$$E_{e,y}^{\text{Inv}} = \hat{E}_{e,y}^{\text{Inv}} + E_{e,y}^{\text{E,Up}} - E_{e,y}^{\text{E,Down}} \quad (6.15)$$

where:

- $\hat{S}_{e,y}^{\text{Inv}}$ and $\hat{E}_{e,y}^{\text{Inv}}$ are the expected investments in power rating and energy capacity, respectively, for shared **ESS** $e \in E^S$ in year $y \in Y$, as provided by the master problem;
- $S_{e,y}^{\text{S,Up}}$ and $S_{e,y}^{\text{S,Down}}$ are slack variables associated with deviations in the rated power of shared **ESS** $e \in E^S$ in year $y \in Y$; and
- $E_{e,y}^{\text{E,Up}}$ and $E_{e,y}^{\text{E,Down}}$ are slack variables representing deviations in the energy capacity of shared **ESS** $e \in E^S$ in year $y \in Y$.

These slack variables are introduced to preserve subproblem feasibility under all operating conditions. Their magnitudes are penalized in the subproblem objective function, as described below, to discourage excessive deviations from the investment targets determined at the master level.

The rated power and energy capacity of each shared **ESS** vary over the planning horizon as a function of the investments made in successive representative years – exploiting

Algorithm 6.1: Operational planning. Integration of the degradation model.

```

1 for  $i \in N^I$  do
2   DSOi: Create operational planning model
3   DSOi: Solve the standalone local operational planning model assuming
       $V_{i,t} = 1.0$  p.u. at the TN-DN interface
4   DSOi: Add consensus variables and augmented Lagrangian terms
5 TSO: Create operational planning model
6 TSO: Solve the standalone operational planning model using forecast-based initial
      values of  $V_{i,t}^{I,0}$ ,  $P_{i,t}^{I,0}$ , and  $Q_{i,t}^{I,0}$ 
7 TSO: Add consensus variables and augmented Lagrangian terms
8 ADMM: Set  $k = 1$ , convergence = False
9 while  $k \leq k^{max}$  do
10  DSO updates:
11  for  $i \in N^I$  do
12    DSOi: Set  $\hat{V}_{i,t}^{I,k}$ ,  $\hat{P}_{i,t}^{I,k}$ ,  $\hat{Q}_{i,t}^{I,k}$ ,  $\hat{P}_{i,t}^{E,k}$ , and  $\hat{Q}_{i,t}^{E,k}$  to Shared ESSs' targets
13    DSOi: Solve local operational planning problem
14    DSOi: Update dual variables  $\pi_{i,t}^{I,V,k}$ ,  $\pi_{i,t}^{I,P,k}$ ,  $\pi_{i,t}^{I,Q,k}$ ,  $\pi_{i,t}^{E,P,k}$ ,  $\pi_{i,t}^{E,Q,k}$ 
15  ADMM: Evaluate convergence criteria
16  if converged then
17    exit
18  TSO update:
19  TSO: Set  $\hat{V}_{i,t}^{I,k}$ ,  $\hat{P}_{i,t}^{I,k}$ ,  $\hat{Q}_{i,t}^{I,k}$ ,  $\hat{P}_{i,t}^{E,k}$ , and  $\hat{Q}_{i,t}^{E,k}$  to DSOs' targets
20  TSO: Solve operational planning problem
21  TSO: Update dual variables  $\pi_{i,t}^{I,V,k}$ ,  $\pi_{i,t}^{I,P,k}$ ,  $\pi_{i,t}^{I,Q,k}$ ,  $\pi_{i,t}^{E,P,k}$ ,  $\pi_{i,t}^{E,Q,k}$ 
22  ADMM: Evaluate convergence criteria
23  if converged then
24    exit
25  Shared ESS operation update:
26  Shared ESS: Set  $\hat{P}_{i,t}^{E,k}$ , and  $\hat{Q}_{i,t}^{E,k}$  to TSO's targets
27  Shared ESS: Solve operation problem
28  Shared ESS: Update dual variables  $\pi_{i,t}^{E,P,k}$ ,  $\pi_{i,t}^{E,Q,k}$ 
29  ADMM: Evaluate convergence criteria
30  if converged then
31    exit
32   $k = k + 1$ 

```

the modular character of these types of resources. To explicitly capture this temporal evolution, auxiliary variables are introduced to represent the contribution of each investment to the available rated power and energy capacity of the shared **ESSs** across their operational lifetime. These auxiliary variables are defined for all $e \in E^S$, $y \in Y$, and $y^{\text{Inv}} \in [y; y + T_{e,y^{\text{Inv}}}^{\text{Cal}}]$ as follows:

$$S_{e,y^{\text{Inv}},y}^{\text{Rated,Unit}} := S_{e,y^{\text{Inv}}}^{\text{Inv}} \quad (6.16)$$

$$E_{e,y^{\text{Inv}},y}^{\text{Rated,Unit}} := E_{e,y^{\text{Inv}}}^{\text{Inv}} \quad (6.17)$$

where:

- $S_{e,y^{\text{Inv}},y}^{\text{Rated,Unit}}$ and $E_{e,y^{\text{Inv}},y}^{\text{Rated,Unit}}$ denote the rated power and energy capacity, respectively, of the shared **ESS** $e \in E^S$ installed in investment year $y^{\text{Inv}} \in Y$ and still operational in subsequent year $y \in [y^{\text{Inv}}; y^{\text{Inv}} + T_{e,y^{\text{Inv}}}^{\text{Cal}}]$;
- $S_{e,y^{\text{Inv}}}^{\text{Inv}}$ and $E_{e,y^{\text{Inv}}}^{\text{Inv}}$ are the corresponding investment decisions in shared **ESS** $e \in E^S$ rated power and energy capacity, in investment year $y^{\text{Inv}} \in Y$; and
- $T_{e,y^{\text{Inv}}}^{\text{Cal}}$ represents the calendar lifetime of the shared **ESS** $e \in E^S$ in year $y^{\text{Inv}} \in Y$.

In practice, each shared **ESS** investment is treated as a distinct unit whose contribution to the total available capacity is explicitly tracked over its entire operational lifetime. This is achieved by indexing the shared **ESS** variables by both the investment year and the corresponding representative operational year.

The total rated power and energy capacity available in each year are then obtained by aggregating the contributions of all units that remain operational, accounting for their respective calendar lifetimes. These quantities are expressed as follows ($\forall e \in E^S, \forall y \in Y$):

$$S_{e,y}^{\text{Rated}} = \sum_{y^{\text{Inv}}=\max(y-T_{e,y}^{\text{Cal}}, y_0)}^y S_{e,y^{\text{Inv}},y}^{\text{Rated,Unit}} \quad (6.18)$$

$$E_{e,y}^{\text{Rated}} = \sum_{y^{\text{Inv}}=\max(y-T_{e,y}^{\text{Cal}}, y_0)}^y E_{e,y^{\text{Inv}},y}^{\text{Rated,Unit}} \quad (6.19)$$

These constraints ensure that a unit investment in shared **ESS** $e \in E^S$, made in year $y^{\text{Inv}} \in Y$, remains available throughout its corresponding calendar lifetime $T_{e,y^{\text{Inv}}}^{\text{Cal}}$.

The available rated power and energy capacity of each shared **ESS** unit are influenced by both calendar aging and cycling-induced degradation resulting from operational use. Accordingly, they are defined as ($\forall e \in E^S, \forall y^{\text{Inv}} \in Y, \forall y \in [y^{\text{Inv}}; y^{\text{Inv}} + T_{e,y^{\text{Inv}}}^{\text{Cal}}]$):

$$S_{e,y^{\text{Inv}},y}^{\text{Av,Unit}} = S_{e,y^{\text{Inv}},y}^{\text{Rated,Unit}} \quad (6.20)$$

$$E_{e,y^{\text{Inv}},y}^{\text{Av,Unit}} = E_{e,y^{\text{Inv}},y}^{\text{Rated,Unit}} SoH_{e,y^{\text{Inv}},y} \quad (6.21)$$

where:

- $S_{e,y^{\text{Inv}},y}^{\text{Av,Unit}}$ and $E_{e,y^{\text{Inv}},y}^{\text{Av,Unit}}$ denote the available rated power and energy capacity, respectively, of unit $e \in E^S$, installed in year $y^{\text{Inv}} \in Y$, in the subsequent year $y \in Y$;

- $SoH_{e,y^{Inv},y} \in [0,1]$ represents the **SoH** of unit $e \in E^S$, installed in year $y^{Inv} \in Y$, in the subsequent year $y \in Y$ – which captures the fraction of usable capacity remaining after degradation; and
- $T_{e,y^{Inv}}^{Cal}$ is the calendar lifetime (in years) of the installation.

It should be noted that, while the available rated power is assumed to remain constant over the unit's lifetime, the available energy capacity decreases proportionally to its state of health, $SoH_{e,y^{Inv},y}$.

The annual energy capacity degradation of each shared **ESS** unit is modeled as a function of its cycling activity. For each unit $e \in E^S$, installed in investment year $y^{Inv} \in Y$ and operating in a subsequent year $y \in [y^{Inv}; y^{Inv} + T_{e,y^{Inv}}^{Cal}]$, the fractional capacity degradation is defined as:

$$\delta_{e,y^{Inv},y} = \frac{E_{e,y^{Inv},y}^{Ch,Dch}}{2CL_e^{Nom} E_{e,y^{Inv},y}^{Rated,Unit}} \quad (6.22)$$

where:

- $\delta_{e,y^{Inv},y}$ is the annual fractional degradation (i.e., the proportion of energy capacity lost due to cycling) of unit $e \in E^S$, installed in year y^{Inv} and operating in year y ;
- $E_{e,y^{Inv},y}^{Ch,Dch}$ is an auxiliary variable representing the total annual charge–discharge energy throughput of the same unit, averaged over representative days in year $y \in Y$;
- CL_e^{Nom} is the nominal cycle life of unit $e \in E^S$, defined as the total number of full equivalent cycles that the battery can perform before reaching its end-of-life; and
- $E_{e,y^{Inv},y}^{Rated,Unit}$ is the nominal (rated) energy capacity of the unit.

This formulation assumes that capacity degradation is proportional to the total energy throughput of the **ESS** and inversely proportional to its nominal cycle life. The factor of two in the denominator accounts for the fact that each full cycle comprises both charging and discharging processes.

The daily average charge–discharge energy throughput of each shared **ESS** unit is computed by aggregating the energy exchanged over all representative days and intra-day time intervals within a year. For a unit $e \in E^S$ installed in investment year $y^{Inv} \in Y$ and operated in year $y \in [y^{Inv}; y^{Inv} + T_{e,y^{Inv}}^{Cal}]$, this quantity is defined as:

$$E_{e,y^{Inv},y}^{Ch,Dch} = \sum_{d \in D} \sum_{t \in T} \frac{D_d}{365} \Delta t \left(S_{e,y^{Inv},y,d,t}^{Ch} + S_{e,y^{Inv},y,d,t}^{Dch} \right) \quad (6.23)$$

where:

- D is the set of representative days, and D_d is the number of calendar days represented by day $d \in D$;

- T is the set of time instants within each representative day, and Δt is the duration of each instant;
- $S_{e,y^{\text{Inv}},y,d,t}^{\text{Ch}}$ and $S_{e,y^{\text{Inv}},y,d,t}^{\text{Dch}}$ denote the charging and discharging apparent powers, respectively, of unit e installed in year y^{Inv} and operating in year y .

The term $E_{e,y^{\text{Inv}},y}^{\text{Ch,Dch}}$ thus represents the estimated energy throughput of the shared **ESS** unit $e \in E^S$ installed in year $y^{\text{Inv}} \in Y$, in operation year $y \in [y^{\text{Inv}}; y^{\text{Inv}} + T_{e,y^{\text{Inv}}}^{\text{Cal}}]$.

The **SoH** of the shared **ESSs** is a function of the **SoH** in the previous representative year, and the capacity degradation experienced in that representative year, and defined as ($\forall e \in E^S, \forall y \in Y, \forall y \in [y^{\text{Inv}}; y^{\text{Inv}} + T_{e,y^{\text{Inv}}}^{\text{Cal}}]$):

$$SoH_{e,y^{\text{Inv}},y} = SoH_{e,y^{\text{Inv}},y-1} \left(1 - \delta_{e,y^{\text{Inv}},y}\right)^{365 \times Y_y} \quad (6.24)$$

where Y_y is the number of years represented by representative year $y \in Y$.

A minimum **SoH** constraint is imposed to ensure that each shared **ESS** retains an acceptable level of usable capacity throughout the planning horizon. For every unit $e \in E^S$, installed in investment year $y^{\text{Inv}} \in Y$ and operating in subsequent year $y \in [y^{\text{Inv}}; y^{\text{Inv}} + T_{e,y^{\text{Inv}}}^{\text{Cal}}]$, the constraint is defined as:

$$SoH_{e,y^{\text{Inv}},y} \geq SoH_{e,y^{\text{Inv}}}^{\min} \quad (6.25)$$

where $SoH_{e,y^{\text{Inv}}}^{\min}$ denotes the minimum admissible **SoH** for unit e installed in year y^{Inv} . This lower bound ensures that all shared **ESSs** remain technically viable and compliant with operational standards over the entire multi-year optimization horizon.

The charging–discharging complementarity constraints ensure that each shared **ESS** cannot simultaneously charge and discharge at any given time step. For every unit $e \in E^S$, installed in year $y^{\text{Inv}} \in Y$, and operating in subsequent year $y \in [y^{\text{Inv}}; y^{\text{Inv}} + T_{e,y^{\text{Inv}}}^{\text{Cal}}]$, representative day $d \in D$, and time instant $t \in T$, the constraint is formulated as:

$$S_{e,y^{\text{Inv}},y,d,t}^{\text{Ch}} \times S_{e,y^{\text{Inv}},y,d,t}^{\text{Dch}} = 0 \quad (6.26)$$

This nonlinear complementarity condition enforces mutual exclusivity between charging and discharging states.

The net apparent power output by shared **ESS** $e \in E^S$ in representative year $y \in Y$, day $d \in D$, and time period $t \in T$ is defined as the aggregate of charging and discharging contributions from all active investments:

$$S_{e,y,d,t}^{\text{Net}} = \sum_{y^{\text{Inv}}=y-T_{e,y}^{\text{Cal}}}^y \left(S_{e,y^{\text{Inv}},y,d,t}^{\text{Ch}} - S_{e,y^{\text{Inv}},y,d,t}^{\text{Dch}} \right) \quad (6.27)$$

The resulting apparent power is then related to the active and reactive power components requested by the **SOs** by ($\forall e \in E^S, \forall y \in Y, \forall d \in D, \forall t \in T$):

$$\left(S_{e,y,d,t}^{\text{Net}}\right)^2 = \left(P_{e,y,d,t}^{\text{Net}}\right)^2 + \left(Q_{e,y,d,t}^{\text{Net}}\right)^2 \quad (6.28)$$

where $P_{e,y,d,t}^{\text{Net}}$ and $Q_{e,y,d,t}^{\text{Net}}$ denote the net active and reactive power requests, respectively, issued by the participating SOs (i.e., the TSO and the DSOs) for each shared ESS $e \in E^S$, in representative year $y \in Y$, representative day $d \in D$, and time instant $t \in T$. This formulation ensures that the joint operation of shared ESSs remains physically consistent throughout the planning horizon.

The objective of the shared ESS subproblem is auxiliary within the ADMM coordination procedure. It penalizes deviations from the investment targets received from the master problem, as well as violations of the relaxed complementarity condition, thereby steering the subproblem toward a physically consistent and investment-compliant operating point:

$$\min \sum_{e \in E^S} \sum_{y \in Y} \left(\left(S_{e,y}^{\text{S,Up}} + S_{e,y}^{\text{S,Down}} + E_{e,y}^{\text{S,Up}} + E_{e,y}^{\text{S,Down}} \right) + \left(\sum_{y^{\text{Inv}}} \sum_{d \in D} \sum_{t \in T} S_{e,y^{\text{Inv}},y,d,t}^{\text{S,Comp}} \right) \right) \quad (6.29)$$

This objective promotes feasibility of the coupled operation–degradation model by minimizing the slack variables associated with deviations from the investment decisions determined at the master level. As a result, any violation of the shared ESSs rated power or energy capacity limits is penalized proportionally, guiding the solution toward physically feasible operation that remains consistent with the active and reactive power requests issued by the participating SOs.

Importantly, the formulation avoids the introduction of binary variables, allowing the shared ESS operation problem to remain a purely continuous NLP. This choice enables the use of efficient nonlinear solvers and ensures full compatibility with the ADMM-based coordination framework adopted at the operational level.

6.3.2.3 Shared ESSs Subproblem ADMM Formulation

Within the consensus-based ADMM coordination framework, the shared ESSs operation subproblem is introduced as a dedicated agent responsible for ensuring feasible and consistent operation of all shared ESSs units throughout the planning horizon. At each ADMM iteration, this agent reconciles the active and reactive power exchange requests issued by the TSO and participating DSOs with the physical operating limits and degradation dynamics of the shared ESSs. Its generic mathematical formulation is given by:

$$\min f(X) + \sum_{e \in E^S} \sum_{y \in Y} \sum_{d \in D} \sum_{t \in T} \mathcal{L}^{E,P} \left(P_{e,y,d,t}^{E,k}, \hat{P}_{e,y,d,t}^{E,k}, \pi_{e,y,d,t}^{E,P,k} \right) \quad (6.30a)$$

$$+ \sum_{e \in E^S} \sum_{y \in Y} \sum_{d \in D} \sum_{t \in T} \mathcal{L}^{E,Q} \left(Q_{e,y,d,t}^{E,k}, \hat{Q}_{e,y,d,t}^{E,k}, \pi_{e,y,d,t}^{E,Q,k} \right)$$

$$\text{s.t. } h \left(X, P_{e,y,d,t}^{E,k}, Q_{e,y,d,t}^{E,k} \right) \leq 0 \quad (6.30b)$$

where:

- Sets and variables:
 - $E^S \subseteq E$: set of shared **ESSs** installed at the **TN–DN** interface nodes.
 - Y : set of representative (investment) years in the planning horizon.
 - D : set of representative days (e.g., seasons).
 - T : set of intra-day time periods.
 - K : set of **ADMM** iterations.
 - X : vector of local decision variables of the shared **ESSs** subproblem.
- Objective function:
 - $f(X)$: local objective function of the shared **ESSs** subproblem.
- Augmented Lagrangian terms:
 - $\mathcal{L}^{E,P}, \mathcal{L}^{E,Q}$: augmented Lagrangians associated with the shared **ESSs** active and reactive power, respectively.
- Primal and dual variables:
 - $P_{e,y,d,t}^{E,k}, Q_{e,y,d,t}^{E,k}$: shared **ESS** $e \in E^S$ active and reactive power, respectively, in year $y \in Y$, representative day $d \in D$, time instant $t \in T$, and **ADMM** iteration $k \in K$. $\hat{P}_{e,y,d,t}^{E,k}$ and $\hat{Q}_{e,y,d,t}^{E,k}$ denote their local copies, representing the counterpart **SO**'s requests.
 - $\pi_{e,y,d,t}^{E,P,k}, \pi_{e,y,d,t}^{E,Q,k}$: dual variables associated with the shared **ESS**' active and reactive power, respectively, in year $y \in Y$, representative day $d \in D$, in time instant $t \in T$, and **ADMM** iteration $k \in K$.
- Constraints:
 - $h(\cdot)$: represents the shared **ESSs**' problem internal constraints.

Through this formulation, the shared **ESSs** subproblem enforces all operational and degradation-related constraints while achieving consensus with the **TSO** and participating **DSOs** on the exchanged active and reactive power profiles at each **ADMM** iteration.

The augmented Lagrangian terms enforcing consensus on the shared **ESSs** active and reactive power exchanges are defined as follows:

$$\mathcal{L}^{E,P} \left(P_{e,y,d,t}^{E,k}, \hat{P}_{e,y,d,t}^{E,k}, \pi_{e,y,d,t}^{E,P,k} \right) = \pi_{e,y,d,t}^{E,P,k} \left(\frac{P_{e,y,d,t}^{E,k} - \hat{P}_{e,y,d,t}^{E,k}}{S_{e,y}^{\text{Rated}}} \right) + \frac{\rho^{E,P,k}}{2} \left\| \frac{P_{e,y,d,t}^{E,k} - \hat{P}_{e,y,d,t}^{E,k}}{S_{e,y}^{\text{Rated}}} \right\|^2 \quad (6.31)$$

$$\mathcal{L}^{E,Q} \left(Q_{e,y,d,t}^{E,k}, \hat{Q}_{e,y,d,t}^{E,k}, \pi_{e,y,d,t}^{E,Q,k} \right) = \pi_{e,y,d,t}^{E,Q,k} \left(\frac{Q_{e,y,d,t}^{E,k} - \hat{Q}_{e,y,d,t}^{E,k}}{S_{e,y}^{\text{Rated}}} \right) + \frac{\rho^{E,Q,k}}{2} \left\| \frac{Q_{e,y,d,t}^{E,k} - \hat{Q}_{e,y,d,t}^{E,k}}{S_{e,y}^{\text{Rated}}} \right\|^2 \quad (6.32)$$

where:

- $S_{e,y}^{\text{Rated}}$ is the rated apparent power of shared **ESS** $e \in E^S$ in year $y \in Y$; and
- $\rho^{E,P,k}$ and $\rho^{E,Q,k}$ are the **ADMM** penalty parameters associated with the active and reactive power consensus constraints, respectively, at iteration $k \in K$.

These augmented terms jointly penalize deviations between the shared **ESS** agent's internal power schedules and the reference values communicated by the **SOs**, effectively steering both parties toward a common solution.

The dual variables corresponding to these coupling constraints are updated at each iteration $k \in K$ according to $(\forall e \in E^S, y \in Y, d \in D, \forall t \in T, \forall k \in K)$:

$$\pi_{e,y,d,t}^{E,P,k} := \pi_{e,y,d,t}^{E,P,k-1} + \rho^{E,P,k} \left(P_{e,y,d,t}^{E,k} - \hat{P}_{e,y,d,t}^{E,k} \right) \quad (6.33)$$

$$\pi_{e,y,d,t}^{E,Q,k} := \pi_{e,y,d,t}^{E,Q,k-1} + \rho^{E,Q,k} \left(Q_{e,y,d,t}^{E,k} - \hat{Q}_{e,y,d,t}^{E,k} \right) \quad (6.34)$$

where $\pi_{e,y,d,t}^{E,P,k}$ and $\pi_{e,y,d,t}^{E,Q,k}$ act as *coordination multipliers* (or price-like signals) that penalize mismatches between the shared **ESSs** power outputs and the target exchanges set by the **SOs**. As the iterations progress, these dual variables drive the system toward agreement on the shared **ESSs** operating point.

To improve numerical stability, the penalty coefficients are updated adaptively:

$$\rho^{E,P,k} := \rho^{E,P,k-1} \left(1 + r^{E,P} \right) \quad (6.35)$$

$$\rho^{E,Q,k} := \rho^{E,Q,k-1} \left(1 + r^{E,Q} \right) \quad (6.36)$$

where $r^{E,P}$ and $r^{E,Q}$ denote user-defined update rates for the active and reactive power penalties of the shared **ESSs**, respectively.

Importantly, because no coupling variables or constraints exist between individual shared **ESS** units within the overall *shared ESSs operation* subproblem, the formulation is inherently separable across storage units. Each shared **ESS** can therefore be optimized independently and in parallel, without loss of optimality. This separability improves numerical conditioning, accelerates convergence, and enhances the computational scalability of the framework for large systems with multiple shared storage assets.

6.4 Conclusions and Future Work

This chapter introduced a novel planning framework for the deployment of shared **ESSs** at **TN–DN** interface nodes, explicitly designed to support coordinated **TSO–DSO** operation in power systems with high shares of distributed flexibility. The proposed approach integrates long-term investment planning with short-term coordinated operation through a two-level optimization structure, ensuring that infrastructure deployment decisions are grounded in realistic, uncertainty-aware operational behavior.

The planning problem was formulated as a two-level optimization model and solved using a Benders’ decomposition approach. At the master level, investment decisions regarding the siting, sizing, and timing of shared **ESSs** installations were determined while explicitly accounting for uncertainty in investment cost projections. At the subproblem level, coordinated operational planning between the **TSO** and participating **DSOs** was simulated using the **ADMM**-based framework developed in the previous chapter. This formulation captures both battery degradation effects and uncertainty arising from market prices and operational forecasts (load and **RES** generation).

A key contribution of this chapter is the explicit integration of shared **ESSs** capacity degradation into the coordinated planning framework. By introducing a dedicated shared **ESS** operation agent, the proposed methodology preserves the decoupling of **TSO** and **DSOs** operational subproblems across representative years, while consistently capturing the long-term impact of short-term operational decisions on battery **SoH**. This design enables scalable multi-year planning without compromising physical accuracy, intertemporal consistency, or data privacy. Simulation results presented in Chapter 7 demonstrate that the proposed framework effectively addresses the computational challenges associated with the large-scale, non-convex, and uncertainty-aware planning problem. To the best of the author’s knowledge, this work represents the first planning framework that combines coordinated **TSO–DSO** operation, detailed shared-**ESS** constraints, degradation dynamics, and multiple sources of uncertainty.

While the proposed framework constitutes a significant step forward in coordinated shared **ESSs** planning, several avenues for future research remain:

- (i) Extension to other shared resources: The proposed two-level coordination and planning framework could be extended to other types of shared assets installed at the **TN–DN** interface, such as power-electronic-based power flow controllers.

- (ii) Alternative and data-driven degradation models: Although battery degradation is rarely addressed in coordinated planning studies – and remains uncommon in staged **ESS** planning formulations – alternative degradation models could be explored, including electrochemical formulations, temperature-dependent aging mechanisms, and data-driven or **ML**-based approaches.
- (iii) Participation of shared resources in **ASs** markets: While participation in **FRR** markets has been investigated by the author within the ATTEST project (**ATTEST**, 2019), the work presented here focuses primarily on coordination-driven operational benefits. A natural extension would be to model the stacking of multiple revenue streams through participation in several **ASs** markets, while simultaneously satisfying the technical requirements of **TSO-DSO** coordinated operation.
- (iv) Risk-averse and robust planning formulations: This work adopts an **SP** framework to represent uncertainty; however, alternative risk-aware approaches – such as **RO**, **DRO**, or **CCO** – could be investigated to assess their impact on investment timing, sizing, and overall system resilience.

Despite the methodological advances presented in this chapter, the practical deployment of shared **ESSs** remains strongly influenced by regulatory and market conditions. In many jurisdictions, unclear or incomplete regulatory frameworks continue to limit the development of viable business models for energy storage, particularly in the presence of long-term revenue uncertainty and in coordinated **TSO-DSO** settings (**IEA**, 2024b). Addressing these regulatory challenges will be essential to fully unlock the potential of shared storage resources and to translate coordinated **TSO-DSO** planning frameworks from advanced research concepts into operational practice.

Chapter 7

Simulations

This chapter presents a set of simulation studies designed to validate the frameworks and tools presented in Chapters 3–6. Each section corresponds to a distinct case study, covering a range of operational and planning contexts, including coordinated TSO–DSO operation, long-term investment planning, and real-time control.

Specifically, the chapter is organized as follows:

- Section 7.1 presents Case Study 1, which analyzes the proposed TSO–DSO coordination mechanism by comparing its effectiveness and efficiency against traditional operation, centralized optimization, and hierarchical coordination schemes.
- Section 7.2 presents Case Study 2, evaluating the TSO–DSO coordinated operational planning framework introduced in Chapter 5 on a large-scale system with multiple participating ADNs, with a focus on the operational efficiency gains enabled by coordinated transmission–distribution operation.
- Section 7.3 presents Case Study 3, which assesses the shared resources planning framework by examining its ability to derive investment plans for shared ESSs at TN–DN interface nodes and to quantify the associated operational benefits.
- Section 7.4 presents Case Study 4, investigating the performance of the proposed real-time OPF module introduced in Section 4.5 of Chapter 4. The algorithm is validated in a HIL environment to assess its robustness and effectiveness under realistic and dynamic operating conditions.
- Section 7.5 summarizes the main findings of the simulation studies and outlines directions for future research.

All optimization models were implemented in Python using Pyomo (Bynum et al., 2021) as the algebraic modeling framework. The resulting NLP problems were solved using Ipopt (Wächter and Biegler, 2006), supported by the HSL sparse linear algebra solvers (HSL, 2026). Unless otherwise stated, the same modeling environment and solver configuration were used throughout the numerical case studies.

7.1 Case Study 1

This section presents a case study designed to assess the effectiveness and efficiency of the **TSO-DSO** coordination framework proposed in this thesis (introduced in Chapter 3 and operationalized through the methodology described in Chapter 5). The proposed framework is benchmarked against a *traditional* (uncoordinated) operation strategy and a representative hierarchical **TSO-DSO** coordination approach from the literature.

The following operational strategies (hereafter referred to as test cases) are considered:

- Centralized coordination: Assumes a single **SO** with full observability and control of both **TN** and **DN**, serving as a theoretical benchmark for optimal system operation.
- Traditional (uncoordinated) operation: Represents current practice, where no active coordination or information exchange takes place between the **TSO** and **DSOs**.
- Hierarchical coordination: Models **ADNs**' flexibility through multi-period **PQ** maps that characterize their **FORs**.
- Distributed coordination: Implements the coordination mechanism proposed in this thesis, evaluated under two variants: with and without shared **ESSs** installed at the **TN-DN** interfaces.

The *centralized* coordination test case serves as a benchmark scenario, assuming that a single **SO** has complete observability and control over the entire system, including both transmission and distribution levels, thereby providing a theoretical upper bound on operational performance. The *traditional* (uncoordinated) test case assumes that no flexibility services are exchanged between the **TSO** and **DSOs**. Each **SO** independently exploits locally available flexibility resources to address its own operational needs, thus reflecting current operational practices. The *hierarchical* test case evaluates the performance of one of the most widely adopted hierarchical coordination frameworks from the literature. In this setting, distribution-level flexibility is represented using a multi-period **PQ** map methodology. Implementation details of this approach are provided in Subsection 7.1.1.3. Finally, two variants of *distributed* coordination based on the operational planning framework proposed in this thesis are evaluated, differing in the availability of shared **ESSs** at the **TN-DN** interfaces. This comparison aims to quantify both the overall efficiency of the proposed coordination mechanism and the additional operational benefits enabled by shared storage resources. For all test cases, the network management models of participating **SOs** are formulated as instances of the **SMOPF** problem described in Chapter 4.

The case study considers a representative day with high **RES** penetration, during which voltage violations are anticipated at the **TN** level under traditional operation. The primary objective is to evaluate the ability of the proposed coordination framework to mitigate such operational issues, while also assessing its potential benefits in terms of operational cost reduction and enhanced **RES** integration, in comparison with both conventional operation strategies and established hierarchical coordination approaches.

7.1.1 Implementation of the Coordination Schemes

As outlined above, this case study evaluates the performance of the proposed **TSO-DSO** coordination mechanism against three alternative operational strategies: centralized coordination, traditional (uncoordinated) operation, and hierarchical coordination. The implementation of each coordination scheme is briefly described in the following subsections.

7.1.1.1 Traditional Operation

The traditional (uncoordinated) benchmark aims to reproduce prevailing operational practice, in which no explicit coordination or exchange of flexibility services occurs between the **TSO** and **DSOs**. This scheme is implemented through a two-stage procedure. First, each **DSO** independently solves an **SMOPF** for its local network, thereby determining the power exchanges at the transmission-distribution interfaces. These interface power flows are subsequently communicated to the **TSO**. In the second stage, the **TSO** solves an **SMOPF** for the transmission system, treating the interface power flows as fixed inputs and relying exclusively on transmission-connected resources to ensure secure operation. Under this configuration, **DNs** do not provide flexibility services to transmission-level operation, and **DERs** are exploited solely to address local operational constraints.

It should be noted that this setup is relatively optimistic when compared to real-world operational practices. In actual system operation, operational planning relies on forecasts that are inherently affected by uncertainty. In contrast, this test case assumes that the **TSO** has access to *perfect* information regarding the interface power flows, which may lead to an overestimation of the effectiveness of uncoordinated operational strategies.

7.1.1.2 Centralized Coordination

In the centralized coordination test case, the entire system – comprising the **TN** and **DNs** participating in the coordination procedure – is modeled as a single integrated network. A single **SO** (representing either the **TSO** or an **ISO**) is assumed to have full observability of the complete system and full controllability over all network assets and resources. This formulation removes the institutional boundary between transmission and distribution levels, enabling an optimal system-wide dispatch. As such, it provides a reference benchmark against which the performance of traditional and coordinated operational strategies can be assessed.

As previously discussed, this test case does not reflect a realistic operational paradigm under current regulatory and institutional frameworks. Instead, it intends to serve as a theoretical upper bound on achievable system efficiency, against which decentralized approaches can be evaluated.

7.1.1.3 Hierarchical Coordination

The hierarchical coordination strategy adopts the “PQ-map” methodology to represent the **FOR** of each **ADN**, extended here to a multi-period setting following an approach similar to that proposed by **Contreras and Rudion (2019)**.

The coordination procedure consists of three main stages:

1. **ADNs FOR** identification: Each **ADN** determines the boundary of its **FOR**, expressed through linear inequality constraints. These constraints, together with the initial operating point, are communicated to the **TSO**.
2. **TSO** optimization: The **TSO** incorporates the received **FOR** constraints into its **SMOPF**, computes the system-wide optimal dispatch, and determines updated interface operating points to **DSOs**. Upward and downward flexibility margins are quantified with respect to the initial operating point.
3. **DSO** settlement: Each **DSO** performs a final dispatch (settlement), fixing the interface active and reactive power exchanges according to the **TSO**’s requests, while ensuring compliance with all local operational constraints.

The **FOR** of each **ADN** is computed as follows. For each discretization (partitioning) level $n \in N^H$ of the **FOR**, the two optimization problems defined in (7.1) are solved:

$$\min \sum_{m \in \Omega_m} \sum_{o \in \Omega_o} \sum_{t \in T} \left(\omega_m \omega_o \left(\alpha P_{0,m,o,t}^g + \beta Q_{0,m,o,t}^g \right) \right) + \text{CM} \quad (7.1a)$$

$$\min \sum_{m \in \Omega_m} \sum_{o \in \Omega_o} \sum_{t \in T} \left(\omega_m \omega_o \left(-\alpha P_{0,m,o,t}^g - \beta Q_{0,m,o,t}^g \right) \right) + \text{CM} \quad (7.1b)$$

$$\text{s.t. } h(X) \leq 0 \quad (7.1c)$$

where:

- $\alpha = 1/n$ and $\beta = 1 - \alpha$ weight the minimization (or maximization) of interface active and reactive power exchanges;
- T denotes the set of time periods in the optimization horizon;
- Ω_m is the set of market scenarios, with associated probabilities ω_m ;
- Ω_o is the set of operational scenarios, with associated probabilities ω_o ;
- $P_{0,m,o,t}^g$ and $Q_{0,m,o,t}^g$ represent the active and reactive power outputs of the reference generator modeling the interconnection with the upstream transmission system, in market scenario $m \in \Omega$, operational scenario $o \in \Omega_m$ and time instant $t \in T$;
- X and $h(X)$ denote the **DSO**’s internal decision variables and constraints; and

- CM generically represents penalties associated with congestion management within the **ADN** (e.g., voltage or branch flow limit violations).

This hierarchical arrangement combines elements of the local **AS** market model – where **DSO**-validated flexibility serves as a prequalification mechanism – with features of the shared balancing responsibility model, under which each **DSO** remains responsible for the secure operation of its own network within agreed interface power exchanges.

7.1.1.4 Distributed Coordination

The distributed coordination schemes are based on the mechanism proposed in Section 3.6. Two variants are considered. In the first, coordination is implemented without shared resources at the transmission–distribution interface nodes. In the second, relatively small shared **ESSs** are installed at each interface node, with their operation coordinated between the **TSO** and the corresponding **DSOs**. This comparison allows a direct quantification of the incremental operational benefits enabled by shared interface storage, relative to distributed coordination relying exclusively on flexibility provided by **DERs**. The results of these distributed coordination schemes, together with those of the centralized, hierarchical, and traditional operation test cases, are presented and discussed in the following subsections. All penalty parameters associated with the consensus variables were initialized to $\rho^0 = 1$.

7.1.2 Case Study Description

The **TN** adopted in this case study is based on a modified version of the **IEEE** 9-bus test system (Zimmerman et al., 2011). Additional **RES** generators were integrated at the transmission level, and three **ADNs** – each modeled after the **IEEE** 33-bus distribution test system – were connected to buses 5, 7, and 9 of the **TN**. To enable the simulation of sufficiently high demand levels and induce stressed operating conditions at the transmission level, selected lines were reinforced. Detailed simulation parameters for both the **TN** and the **DNs** are provided in Appendix A, specifically in Sections A.1 and A.2. The single-line diagram of the resulting integrated system is shown in Figure 7.1.

The case study is conducted for a representative summer day characterized by high solar **PV** penetration. A total of nine operational scenarios are analyzed, capturing uncertainty in both load and **RES** generation. Simulations are intentionally performed under stressed operating conditions to assess the performance of the different operational strategies not only in terms of operational cost and **RES** integration, but also in their ability to mitigate potential network-related operational issues. Within the distributed coordination framework, shared **ESSs** – when considered – are assumed to be installed at each transmission–distribution interface with a rated power and energy capacity of 1 MW/2 MWh.

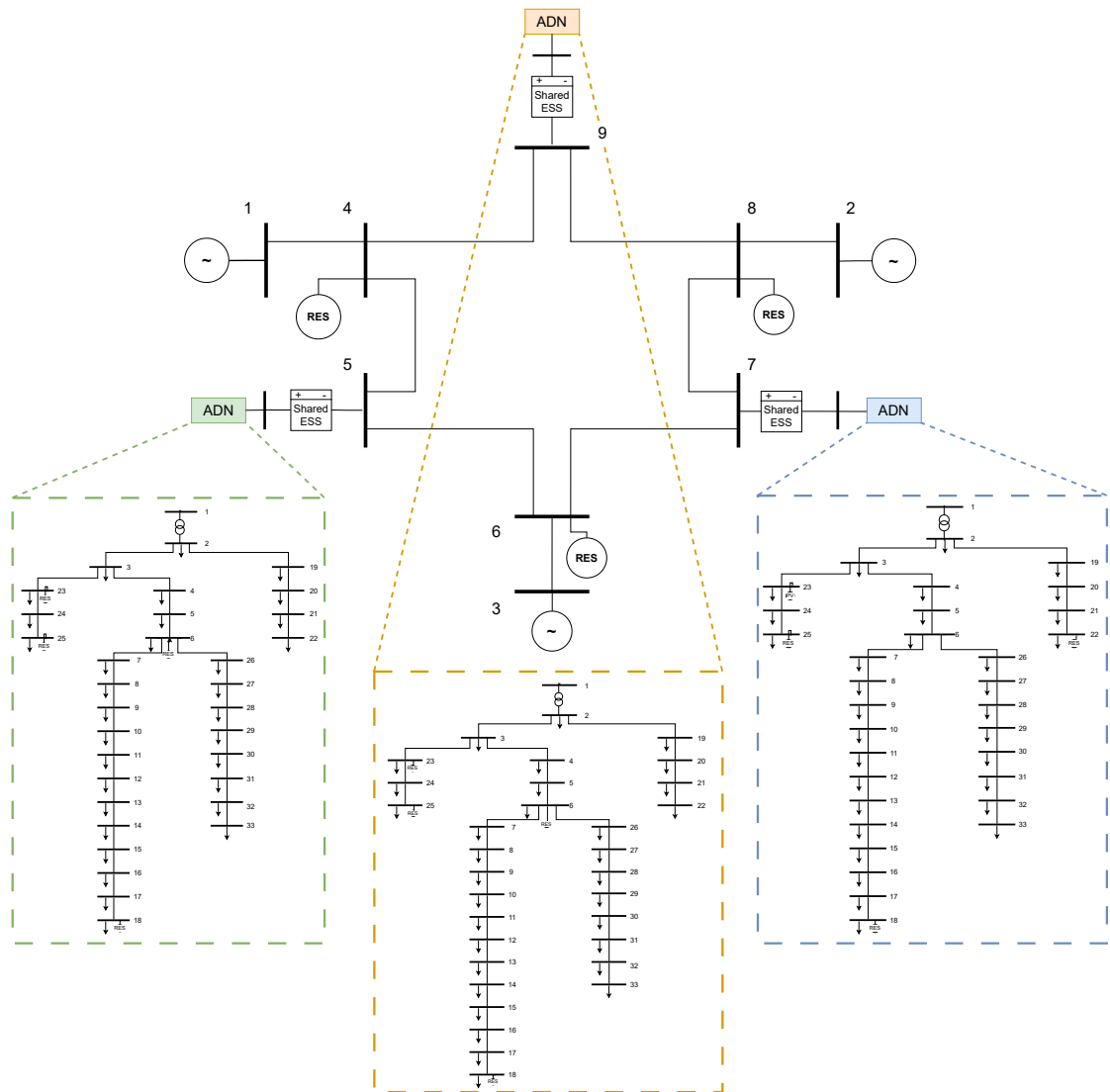


Figure 7.1: Case Study 1. Single-line diagram of the adopted test system, including ADNs participating in the coordination procedure.

In addition, multiple partitioning levels are investigated within the hierarchical coordination framework to assess their impact on coordination effectiveness and overall system performance.

7.1.2.1 Transmission Network

As noted above, the **TN** is based on the **IEEE** 9-bus test system, which was modified to include additional **RES** generators. The technical characteristics of these generators are summarized in Table 7.1. Detailed bus, branch, and conventional generator data are provided in Tables A.1, A.2, and A.3 of Appendix A.1.

Table 7.1: Case Study 1. TN. Characterization of RES generators.

Generator	Bus	Generator	$S_g^{G,\max}$	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	ID	Type	[MVA]	[N/A]	[N/A]
4	4	Wind	25.00	-0.90	0.90
5	6	Wind	50.00	-0.90	0.90
6	8	Wind	40.00	-0.90	0.90
7	4	Solar PV	100.00	-0.90	0.90
8	6	Solar PV	75.00	-0.90	0.90
9	8	Solar PV	75.00	-0.90	0.90

Figure 7.2 illustrates the **RES** generation scenarios adopted for all **TN**-connected generators. As can be observed, solar **PV** generation significantly exceeds wind generation over the considered time horizon.

7.1.2.2 ADN Connected to Node 5 of the TN

All **ADNs** considered in this case study are derived from the **IEEE** 33-bus distribution test system and, similarly to the **TN**, were modified to incorporate **RES** generators.

Within each **ADN**, all 32 loads are assumed to represent downstream networks operating at lower voltage levels and are modeled as capable of providing flexibility services to network operation. The three **DNs** differ in their levels of wind and solar **PV** integration, availability of flexible **DERs**, and presence of **ESSs**. Table 7.2 characterizes the **RES** generators of the **ADN** connected to node 5 of the **TN**. The corresponding **RES** generation and load scenarios are shown in Figure 7.3. As it can be seen, the **ADN** connected to node 5 exhibits a relatively balanced mix of wind and solar **PV** generation.

Figure 7.4 presents the flexible load profiles considered. The total flexible demand is allocated among the **FLs** according to the flexibility ratios reported in Table A.7. Flexible load data were obtained from the ATTEST project repository (ATTEST, 2019).

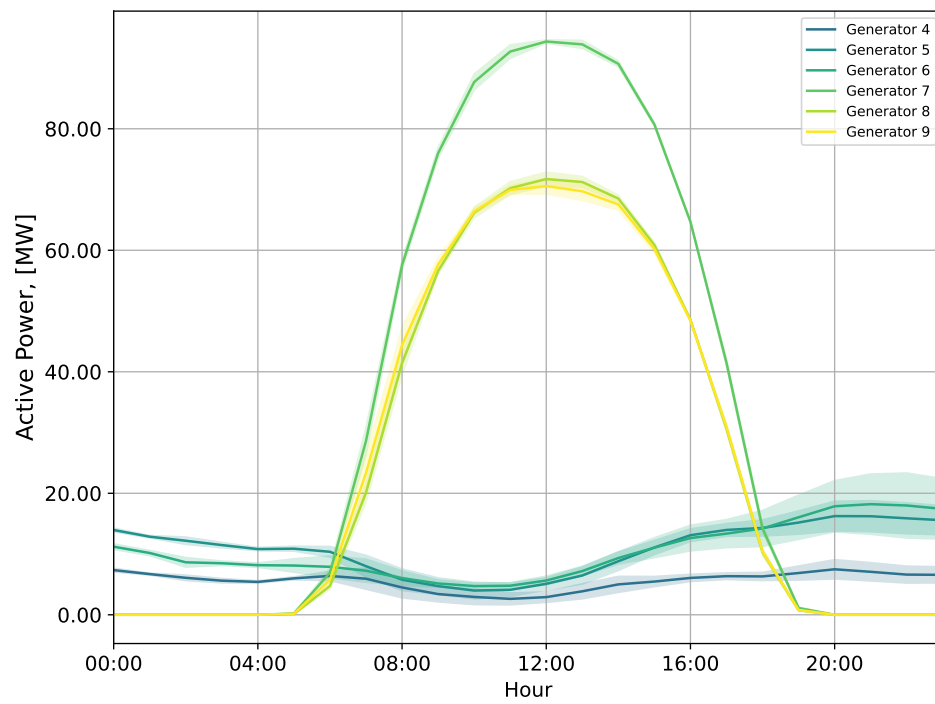
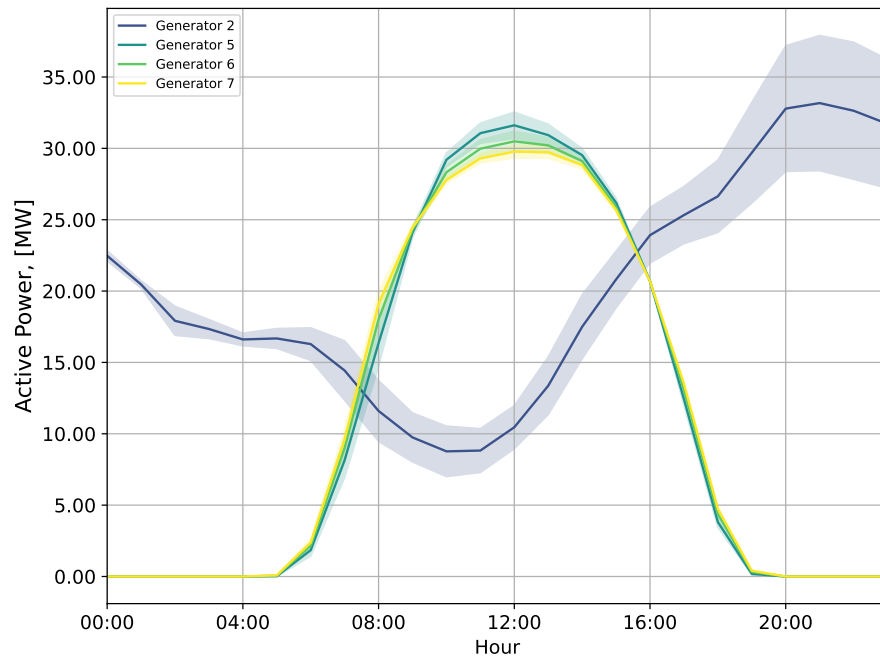


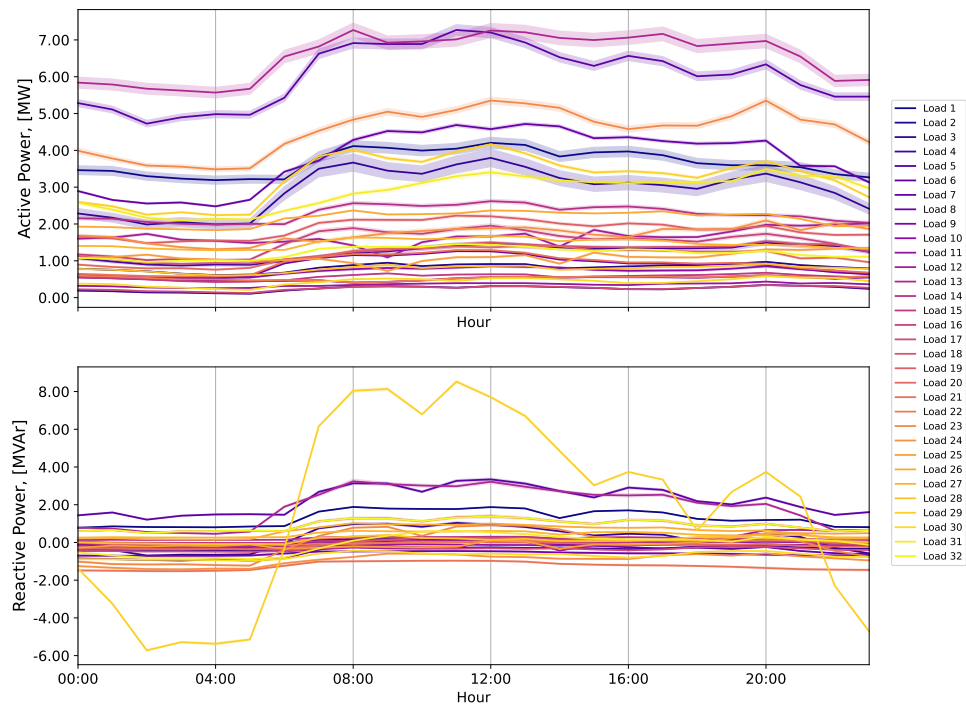
Figure 7.2: Case Study 1. TN. RES generation scenarios.

Table 7.2: Case Study 1. ADN node 5. Characterization of RES generators.

Generator	Bus	Generator	$S_g^{G,\max}$	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	ID	Type	[MVA]	[N/A]	[N/A]
2	6	Wind	80.00	-0.90	0.90
5	23	Solar PV	32.00	-0.90	0.90
6	25	Solar PV	32.00	-0.90	0.90
7	18	Solar PV	32.00	-0.90	0.90



(a) RES generation.



(b) Load.

Figure 7.3: Case Study 1. ADN node 5. RES generation and load scenarios.

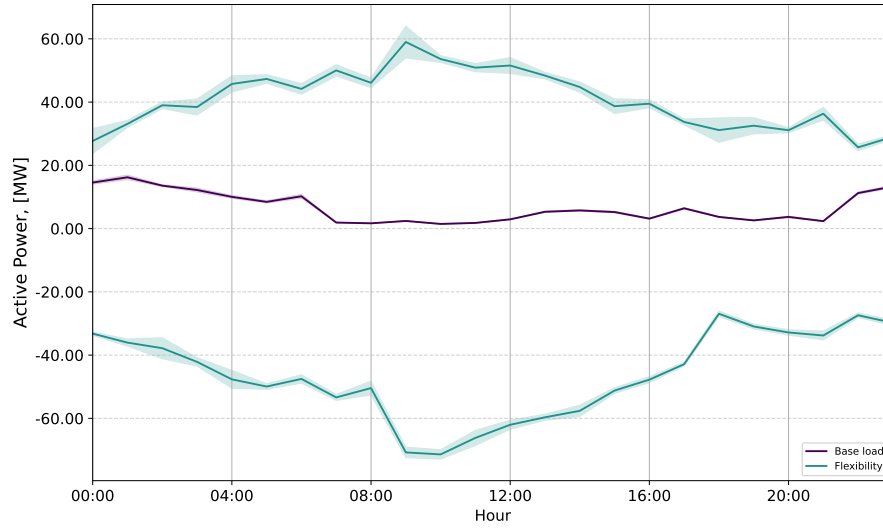


Figure 7.4: Case Study 1. ADN node 5. Flexible load profiles.

7.1.2.3 ADN Connected to Node 7 of the TN

Table 7.3 summarizes the RES generators installed in the ADN connected to node 7 of the TN, while Figure 7.5 presents the associated RES generation and load scenarios.

Table 7.3: Case Study 1. ADN node 7. Characterization of RES generators.

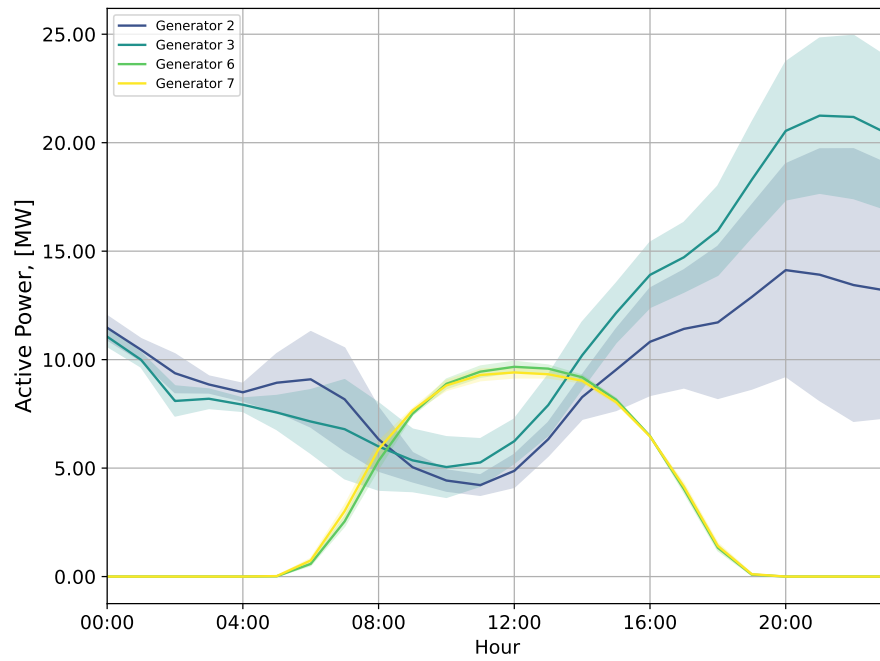
Generator	Bus	Generator	$S_g^{G,\max}$	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	ID	Type	[MVA]	[N/A]	[N/A]
2	22	Wind	40.00	-0.90	0.90
5	25	Wind	40.00	-0.90	0.90
6	23	Solar PV	10.00	-0.90	0.90
7	18	Solar PV	10.00	-0.90	0.90

In contrast to the ADN connected to node 5, the ADN connected to node 7 is largely dominated by wind generation. Figure 7.6 presents the flexible load profiles considered. The total flexible demand is allocated among the FLs according to the flexibility ratios reported in Table A.7.

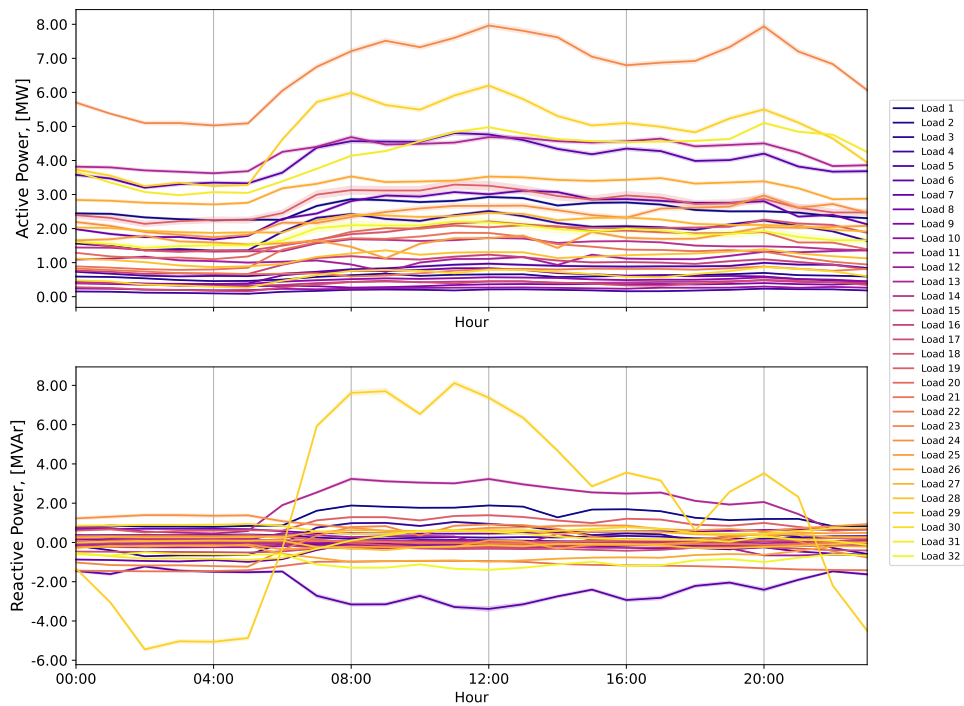
7.1.2.4 ADN Connected to Node 9 of the TN

Table 7.4 characterizes the RES generators installed in the ADN connected to node 9 of the TN, and Figure 7.7 shows the corresponding RES generation and load scenarios.

In addition to RES generation, the ADN connected to node 9 includes two ESSs, whose technical characteristics are reported in Table 7.5. As indicated by Table 7.4 and Figure 7.7, this ADN is predominantly characterized by solar PV generation.



(a) RES generation.



(b) Load.

Figure 7.5: Case Study 1. ADN node 7. RES generation and load scenarios.

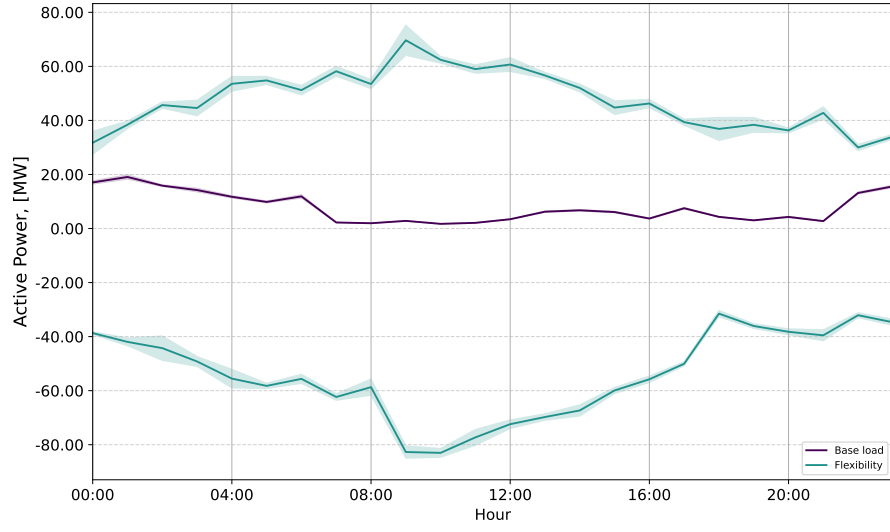


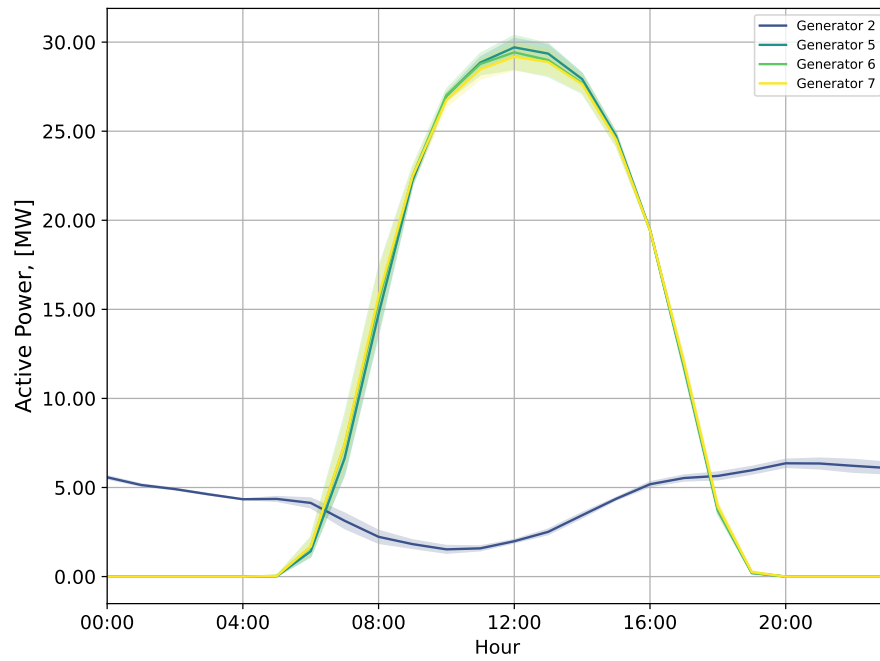
Figure 7.6: Case Study 1. ADN node 7. Flexible load profiles.

Table 7.4: ADN connected to node 9 of the TN. RES characterization.

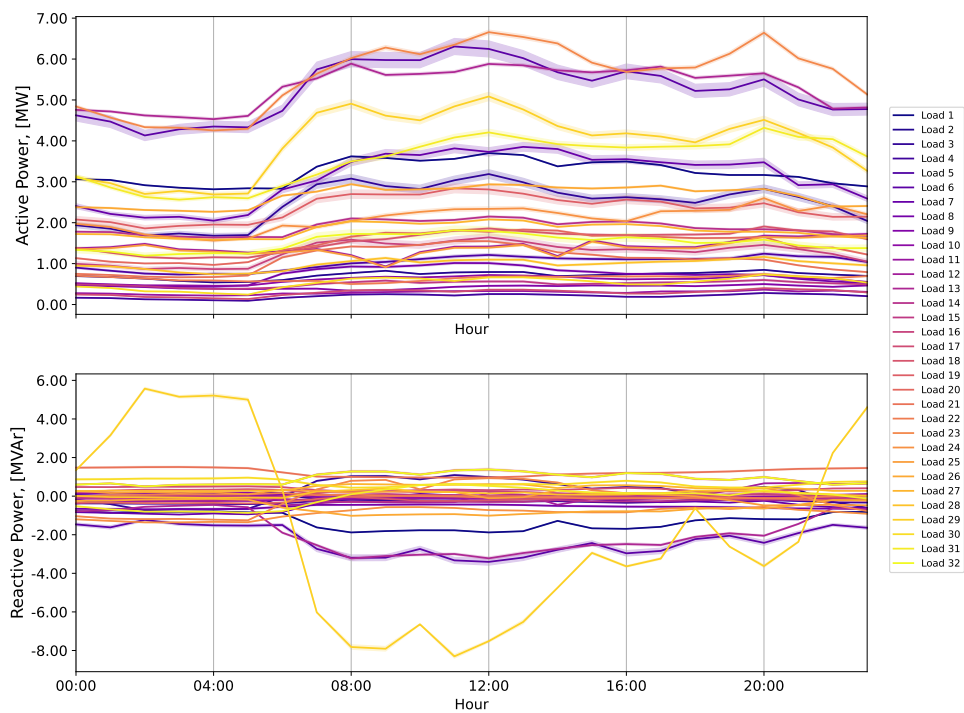
Generator	Bus	Generator	$S_g^{G,\max}$	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	ID	Type	[MVA]	[N/A]	[N/A]
2	22	Wind	20.00	-0.90	0.90
5	25	Solar PV	30.00	-0.90	0.90
6	23	Solar PV	30.00	-0.90	0.90
7	18	Solar PV	30.00	-0.90	0.90

Table 7.5: ADN connected to node 9 of the TN. ESS characterization.

ESS	Bus	S_e^{Rated}	E_e^{Rated}	$\cos(\varphi_e^{E,\min})$	$\cos(\varphi_e^{E,\max})$
ID	ID	[MVA]	[MWh]	[N/A]	[N/A]
1	23	0.50	1.00	-0.90	0.90
2	18	0.50	1.00	-0.90	0.90



(a) RES generation.



(b) Load.

Figure 7.7: Case Study 1. ADN node 9. RES generation and load scenarios.

Figure 7.8 presents the flexible load profiles considered. The total flexible demand is allocated among the FLs according to the flexibility ratios reported in Table A.7.

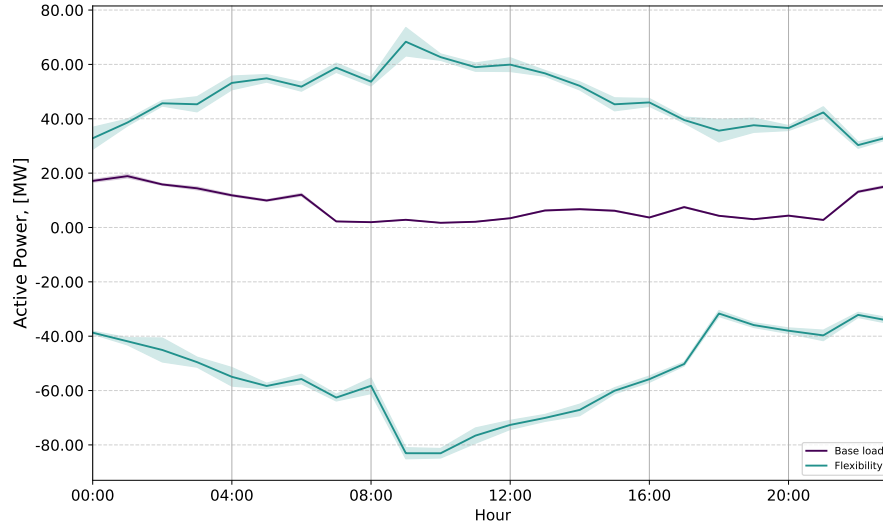


Figure 7.8: Case Study 1. ADN node 9. Flexible load profiles.

7.1.2.5 Market Data

As described in Chapter 4, conventional generators are remunerated according to wholesale energy market prices, while FSPs are compensated based on flexibility market prices. It is assumed that both wholesale energy and flexibility prices are known *a priori*; therefore, a single market scenario is considered in this case study.

Figure 7.9 presents the wholesale energy and flexibility price profiles adopted in the simulations. Wholesale energy prices were obtained from the Portuguese TSO's market platform (REN, 2025), while flexibility market prices were sourced from the ATTEST project repository (ATTEST, 2020).

7.1.3 Results

As discussed previously, this case study considers a day characterized by very high RES penetration, during which voltage magnitude violations are forecasted to occur under typical operation, i.e., when DNs do not actively participate in TN operation. Five operational frameworks are analyzed: (i) traditional (uncoordinated) operation; (ii) centralized operation; (iii) hierarchical coordination; (iv) distributed coordination without shared ESSs; and (v) distributed coordination with shared ESSs. In addition, four partitioning levels are examined within the hierarchical coordination framework, with the objective of assessing their impact on the outcome of the coordinated operation process.

All simulations related to this case study were run on a MacBook Air laptop, equipped with an M3 processor and 16 GB of RAM.

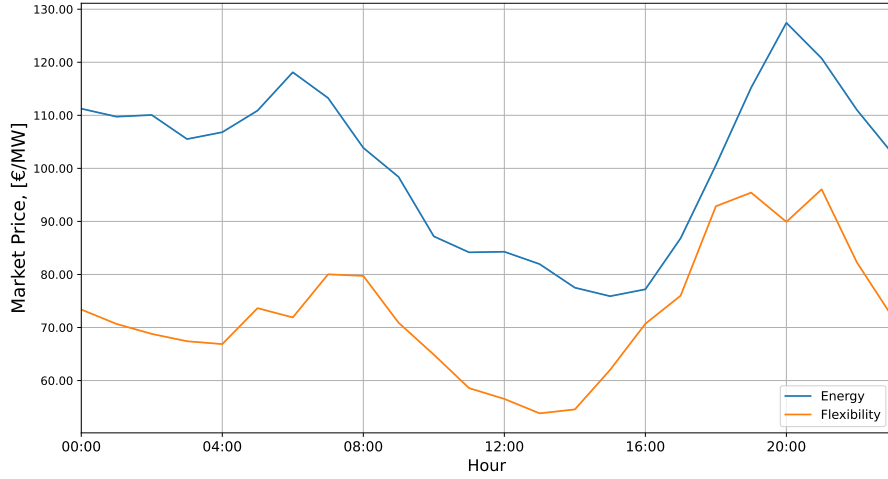
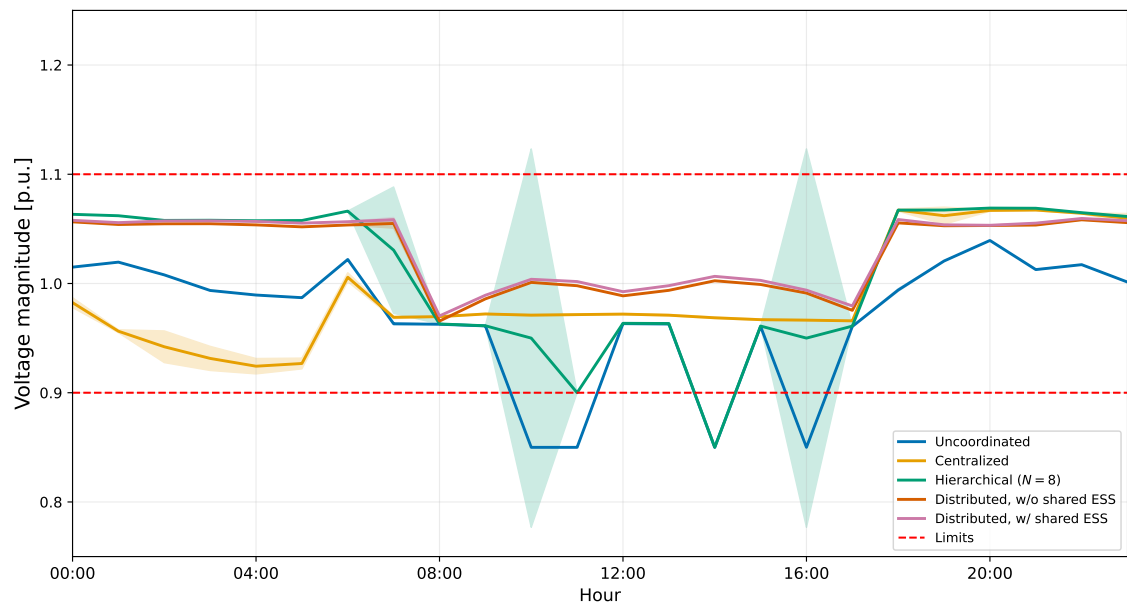


Figure 7.9: Case Study 1. Wholesale energy and flexibility market prices.

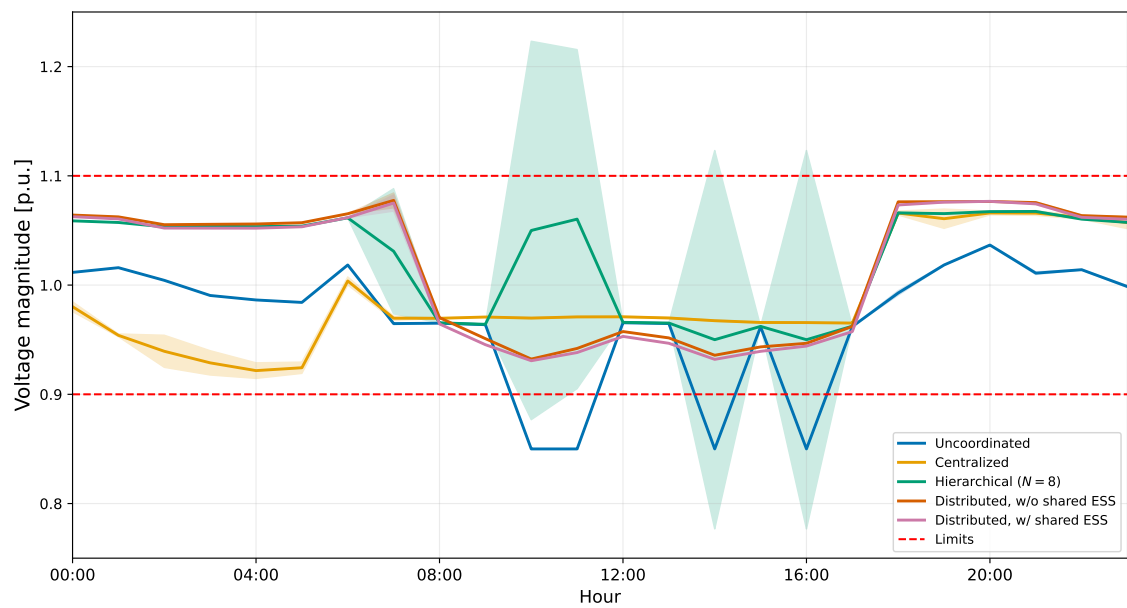
7.1.3.1 Voltage Magnitude Profiles

Figure 7.10 presents the voltage magnitude profiles of the **TN** buses that experience voltage violations under uncoordinated operation, namely buses 2 and 3, for all five operational frameworks considered. As it can be seen from Figure 7.10, significant undervoltages are forecasted under traditional (uncoordinated) operation. Specifically, undervoltage violations occur at buses 2 and 3 between 10 h and 11 h, at 14 h, and again at 16 h. Figure 7.11 illustrates the multi-period **FORs** computed for each **ADN**.

A closer inspection of the results reveals that not all coordinated strategies are able to fully resolve the forecasted voltage violations. In particular, the hierarchical coordination scheme fails to mitigate the undervoltage at bus 2 at 14 h. In contrast, all voltage violations at bus 3 are successfully resolved through coordinated operation between the **TN** and **DN**. These results highlight a fundamental limitation of **PQ**-map-based hierarchical coordination schemes. In this approach, **DSOs** construct their multi-period **FORs** by maximizing and minimizing the (weighted) active and reactive *energy* exchanges at the **TN-DN** interface over the entire optimization horizon (see Subsection 7.1.1.3), without *a priori* knowledge of the **TSO**'s time-specific flexibility *power* requirements. As a consequence, the resulting **FORs** may not guarantee the availability of sufficient active or reactive power flexibility at critical time instants – even when adequate flexibility exists within the **DN**. This temporal mismatch between energy-based envelopes and instantaneous system needs can lead to unresolved operational issues, as demonstrated in this case study. Importantly, this limitation is structural to the **PQ**-map formulation and cannot be fully mitigated through finer discretization or increased partitioning resolution.

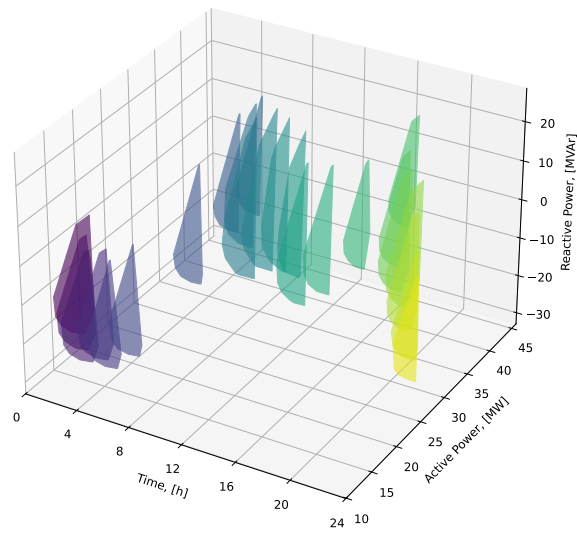


(a) Node 2.

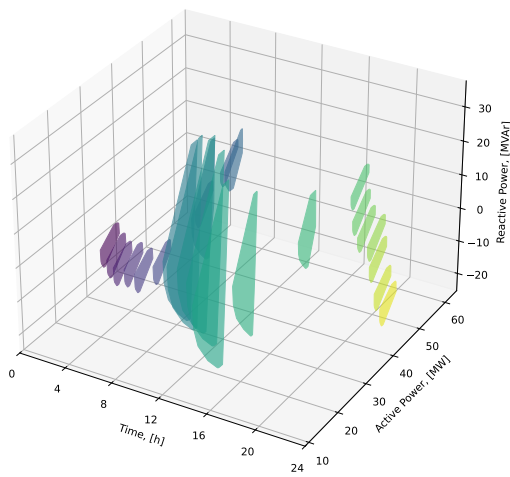


(b) Node 3.

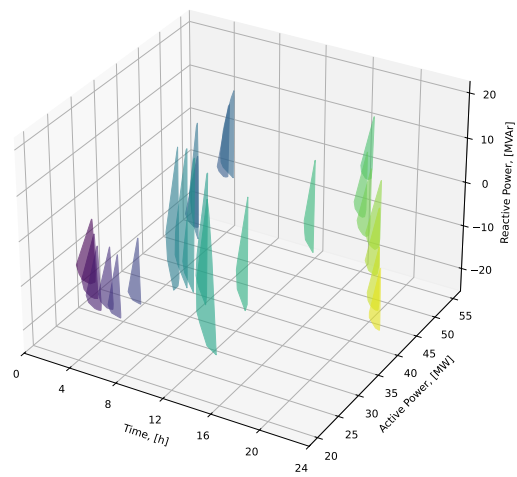
Figure 7.10: Case Study 1. Voltage magnitude profiles of the nodes that present violations.



(a) ADN connected to node 5 of the TN.



(b) ADN connected to node 7 of the TN.



(c) ADN connected to node 9 of the TN.

Figure 7.11: Case Study 1. ADNs' multi-period FORs.

7.1.3.2 Main Indicators

Table 7.6 summarizes the main quantitative results of the case study, including computational effort (normalized with respect to the uncoordinated benchmark runtime of 33.07 s), total operational cost, RES curtailment, and network power losses, together with their relative variations compared to the uncoordinated baseline.

Table 7.6: TSO-DSO coordination strategies. Multi-period. Main results.

Test Case	Comp. Effort ¹ , [N/A]	Oper. Cost, [€]	Δ Cost, [%]	RES Curt., [MVAh]	Δ RES Curt., [%]	Losses, [MWh]	Δ Losses, [%]
Uncoordinated	1.00	153 082.88	–	1 963.02	–	27.56	–
Coordinated							
Centralized	1.99	124 425.62	-18.72%	1 403.73	-28.49%	173.39	529.15%
Hierarchical							
$N = 1$	4.49	206 304.56	34.77%	1 960.36	-0.14%	75.39	173.57%
$N = 2$	5.48	210 335.55	37.40%	1 971.06	-0.41%	79.95	190.10%
$N = 4$	7.71	216 281.26	41.28%	1 972.09	0.46%	79.24	187.53%
$N = 8$	11.41	198 439.05	29.63%	1 961.82	-0.06%	69.00	150.38%
Distributed							
W/o shared ESSs	5.41	145 088.75	-5.22%	954.22	-51.39%	14.03	-49.11%
W/ shared ESSs	5.35	144 237.08	-5.78%	963.59	-50.91%	14.35	-47.95%

With respect to computational effort, the centralized coordination scheme exhibits the lowest runtime among the coordinated strategies. Although this result may appear counterintuitive, it is explained by the limited size of the test system: when system-wide flexibility is directly accessible and the problem dimension remains modest, the resulting centralized optimization problem is better conditioned and converges more rapidly. The distributed coordination schemes also demonstrate competitive computational performance, with normalized runtimes of 5.35 (with shared ESSs) and 5.41 (without shared ESSs), comparable to those of hierarchical coordination with lower partitioning levels (4.49 for $N = 1$ and 5.48 for $N = 2$). By contrast, the highest-resolution hierarchical scheme ($N = 8$) requires a normalized computational effort of 11.41, more than twice that of the distributed approaches. It is worth noting that, despite their higher aggregated computational effort relative to the centralized case, both hierarchical and distributed schemes enable the DSOs subproblems to be solved in parallel. In practical implementations, this parallelism can substantially reduce the effective wall-clock computation time, an advantage that centralized coordination does not offer.

In terms of economic performance, centralized and distributed coordination strategies achieve substantial reductions in operational costs relative to the uncoordinated benchmark. The centralized strategy yields the largest cost reduction (18.72%), followed by distributed coordination with shared ESSs (5.78%) and without shared ESSs (5.22%), whereas the hierarchical coordination schemes result in higher operational costs. With respect to RES curtailment, the distributed coordination schemes clearly outperform all other strategies, achieving reductions of 50.91% when shared ESSs are available and

¹Normalized to “uncoordinated” test case runtime (33.07 s).

51.39% in their absence. These results underscore the effectiveness of distributed coordination in exploiting **DN**-level flexibility to enhance **RES** integration. Finally, regarding network power losses, both centralized and hierarchical coordination schemes lead to substantial increases relative to the uncoordinated baseline, ranging from 150.38% (hierarchical, $N = 8$) to 529.15% (centralized). In contrast, both distributed coordination variants achieve significant loss reductions: 47.95% with shared **ESSs** and 49.11% without shared **ESSs**. Notably, loss minimization is not an explicit objective of the optimization problem, making this result particularly relevant.

7.1.4 Conclusions

Despite its relatively simple setup, this case study yields several important insights into the performance, benefits, and limitations of the **TSO-DSO** coordination strategies considered.

Based on the results presented above, the following main conclusions can be drawn:

1. System-wide benefits of distributed coordination: Distributed coordination between the **TN** and the **DNs** consistently resolves forecasted network constraint violations – unlike the hierarchical coordination framework – while simultaneously reducing total operational costs and enabling higher levels of **RES** integration across all analyzed operational strategies.
2. Computational performance of hierarchical versus distributed approaches: The proposed distributed coordination mechanism achieves computational performance comparable to low-resolution hierarchical coordination schemes. This finding is particularly relevant, as computational efficiency is often cited as a primary justification for hierarchical coordination. The results demonstrate that distributed coordination can attain similar – or superior – computational performance while delivering improved operational outcomes.
3. Privacy and regulatory considerations: From a practical deployment perspective, centralized coordination poses significant challenges related to data privacy and regulatory compliance, as it requires a single **SO** to access detailed, system-wide operational information. Such requirements are difficult to reconcile with existing unbundling principles and regulatory frameworks that mandate a clear separation of **TN** and **DN** responsibilities.

For this specific case study, centralized coordination yields the largest cost reductions and the lowest computational effort. However, centralized **OPF**-based formulations are well known to face scalability limitations as system size, network complexity, and uncertainty increase (Capitanescu, 2016). Both hierarchical and distributed approaches mitigate these issues by decomposing the problem into smaller **TN**- and **DN**-level subproblems, thereby enabling parallel solution and reducing effective computation times in large-scale implementations. Nevertheless, hierarchical coordination remains subject to structural

limitations. In particular, the use of static **PQ** maps provides only an approximate representation of distribution-level flexibility and neglects temporal interdependencies that influence the *actual* availability of flexible resources – an issue that has yet to be fully resolved in the literature.

The main practical challenges associated with distributed coordination relate to the need for iterative information exchange between **SOs** and the convergence properties of distributed optimization algorithms, especially when addressing non-convex subproblems such as the **SMOPF** considered in this work. Importantly, the results indicate that the inclusion of shared **ESSs** does not necessarily increase the computational burden. This suggests that shared **ESSs** not only provide operational benefits, but may also enhance the efficiency and robustness of the coordination and negotiation process.

7.2 Case Study 2

This section presents a second case study designed to evaluate the performance of the proposed **TSO–DSO** coordinated operational planning framework under “normal” operating conditions. Unlike Case Study 1, which focused on stressed system scenarios, this analysis examines the effectiveness of coordinated decision-making during routine system operation. The primary objective is to assess the extent to which the proposed coordination mechanism improves overall operational efficiency. In particular, the case study evaluates the economic benefits, scalability, and robustness of the framework when applied to diverse network topologies and seasonal operating conditions, thereby providing insight into its applicability under realistic day-to-day system operation.

7.2.1 Case Study Description

A relatively large-scale test system is considered, based on the **IEEE** 57-bus **TN** (Zimmerman et al., 2011). Within this system, nine **ADNs** – out of a total of 42 **FLs** – are explicitly modeled and participate in the proposed coordination procedure. These **ADNs** are derived from the **IEEE** 18-, 22-, and 33-bus radial distribution test systems (Grady et al., 1992; Ramalinga Raju et al., 2012; Baran and Wu, 1989, respectively), and are connected to selected transmission buses. Within the distributed implementation, each participating **ADN** is represented by an independent local **DSO** subproblem. The case study therefore evaluates the coordination framework with multiple distribution-level agents.

Table 7.7 identifies the **TN** buses to which the participating **ADNs** are connected, their corresponding reference **IEEE** test systems, and the appendix subsections where their detailed descriptions are provided. All penalty parameters associated with the consensus variables were initialized to $\rho^0 = 1$, consistently with Case Study 1.

Four representative days – one for each season – are considered to evaluate the robustness of the proposed coordination mechanism under diverse operating conditions. For each representative day, nine operational scenarios are modeled at both the **TN** and **DN**

Table 7.7: Case Study 2. ADNs participating in the coordination procedure.

Bus ID	Reference Test System	Descriptive Subsection
2	IEEE 33-bus	B.2.2
18	IEEE 18-bus	B.2.3
19	IEEE 33-bus	B.2.4
20	IEEE 33-bus	B.2.5
30	IEEE 33-bus	B.2.6
32	IEEE 22-bus	B.2.7
33	IEEE 33-bus	B.2.8
43	IEEE 22-bus	B.2.9
47	IEEE 18-bus	B.2.10

levels to capture uncertainty in load and RES generation. As in Case Study 1, wholesale energy and flexibility market prices are assumed to be known *a priori*; consequently, a single market scenario is adopted.

The technical characteristics of the shared ESSs included in this distributed coordination case study are summarized in Table 7.8. Comprehensive simulation parameters for both the TN and the participating DNs are provided in Appendix B.

Table 7.8: Case Study 2. Shared ESSs characterization.

TN Bus	S_e^{Rated}	E_e^{Rated}	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	[MW]	[MWh]	[N/A]	[N/A]
10	5.00	10.00	-0.90	0.90
47	5.00	10.00	-0.90	0.90

7.2.1.1 Market Data

As described in Section 7.1, conventional generators are remunerated based on wholesale energy market prices, while FSPs are compensated according to flexibility market prices. Both wholesale energy and flexibility market prices are assumed to be known *a priori*, and therefore a single market scenario is considered. Energy market price data were obtained from the Portuguese TSO's market platform (REN, 2025), while flexibility market prices were sourced from the ATTEST project repository (ATTEST, 2020).

Figure 7.12 illustrates the wholesale energy and flexibility price profiles adopted for the spring representative day. Corresponding price data for the summer, autumn, and winter representative days are provided in Figures B.50, B.51, and B.52, respectively, in Appendix B.3.

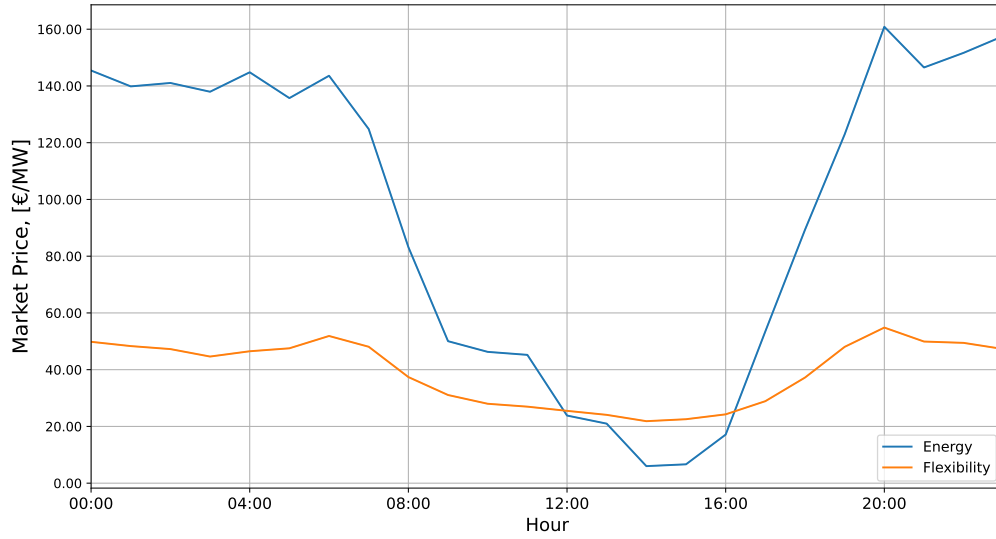


Figure 7.12: Case Study 2. Wholesale energy and flexibility market prices. Spring.

7.2.1.2 Transmission Network

The **TN** adopted in this case study is based on the **IEEE** 57-bus test system. Figure 7.13 presents the corresponding single-line diagram. Detailed data for buses, branches, conventional generators, and loads are provided in Appendix B.1 (Tables B.1–B.4). The test system was extended to include **RES** generators, whose technical characteristics are listed in Table 7.9.

Table 7.9: Case Study 2. TN. Characterization of RES generators.

Generator	Bus	Generator	$S_g^{G,\max}$	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	ID	Type	[MVA]	[N/A]	[N/A]
8	18	Wind	150.00	-0.90	0.90
9	38	Wind	200.00	-0.90	0.90
10	34	Wind	250.00	-0.90	0.90
11	29	Solar PV	150.00	-0.90	0.90
12	55	Solar PV	250.00	-0.90	0.90
13	30	Solar PV	200.00	-0.90	0.90

Figure 7.14 illustrates the **RES** generation and load profiles adopted for the spring representative day. The corresponding profiles for the summer, autumn, and winter representative days are provided in Appendix B.1, Figures B.1–B.3. Figure 7.15 presents the flexible load profiles considered in the **TN**. The total flexible demand is allocated among the **FLs** according to the flexibility ratios reported in Table B.4. Flexible load data were obtained from the ATTEST project repository (ATTEST, 2019), and identical profiles are assumed for all representative days.

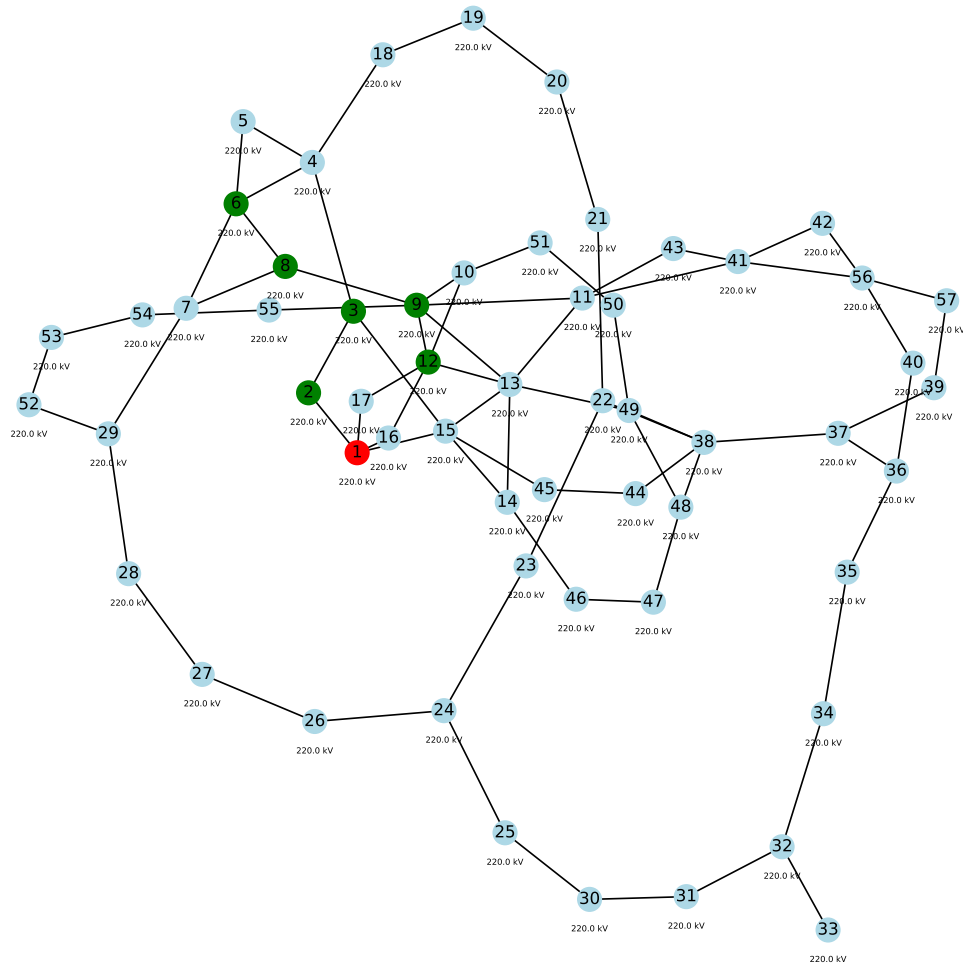
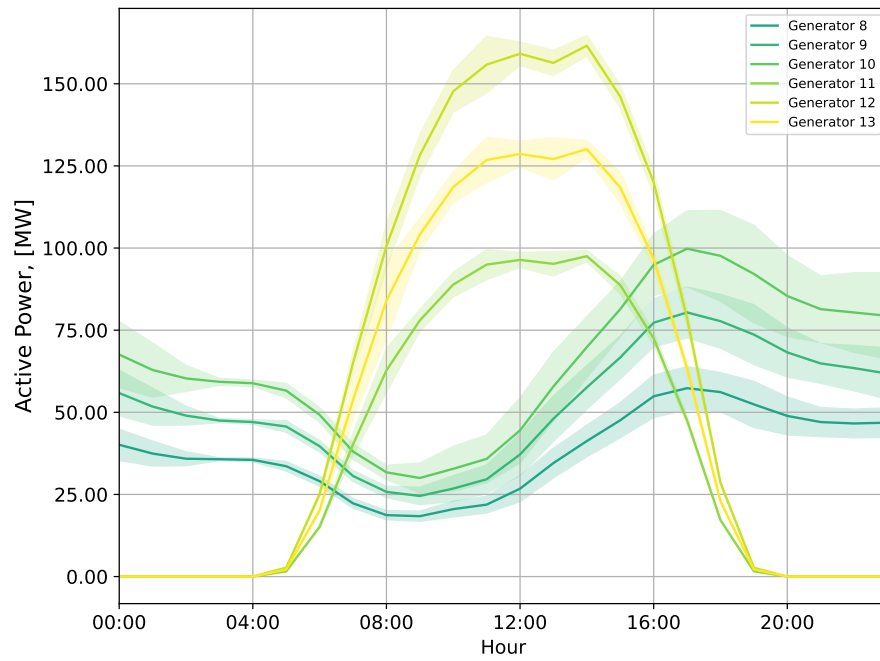
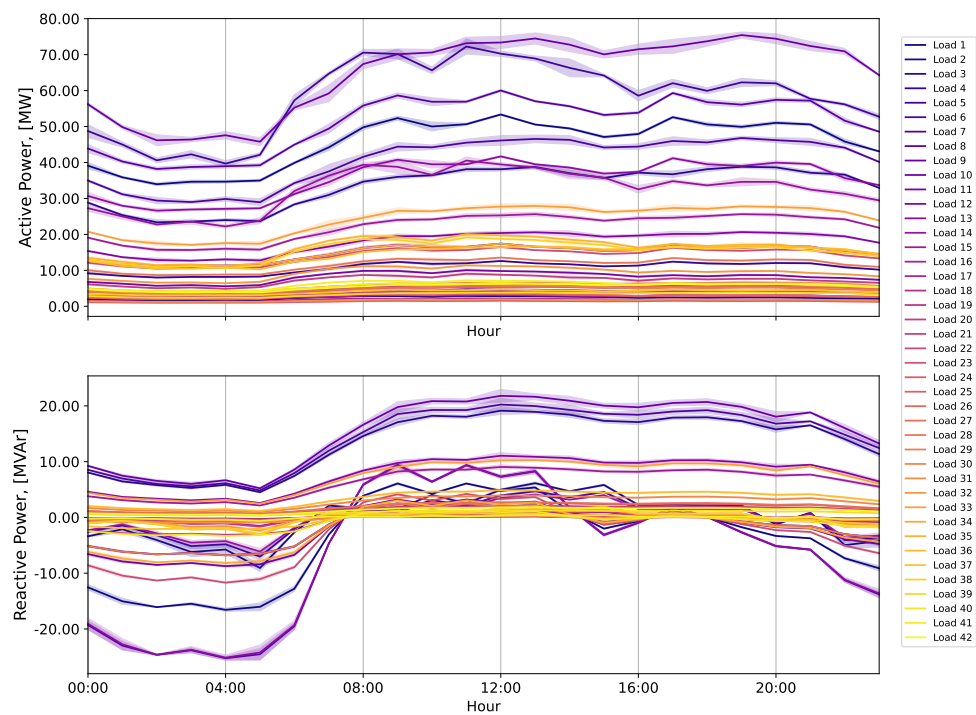


Figure 7.13: Case Study 2. Single-line diagram of the TN adopted. Node in red denotes the reference (slack) bus; nodes in green denote buses where conventional generators are located; and nodes in light blue denote PQ buses.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure 7.14: Case Study 2. TN. RES generation and load scenarios. Spring.

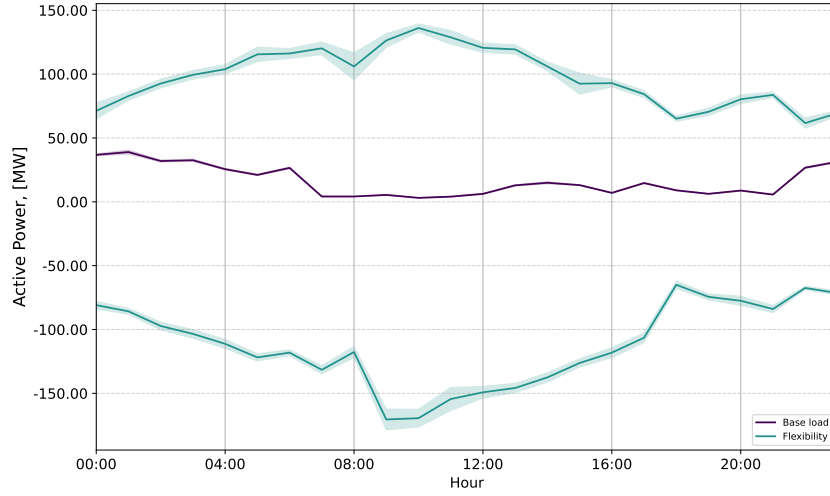


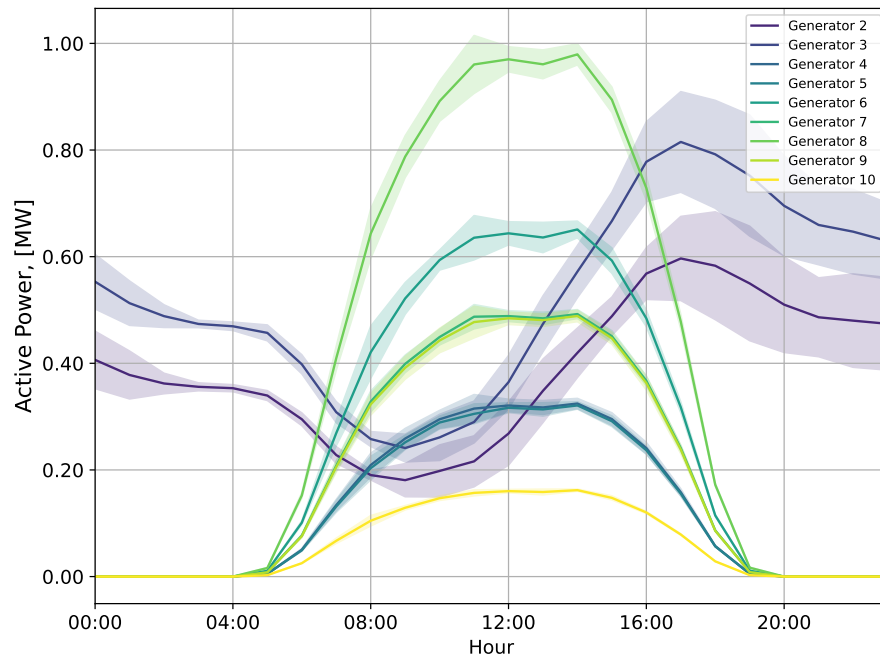
Figure 7.15: Case Study 2. TN. Flexible load profiles.

7.2.1.3 Active Distribution Networks

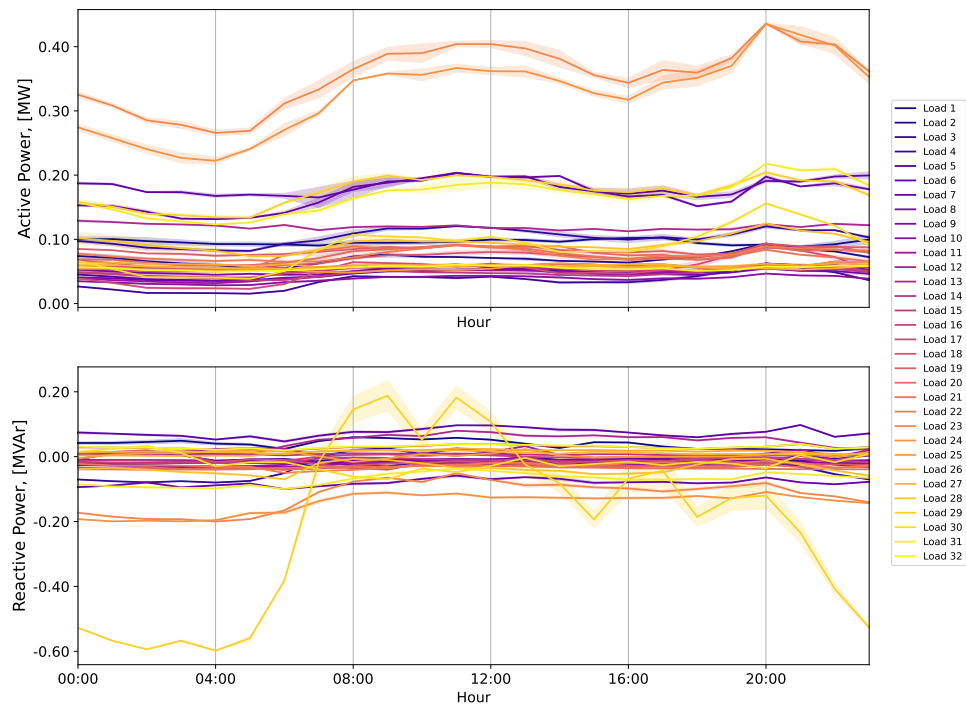
This subsection describes the **ADNs** participating in the coordination procedure. As noted previously, the **ADNs** are derived from the **IEEE** 18-, 22-, and 33-bus distribution test systems, which were adapted to represent different penetration levels and technology mixes of wind and solar **PV** generation. For illustrative purposes, the **ADN** connected to node 2 of the **TN** is described in detail below. The remaining **ADNs** follow the same modeling assumptions and are documented in Appendix B.2.

The **ADN** connected to node 2 is based on the **IEEE** 33-bus test system (Baran and Wu, 1989). Its network topology is presented in Section B.2.1.3, with the corresponding single-line diagram shown in Figure B.6. Detailed bus, branch, and conventional generator data are provided in Tables B.13–B.15. The system was extended to include **RES** generators, whose characteristics are summarized in Table 7.10. Figure 7.16 illustrates the **RES** generation and load profiles for the spring representative day. The corresponding profiles for the remaining seasons are provided in Figures B.7–B.9. Flexible load profiles for this **ADN** are shown in Figure 7.17.

The remaining eight **ADNs** follow the same modeling assumptions, differing primarily in network size, **RES** technology mix, and installed capacity. Specifically, **ADNs** based on the **IEEE** 18-bus test system exhibit the highest total load and **RES** penetration, followed by those derived from the **IEEE** 33-bus system, while **ADNs** based on the **IEEE** 22-bus system present the lowest total load and **RES** generation levels. Wind-dominated **ADNs** are connected at transmission nodes 18 and 47, whereas the remaining **ADNs** are primarily characterized by solar **PV** generation. Detailed topological data, generator characteristics, and seasonal **RES** and load profiles for each **ADN** are provided in Appendix B, Subsections B.2.2–B.2.10.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure 7.16: Case Study 2. ADN node 2. RES generation and load scenarios. Spring.

Table 7.10: Case Study 2. ADN node 2. Characterization of RES generators.

Generator	Bus	Generator	$S_g^{G,\max}$	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	ID	Type	[MVA]	[N/A]	[N/A]
2	20	Wind	1.50	-0.90	0.90
3	22	Wind	2.00	-0.90	0.90
4	3	Solar PV	0.50	-0.90	0.90
5	25	Solar PV	0.50	-0.90	0.90
6	6	Solar PV	1.00	-0.90	0.90
7	28	Solar PV	0.75	-0.90	0.90
8	33	Solar PV	1.50	-0.90	0.90
9	9	Solar PV	0.75	-0.90	0.90
10	18	Solar PV	0.25	-0.90	0.90

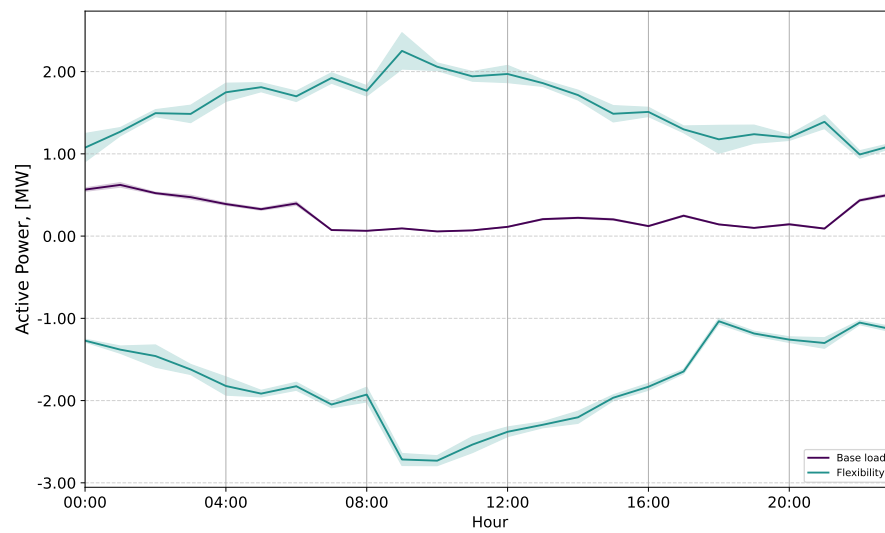


Figure 7.17: Case Study 2. ADN node 2. Flexible load profiles.

7.2.2 Results

Table 7.11 summarizes the main outcomes of Case Study 2, including total operational costs, RES integration levels, RES curtailment, and computational effort for the four representative days analyzed. Computational effort is expressed as the runtime of each coordinated test case normalized to the corresponding uncoordinated baseline.

Table 7.11: Case Study 2. TSO-DSO coordinated operational planning. Main results. Computational effort is normalized to the corresponding uncoordinated test case runtime.

Test Case	Season			
	Spring	Summer	Autumn	Winter
Uncoordinated				
Operational Cost, [€]	888 421.68	1 145 381.41	925 203.44	1 252 338.50
RES Generation, [MWh]	5 717.92	5 902.51	6 523.26	5 529.90
RES Curtailment, [MVAh]	2 073.65	2 931.46	2 301.38	3 211.10
Computation Time, [s]	328.75	348.08	200.38	154.93
Without Shared ESSs				
Operational Cost				
Total, [€]	707 847.47	938 700.02	718 185.81	922 019.67
Variation, [%]	-20.33%	-18.04%	-22.38%	-26.38%
RES Generation				
Total, [MWh]	7 067.18	8 308.05	8 869.34	8 869.54
Variation, [%]	23.60%	40.75%	35.96%	60.39%
RES Curtailment				
Total, [MVAh]	893.35	768.27	161.79	72.73
Variation, [%]	-56.92%	-73.79%	-92.97%	-97.74%
Comp. Effort, [N/A]	3.10	3.04	3.86	5.84
With Shared ESSs				
Operational Cost				
Total, [€]	705 566.94	940 202.61	717 270.42	925 116.20
Variation, [%]	-20.58%	-17.91%	-22.47%	-26.13%
RES Generation				
Total, [MWh]	7 063.16	8 293.52	8 875.11	8 849.08
Variation, [%]	23.53%	40.51%	36.05%	60.02%
RES Curtailment				
Total, [MVAh]	901.82	784.36	165.23	73.77
Variation, [%]	-56.51%	-73.24%	-92.82%	-97.70%
Comp. Effort, [N/A]	4.26	4.38	5.50	8.61

The following subsections provide a detailed assessment of the Case Study 2 results, focusing on economic performance, flexibility utilization, RES integration, convergence behavior, and interface-level operation.

7.2.2.1 Operational Costs

Table 7.11 shows that coordinated TSO–DSO operation consistently delivers substantial economic benefits across all representative days. Compared to the uncoordinated benchmark, total operational costs are reduced for all representative days analyzed. In the absence of shared ESSs, cost reductions range from 18.04% in summer to 26.38% in winter. When shared ESSs are available, cost reductions range from 17.91% (Summer) to 26.13% (Winter).

Figure 7.18 illustrates the operational cost breakdown by representative day and test case, distinguishing between conventional generation costs and flexibility procurement costs. As shown in Figure 7.18, both coordinated schemes exhibit similar cost structures. Across all representative days, coordinated operation systematically reduces conventional generation costs, while expenditures on flexibility services generally increase – the only exception occurs in the autumn representative day, where flexibility costs decrease by 11.19% without shared ESSs and by 10.98% with shared ESSs.

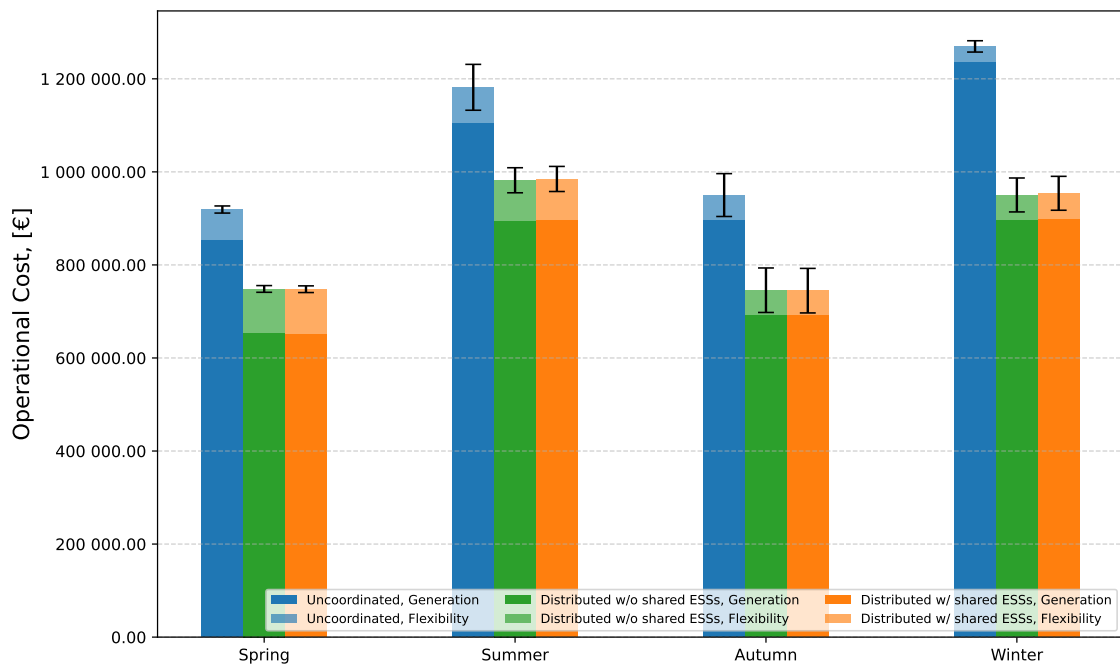
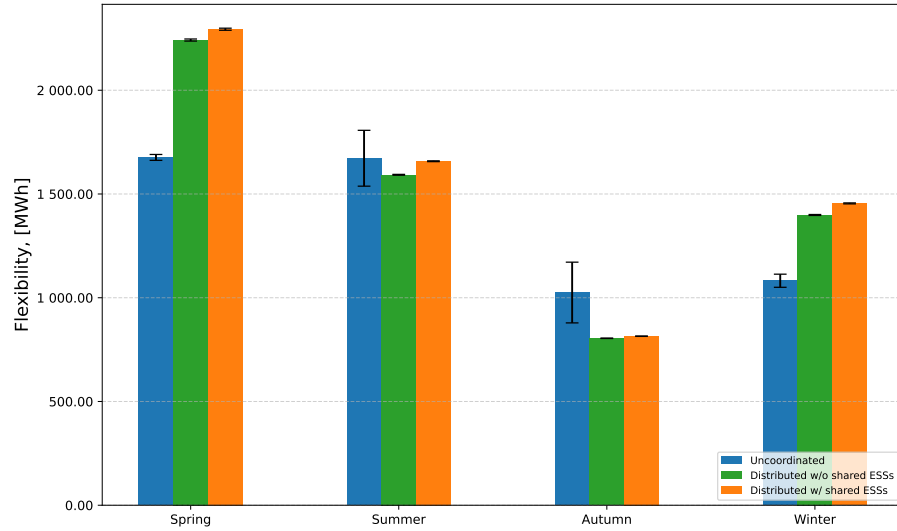


Figure 7.18: Case Study 2. Operational costs per representative day and test case.

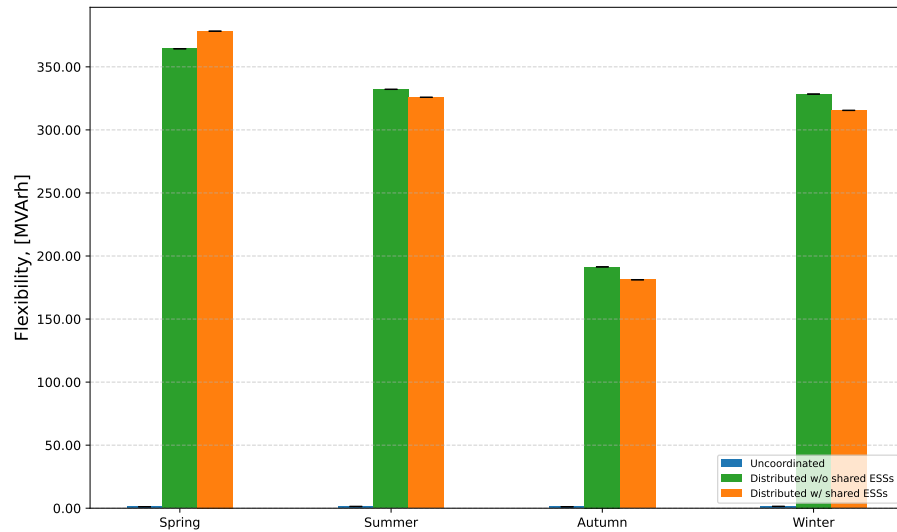
In contrast to Case Study 1 (Section 7.1), where shared ESSs consistently yielded lower operational costs, the results under normal operating conditions are more nuanced. Shared ESSs lead to slightly lower costs in the spring and autumn representative days, while marginally lower costs are observed without shared ESSs in summer and winter.

7.2.2.2 Flexibility Procurement

Figure 7.19 reports the total active and reactive energy associated with flexibility procurement for each representative day and test case.



(a) Active energy.



(b) Reactive energy.

Figure 7.19: Case Study 2. Flexibility procurement per representative day and test case.

The results indicate that coordinated operation does not necessarily require higher volumes of procured flexibility. In particular, active power flexibility procurement decreases under coordinated operation in both the autumn and summer representative days. For the autumn representative day, active flexibility procurement decreases by 20.53% with shared ESSs and by 21.51% without shared ESSs. For the summer representative day, reductions range from 0.86% (with shared ESSs) to 4.77% (without shared ESSs).

When analyzed jointly with Figure 7.18, these results indicate that coordinated operation improves system efficiency primarily by enabling a more effective utilization of existing flexibility resources and reducing reliance on conventional generation, rather than through a systematic increase in flexibility procurement.

7.2.2.3 RES Generation

Figure 7.20 illustrates the total active and reactive energy produced by RES for each representative day and test case.

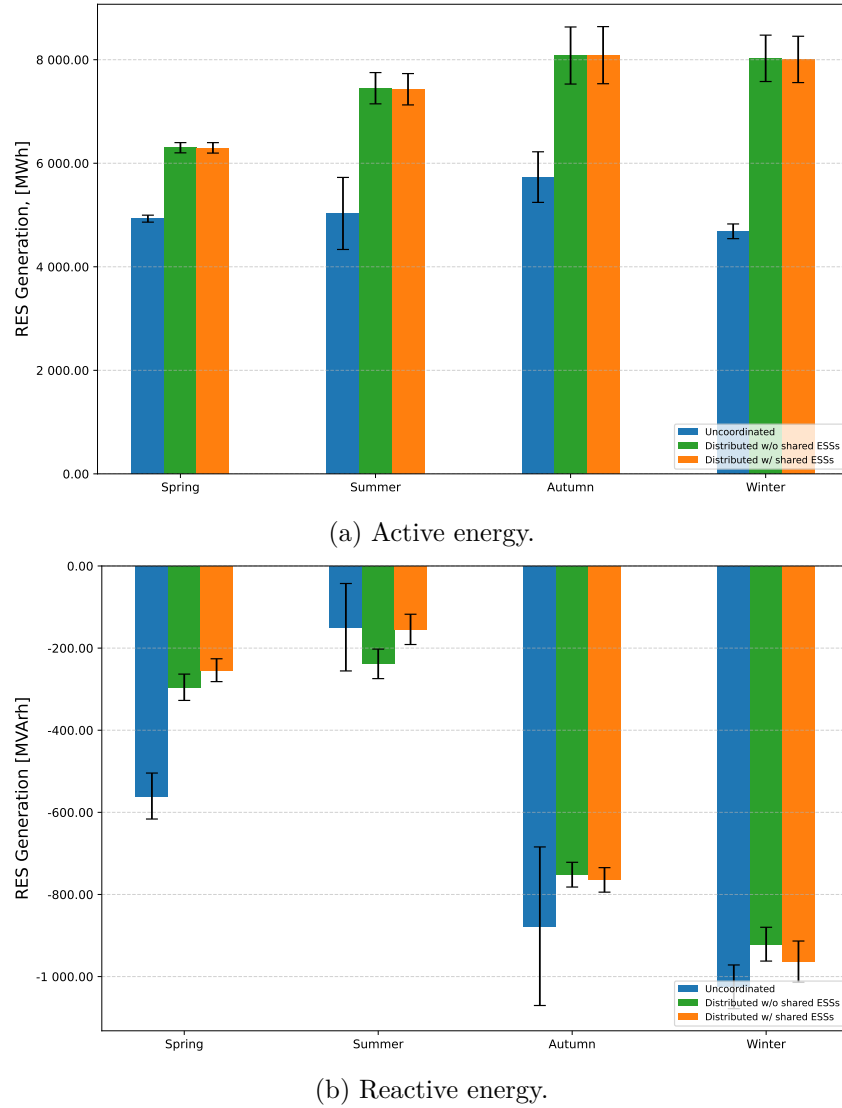


Figure 7.20: Case Study 2. RES generation per representative day and test case.

Across all seasons, coordinated operation enables significantly higher levels of active RES integration compared to the uncoordinated benchmark. Moreover, coordinated operation generally allows RES units to operate closer to unitary power factor, as evidenced by reduced reactive power absorption in most representative days.

Under uncoordinated operation, RES generators are often required to absorb larger amounts of reactive power to support transmission-level voltage regulation. Coordinated operation alleviates this burden by optimally allocating reactive power support across the TN and DNs. The main exception occurs during the summer representative day, where reactive power absorption increases by 59.82% without shared ESSs and by 3.52% with shared ESSs. However, the absolute magnitude of reactive power support required during summer is significantly lower than in the other representative days, limiting its overall impact. Figure 7.21 shows total RES generation and curtailed energy for each representative day and test case.

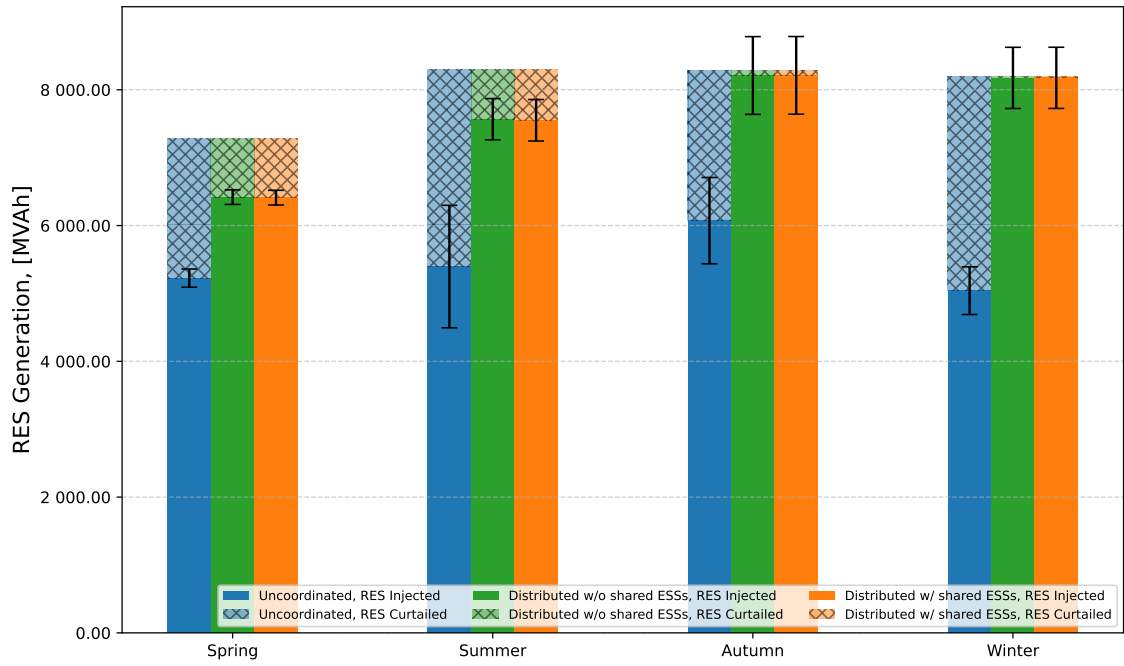


Figure 7.21: Case Study 2. RES curtailment per representative day and test case.

For the autumn and winter representative days, coordinated operation nearly eliminates RES curtailment. For spring and summer, curtailment is substantially reduced: by 56.92% and 56.51% in spring (without and with shared ESSs, respectively), and by 73.79% and 73.24% in summer.

7.2.2.4 Convergence Characteristic

Figure 7.22 illustrates the convergence behavior of the distributed coordination algorithm for the spring representative day. Both coordinated test cases, with and without shared ESSs, converged after six ADMM iterations. Here, iteration $k = 0$ represents the initialization and is not counted as an ADMM iteration. The corresponding results for the remaining representative days are provided in Appendix B.4.1, Figures B.53–B.55.

Convergence was achieved after seven iterations in summer, five in autumn, and seven in winter. Therefore, all analyzed operating conditions converged within five to seven

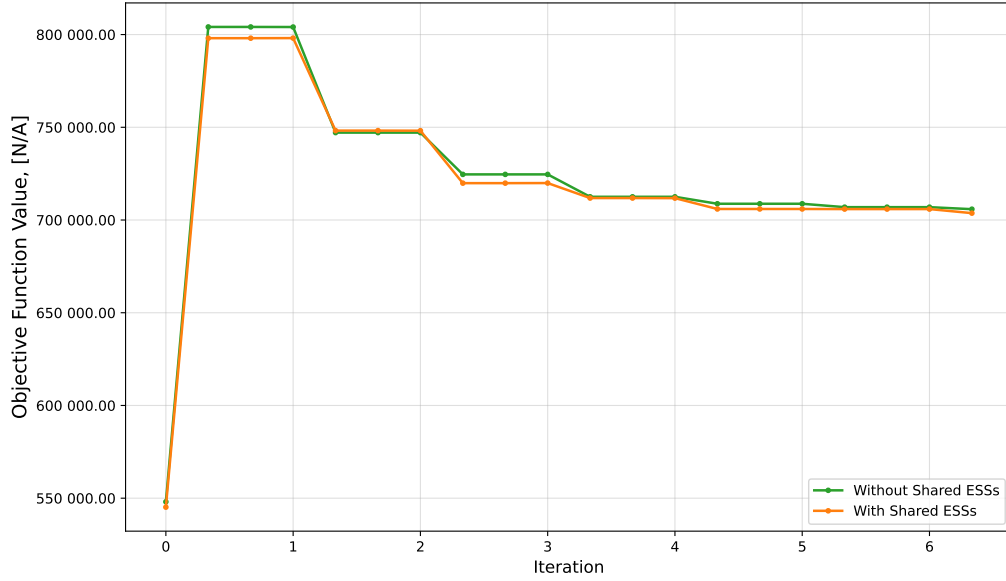


Figure 7.22: Case Study 2. Primal evolution. Spring representative day.

ADMM iterations, indicating consistent convergence behavior across seasons and regardless of whether shared ESSs were included.

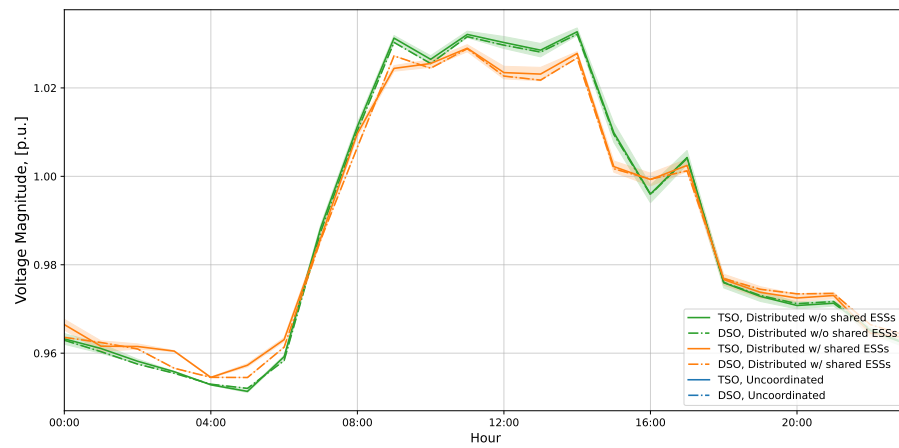
7.2.2.5 Interface Voltage Magnitude, Power Flows, and Shared ESSs

Figures 7.23 and 7.24 illustrate voltage magnitudes and active/reactive power flows at interface nodes 2 and 18 for the spring representative day. These nodes were selected to compare interface behavior with and without shared ESSs. Figure 7.25 presents the active and reactive power profiles of the shared ESS installed at node 18.

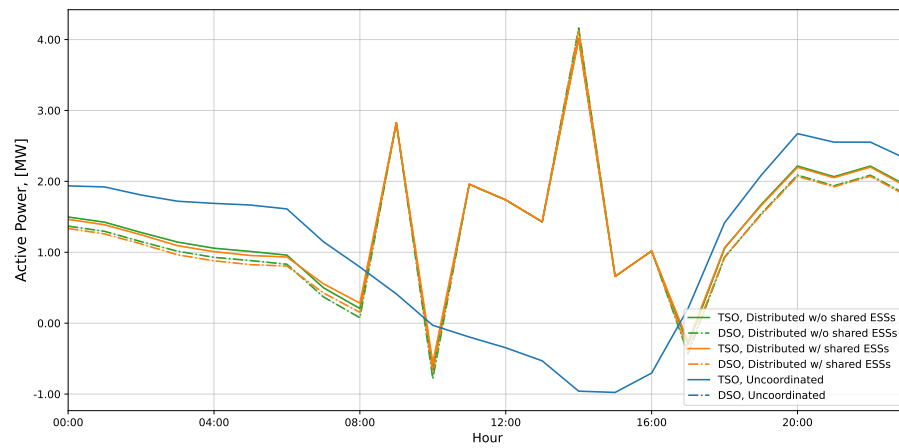
Despite requiring only a limited number of iterations to converge, the results show that the proposed coordination mechanism enables the TSO and DSOs to reach consistent agreements on interface voltage magnitudes, power flow profiles, and shared ESS operation. Compared to uncoordinated operation, coordinated operation results in significant changes in both active and reactive power flows at the TN–DN interfaces. These differences are particularly pronounced for reactive power flows, underscoring the importance of coordinated voltage support across network levels. For completeness, interface voltage magnitude and power flow results for the remaining interface nodes, as well as shared ESSs operating profiles, are provided in Subsections B.4.2 and B.4.3, respectively.

7.2.3 Conclusions

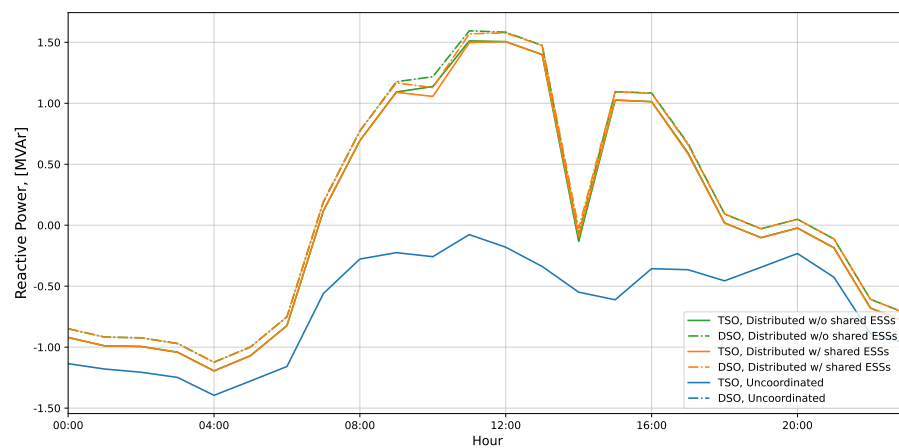
In contrast to Case Study 1, which focused on highly stressed operating conditions, this case study evaluated the operational value of coordinated TSO–DSO operation under “normal” system conditions. The analysis considered a larger and more heterogeneous test system, comprising multiple ADNs with varying levels of RES penetration and flexibility



(a) Voltage magnitude.

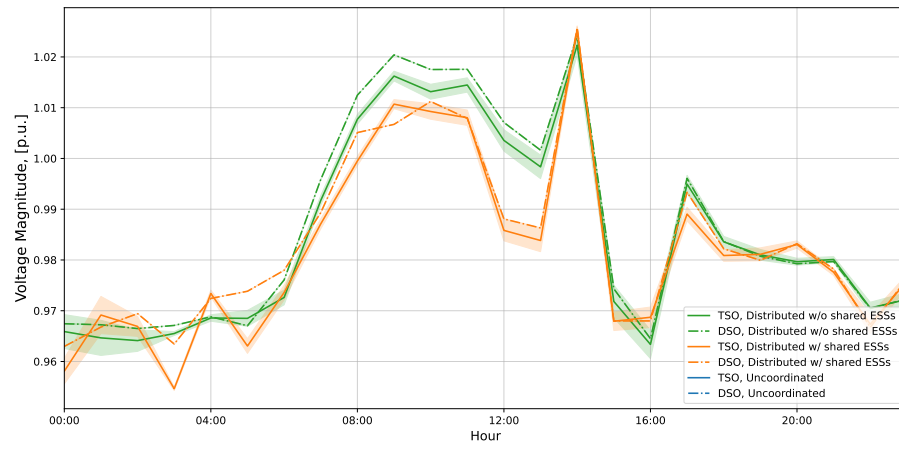


(b) Active power.

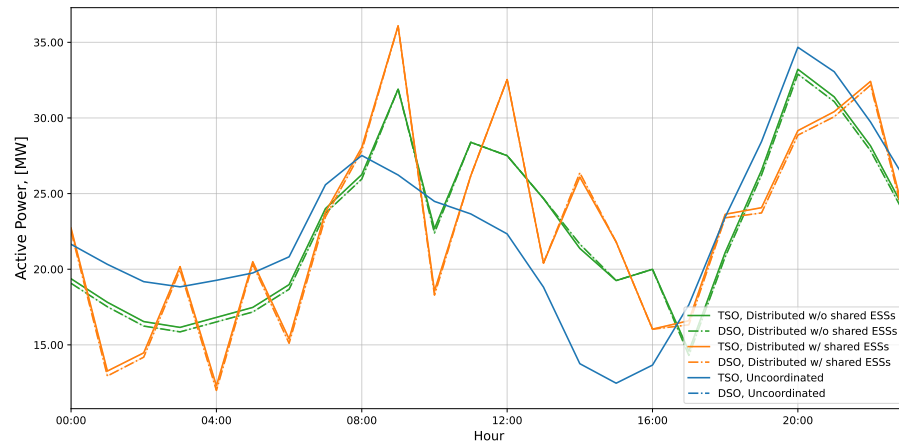


(c) Reactive power.

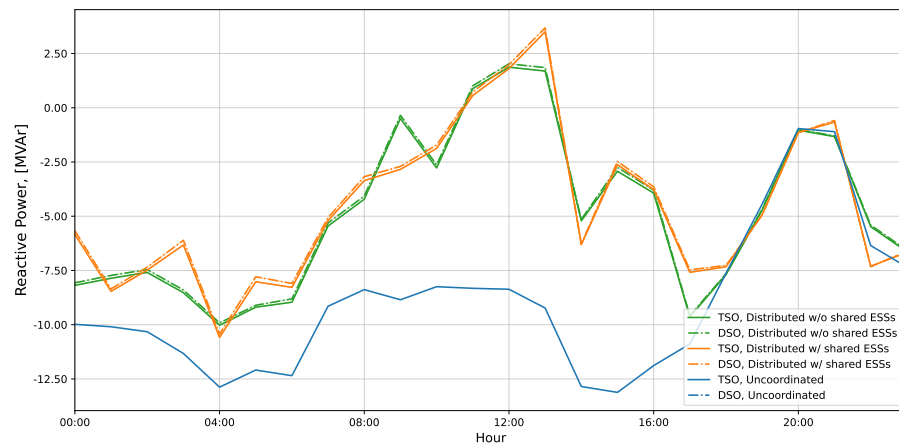
Figure 7.23: Case Study 2. ADN node 2. Comparison of interface voltage magnitude and power flows for the three test cases analyzed. Spring representative day.



(a) Voltage magnitude.



(b) Active power.



(c) Reactive power.

Figure 7.24: Case Study 2. ADN node 18. Comparison of interface voltage magnitude and power flows for the three test cases analyzed. Spring representative day.

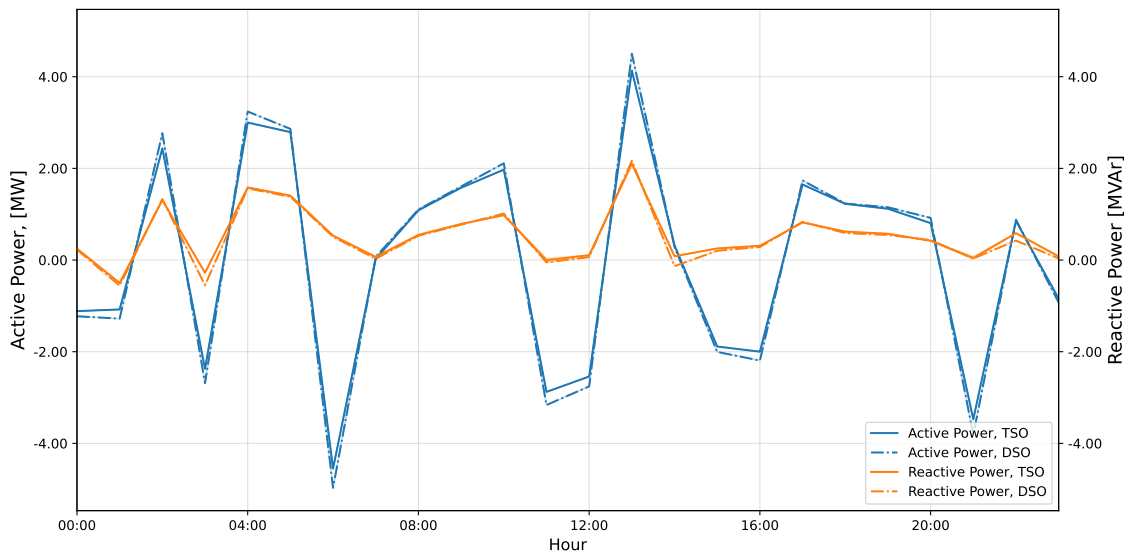


Figure 7.25: Case Study 2. ADN node 18. Comparison of shared ESS active and reactive power profiles. Spring representative day.

availability. Seasonal variability was captured through one representative day per season, enabling a systematic assessment of the proposed coordination framework across a wide range of operating conditions.

Based on the results presented above, the following main conclusions can be drawn:

1. Operational costs: Coordinated operation of the **TN** and **DN**s yields *substantial* reductions in total operational costs across all representative days. These savings are primarily driven by a reduced reliance on conventional generation. Overall cost reductions range from a minimum of 17.91% (Summer, with shared **ESS**s) to a maximum of 26.38% (Winter, without shared **ESS**s). Importantly, coordinated operation does not systematically increase flexibility procurement costs. For instance, during the autumn representative day, flexibility costs decrease by 10.98% (with shared **ESS**s) and 11.19% (without shared **ESS**s).
2. **RES** integration: Coordinated operation significantly enhances **RES** integration. **RES** curtailment is virtually eliminated for the autumn and winter representative days and substantially reduced for spring and summer. Specifically, curtailment decreases by 56.51%–56.92% in spring and by 73.24%–73.79% in summer, depending on the availability of shared **ESS**s.
3. Flexibility procurement: The volume of procured active power flexibility does not systematically increase under coordinated operation. By contrast, reactive power flexibility procurement consistently increases, highlighting the critical role of **ADNs** in supporting transmission-level voltage regulation. When considered alongside the

observed reductions in operating costs, these findings indicate that coordinated operation enables a more efficient utilization of *existing* FSPs, delivering system-wide benefits relative to uncoordinated operation.

4. Efficiency of the distributed coordination algorithm: The proposed distributed coordination algorithm demonstrates robust and computationally efficient performance. Normalized computational effort ranges from 3.10 (Spring, without shared ESSs) to 8.61 (Winter, with shared ESSs), with convergence achieved within 5 to 7 iterations across all representative days. Furthermore, the decomposed structure of the optimization framework allows the SOs' subproblems to be solved in parallel, which can substantially reduce effective computation times in practical implementations.

Case Studies 1 and 2 demonstrate that distributed TSO–DSO coordination is both robust under stressed operating conditions and economically efficient under normal system operation. Case Study 1 showed that, in highly stressed scenarios where uncoordinated operation leads to voltage violations, the proposed coordination mechanism successfully eliminates all network violations while simultaneously reducing operational costs and increasing RES integration. Case Study 2 extended this analysis to a larger and more heterogeneous system operating under normal conditions, with a higher number of participating ADNs and across multiple seasons. The results confirm that coordinated operation can substantially reduce operational costs and RES curtailment, while enabling a more effective exploitation of distribution-level flexibility services. Finally, although coordinated operation entails higher computational effort than uncoordinated strategies, the proposed algorithm converges rapidly and benefits from a highly parallelizable subproblem structure, making it well suited for large-scale and real-world applications.

The computational results provide evidence of the feasibility of the proposed ADMM-based framework for coordinated operational planning involving multiple DN-level agents. Despite the increase in network size and the number of participating ADNs relative to Case Study 1, the normalized computational effort remained within the same order of magnitude. Moreover, the local DSO subproblems are mutually independent within each coordination step and may be solved in parallel, reducing the effective wall-clock computation time. The observed computational performance is compatible with the day-ahead operational-planning context considered in this work and supports the application of the framework to larger coordinated planning problems. Nevertheless, validation using full-scale utility networks remains an important direction for future work.

Another important insight is that all consensus penalty parameters were initialized to $\rho^0 = 1$. Since the coupling-variable deviations are normalized by their corresponding base quantities, the same initial value was adopted across the case studies without case-specific tuning. Although the penalty parameters influence the convergence rate of ADMM, a systematic sensitivity analysis was outside the scope of this work. More sophisticated

strategies could be investigated to further improve computational performance in larger or more heterogeneous systems.

Finally, the results of both case studies indicate that the inclusion of shared ESSs does not *systematically* guarantee additional operational or convergence benefits. In Case Study 1, shared ESSs improved convergence speed and reduced operational costs, albeit at the expense of slightly higher RES curtailment. In contrast, Case Study 2 revealed a more heterogeneous impact: shared ESSs provided clear benefits for some representative days, while yielding marginal or even negative effects for others. These findings underscore the importance of dedicated planning methodologies for shared resources, which explicitly account for network characteristics, operating conditions, and seasonal variability.

7.3 Case Study 3

As demonstrated in Case Studies 1 and 2, the deployment of shared ESSs at TN–DN interface nodes can deliver tangible benefits for power system operation. These benefits include not only improved convergence and robustness of the TSO–DSO coordination process, but also measurable operational gains, such as reduced system operating costs and lower RES curtailment. At the same time, the results of the previous case studies indicate that these benefits are not systematic and depend critically on the sizing, siting, and operational utilization of the shared storage resources. Inappropriate or *ad hoc* deployment strategies may therefore limit – or even negate – the potential advantages of shared ESSs in coordinated transmission-distribution operation.

Motivated by these observations, this section presents a third case study aimed at evaluating the performance of the shared resources planning framework introduced in Chapter 6. The objective of this case study is to assess the ability of the proposed planning tool to determine effective siting and sizing strategies for shared ESSs that enhance system-wide operational performance under coordinated TSO–DSO operation. In contrast to the previous case studies, this analysis explicitly accounts for uncertainty in market price forecasts.

7.3.1 Case Study Description

The test system adopted in this case study closely follows that of Case Study 1 (Section 7.1), enabling a consistent comparison between operational and planning analyses. It consists of an IEEE 9-bus TN coupled with three ADNs, each derived from the IEEE 33-bus radial distribution test system (Zimmerman et al., 2011; Baran and Wu, 1989). A representative single-line diagram of the integrated transmission–distribution system is shown in Figure 7.1 of Section 7.1.

The planning horizon spans 15 years and is discretized into five representative years (2025, 2028, 2031, 2034, and 2037), each representing a three-year interval. The horizon was selected as a representative medium- to long-term planning period, approximately

aligned with the assumed calendar lifetime of the shared **ESSs**. It does not represent the time required to deploy an **ESS**; rather, it allows the planning framework to capture the long-term operational value, degradation, and timing of candidate investments while accounting for the evolution of demand, **RES** capacity, operating conditions, and investment costs. The proposed methodology is not restricted to this assumption and may be applied to shorter or longer planning horizons. For each representative year, four representative days – one per season – are considered to capture seasonal variability in load demand and **RES** generation across the planning horizon. Uncertainty is represented at both the planning and operational levels. At the planning level, three investment cost scenarios are considered for shared **ESSs**. At the operational level, five load and **RES** generation scenarios are combined with five market price scenarios, resulting in 25 operational scenarios per representative day.

To assess the operational value of the investment decisions produced by the proposed planning framework, the resulting shared **ESS** deployment strategy is benchmarked against the following cases:

- Traditional (uncoordinated) operation: serving as a baseline for quantifying the overall benefits of **TSO–DSO** coordination.
- Coordinated operation without shared **ESSs**: enabling the assessment of the additional operational value attributable specifically to shared **ESSs**.

A total investment budget of 1 M€ is assumed for shared **ESS** deployment. For each interface node $e \in E^S$ and representative year $y \in Y$, the maximum installable energy capacity is limited to $E_{e,y}^{\text{Max}} = 5.00$ MWh. All shared **ESSs** are assigned a calendar lifetime of $T_{e,y}^{\text{cal}} = 15$ years, and a discount rate of 2.00% is applied to all investment-related cash flows.

All simulations associated with this case study were conducted on a Mac Studio workstation equipped with an Apple M2 Max processor and 32 GB of RAM.

7.3.1.1 Investment Costs

Table 7.12 summarizes the assumed investment costs associated with the power rating and energy capacity of shared **ESSs**, along with the corresponding probabilities assigned to each investment scenario. To explicitly account for uncertainty in future **ESS** cost evolution, three alternative cost trajectories are considered – *low*, *medium*, and *high*. These scenarios are derived from the cost projections reported in NREL’s *Annual Technology Baseline* (NREL, 2024) and represent plausible ranges of technological progress and market development over the planning horizon.

Table 7.12: Case Study 3. Investment costs of shared ESSs (NREL, 2024).

Parameter	Scen.	Prob., [%]	2025	2028	2031	2034	2037
$c_{y,c}^{\text{Inv},S}$, [k€/MVA]	1	35.00%	214.17	186.90	165.76	156.88	148.01
	2	55.00%	267.53	241.56	220.79	210.42	200.04
	3	10.00%	342.17	303.72	276.19	270.48	264.77
$c_{y,c}^{\text{Inv},E}$, [k€/MWh]	1	35.00%	169.71	148.10	131.35	124.31	117.28
	2	55.00%	211.99	191.41	174.95	166.73	158.51
	3	10.00%	271.13	240.67	218.85	214.33	209.80

As shown in Table 7.12, both power- and energy-related investment costs are assumed to decline over time across all scenarios. This trend reflects expected technological learning effects, economies of scale, and continued reductions in manufacturing and balance-of-system costs (NREL, 2024; IEA, 2024b). The spread between scenarios captures uncertainty in the pace of cost reductions and market maturation.

By explicitly modeling multiple investment cost trajectories and their associated probabilities, the proposed planning framework accounts for investment cost uncertainty directly within the optimization process. This enables the model not only to identify the optimal *siting* and *sizing* of shared ESSs, but also to make informed decisions regarding the *timing* of capacity deployment. In particular, the staged structure of the planning formulation allows investment decisions to be deferred or anticipated in response to evolving cost projections, while ensuring that system operation under coordinated TSO–DSO control remains feasible and economically efficient throughout the planning horizon.

7.3.1.2 Market Data

Similarly to the previous case studies, conventional generators are remunerated based on wholesale energy market prices, while FSPs are compensated according to flexibility market prices. In contrast to Case Studies 1 and 2, however, market prices are not assumed to be known *a priori*. Instead, uncertainty associated with market price forecasts is explicitly incorporated into the shared ESSs planning framework.

Baseline wholesale energy price profiles were obtained from the Portuguese TSO’s market platform (REN, 2025), while flexibility market price data were sourced from the ATTEST project repository (ATTEST, 2020). Figure 7.26 illustrates the wholesale energy and flexibility price profiles adopted for the spring representative day of the initial planning year (2025). Corresponding profiles for the summer, autumn, and winter representative days are provided in Figures C.13–C.15 in Appendix C.3.

These baseline profiles serve as reference trajectories for generating multiple market price scenarios over the planning horizon. Wholesale energy prices are assumed to increase at an average annual growth rate of 2.50%, while flexibility market prices are assumed

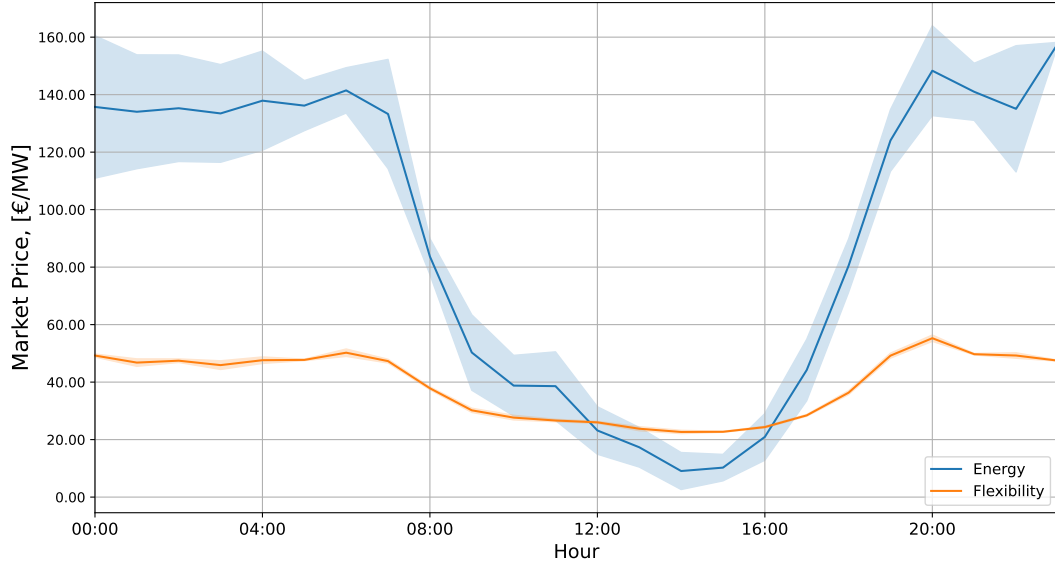


Figure 7.26: Case Study 3. Wholesale energy and flexibility market prices. Spring 2025.

to grow at an annual rate of 2.00%. These assumptions reflect anticipated long-term market evolution and introduce uncertainty that directly affects both operational revenues and the economic attractiveness of shared ESSs investments. By explicitly representing market price uncertainty across representative years and scenarios, the proposed planning framework captures the trade-offs between near-term and long-term operational value, thereby informing the optimal timing and sizing of storage investments within the staged planning process.

7.3.1.3 Transmission Network

The TN considered in this case study is based on the IEEE 9-bus test system and largely follows the configuration described in Section 7.1 and Appendix A. The key distinction with respect to Case Study 1 lies in the assumed evolution of installed RES capacity over the planning horizon. Figure A.1 shows the single-line diagram of the adopted TN. Detailed data for buses, branches, and conventional generators are provided in Tables A.1, A.2, and A.3 in Appendix A.1.

To capture the progressive increase in renewable penetration, the installed capacities of RES generators are assumed to vary across the representative years of the planning horizon. The corresponding wind and solar PV capacities for each representative year are summarized in Table 7.13. Figure 7.27 illustrates the RES generation profiles adopted for the spring representative day of the initial planning year (2025), while the profiles for the summer, autumn, and winter representative days are provided in Figures C.1–C.3 in Appendix C.

Table 7.13: Case Study 3. TN RES installed capacity per representative year.

Generator	Node	Generator	Installed capacity, [MW]				
ID	ID	Type	2025	2028	2031	2034	2037
4	4	Wind	20.00	20.00	30.00	30.00	50.00
5	6	Wind	40.00	40.00	60.00	60.00	60.00
6	8	Wind	25.00	25.00	40.00	40.00	40.00
7	4	Solar PV	12.00	12.00	20.00	20.00	20.00
8	6	Solar PV	20.00	20.00	30.00	30.00	50.00
9	8	Solar PV	15.00	15.00	25.00	25.00	25.00

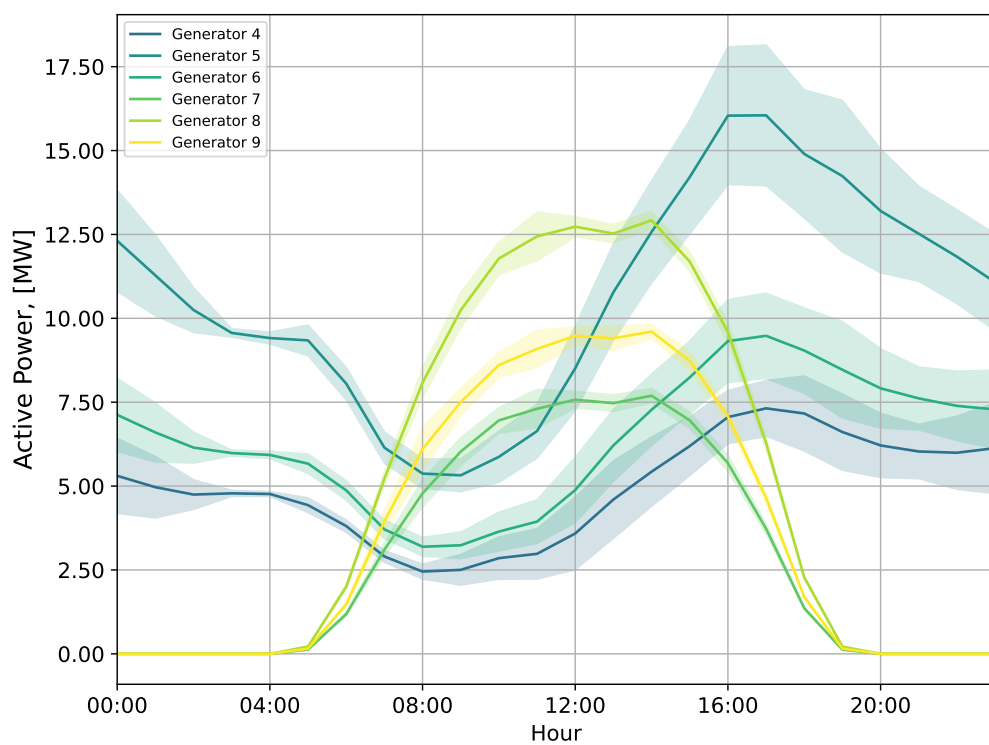


Figure 7.27: Case Study 3. TN RES generation profiles. Spring 2025.

7.3.1.4 ADN Connected to Node 5 of the TN

This subsection describes the **ADN** connected to node 5 of the **TN** and participating in the coordinated planning framework. As noted previously, all **ADNs** considered in this case study are derived from the **IEEE 33-bus** radial distribution test system (**Baran and Wu, 1989**), which has been adapted to represent different levels and mixes of wind and solar **PV** generation over the planning horizon. For clarity, the spring representative day of the initial planning year (2025) is described in detail in this subsection, while the remaining representative days are documented in Appendix **C.2**.

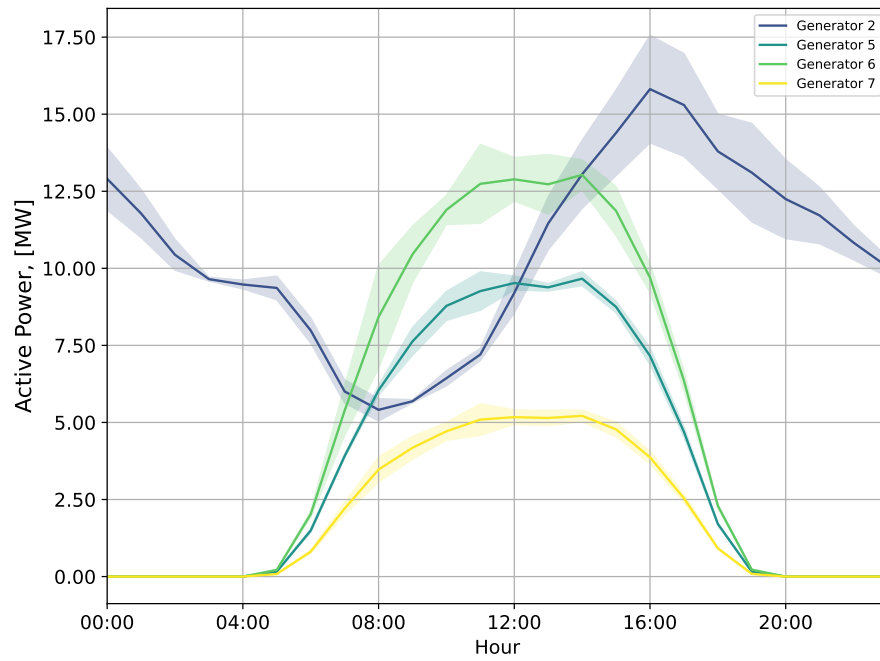
The network topology of the underlying **IEEE 33-bus** system is presented in Appendix **A.2**, with the corresponding single-line diagram shown in Figure **A.2**. Detailed data for buses, branches, and conventional generators are provided in Tables **A.4**, **A.5**, and **A.6**, respectively. Within each **ADN**, all 32 loads are assumed to represent downstream networks operating at lower voltage levels and are modeled as **FLs** capable of providing flexibility services. The three **ADNs** considered in this case study differ in their installed **RES** capacities, technology mix, and availability of flexible **DERs**, thereby enabling the planning framework to be evaluated under heterogeneous distribution-level conditions.

Table **7.14** summarizes the installed **RES** capacity of the **ADN** connected to node 5 of the **TN** for all representative years considered in the planning horizon. The corresponding **RES** generation and load profiles for the spring representative day of 2025 are shown in Figure **7.28**. Seasonal profiles for the summer, autumn, and winter representative days are provided in Figures **C.4**, **C.5**, and **C.6** of Appendix **C.2.1**, respectively.

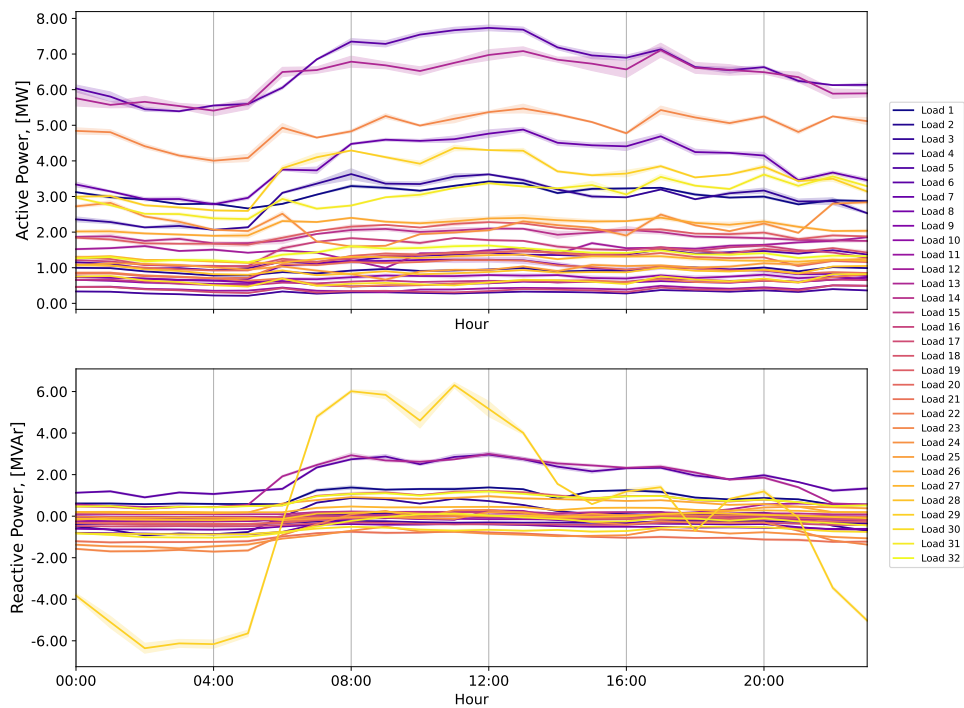
Table 7.14: Case Study 3. ADN node 5. RES installed capacity, per simulation year.

Generator	Node	Generator	Installed capacity, [MW]				
ID	ID	Type	2025	2028	2031	2034	2037
2	6	Wind	40.00	40.00	50.00	50.00	50.00
3	23	Solar PV	15.00	15.00	25.00	25.00	25.00
4	25	Solar PV	20.00	20.00	20.00	20.00	30.00
5	18	Solar PV	8.00	8.00	15.00	15.00	35.00

Figure **7.29** presents the flexible load profiles considered for the **ADN** connected to node 5 of the **TN**. The total flexible demand is allocated among the **FLs** according to the **FL** ratios reported in Table **A.7**. The “static” and flexible load portions of the total load are assumed to grow at average rates of 1.25% and 3.00% per year, respectively.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure 7.28: Case Study 3. ADN node 5. RES generation and load profiles. Spring 2025.

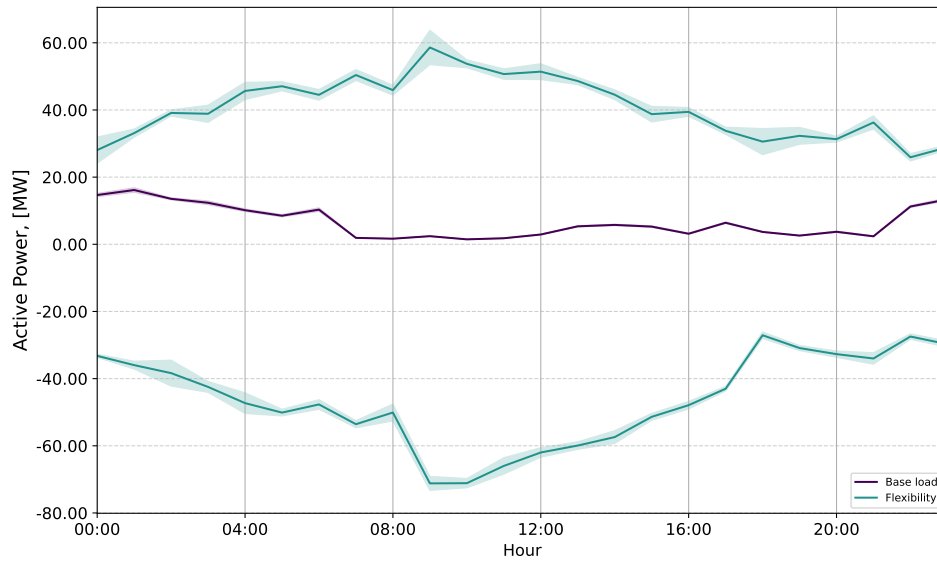


Figure 7.29: Case Study 3. ADN node 5. Flexible load profiles.

7.3.1.5 ADN Connected to Node 7 of the TN

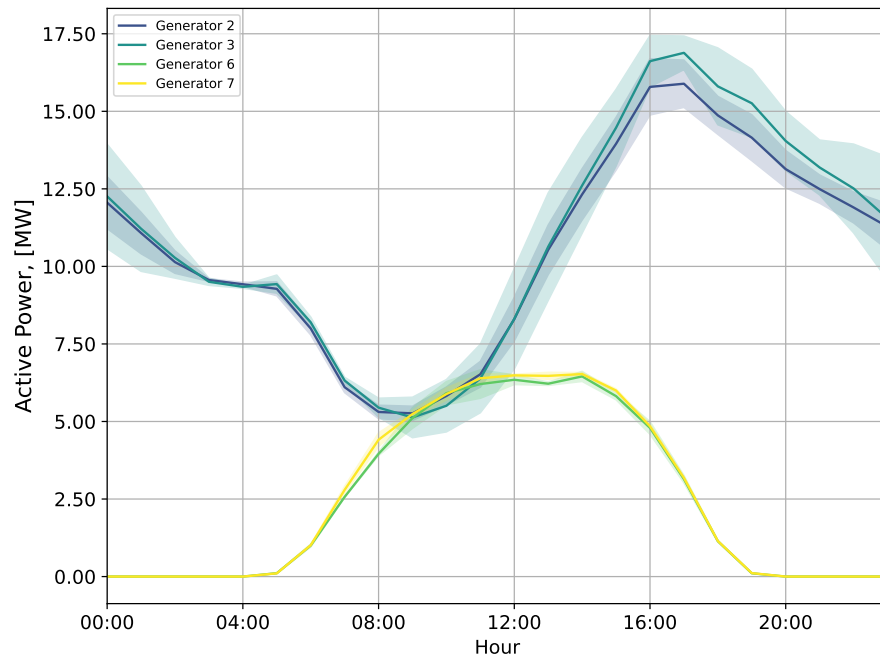
The ADN connected to node 7 of the TN follows the same modeling assumptions as the ADN described in the previous subsection, while differing in its installed RES capacity, technology mix, and their evolution over the planning horizon.

Table 7.15 summarizes the evolution of installed RES capacity for this ADN across the representative years of the planning horizon. Figure 7.30 illustrates the corresponding RES generation and load profiles for the spring representative day of the initial planning year (2025). Seasonal profiles for the remaining representative days are provided in Figures C.7, C.8, and C.9 of Appendix C.2.2, respectively.

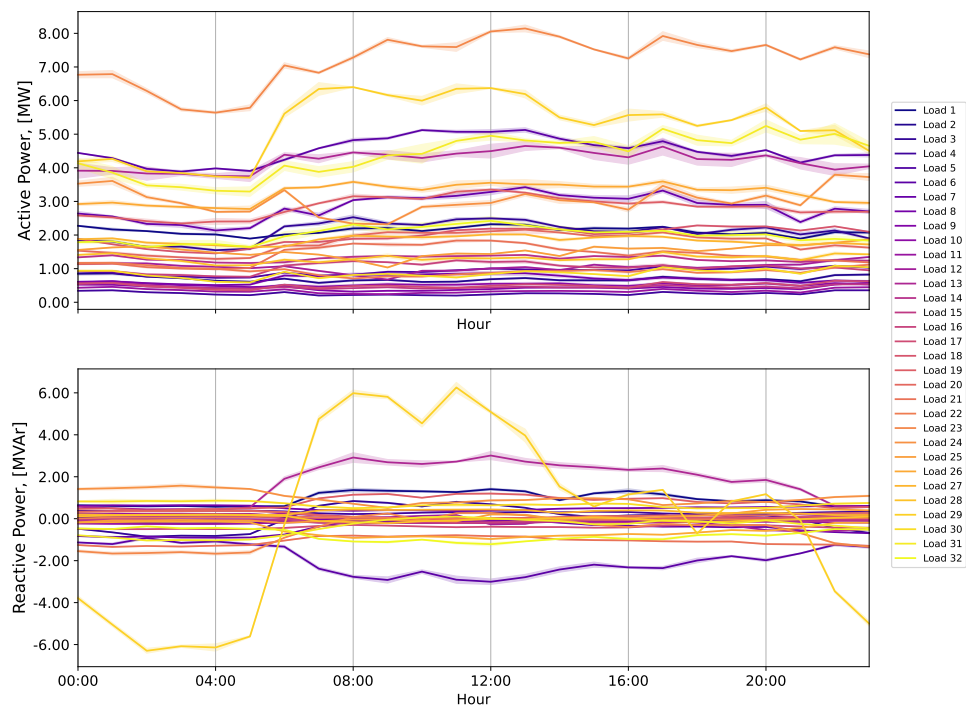
Table 7.15: Case Study 3. ADN node 7. RES installed capacity, per simulation year.

Generator ID	Node ID	Generator Type	Installed capacity, [MW]				
			2025	2028	2031	2034	2037
2	6	Wind	40.00	40.00	50.00	50.00	50.00
3	23	Wind	40.00	40.00	40.00	40.00	40.00
4	25	Solar PV	10.00	10.00	20.00	20.00	20.00
5	18	Solar PV	10.00	10.00	10.00	10.00	30.00

Figure 7.31 presents the flexible load profiles adopted for this ADN. As in the previous case, the total flexible demand is distributed among the individual FLs according to the ratios reported in Table A.7. The static and flexible portions of the total demand are assumed to grow at average annual rates of 1.25% and 3.00%, respectively, reflecting the increasing availability and participation of DERs over the planning horizon.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure 7.30: Case Study 3. ADN node 7. RES generation and load profiles. Spring 2025.

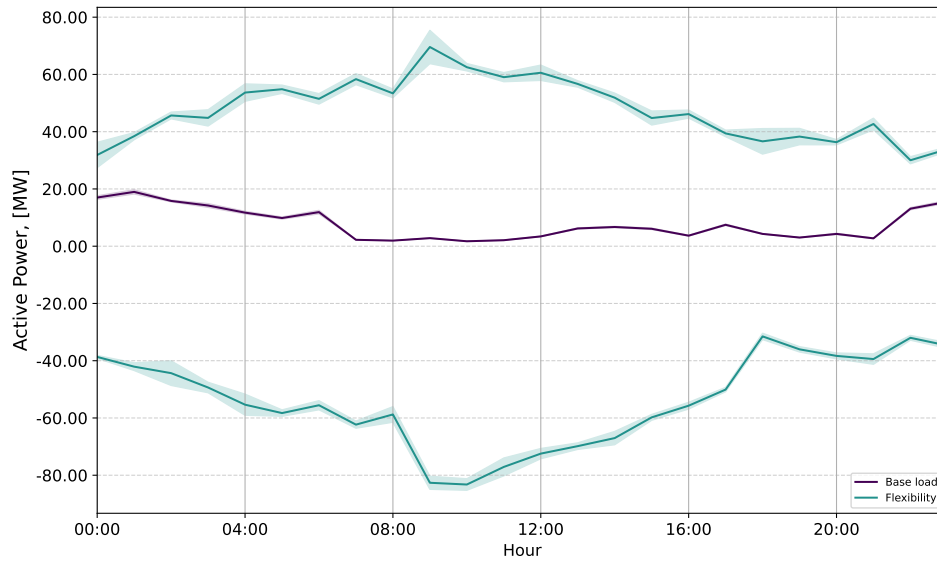


Figure 7.31: Case Study 3. ADN node 7. Flexible load profiles.

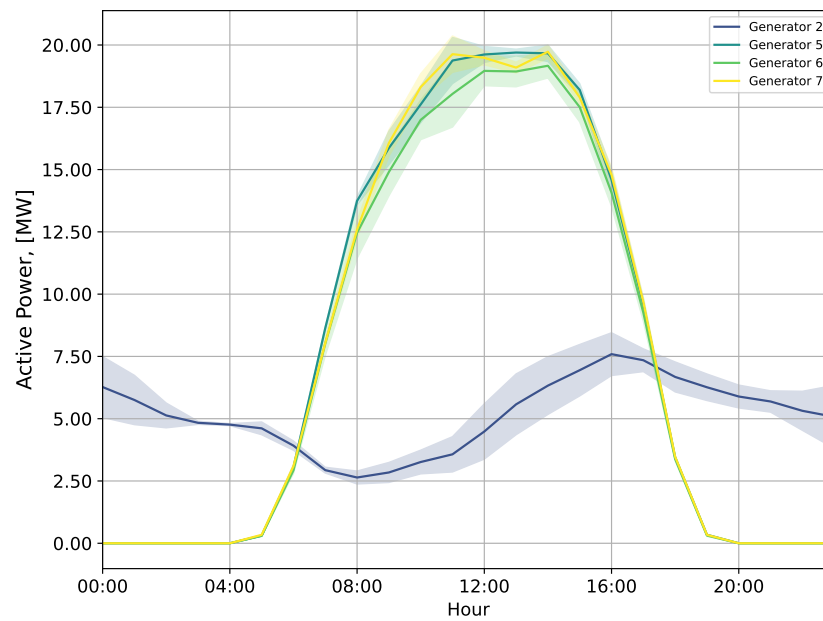
7.3.1.6 ADN Connected to Node 9 of the TN

The **ADN** connected to node 9 of the **TN** represents a distribution area with comparatively higher overall **RES** penetration, predominantly driven by solar **PV** generation. Table 7.16 summarizes the evolution of installed **RES** capacity for this **ADN** across the representative years of the planning horizon. Figure 7.32 illustrates the corresponding **RES** generation and load profiles for the spring representative day of the initial planning year (2025). Seasonal profiles for the summer, autumn, and winter representative days are provided in Figures C.10, C.11, and C.12 of Appendix C.2.3, respectively.

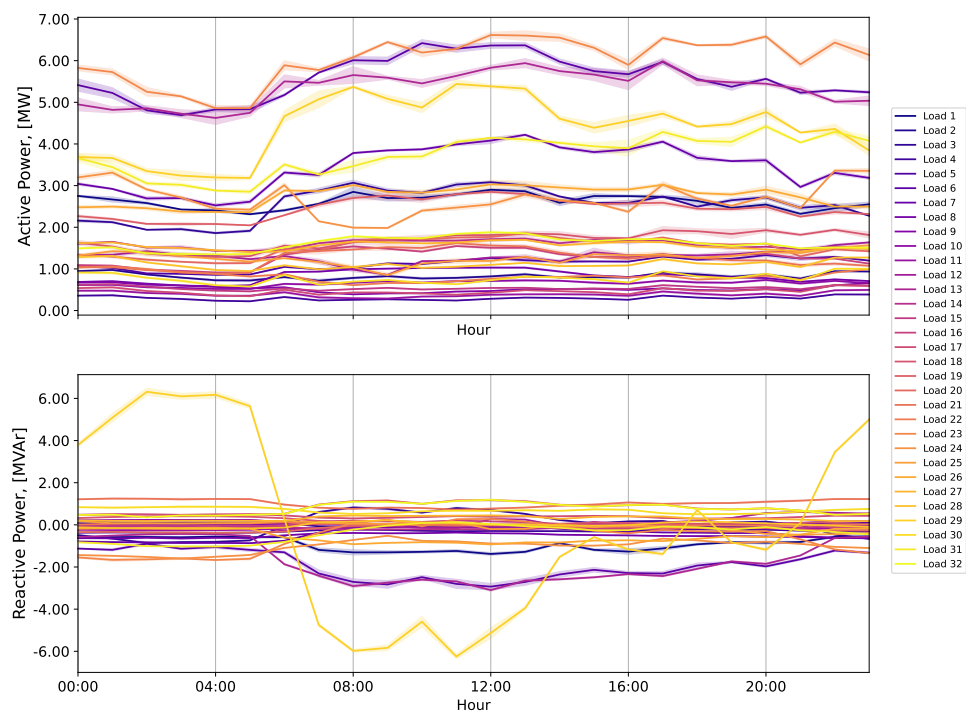
Table 7.16: Case Study 3. ADN node 9. RES installed capacity, per simulation year.

Generator ID	Node ID	Generator Type	Installed capacity, [MW]				
			2025	2028	2031	2034	2037
2	6	Wind	20.00	20.00	50.00	50.00	50.00
3	25	Solar PV	30.00	30.00	30.00	30.00	30.00
4	23	Solar PV	30.00	30.00	30.00	30.00	50.00
5	18	Solar PV	30.00	30.00	30.00	30.00	40.00

Figure 7.33 presents the flexible load profiles adopted for the **ADN** connected to node 9. As in the other **ADNs**, the allocation of flexible demand among individual **FLs** follows the ratios reported in Table A.7. The static and flexible components of total demand are assumed to grow at average annual rates of 1.25% and 3.00%, respectively, reflecting the increasing availability of demand-side flexibility over the planning horizon.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure 7.32: Case Study 3. ADN node 9. RES generation and load profiles. Spring 2025.

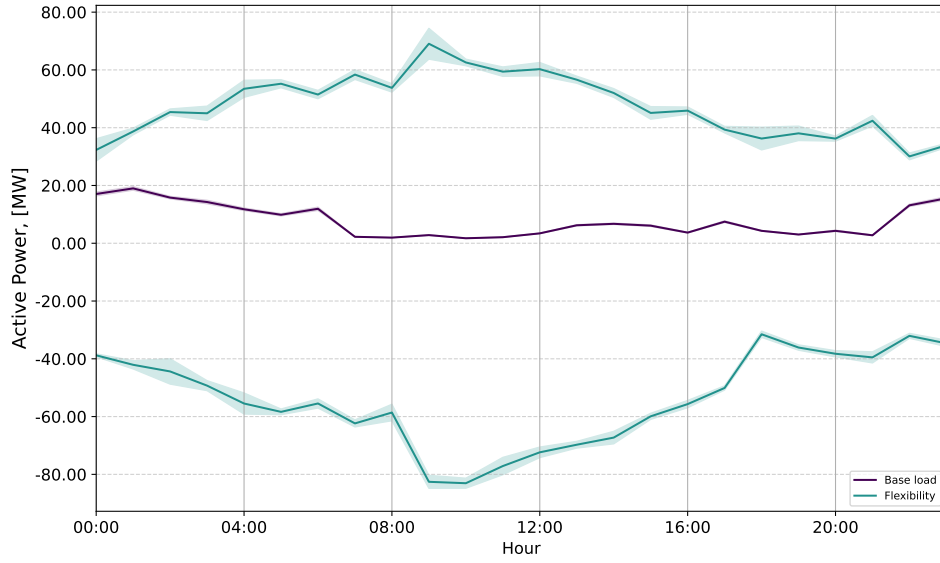


Figure 7.33: Case Study 3. ADN node 9. Flexible load profiles.

7.3.2 Results

This subsection summarizes the main results obtained in Case Study 3. Given the large volume of data generated by the multi-year, multi-scenario planning analysis, only the most relevant findings are highlighted here.

7.3.2.1 Investment Plan

Table 7.17 reports the optimal investment plan for shared resources obtained with the proposed planning framework. The table presents the investment decisions per transmission–distribution interface node and investment cost scenario, together with the corresponding expected yearly investment expenditures expressed in Net Present Value (NPV).

The results reveal a clear preference for early deployment of shared ESSs: the entire available investment budget is allocated in the first representative year (2025), with no additional investments selected in subsequent years. This outcome indicates that, for the considered system configuration and uncertainty assumptions, the operational benefits associated with early deployment outweigh the long-term effects of capacity degradation due to battery cycling. In other words, deferring investments to later years does not generate sufficient economic advantage to offset the operational benefits obtained in the initial stages of the planning horizon. Furthermore, node 7 is consistently selected as the preferred location for shared ESSs installation. A single storage unit is deployed at this node, while no investments are selected at nodes 5 and 9. This result reflects the strategic importance of node 7 in terms of its impact on coordinated system operation, local congestion patterns, and flexibility requirements at the TN–DN interface.

Table 7.17: Investment plan in shared resources.

Bus ID	Parameter	Scenario	2025	2028	2031	2034	2037
5	$S_{e,y}^{\text{Inv}}$, [MVA]	1	-	-	-	-	-
		2	-	-	-	-	-
		3	-	-	-	-	-
		Expected	-	-	-	-	-
	$E_{e,y}^{\text{Inv}}$, [MWh]	1	-	-	-	-	-
		2	-	-	-	-	-
		3	-	-	-	-	-
		Expected	-	-	-	-	-
7	$S_{e,y}^{\text{Inv}}$, [MVA]	1	2.50	-	-	-	-
		2	1.36	-	-	-	-
		3	-	-	-	-	-
		Expected	1.62	-	-	-	-
	$E_{e,y}^{\text{Inv}}$, [MWh]	1	5.00	-	-	-	-
		2	2.71	-	-	-	-
		3	-	-	-	-	-
		Expected	3.24	-	-	-	-
9	$S_{e,y}^{\text{Inv}}$, [MVA]	1	-	-	-	-	-
		2	-	-	-	-	-
		3	-	-	-	-	-
		Expected	-	-	-	-	-
	$E_{e,y}^{\text{Inv}}$, [MWh]	1	-	-	-	-	-
		2	-	-	-	-	-
		3	-	-	-	-	-
		Expected	-	-	-	-	-
-	Inv., [NPV M€]	Expected	1.00	0.00	0.00	0.00	0.00

A scenario-level analysis further illustrates the influence of investment cost uncertainty on the optimal deployment strategy. Under the *low-cost* scenario (Scenario 1 in Table 7.12), the model installs a shared ESS with the maximum admissible energy capacity at node 7 (5.00 MWh). In the *medium-cost* scenario (Scenario 2), a smaller unit of 1.36 MW/2.71 MWh is selected. In contrast, no investment is undertaken under the *high-cost* scenario (Scenario 3), indicating that the expected operational benefits may be insufficient to justify deployment when investment costs remain elevated. Overall, these results demonstrate the ability of the proposed planning framework to adapt both the timing and sizing of shared ESSs investments to cost uncertainty, while maintaining consistency with system-wide operational performance under coordinated TSO–DSO operation.

Table 7.18 reports the rated power, rated energy capacity, available energy capacity, and SoH of the installed shared ESS at the end of each representative year. The results clearly show a substantial degradation of the available energy capacity over the planning horizon, underscoring the importance of explicitly modeling battery degradation in long-term planning studies – a feature that remains largely overlooked in the power system planning literature.

Table 7.18: Shared ESSs rated power, energy capacity, and SoH.

Node ID	Parameter	2025	2028	2031	2034	2037
5	$S_{e,y}^{\text{Rated}}$, [MVA]	-	-	-	-	-
	$E_{e,y}^{\text{Rated}}$, [MWh]	-	-	-	-	-
	$E_{e,y}^{\text{Av}}$, [MWh]	-	-	-	-	-
	SoH, [%]	-	-	-	-	-
7	$S_{e,y}^{\text{rated}}$, [MVA]	1.62	1.62	1.62	1.62	1.62
	$E_{e,y}^{\text{rated}}$, [MWh]	3.24	3.24	3.24	3.24	3.24
	$E_{e,y}^{\text{Av}}$, [MWh]	2.62	2.27	1.99	1.76	1.61
	SoH, [%]	80.90%	69.88%	61.24%	54.41%	49.62%
9	$S_{e,y}^{\text{rated}}$, [MVA]	-	-	-	-	-
	$E_{e,y}^{\text{rated}}$, [MWh]	-	-	-	-	-
	$E_{e,y}^{\text{Av}}$, [MWh]	-	-	-	-	-
	SoH, [%]	-	-	-	-	-

For the shared ESS installed at node 7, the available energy capacity decreases by approximately 19.10% within the first three years of operation. By the end of the planning horizon – coinciding with the assumed calendar lifetime of the battery – the ESS reaches an SoH of 49.62%, while remaining above the minimum admissible threshold enforced by the model. This outcome confirms that the proposed planning framework is capable of balancing intensive operational utilization with long-term technical feasibility, ensuring that storage assets remain within their physical and degradation constraints throughout the entire planning horizon.

An additional insight emerging from Table 7.18 is that the shared ESS has the minimum admissible energy-to-power ratio of 2 h. This result indicates that, for the considered case study, power capacity is valued more highly than energy capacity. From an operational perspective, this suggests that flexibility requirements at the TN–DN interface are predominantly short-term in nature, supporting fast adjustments of active and reactive power flows, rather than longer-duration services such as energy arbitrage.

7.3.2.2 Operational Planning Analysis

At the operational level, the results indicate that under traditional (uncoordinated) operation, voltage magnitude violations emerge as early as the first representative year of the planning horizon (2025). As an illustrative example, Figure 7.34 shows the voltage magnitude profile at node 3 of the TN for the winter representative day of 2025, comparing uncoordinated operation with coordinated operation both with and without shared ESSs. Under uncoordinated operation, an undervoltage condition occurs around hour 2 and cannot be mitigated through local control actions alone. In contrast, both coordinated operation cases successfully eliminate the voltage violation through the coordinated activation of transmission- and distribution-level flexibility.

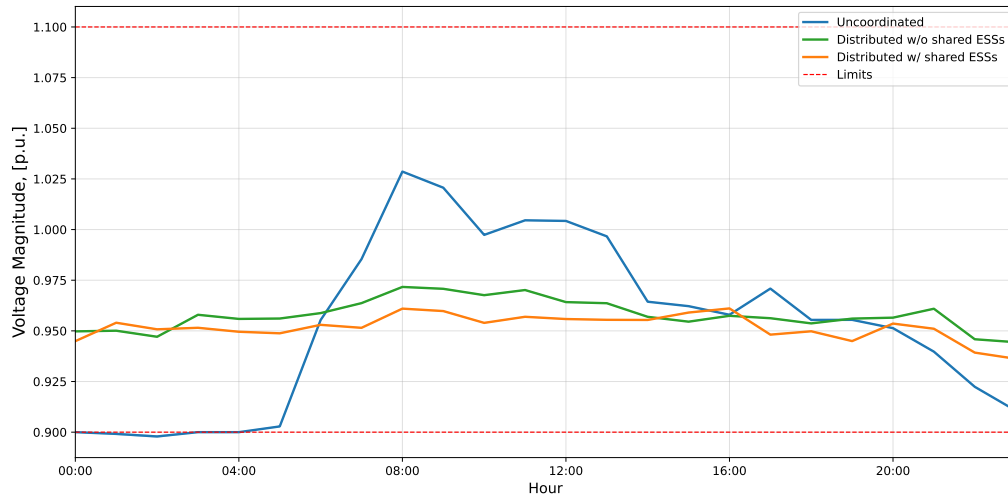


Figure 7.34: Case Study 3. TN. Voltage magnitude profiles of bus 3 of the TN for the winter representative day of 2025. Comparison between uncoordinated operation, and coordinated operation with and without shared ESSs.

These results lead to an important operational insight. In the absence of coordination, maintaining compliance with voltage limits would likely require conventional network reinforcements. Coordinated TSO–DSO operation, by contrast, resolves such violations by leveraging existing distributed flexibility resources. This demonstrates the potential of coordinated operation – and, more broadly, DER-based flexibility – as a cost-effective and operationally viable alternative to traditional grid reinforcement measures.

Table 7.19 summarizes the main operational outcomes of Case Study 3, reporting total operational costs, RES generation, and RES curtailment for each representative year of the planning horizon and for the three test cases considered. All values correspond to daily averages computed across the four representative days of each year. Complementary results disaggregated by representative day are reported in Table C.1 of Appendix C.

Table 7.19: Case Study 3. Operational planning summary. The results reported correspond to the daily average values for each representative year in the planning horizon.

Test Case	Year				
	2025	2028	2031	2034	2037
Uncoordinated					
Operational Cost, [€]	228 160.22	259 520.80	211 683.68	247 772.49	273 955.22
RES Generation, [MWh]	917.65	962.18	1 348.91	1 381.60	1 314.22
RES Curtailment, [MVAh]	1.30	2.77	81.23	54.34	409.29
Without Shared ESSs					
Operational Cost					
Total, [€]	222 309.25	250 720.96	202 001.02	236 819.08	228 540.87
Variation, [%]	-2.56%	-3.39%	-4.57%	-4.42%	-16.58%
RES Generation					
Total, [MWh]	907.86	947.99	1 415.01	1 422.13	1 677.43
Variation, [%]	-1.07%	-1.47%	4.90%	2.93%	27.64%
RES Curtailment					
Total, [MVAh]	12.95	17.82	15.24	13.80	46.89
Variation, [%]	894.07%	543.90%	-81.24%	-74.60%	-88.54%
With Shared ESSs					
Operational Cost					
Total, [€]	222 393.22	249 768.49	202 309.71	239 441.31	223 948.57
Variation, [%]	-2.53%	-3.76%	-4.43%	-3.36%	-18.25%
RES Generation					
Total, [MWh]	907.86	947.97	1 414.95	1 410.36	1 692.24
Variation, [%]	-1.07%	-1.48%	4.90%	2.08%	28.76%
RES Curtailment					
Total, [MVAh]	12.94	17.81	15.28	25.57	32.08
Variation, [%]	893.89%	543.59%	-81.19%	-52.95%	-92.16%

Consistent with the findings of the previous case studies, coordinated operation leads to systematic reductions in total operational costs relative to uncoordinated operation, with benefits becoming increasingly pronounced toward the end of the planning horizon. In the early stages (2025), when flexibility availability at the distribution level remains limited, coordinated operation yields modest cost reductions of approximately 2.53%–2.56%. As the system evolves and both RES penetration and flexibility availability increase, the economic value of coordination grows substantially. By 2037, operational cost reductions reach 16.58% without shared ESSs and 18.25% when shared ESSs are deployed.

Figure 7.35 illustrates the evolution of operational costs per representative year, day, and test case, disaggregated into conventional generation and flexibility procurement components. Although uncoordinated operation may outperform coordinated operation for specific representative days in the early years, these instances coincide with relatively low flexibility availability. As flexibility-providing DERs become more widespread, the economic advantages of coordinated operation become increasingly robust and consistent across seasons. Importantly, these cost reductions are achieved while simultaneously preventing voltage magnitude violations (Figure 7.34) that would otherwise require conventional network reinforcements.

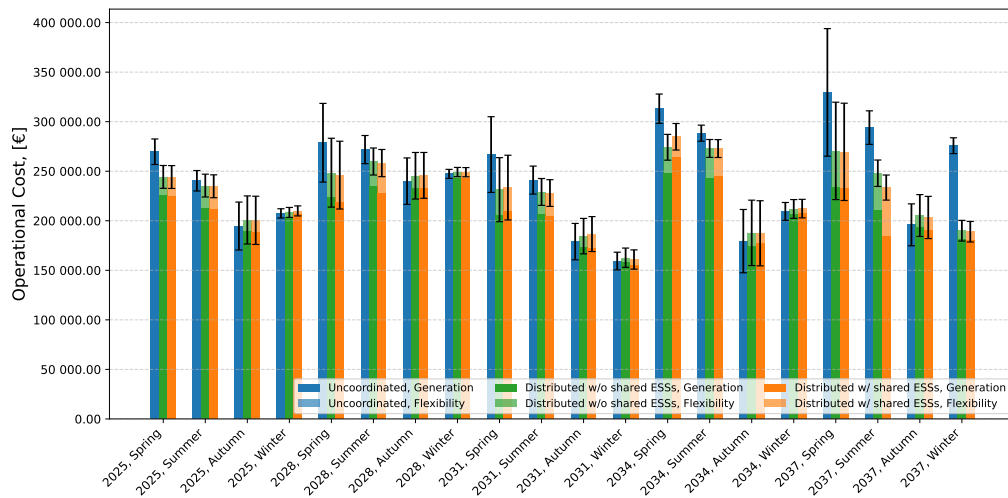
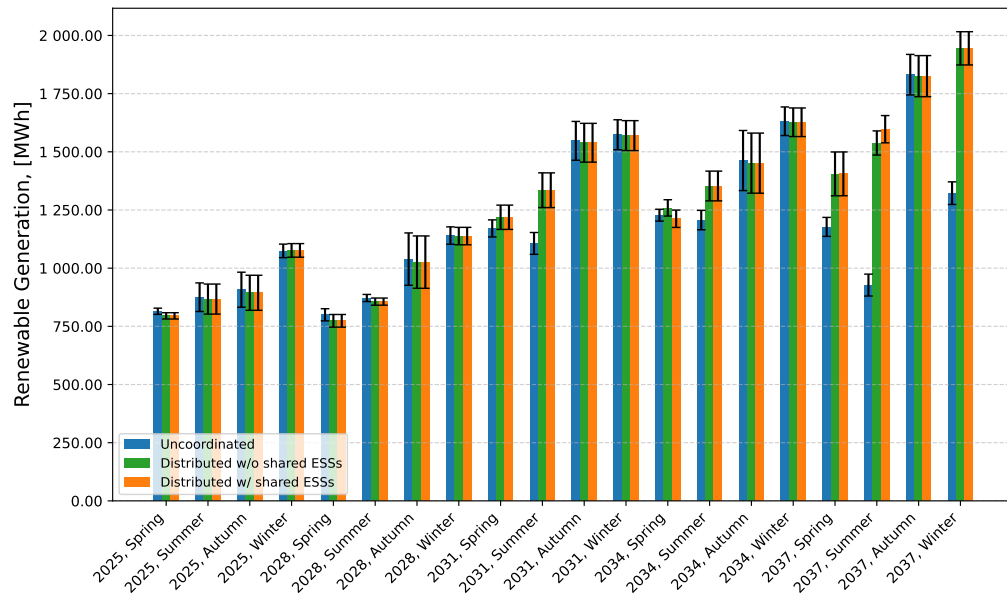
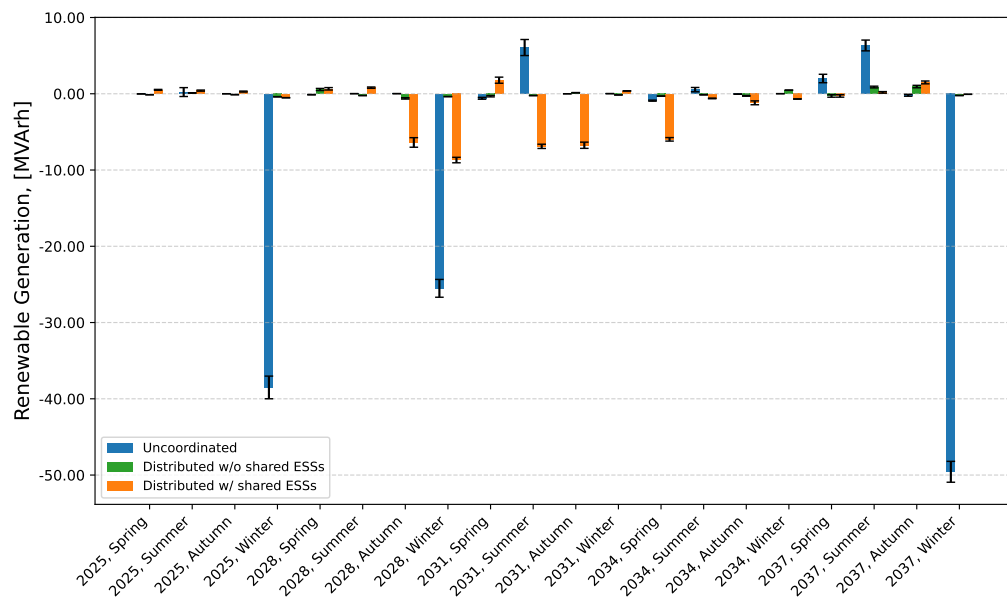


Figure 7.35: Case Study 3. Operational costs per representative year, day and test case.

With respect to RES integration, Table 7.19 shows that from 2031 onward – when RES curtailment under uncoordinated operation becomes significant – coordinated operation delivers substantial reductions in curtailed energy. Figures 7.36 and 7.37 provide a more detailed view of RES generation and curtailment patterns across representative years and seasons. While curtailment levels remain comparable across all test cases in the early years of the planning horizon, coordinated operation dramatically reduces curtailment in later years, particularly during autumn and winter. In 2037, average RES curtailment is reduced by 88.54% under coordinated operation without shared ESSs, and by 92.16% when shared ESSs are included. These results confirm that coordinated activation of flexibility resources is essential for sustaining high levels of RES integration as system stress increases over time. The analysis of reactive power generation in Figure 7.36b further underscores the benefits of coordinated operation. Under uncoordinated operation, RES generators are required to absorb large amounts of reactive power in an attempt to support transmission-level voltage regulation – yet these efforts remain insufficient to prevent voltage violations. In contrast, coordinated operation enables a more efficient and system-wide allocation of reactive power support, allowing RES generators to operate closer to unitary power factor, particularly in the test case without shared ESSs.



(a) Active energy.



(b) Reactive energy.

Figure 7.36: Case Study 3. RES generation per representative year, day and test case.

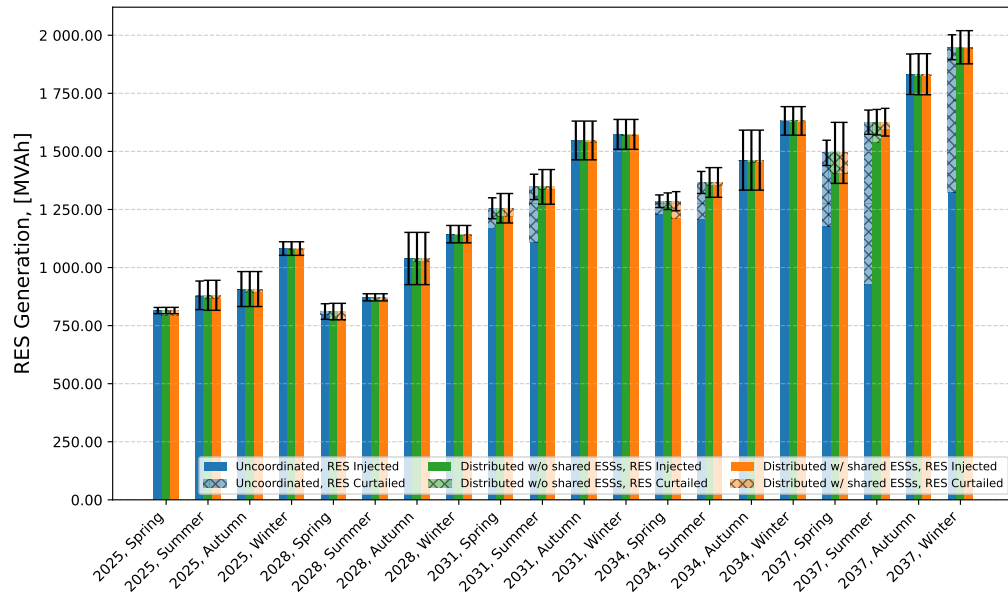
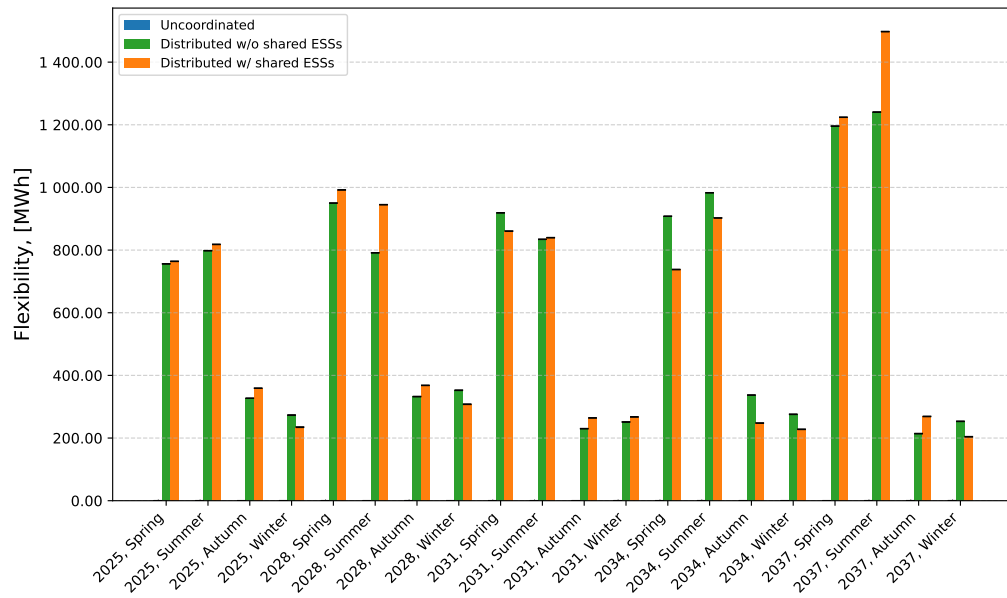


Figure 7.37: Case Study 3. RES curtailment per representative year, day and test case.

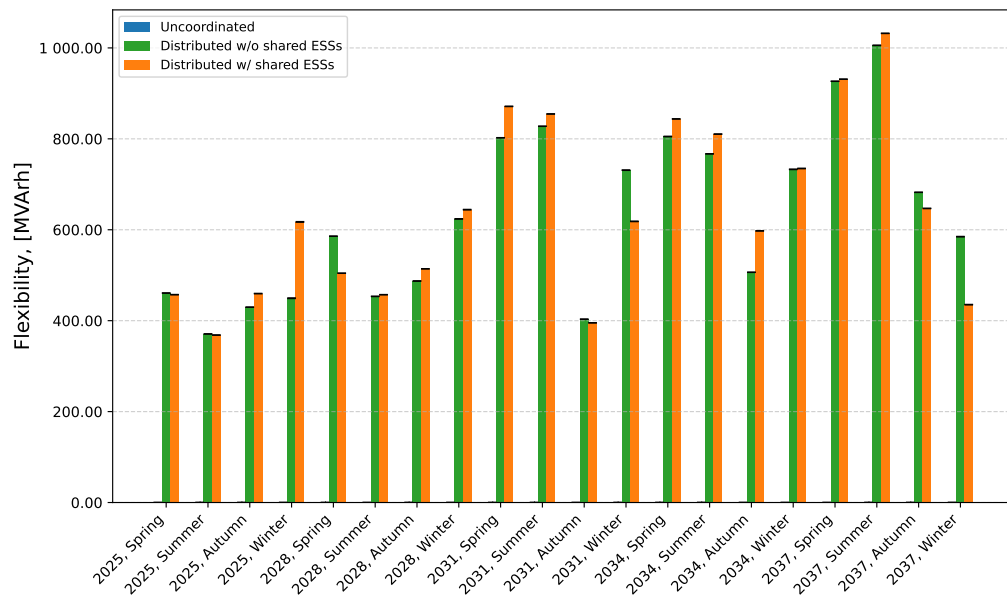
Figure 7.38 reports the total flexibility services procurement across representative years, days, and test cases. Spring and summer consistently exhibit higher active power flexibility requirements than autumn and winter, reflecting the temporal concentration of solar PV generation around midday hours. As solar PV penetration increases over the planning horizon, demand-side flexibility becomes progressively more important for shifting consumption toward periods of high renewable generation, thereby mitigating curtailment. These results confirm that coordinated operation enables a more effective utilization of existing flexibility resources, aligning flexibility activation with evolving generation patterns and reinforcing the role of ADNs as key contributors to system-wide balancing and voltage support.

7.3.2.3 Convergence Characteristic

Figure 7.39 illustrates the convergence behavior of the proposed planning algorithm. The evolution of the upper and lower bounds of the objective function, expressed in terms of NPV, is reported across iterations of the Benders' decomposition procedure. As shown, the algorithm converges within four iterations to a relative optimality gap of 0.50%, with a total runtime of 30 560.54 s. Despite the large-scale nature of the planning problem – characterized by a multi-year horizon, multiple investment cost scenarios, and a high number of operational subproblems – the framework can be solved on a consumer-grade workstation within a runtime that is acceptable for long-term planning applications. This performance is primarily enabled by the two-layer decomposition structure of the proposed formulation, which separates the investment and operational problems and decomposes the coordinated operational problem into smaller subproblems.



(a) Active energy.



(b) Reactive energy.

Figure 7.38: Case Study 3. Flexibility procurement per representative year and day.

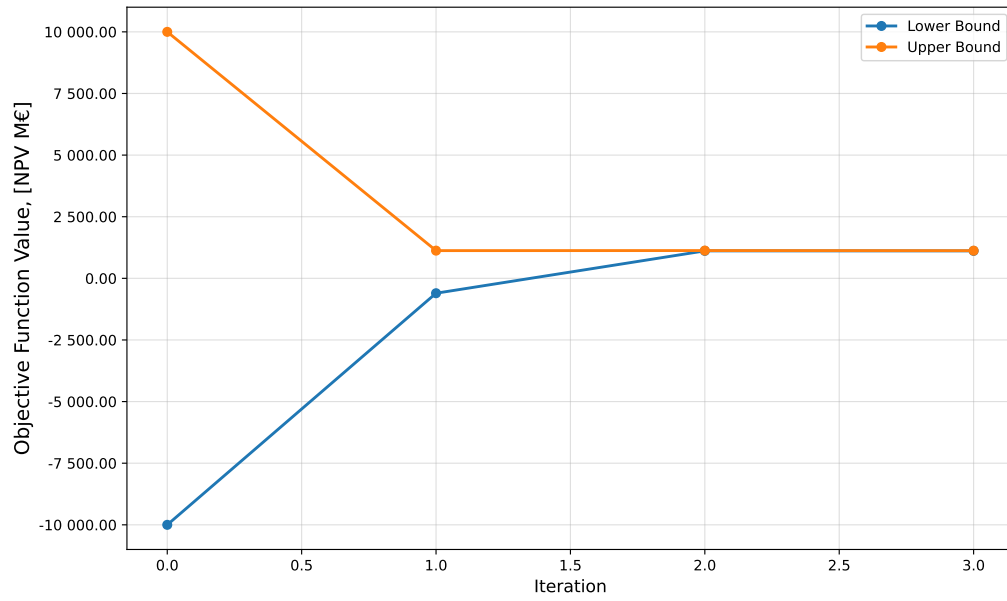


Figure 7.39: Case Study 3. Convergence characteristic of the Benders' decomposition algorithm. The upper and lower bounds are reported in NPV.

Moreover, the inherently distributed structure of the coordinated operational planning layer enables straightforward parallelization of the subproblem solution process. In practical implementations, parallel execution across multiple processing units could significantly reduce wall-clock computation times, further enhancing the scalability and real-world applicability of the proposed shared-resources planning framework.

7.3.2.4 Impact of Planning Horizon Discretization

An important modeling criterion in multi-year planning problems is the discretization of the planning horizon. This issue is particularly critical for **ESS** planning, as battery systems may experience significant capacity degradation over relatively short time spans. If the discretization step is inadequate, cumulative degradation effects may be misrepresented, potentially leading to suboptimal or misleading investment recommendations.

To assess the sensitivity of the proposed shared **ESSs** planning framework to temporal discretization, two alternative planning configurations were evaluated in addition to the baseline case with a 3-year discretization step:

- 5-year discretization step: This configuration reduces temporal resolution while preserving all other modeling assumptions, including the number of investment scenarios, representative days per year, market price scenarios, and operational scenarios.
- 1-year discretization step: This configuration increases temporal resolution to annual intervals. Owing to memory limitations, the number of market price and operational scenarios was reduced to three, while the number of representative days per year (four) and investment scenarios (three) was maintained.

Tables 7.20 and 7.21 report, respectively, the resulting investment plan and the corresponding evolution of rated power, energy capacity, and SoH when a 5-year discretization step is adopted in the planning procedure.

Table 7.20: Investment plan in shared resources. Effect of planning time step granularity. Planning horizon discretized in 5 year intervals.

Node	Parameter	Scenario	2025	2030	2035
5	$S_{e,y}^{\text{Inv}}$, [MVA]	1	-	-	-
		2	-	-	-
		3	-	-	-
		Expected	-	-	-
	$E_{e,y}^{\text{Inv}}$, [MWh]	1	-	-	-
		2	-	-	-
		3	-	-	-
		Expected	-	-	-
7	$S_{e,y}^{\text{Inv}}$, [MVA]	1	2.50	-	-
		2	1.22	-	-
		3	-	-	-
		Expected	1.54	-	-
	$E_{e,y}^{\text{Inv}}$, [MWh]	1	5.00	-	-
		2	2.43	-	-
		3	-	-	-
		Expected	3.09	-	-
9	$S_{e,y}^{\text{Inv}}$, [MVA]	1	0.27	-	-
		2	-	-	-
		3	-	-	-
		Expected	0.10	-	-
	$E_{e,y}^{\text{Inv}}$, [MWh]	1	0.55	-	-
		2	-	-	-
		3	-	-	-
		Expected	0.19	-	-
-	Inv., [NPV M€]	Expected	1.00	0.00	0.00

As shown in Table 7.20, increasing the discretization step from 3 to 5 years alters the optimal investment strategy. Rather than allocating the entire budget to a single shared ESS at node 7 – as observed in the baseline case – the investment is now split between two units installed in 2025: a larger system at node 7, rated at 1.54 MVA/3.09 MWh, and a smaller one at node 9, rated 0.10 MVA/0.19 MWh.

Although investment remains concentrated in the first planning year, this result illustrates that coarser temporal aggregation can affect both the spatial allocation and sizing of shared resources.

Table 7.21: Shared ESSs rated power, energy capacity, and SoH. Effect of planning time step granularity. Planning horizon discretized in 5 year intervals.

Node ID	Parameter	2025	2030	2035
5	$S_{e,y}^{\text{Rated}}$, [MVA]	-	-	-
	$E_{e,y}^{\text{Rated}}$, [MWh]	-	-	-
	$E_{e,y}^{\text{Av}}$, [MWh]	-	-	-
	SoH, [%]	-	-	-
7	$S_{e,y}^{\text{rated}}$, [MVA]	1.54	1.54	1.54
	$E_{e,y}^{\text{rated}}$, [MWh]	3.09	3.09	3.09
	$E_{e,y}^{\text{Av}}$, [MWh]	2.27	1.83	1.57
	SoH, [%]	73.48%	59.15%	50.80%
9	$S_{e,y}^{\text{rated}}$, [MVA]	0.10	0.10	0.10
	$E_{e,y}^{\text{rated}}$, [MWh]	0.19	0.19	0.19
	$E_{e,y}^{\text{Av}}$, [MWh]	0.13	0.10	0.07
	SoH, [%]	60.76%	50.91%	38.43%

From Table 7.21, it can be observed that the ESS installed at node 7 reaches an end-of-horizon SoH of 50.80%, closely matching the 49.62% obtained under the 3-year discretization. This similarity indicates that the framework is robust in identifying consistent long-term degradation trajectories for dominant investments despite changes in temporal resolution. By contrast, the smaller ESS installed at node 9 exhibits substantially higher relative degradation, reflecting more intensive cycling. This outcome highlights the sensitivity of marginal investments to discretization choices and underscores the importance of accurately capturing operational usage patterns when multiple shared assets are deployed.

Tables 7.22 and 7.23 present the corresponding results for the 1-year discretization case. In this configuration, the investment plan is identical to that obtained with the baseline test case: a single shared ESS rated at 1.62 MVA/3.24 MWh is installed at node 7 in 2025.

Overall, these results highlight the critical role of planning horizon discretization in investment problems involving degradable assets. While coarser discretization can provide computational advantages, it may distort degradation estimates and lead to altered investment allocations. Conversely, finer discretization improves physical accuracy but increases computational and memory requirements. The observed differences between the 1-year and 3-year discretization cases suggest that the baseline planning model may slightly overestimate ESS degradation due to temporal aggregation effects. Investigating this trade-off more systematically – particularly together with adaptive scenario reduction and degradation-aware aggregation techniques – constitutes an important avenue for future research.

Table 7.22: Investment plan in shared resources. Effect of planning time step granularity. Planning horizon discretized in 1 year intervals.

Node	Parameter	Scenario	2025	2026	2027	...	2039
5	$S_{e,y}^{\text{Inv}}$, [MVA]	1	-	-	-	...	-
		2	-	-	-	...	-
		3	-	-	-	...	-
		Expected	-	-	-	...	-
	$E_{e,y}^{\text{Inv}}$, [MWh]	1	-	-	-	...	-
		2	-	-	-	...	-
		3	-	-	-	...	-
		Expected	-	-	-	...	-
7	$S_{e,y}^{\text{Inv}}$, [MVA]	1	2.50	-	-	...	-
		2	1.36	-	-	...	-
		3	-	-	-	...	-
		Expected	1.62	-	-	...	-
	$E_{e,y}^{\text{Inv}}$, [MWh]	1	5.00	-	-	...	-
		2	2.71	-	-	...	-
		3	-	-	-	...	-
		Expected	3.24	-	-	...	-
9	$S_{e,y}^{\text{Inv}}$, [MVA]	1	-	-	-	...	-
		2	-	-	-	...	-
		3	-	-	-	...	-
		Expected	-	-	-	...	-
	$E_{e,y}^{\text{Inv}}$, [MWh]	1	-	-	-	...	-
		2	-	-	-	...	-
		3	-	-	-	...	-
		Expected	-	-	-	...	-
-	Inv., [NPV M€]	Expected	1.00	0.00	0.00	...	0.00

Table 7.23: Shared ESSs rated power, energy capacity, and SoH. Effect of planning time step granularity. Planning horizon discretized in 1 year intervals.

Node ID	Parameter	2025	2026	2027	...	2037	2038	2039
5	$S_{e,y}^{\text{Rated}}$, [MVA]	-	-	-	...	-	-	-
	$E_{e,y}^{\text{Rated}}$, [MWh]	-	-	-	...	-	-	-
	$E_{e,y}^{\text{Av}}$, [MWh]	-	-	-	...	-	-	-
	SoH, [%]	-	-	-	...	-	-	-
7	$S_{e,y}^{\text{rated}}$, [MVA]	1.62	1.62	1.62	...	1.62	1.62	1.62
	$E_{e,y}^{\text{rated}}$, [MWh]	3.24	3.24	3.24	...	3.24	3.24	3.24
	$E_{e,y}^{\text{Av}}$, [MWh]	3.16	3.07	2.96	...	2.13	2.06	1.99
	SoH, [%]	97.56%	94.56%	91.42%	...	65.83%	63.65%	61.49%
9	$S_{e,y}^{\text{rated}}$, [MVA]	-	-	-	...	-	-	-
	$E_{e,y}^{\text{rated}}$, [MWh]	-	-	-	...	-	-	-
	$E_{e,y}^{\text{Av}}$, [MWh]	-	-	-	...	-	-	-
	SoH, [%]	-	-	-	...	-	-	-

7.3.3 Conclusions

This case study evaluated the proposed shared resources planning framework over a 15-year horizon. The planning problem incorporated four representative days per year (one per season), three investment cost scenarios, five market price scenarios, and five operational scenarios per network. The results demonstrate that the proposed framework is capable of producing a consistent and economically meaningful investment plan, while effectively handling a very large-scale, non-convex, and uncertainty-aware optimization problem.

Beyond investment-level insights, the results confirm that coordinated **TSO-DSO** operational planning with shared **ESSs** installed at the **TN-DN** interface delivers tangible system-wide benefits. Coordinated operation consistently reduces operational costs, with the magnitude of these gains increasing toward the end of the planning horizon, while simultaneously enabling higher levels of **RES** integration. The added value of shared **ESSs** becomes particularly pronounced in later years. While differences between coordinated operation with and without shared storage are marginal in the early stages – and in some cases coordination without shared **ESSs** may even perform slightly better – by 2037 a relatively modest investment in shared **ESSs** yields an average daily operational cost reduction of approximately 2.01%. This corresponds to an estimated payback period of roughly seven months for the initial 1 M€ investment, highlighting the strong economic potential of well-sited and appropriately sized shared storage assets. In addition to economic benefits, coordinated operation is shown to fully eliminate voltage magnitude violations forecasted under uncoordinated operation. This finding underscores the role of coordinated **TSO-DSO** operation and distributed flexibility as a viable alternative to traditional network reinforcements.

The impact of planning-horizon discretization was assessed by comparing the baseline 3-year discretization with both coarser (5-year) and finer (1-year) alternatives. The results show that temporal resolution can affect sizing decisions. Under a 5-year discretization, the optimal strategy shifts from a single shared **ESS** to two smaller units installed in the initial year, while still allocating the majority of the investment to the same network node selected in the baseline case. Importantly, the framework consistently identifies node 7 as the preferred installation location across all discretization levels, indicating strong robustness of spatial siting decisions with respect to temporal modeling granularity.

Overall, the proposed methodology provides valuable decision-support insights by explicitly linking long-term investment planning with short-term coordinated operation under uncertainty. By capturing the interdependencies between investment decisions and operational performance, the framework supports adaptive planning strategies as cost structures and system conditions evolve. Moreover, its generic and modular design provides an extensible foundation applicable not only to shared resource planning at the transmission–distribution interface, but also to **ESS** planning problems more broadly.

7.4 Case Study 4

The previous case studies examined the proposed coordination and planning tools at the operational planning (day-ahead) and long-term investment horizons. In contrast, this case study shifts the focus to the real-time operation layer, evaluating the performance of the real-time **OPF** module introduced in Section 4.5 of Chapter 4.

To assess the proposed real-time **OPF** under realistic operating conditions, the algorithm was implemented and experimentally validated at INESC TEC’s *X-Energy Lab* using the OPAL-RT **HIL** simulation platform. This setup enables a comprehensive evaluation of the algorithm’s ability to process live measurements and deploy adaptive control actions under dynamic and time-varying grid conditions.

7.4.1 Laboratory Implementation

The OPAL-RT real-time simulation platform interfaces with the laboratory infrastructure via the **IEC 61850**² communication standard. To ensure seamless interoperability with the real-time **AC-OPF** module, dedicated data conversion interfaces were developed to translate **IEC 61850** messages into JSON³. These JSON-formatted data are exchanged through an MQTT⁴-based communication layer, enabling reliable, low-latency interaction among the OPAL-RT simulator, the protocol conversion interfaces, and the emulated

²**IEC 61850** is a standardized communication protocol for substation automation, enabling fast and reliable exchange of grid measurement and control signals.

³JSON (JavaScript Object Notation) is a lightweight, structured data format widely used for structured data exchange.

⁴MQTT (Message Queuing Telemetry Transport) is a lightweight publish–subscribe messaging protocol optimized for low-latency and bandwidth-efficient communication.

SCADA environment hosting the real-time optimization module. This architecture allows the **OPF** module to process live measurements and deploy control setpoints in a manner consistent with practical substation and control-center implementations.

Figure 7.40 illustrates the laboratory setup and the end-to-end data flow between the OPAL-RT simulator, the protocol conversion interfaces, the MQTT broker, and the emulated **SCADA** system executing the real-time **OPF** algorithm.

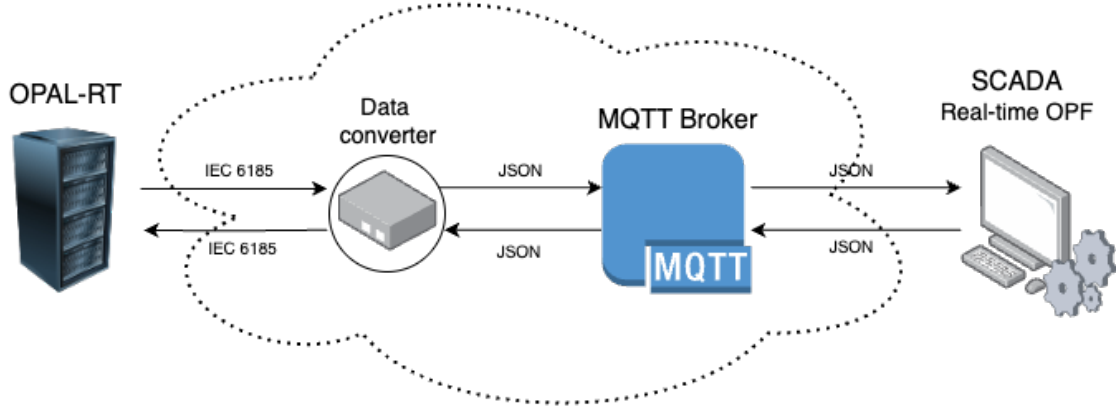


Figure 7.40: Laboratory test system for the real-time OPF module using HIL simulation.

7.4.2 Case Study Description

As in Case Study 1, the network adopted in this case study is based on the **IEEE** 9-bus **TN**. The original test system was extended to incorporate **RES** generators, multiple voltage levels, an additional transmission line, and **OLTC** transformers, enabling a realistic assessment of real-time operational control under heterogeneous grid conditions. Figure 7.41 presents an illustrative diagram of the adopted test system. Detailed descriptions of buses, branches (including lines and transformers), generators, and loads are provided in Tables 7.24, 7.25, 7.26, and 7.27, respectively.

This case study represents an independently managed power system electrically interconnected with a neighboring network, which is emulated through Generator 1. The operational objective is to maximize **RES** generation. In the initial (pre-optimization) operating state, **RES** units are curtailed and operate at approximately half of their rated capacity. The role of the real-time control module is therefore to compute a *staged* sequence of control actions that progressively increases **RES** output, while ensuring that all network constraints are satisfied throughout the transition. To achieve this, the real-time **OPF** exploits locally available controllable resources; in this case study, generators and **OLTC** transformers are assumed to be directly controllable by the **SO**.

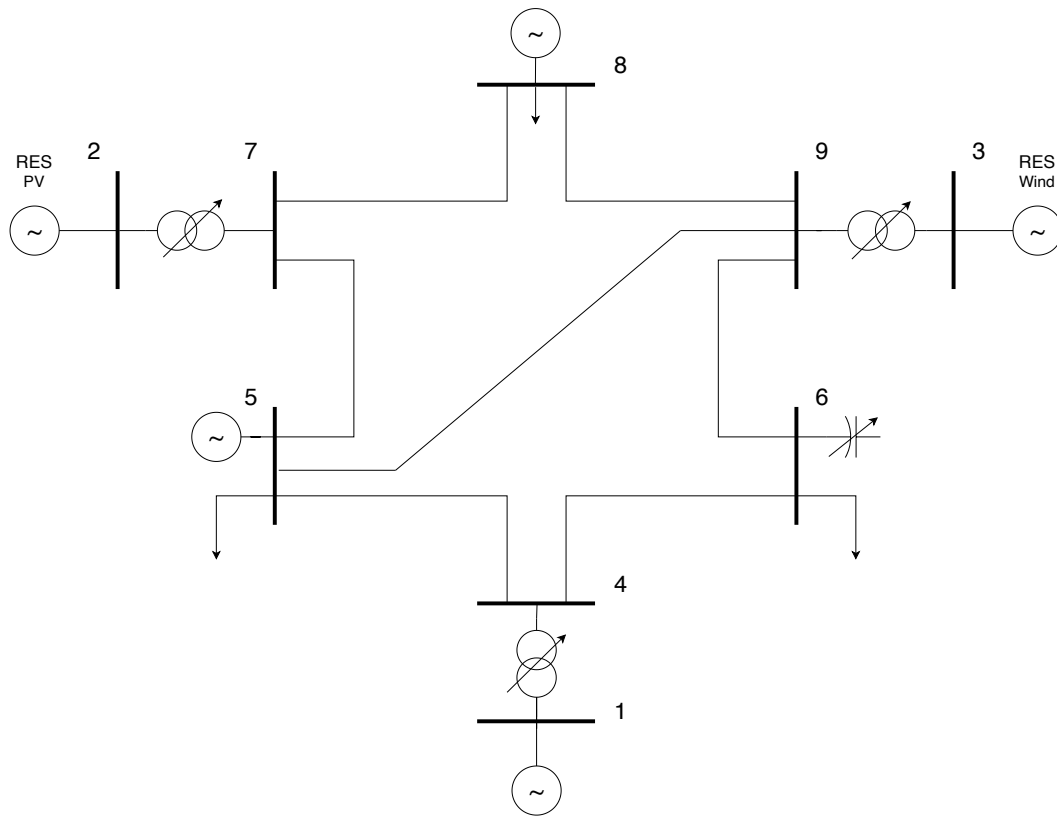


Figure 7.41: Case Study 4. Network diagram.

Table 7.24: Case Study 4. Network description. Bus data.

Bus	Bus	g_i	b_i	V_i^{Base}	V_i^{max}	V_i^{min}
ID	Type	[p.u.]	[p.u.]	[kV]	[p.u.]	[p.u.]
1	Ref.	0.00	0.00	16.50	1.10	0.90
2	PQ	0.00	0.00	18.00	1.10	0.90
3	PQ	0.00	0.00	13.80	1.10	0.90
4	PQ	0.00	0.00	230.00	1.10	0.90
5	PV	0.00	0.00	230.00	1.10	0.90
6	PQ	0.00	0.00	230.00	1.10	0.90
7	PQ	0.00	0.00	230.00	1.10	0.90
8	PV	0.00	0.00	230.00	1.10	0.90
9	PQ	0.00	0.00	230.00	1.10	0.90

Table 7.25: Case Study 4. Branch data.

Branch	From	To	r_{ij}	x_{ij}	b_{ij}^{Sh}	S_{ij}^{Rated}	n_{ij}^B	$r_{ij}^{\min}$	$r_{ij}^{\max}$
ID	Bus ID	Bus ID	[p.u.]	[p.u.]	[p.u.]	[MVA]	[N/A]	[N/A]	[N/A]
1	5	4	0.010000	0.068000	0.176000	1000.00	—	—	—
2	6	4	0.034000	0.184000	0.316000	1000.00	—	—	—
3	7	5	0.016000	0.080500	0.153000	400.00	—	—	—
4	9	6	0.039000	0.173800	0.358000	1000.00	—	—	—
5	7	8	0.008500	0.057600	0.149000	1000.00	—	—	—
6	8	9	0.011900	0.100800	0.209000	1000.00	—	—	—
7	5	9	0.048000	0.241500	0.459000	250.00	—	—	—
8	4	1	0.000000	0.038400	0.000000	1000.00	20	0.90	1.10
9	2	7	0.000000	0.041667	0.000000	1000.00	34	0.83	1.17
10	9	3	0.000000	0.039067	0.000000	1000.00	34	0.83	1.17

Table 7.26: Case Study 4. Generator data.

Generator	Bus	Generator	$P_g^{G,\max}$	$P_g^{G,\min}$	$Q_g^{G,\max}$	$Q_g^{G,\min}$	V_g^S
ID	ID	Type	[MW]	[MW]	[MVA]	[MVA]	[p.u.]
1	1	Interconn.	1000.00	-1000.00	1000.00	-1000.00	1.04
2	2	Solar PV	500.00	0.00	500.00	-500.00	—
3	3	Solar PV	300.00	0.00	300.00	-300.00	—
4	5	Conventional	385.00	285.00	500.00	-500.00	1.025
5	8	Conventional	385.00	85.00	500.00	-500.00	1.025

Table 7.27: Case Study 4. Load data.

Load	Bus	P^L	Q^L
ID	ID	[MW]	[MVA]
1	5	325.00	80.00
2	6	180.00	0.00
3	8	300.00	80.00

7.4.3 Results

Table 7.28 summarizes the staged control actions computed by the real-time OPF module, including the target active power setpoints for the RES generators and the corresponding tap positions of the OLTC transformers at each control stage. The total runtime required to compute the complete control sequence for this case study is 0.22 s, confirming the suitability of the proposed approach for real-time applications.

Table 7.28: Case Study 4. Staged control action.

	RES Generators		OLTC Transf.		
	P_g^G , [MW]		Tap Pos., [N/A]		
Stage	2	3	8	9	10
1	269.02	158.86	10	17	17
2	292.94	161.52	10	17	18
3	317.96	163.08	10	17	19
4	343.33	164.29	10	17	20
5	368.79	165.40	10	17	21
6	394.26	166.51	10	17	22
7	418.37	168.99	10	17	22
8	435.47	178.47	10	17	22
9	430.57	209.95	10	17	22
10	443.97	223.13	11	18	22
11	456.46	237.22	12	18	22
12	468.12	252.14	13	18	22
13	478.75	268.09	14	18	22
14	488.65	284.77	15	18	22
15	500.00	300.00	15	18	22

Figure 7.42 illustrates the evolution of bus voltage magnitudes during the execution of the staged control sequence, while Figure 7.43 reports the corresponding apparent power flows in each branch, expressed as a percentage of rated capacity. Figures 7.44 and 7.45 present the active and reactive power outputs of the generators and the evolution of OLTC transformer tap positions, respectively, throughout the control action implementation.

A comparison of Figure 7.44a with Figures 7.42 and 7.43 shows that Generators 2 and 3 progressively reach their maximum active power operating points without inducing voltage violations or branch overloads. As a result, the net consumption of the network shifts from approximately 40 MW to -490 MW, indicating a transition from net import to net export toward the neighboring system – emulated through Generator 1. Importantly, this transition is not solely attributable to increased RES integration. The observed net power change exceeds the additional RES generation (approximately 525 MW), indicating a concurrent reduction in network losses. These loss reductions are enabled by coordinated voltage regulation through OLTC transformers and reactive power support provided by conventional generators, which together improve overall power flows.

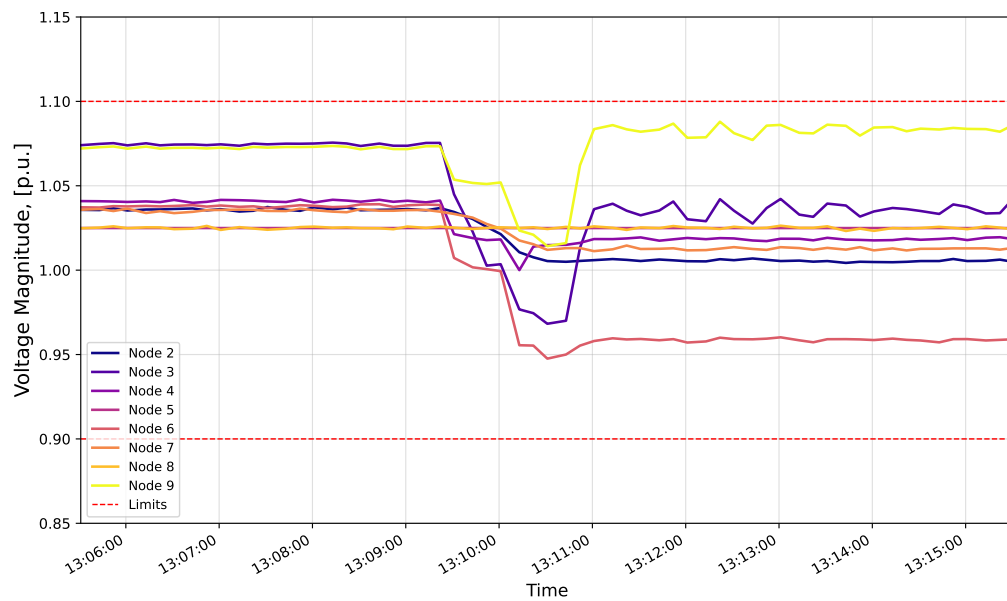


Figure 7.42: Case Study 4. Voltage magnitude profiles.

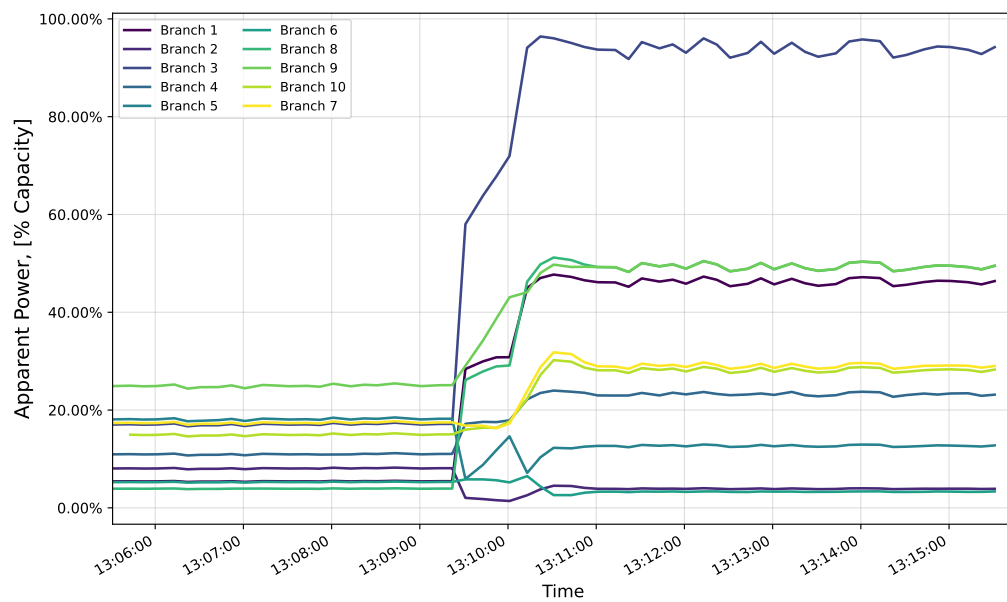
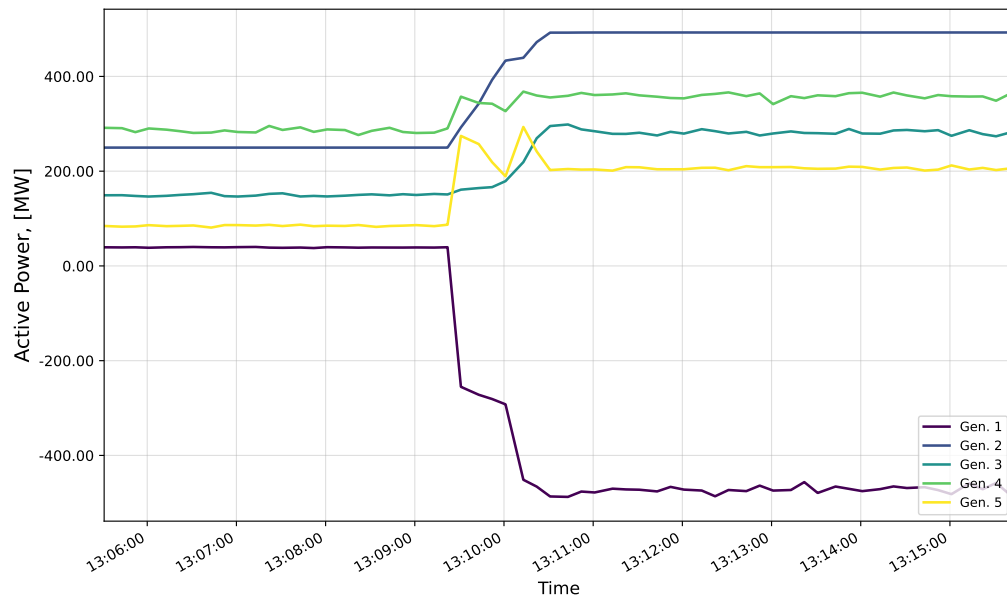
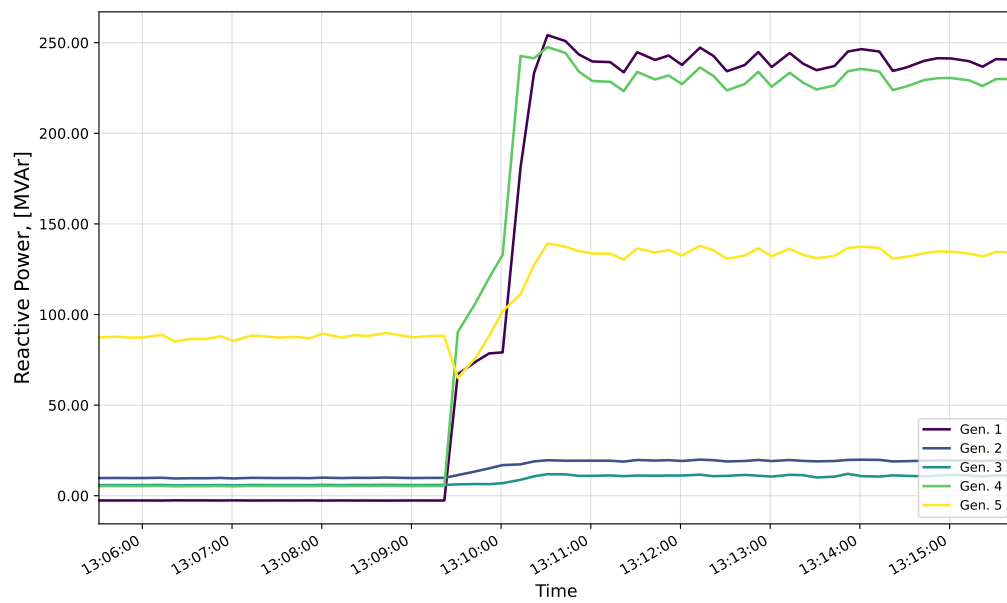


Figure 7.43: Case Study 4. Apparent power flows, expressed as a percentage of the branch (line, transformer) rated capacity.



(a) Active power.



(b) Reactive power.

Figure 7.44: Case Study 4. Generation results. Active and reactive power.

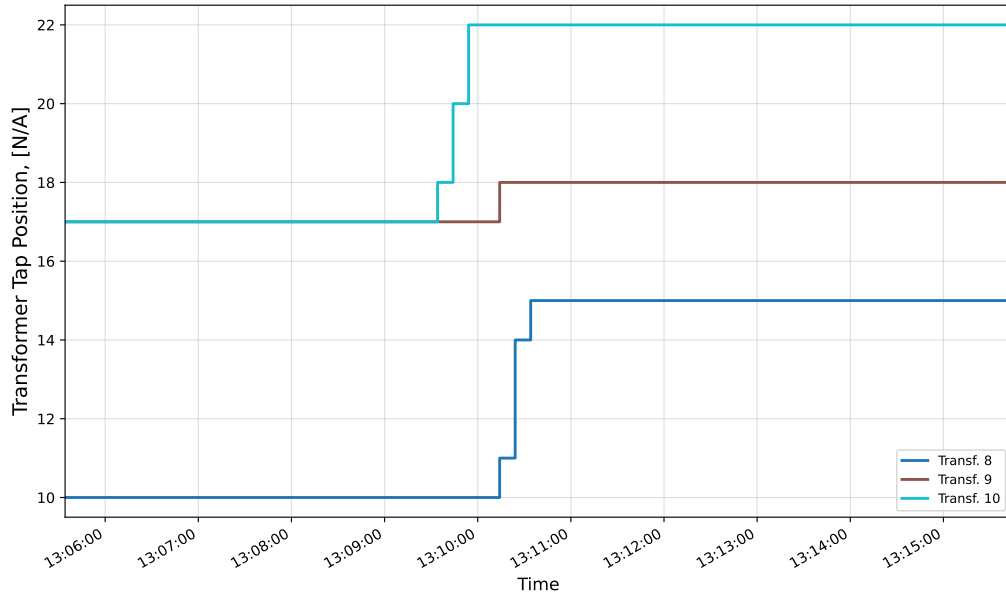


Figure 7.45: Case Study 4. Transformer tap positions.

An analysis of Figure 7.45 further indicates that Transformers 8 and 10 undergo the largest number of tap adjustments as the system is steered toward its optimal operating point. Specifically, Transformer 8 transitions from tap position 10 to 15, while Transformer 10 moves from position 17 to 22. In contrast, Transformer 9 requires only a single tap change, from position 17 to 18. These observations highlight the critical role of OLTC transformers in voltage regulation, particularly in areas with high RES penetration. In this case study, Bus 9 – located in close electrical proximity to RES Generator 3 – is especially susceptible to overvoltage conditions (Figure 7.42). The real-time OPF algorithm effectively mitigates this risk by dynamically adjusting transformer tap positions, thereby maintaining voltage magnitudes within admissible bounds throughout the execution of the control sequence. Overall, these results confirm that the staged control action computed by the real-time OPF module remain feasible across all intermediate (transient) stages of the control process, while simultaneously improving network operating conditions in terms of efficiency and RES integration.

7.4.4 Conclusions

The experimental results confirm the capability of the proposed real-time OPF module to compute and deploy a staged control action within a realistic HIL environment. The module successfully generates sequences of control setpoints that progressively steer the power system toward its optimal operating point, while explicitly avoiding abrupt changes that could otherwise induce transient violations. As a result, operational feasibility and system security are preserved throughout the entire control process.

The experiments further demonstrate that the computational performance of the proposed real-time **OPF** formulation is compatible with practical real-time operation, even in the presence of discrete control variables such as **OLTC** transformer tap positions. This capability is particularly significant for real-world deployment, where control actions must be coordinated and executed reliably within tight time constraints.

Originally developed in the context of a consultancy project with GE Vernova, the real-time **AC-OPF** module is currently being prepared for demonstration. Ongoing validation activities as well as future plans include collaborations with National Grid, as well as additional partnership projects with GE Vernova. These efforts aim to further evaluate the scalability, robustness, and operational value of the proposed solution under realistic system conditions, thereby providing a concrete pathway toward industrial adoption.

7.5 Conclusions and Future Work

This chapter provided an extensive numerical and experimental validation of the methodologies developed in this thesis, spanning coordinated operational planning, shared resource planning, and real-time control. Through four complementary case studies, the proposed approaches were evaluated under stressed operating conditions, normal system regimes, long-term planning horizons, and real-time operational constraints. Together, these studies assessed not only performance and scalability, but also the practical relevance and deployability of the proposed frameworks in realistic power system settings.

7.5.1 Main Conclusions

The simulation results support the following overarching conclusions:

- (i) The case studies consistently demonstrate the *system-wide benefits of TSO-DSO co-ordination*. Under both stressed (Case Study 1) and normal (Case Study 2) operating conditions, coordinated operation effectively resolved network constraint violations, reduced operational costs, and enabled higher levels of **RES** integration relative to uncoordinated operation. In particular, the distributed coordination approach proved more effective than hierarchical coordination in fully eliminating voltage violations, while maintaining comparable computational performance.
- (ii) The results highlight *fundamental trade-offs between centralized efficiency, scalability, and regulatory feasibility*. Although centralized coordination achieved the largest cost reductions, its reliance on full system observability and centralized data access raises concerns related to scalability, data privacy, and regulatory compliance. By contrast, the proposed distributed coordination framework delivers strong performance while preserving data confidentiality, complying with unbundling requirements, and enabling parallel solution of **TN** and **DN** subproblems, making it well suited for large-scale, real-world deployment.

- (iii) The simulations confirm that *coordinated operation improves the effective utilization of existing flexibility resources*. In Case Study 2, coordinated operation reduced reliance on conventional generation and increased RES integration without systematically increasing the volume or cost of flexibility procurement. Reactive power flexibility from ADNs was shown to play a critical role in supporting transmission-level voltage regulation, underscoring the growing importance of DERs in future power system operation.
- (iv) The planning-oriented results (Case Study 3) demonstrate the value of *explicitly linking long-term investment decisions with short-term coordinated operation under uncertainty*. The proposed shared resource planning framework successfully addresses a very large-scale, non-convex, and uncertainty-aware problem, yielding economically meaningful and operationally consistent investment strategies. The results reveal a clear trade-off between early deployment of shared ESSs – which enables earlier realization of operational benefits – and deferred investment under uncertain cost trajectories. In high-DER, high-RES scenarios, well-sited and appropriately sized shared ESSs are shown to deliver substantial operational benefits in later years.
- (v) Finally, Case Study 4 demonstrates the *practical feasibility of the proposed real-time OPF framework*. HIL experiments confirmed that the real-time module can compute secure, staged control actions with computational performance compatible with real-time operation, even in the presence of discrete control variables such as OLTC tap positions. These results show that the proposed approach can safely steer the system toward optimal operating points while avoiding transient violations, effectively bridging the gap between operational planning and real-time control.

7.5.2 Future Work

While the results presented in this chapter provide strong validation of the proposed methodologies, several directions for future research remain:

- (i) From an operational perspective, future work could extend the coordinated frameworks to multi-area or multi-TSO settings, explicitly addressing inter-TSO coordination and cross-border interactions. Incorporating communication delays, packet losses, and asynchronous information exchange would further improve realism and robustness assessment. Another relevant extension is the integration of $N-1$ security criteria into the SMOPF formulation, leading to a security-constrained SMOPF.
- (ii) At the planning level, future research could explore risk-averse formulations for shared resource planning, alongside the integration of more detailed degradation models for ESSs. The interplay between planning horizon discretization, scenario reduction techniques, and degradation modeling accuracy warrants deeper investigation. In addition, alternative mathematical decomposition approaches and convex

relaxation strategies could further enhance scalability, numerical robustness, and computational efficiency of the planning algorithm.

- (iii) Regarding real-time operation, future developments should include large-scale field demonstrations and long-duration pilot projects, with the objective of fully assessing scalability, reliability, and operational acceptance in real system environments.

Regarding scalability, the largest operational coordination problem evaluated in this work comprised a 57-bus **TN** and nine participating **ADNs**. The largest planning problem comprised a 9-bus **TN**, three 33-bus **ADNs**, five representative years, four representative days per year, three investment scenarios, and 25 operational scenarios per representative day. The planning instance was solved on the workstation described in Subsection 7.3. These instances represent the largest problems evaluated in this work rather than formal computational limits of the proposed methodologies. The maximum tractable problem size depends on the available memory and processing resources, the dimensions of the network, temporal, and scenario sets, and the numerical behavior of the underlying non-convex **NLP** subproblems. The adopted decomposition structure nevertheless supports the treatment of larger instances. The coordinated operational problem is separated into one **TSO** subproblem and multiple local **DSO** subproblems, with the latter being mutually independent within each coordination step and therefore amenable to parallel execution. In the planning framework, the investment and operational layers are separated, while the shared-**ESS** operational problem is also separable across storage units. Scenario-specific and representative-day evaluations may likewise be parallelized where no intertemporal coupling is present. Future work should include a systematic scalability assessment using full-scale utility networks and distributed computing architectures.

Overall, the simulation results presented in this chapter demonstrate that coordinated **TSO–DSO** operation constitutes a viable and effective pathway toward the secure, efficient, and sustainable operation of future power systems. In the near term, the real-time **OPF** module and inter-area control capabilities will be demonstrated through collaborations with the **UK's TSO**, National Grid, and ongoing partnership projects with GE Vernova. In parallel, the **SMOPF** module is being extended to explicitly incorporate $N-1$ security criteria.

Chapter 8

Conclusions

This chapter synthesizes the main contributions, findings, and broader implications of the work presented in this thesis, situating them within the ongoing transformation of electric power systems driven by the increasing penetration of RES and DERs. It consolidates the methodological advances developed throughout the thesis and reflects on the insights gained from extensive numerical and experimental validation, highlighting their relevance for both current power system operation and the future evolution of planning and control practices.

Beyond summarizing the technical results, this chapter places them within a broader institutional and regulatory context. In particular, it examines the implications of the proposed coordination frameworks in light of system unbundling principles, data privacy requirements, and the practical implementation constraints faced by TSOs and DSOs. The discussion is framed within current and emerging European regulatory developments, underscoring the relevance of the presented results for the practical evolution of coordinated transmission–distribution operation. Building on these considerations, the chapter formulates key recommendations and identifies promising directions for future research, emphasizing areas where further methodological refinement, large-scale validation, and regulatory adaptation are required to enable real-world deployment.

Specifically, the chapter is organized as follows:

- Section 8.1 summarizes the main contributions of this thesis, structured according to the proposed frameworks and methodological developments;
- Section 8.2 synthesizes and discusses the key findings derived from the numerical and experimental studies;
- Section 8.3 presents recommendations, discusses the regulatory and institutional alignment required for large-scale deployment of TSO–DSO coordination, and outlines directions for future research; and
- Section 8.4 concludes the chapter and the thesis.

8.1 Main Contributions

This thesis addresses a central challenge in the ongoing transformation of electric power systems: ensuring secure and economically efficient operation under rapidly increasing penetration of RESs, as traditional sources of controllability and ASs progressively erode. In this evolving context, maintaining system security and economic efficiency increasingly depends on the effective mobilization and coordination of flexibility provided by DERs.

Despite the growing technical capability of DERs to deliver flexibility and ASs, their large-scale integration into system operation remains fundamentally constrained by the institutional separation between TSOs and DSOs. These SOs operate under distinct regulatory frameworks, pursue different operational objectives, and typically rely on limited and static information exchange mechanisms. As a result, a substantial share of DN-level flexibility remains inaccessible to transmission system operation, even in situations where its activation could prevent network violations, reduce operational costs, increase RES integration, or defer network reinforcements.

In response to these challenges, this thesis proposes a set of coordinated operational and planning frameworks that explicitly bridge the transmission–distribution interface. The contributions developed in this work enable TSO and DSOs to jointly exploit distribution-level flexibility in a manner that is technically robust in the evaluated cases and designed to support scalability to larger and more heterogeneous systems, and compatible with existing and foreseeable regulatory and unbundling requirements. By addressing coordination across multiple time horizons – namely long-term investment decisions, operational planning, and real-time control – the proposed methodologies establish a comprehensive and practically oriented foundation for coordinated operation of future power systems.

8.1.1 TSO-DSO Coordination Framework

The first major contribution of this thesis is the development of a TSO–DSO coordination framework based on a fully distributed architecture, presented in Chapter 3 and operationalized through the coordinated operational planning tool introduced in Chapter 5. In contrast to the most widely adopted approaches in the literature, the proposed framework explicitly respects the institutional separation and operational autonomy of the participating SOs, while also delivering substantial system-wide operational benefits.

At its core, the framework enables coordinated decision-making through an iterative negotiation process based on the exchange of a limited set of coupling variables at the TN–DN interface. These variables – specifically voltage magnitudes, active and reactive power exchanges at boundary buses, and active and reactive power profiles of shared ESSs, if installed – are shown in the evaluated cases to support consistent and secure operation across voltage levels without requiring full operational information disclosure. By design, this approach directly addresses regulatory constraints arising from unbundling principles and is well aligned with current and emerging European regulatory practices.

Several distinguishing features characterize the proposed coordination mechanism:

- **Distributed and privacy-preserving architecture:** The coordination problem is decomposed into **TN**- and **DN**-level subproblems that are solved independently by the respective **SOs**. Only limited boundary information is exchanged, preserving data confidentiality while enabling convergence toward coordinated system-wide solutions.
- **Explicit modeling of shared resources at the **TN–DN** interface:** The framework introduces the concept of resources located at the **TN–DN** interface whose operation is coordinated between the **TSO** and participating **DSOs**. While this thesis focuses on shared **ESSs**, the formulation is generic and readily extensible to other classes of shared assets, such as power-electronic-based power flow control devices.
- **Accurate representation of **ADNs** flexibility:** In contrast to coordination schemes based on static or highly simplified **DN** models, the proposed framework explicitly captures network constraints, temporal dynamics, and flexibility limits of **ADNs**. This improves robustness and increases **TSO** confidence in the feasibility and reliability of distribution-level flexibility offers.
- **Expanded provision of **ASs**:** Beyond congestion management and voltage control, the inclusion of shared resources enables the provision of frequency-related services at the transmission level. This broadens the portfolio of **ASs** that can be supplied by coordinated operation and enhances overall system flexibility.
- **Industry-informed design and validation:** The coordination mechanism was developed in close collaboration with the Croatian **TSO** (HOPS) and the main **DSO** (HEP ODS), ensuring that institutional roles, operational practices, and regulatory constraints were explicitly embedded in both the framework design and its validation.

Overall, the proposed **TSO–DSO** coordination framework provides a technically robust, institutionally compatible, and scalable approach for unlocking distribution-level flexibility. By accurately representing the operational capabilities of modern **ADNs** while preserving **SO** autonomy and data privacy, the framework offers a practical pathway for the large-scale integration of **DERs** into coordinated power system operation.

Despite these advances, a key limitation of the approach lies in the inherently iterative nature of the underlying decomposition technique. While distributed optimization constitutes a viable and effective alternative to prevailing coordination mechanisms, convergence may require a non-negligible number of iterations in large-scale or tightly constrained systems. Further research is therefore needed to enhance numerical robustness, strengthen convergence guarantees, and improve computational efficiency. Moreover, as **TSO–DSO** coordination moves closer to real-world implementation, information security and cyber-resilience will become increasingly critical. Future implementations must explicitly address secure communication, data integrity, and protection against cyber-physical threats to ensure reliable, trustworthy, and regulatory-compliant operation.

8.1.2 Stochastic Multi-Period OPF and Online Real-Time OPF

The second major contribution of this thesis is the development of a **SMOPF** framework, presented in Chapter 4. The proposed framework provides a unified architecture that consistently links uncertainty-aware operational planning with real-time control, enabling coherent, physically consistent decision-making across multiple time scales.

At the operational planning level, the **SMOPF** formulation explicitly accounts for uncertainty in load, **RES** generation, and market prices. By relying on a full nonlinear **AC** formulation, the framework preserves a high degree of physical fidelity in representing network constraints and power flow behavior. This accuracy is particularly critical under stressed operating conditions and high penetration of distributed flexibility, where simplified or linearized models may yield infeasible, insecure, or misleading solutions. In contrast to many large-scale studies that trade physical accuracy for tractability, the proposed approach maintains operational feasibility and security even in scenarios close to system limits, and remains applicable at both transmission and distribution levels.

The **SMOPF** framework is characterized by the following key features:

- **Comprehensive uncertainty modeling:** Joint representation of operational uncertainty (load and **RES** variability) and economic uncertainty (market price forecasts), enabling robust techno-economic decision-making across multiple time scales, from operational planning to long-term investment analysis.
- **Detailed yet computationally tractable resource models:** Realistic modeling of controllable assets and **DERs**, capturing inter-temporal constraints and flexibility capabilities while remaining tractable in large-scale implementations.
- **Seamless integration with coordinated TSO–DSO operation:** Its modular design enables straightforward integration into the coordination framework proposed in this thesis, while preserving institutional autonomy and data privacy.

Building on the operational planning layer, this thesis further introduces an online real-time **OPF** module that translates optimal operating points into secure and implementable control actions. Instead of issuing instantaneous setpoint changes, the real-time module computes a *staged* control action that progressively steers the system toward its optimal state, thereby avoiding abrupt transitions that could trigger transient violations. The real-time **OPF** module was experimentally validated in a **HIL** environment, demonstrating that optimization-based control can be executed with computational performance compatible with real-time operation. This experimental validation constitutes a significant step beyond purely numerical studies, providing concrete evidence that advanced optimization techniques can be reliably deployed in practical power system control settings, while also confirming the numerical accuracy and robustness of the proposed **OPF** formulation.

8.1.3 Shared Resources Planning Framework

The third major contribution of this thesis is the development of a planning framework for shared resources at the **TN–DN** interface. The proposed methodology explicitly links long-term investment decisions with short-term coordinated operation, while accounting for uncertainty and asset degradation – an aspect that remains largely overlooked in existing **TSO–DSO** coordination literature and in **ESS** planning frameworks more broadly.

The main features and contributions of the proposed shared resources planning framework can be summarized as follows:

- **Integrated planning and operation across time scales:** The planning problem is formulated as a two-level optimization framework, in which investment decisions for shared resources are taken at the master level, while coordinated **TSO–DSO** operational planning is simulated at the subproblem level. This structure establishes a consistent link between long-term investment decisions and realistic short-term operational behavior under coordinated operation.
- **Scalable solution via mathematical decomposition:** The interaction between planning and operation is handled through Benders’ decomposition, while the operational coordination problem is solved using a distributed algorithm based on **ADMM**. This two-layer decomposition strategy preserves computational tractability despite the large scale, non-convexity, and uncertainty inherent to the large-scale problem.
- **Explicit modeling of asset degradation and **SoH** evolution:** A key novelty of the framework is the explicit representation of battery capacity degradation and **SoH** dynamics over the planning horizon. By embedding the long-term operational impact of cycling behavior, the framework accurately reflects the evolving performance of shared resources and captures the fundamental trade-off between early deployment – enabling earlier operational benefits – and deferred investment under uncertain cost trajectories.
- **Demonstrated system-wide value of shared resources:** The results demonstrate that well-sited and appropriately sized shared **ESSs** can deliver substantial system-wide benefits, particularly in high-**RES** scenarios, reducing operational costs, enhancing voltage regulation, and reducing renewable energy curtailment.

Overall, the proposed framework provides a flexible and extensible decision-support tool for evaluating investment strategies in shared resources. Through the consistent integration of uncertainty, asset degradation, and coordinated operation, it enables informed and adaptive planning and offers a solid foundation for extending the analysis to other classes of shared flexibility assets beyond energy storage.

8.2 Main Findings

The results obtained across the four case studies conducted lead to a set of overarching and consistent findings:

- Effectiveness of distributed coordination:** The thesis demonstrates that distributed TSO–DSO coordination is both technically effective and operationally robust. Across a wide range of operating conditions – from highly stressed scenarios to normal system regimes – coordinated strategies consistently outperform uncoordinated operation by resolving network constraint violations, reducing operational costs, and enabling higher levels of renewable energy integration. Importantly, these benefits are achieved without intrusive data sharing or centralized control, thereby preserving the operational autonomy of the participating SOs.
- Balance between performance, scalability, and regulatory compliance:** The results confirm that distributed coordination offers a well-balanced compromise between economic and operational efficiency, scalability, and regulatory feasibility. While centralized coordination can yield larger cost reductions, its reliance on full system observability and centralized decision-making limits scalability and conflicts with existing unbundling requirements. In contrast, the distributed framework proposed in this thesis preserves data privacy and institutional independence of TSO and DSOs – aligning it more closely with real-world deployment conditions - while delivering strong operational performance.
- Central role of distribution-level flexibility:** The simulations and numerical results highlight the pivotal role of DN-level flexibility in supporting transmission system operation. Coordinated operation enables a more efficient utilization of existing flexibility resources – particularly for voltage regulation – without systematically increasing either the volume or the cost of flexibility procurement. Reactive power support from ADNs emerges as a key enabler of secure transmission-level operation, underscoring the growing importance of DERs in the provision of ASs. Moreover, the results indicate that coordinated operation can contribute to deferring or reducing investments in conventional network reinforcements.
- Value of degradation-aware shared resource planning:** The planning-oriented analyses show that the value of shared flexibility assets fundamentally depends on coordinated operation and degradation-aware investment planning. Shared ESSs installed at the TN–DN interface can deliver substantial system-wide benefits in high-RES scenarios, including lower operational costs, reduced renewable curtailment, and enhanced voltage control. However, these benefits are *highly* sensitive to investment timing, cost uncertainty, and asset degradation dynamics, reinforcing the necessity of integrated planning frameworks that jointly account for long-term investment decisions, short-term operational behavior, and asset lifetime effects.

- **Feasibility of optimization-based real-time control:** The experimental validation confirms that optimization-based real-time control is feasible under realistic operating conditions. The proposed real-time OPF module computes secure, staged control actions within real-time computational constraints, even in the presence of discrete control variables. This result bridges a critical gap between operational planning and practical deployment, demonstrating that optimization-based control can be safely and reliably implemented in real-time power system operation.

Taken together, these findings establish TSO–DSO coordination as a viable and effective pathway toward the secure, efficient, and sustainable operation of future power systems. More broadly, they demonstrate that the large-scale integration of DERs is not solely a technical challenge, but also an institutional one – and that distributed coordination provides a practical, scalable, and institutionally compatible means of coherently addressing both dimensions.

8.3 Discussion, Recommendations, and Future Work

Despite the encouraging results obtained in this thesis, the large-scale deployment of coordinated TSO–DSO operation remains constrained by a combination of technical, regulatory, and institutional challenges. While distributed coordination frameworks have matured substantially from a methodological standpoint, their transition from advanced research concepts to operational practice will require sustained technical development, regulatory adaptation, and market evolution.

8.3.1 Regulatory and Institutional Alignment

Beyond technical considerations, regulatory and institutional alignment constitutes a decisive factor for the widespread adoption of coordinated TSO–DSO operation. Current market designs and regulatory frameworks often provide limited incentives for active coordination between TSOs and DSOs, as well as insufficient remuneration mechanisms for distribution-level flexibility. As a result, many of the technical capabilities demonstrated in this thesis cannot yet be fully exploited or systematically evaluated in real-world settings, underscoring the need for regulatory innovation alongside methodological development.

From a regulatory perspective, the role of the DSO requires the most significant evolution to enable the practical implementation of TSO–DSO coordinated operation. Although DSOs are already transitioning toward more active network management practices, their institutional responsibilities must expand further. In particular, DSOs are expected to increasingly act as intermediaries between TSOs and DERs, either directly or through aggregators. Such a transition requires clear regulatory mandates, well-defined operational responsibilities, and incentive structures that appropriately reflect the value of flexibility provision and coordination.

The practical deployment of shared resources requires suitable ownership, investment, remuneration, and cost-allocation arrangements. The methodologies developed in this thesis do not prescribe a specific ownership or financing model; instead, they quantify the techno-economic and operational value of shared resources from a system-wide perspective. Accordingly, the results should be interpreted as evidence of their potential system-wide benefits rather than as a recommendation for a particular governance arrangement. Possible implementation models include ownership and operation by an independent third-party entity providing contracted services to the TSO and participating DSOs, or deployment through a regulator-approved investment mechanism, with cost recovery through network tariffs where justified by demonstrable system-wide benefits. No single governance model is expected to be universally preferable; the most appropriate ownership, remuneration, and cost-allocation arrangements will depend on the regulatory and institutional context of each jurisdiction.

The evolution of the DSO role is closely aligned with recent European electricity market reforms, which place increasing emphasis on active system management, flexibility procurement, and enhanced TSO–DSO coordination. Within this context, regulatory sandboxes and experimental market platforms can play a crucial enabling role. By allowing controlled experimentation with novel coordination schemes, institutional arrangements, and flexibility procurement mechanisms, these environments provide a structured pathway to assess technical performance, economic efficiency, and regulatory implications of TSO–DSO coordination mechanisms prior to large-scale deployment.

8.3.2 Recommendations and Future Work

From a technical perspective, further research is required to enhance the scalability, robustness, and resilience of coordinated TSO–DSO operation frameworks. Although the algorithms proposed in this thesis demonstrated stable empirical convergence in the evaluated cases and favorable computational performance, future work should explicitly address coordination under more adverse and realistic conditions, including asynchronous information exchange, communication delays, data losses, and partial observability. Extending the proposed methodologies to multi-area and multi-TSO settings – particularly in cross-border contexts – represents a natural and necessary next step. In addition, the integration of explicit security constraints, such as $N - 1$ criteria, into stochastic multi-period OPF formulations remains a critical requirement for real-world deployment.

At the planning level, future research should further investigate risk-aware and robust investment strategies for shared resources. While this thesis adopts a stochastic optimization framework, alternative formulations based on RO or DRO could provide stronger guarantees under deep uncertainty, particularly in the presence of long-term policy, technology, and market volatility. The interaction between planning horizon discretization and asset degradation modeling – especially for battery-based ESSs – also warrants deeper

investigation. More detailed electrochemical or data-driven degradation models could significantly enhance the fidelity and reliability of long-term planning outcomes.

With respect to real-time operation, the laboratory validation conducted in this thesis constitutes an important step toward practical adoption; however, large-scale field demonstrations remain essential. Long-duration pilot projects are required to assess not only computational feasibility, but also operator trust in optimization-based decision support. In safety-critical environments such as power system operation, the acceptance of advanced control tools depends not only on performance, but also on their transparency, predictability, and alignment with established operational practices. Future work should therefore place greater emphasis on human-in-the-loop considerations, including explainability of control actions, interaction with control room workflows, and mechanisms for operator override and supervision. Such demonstrations would also enable systematic evaluation of cyber-security, fail-safe operation, and fallback strategies, all of which are prerequisites for deployment in critical infrastructure environments.

The increasing availability of high-resolution operational data further opens opportunities for integrating data-driven and AI-based methods into coordinated operation and planning. ML techniques could support scenario generation, uncertainty quantification, surrogate modeling, and the acceleration of optimization algorithms, provided that transparency, interpretability, and reliability are preserved. The careful integration of data-driven approaches with physics-based optimization frameworks therefore remains an important and open research challenge.

Finally, a fundamental aspect that warrants deeper investigation – and that underpins many of the methods developed in this thesis – concerns the development of mathematical decomposition techniques that are robust to the inherent non-convexity of power system optimization problems. While decomposition-based approaches enable scalability, their convergence behavior can be sensitive to problem structure and parameterization. A complementary research direction lies in the development of *tight* convex network models that retain sufficient physical accuracy for safety-critical applications, thereby enabling stronger theoretical guarantees without sacrificing practical relevance.

8.4 Concluding Remarks

In conclusion, advancing coordinated TSO–DSO operation requires a holistic approach that integrates methodological innovation, rigorous validation, and regulatory enablement. As electric power systems evolve toward higher shares of DERs and increasingly decentralized operation, traditional paradigms based on hierarchical control and limited information exchange become progressively less effective. In this context, coordinated transmission–distribution operation emerges not as a theoretical refinement, but as a necessary enabler of secure, efficient, and sustainable system operation.

The frameworks and tools developed in this thesis demonstrate that it is technically feasible to unlock distribution-level flexibility through distributed coordination mechanisms that respect system unbundling, preserve data privacy, and remain compatible with existing regulatory principles. By explicitly embedding institutional separation and limited information exchange into the design of the coordination algorithms, this work shows that enhanced coordination does not require regulatory overreach or full system centralization. Instead, it can be achieved through carefully designed coordination frameworks that align operational efficiency with regulatory compliance. These findings carry direct implications for future regulatory and market design. In particular, they highlight the need for market arrangements and incentive structures that recognize and reward active **TSO–DSO** coordination, enable the provision of flexibility services across voltage levels, and clearly define the evolving role of **DSOs** as active system managers. In this regard, regulatory sandboxes emerge as critical instruments for validating such coordination mechanisms in practice, allowing policymakers to assess technical performance, economic outcomes, and institutional impacts under controlled conditions prior to wide-scale adoption.

Ultimately, this thesis supports a policy perspective in which coordinated **TSO–DSO** operation becomes a cornerstone of future electricity market design. By demonstrating that distributed coordination can reconcile technical efficiency with institutional boundaries, this work contributes to the development of regulatory frameworks capable of supporting secure, flexible, and sustainable power systems in the decades to come.

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Appendix A

Case Study 1

This appendix details the simulation data associated with the transmission and distribution test systems used in Case Study 1 (Section 7.1). The characteristics of the **TN** are presented in Section A.1, while Section A.2 describes the **DN**s adopted in the study.

A.1 Transmission Network

The **TN** adopted in this case study is based on the **IEEE** 9-bus transmission test system, obtained from the MATPOWER package (Zimmerman et al., 2011). The system base power is set to $S^{\text{Base}} = 100.00$ MVA.

Figure A.1 presents the single-line diagram of the adopted **IEEE** 9-bus **TN**. In the figure, the reference bus is highlighted in red, **PV** buses in green, and **PQ** buses in light blue. Table A.1 reports the main characteristics of the transmission buses, while Table A.2 details the branch data, including transmission lines and transformers. Conventional generator data are provided in Table A.3. It should be noted that **RES** generators connected to the **TN** are described separately in the corresponding section.

Table A.1: Case Study 1. IEEE 9-bus test system. Bus data.

Bus	Bus	g_i	b_i	V_i^{Base}	V_i^{max}	V_i^{min}
ID	Type	[p.u.]	[p.u.]	[kV]	[p.u.]	[p.u.]
1	Ref.	0.00	0.00	345.00	1.10	0.90
2	PV	0.00	0.00	345.00	1.10	0.90
3	PV	0.00	0.00	345.00	1.10	0.90
4	PQ	0.00	0.00	345.00	1.10	0.90
5	PQ	0.00	0.00	345.00	1.10	0.90
6	PQ	0.00	0.00	345.00	1.10	0.90
7	PQ	0.00	0.00	345.00	1.10	0.90
8	PQ	0.00	0.00	345.00	1.10	0.90
9	PQ	0.00	0.00	345.00	1.10	0.90

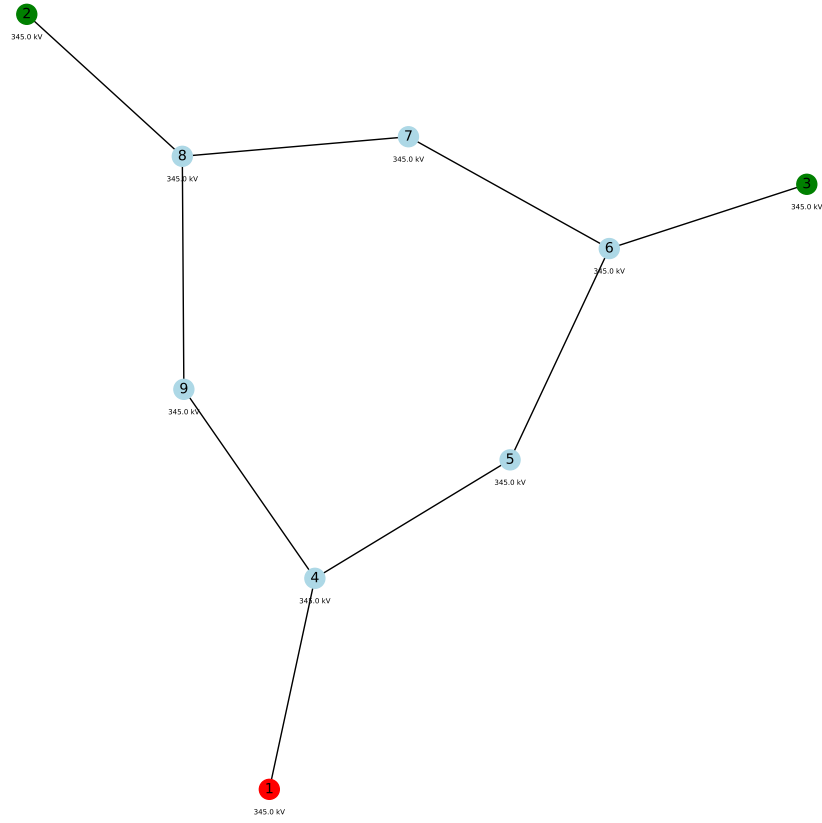


Figure A.1: Case study 1. TN single-line diagram.

Table A.2: Case Study 1. IEEE 9-bus test system. Branch data.

Branch	From	To	r_{ij}	x_{ij}	b_{ij}^{Sh}	S_{ij}^{Rated}
ID	Bus ID	Bus ID	[p.u.]	[p.u.]	[p.u.]	[MVA]
1	1	4	0.000000	0.057600	0.000000	250.00
2	4	5	0.017000	0.092000	0.158000	250.00
3	5	6	0.039000	0.170000	0.358000	150.00
4	3	6	0.000000	0.058600	0.000000	300.00
5	6	7	0.011900	0.100800	0.209000	150.00
6	7	8	0.008500	0.072000	0.149000	250.00
7	8	2	0.000000	0.062500	0.000000	250.00
8	8	9	0.032000	0.161000	0.306000	250.00
9	9	4	0.010000	0.085000	0.176000	250.00

Table A.3: Case Study 1. IEEE 9-bus test system. Conventional generator data.

Generator	Bus	$P_g^{G,\max}$	$P_g^{G,\min}$	$Q_g^{G,\max}$	$Q_g^{G,\min}$	V_g^S
ID	ID	[MW]	[MW]	[MVar]	[MVar]	[p.u.]
1	1	250.00	10.00	300.00	-300.00	1.040
2	2	300.00	10.00	300.00	-300.00	1.025
3	3	270.00	10.00	300.00	-300.00	1.025

A.2 Distribution Networks

This section describes the simulation data associated with the **DN**s adopted in the case studies presented in Case Study 1 (Section 7.1). All **DN**s are based on the **IEEE** 33-bus radial distribution test system, with topological data obtained from the MATPOWER package (Zimmerman et al., 2011). The system base power is $S^{\text{Base}} = 100.00$ MVA.

Figure A.2 presents the single-line diagram of the adopted **IEEE** 33-bus distribution network. In the figure, the reference bus is highlighted in red, while **PQ** buses are shown in light blue. Branches highlighted in red indicate elements that are out of service. Table A.4 reports the main characteristics of the distribution buses, whereas Table A.5 details the branch data, including distribution lines and transformers. Generator data, representing the connection of the **DN** to the upstream **TN**, are provided in Table A.6, while load data are summarized in Table A.7.

Table A.4: Case Study 1. IEEE 33-bus test system. Bus data.

Bus	Bus	g_i	b_i	V_i^{Base}	$V_i^{\max}$	$V_i^{\min}$	Bus	Bus	g_i	b_i	V_i^{Base}	$V_i^{\max}$	$V_i^{\min}$
ID	Type	[p.u.]	[p.u.]	[kV]	[p.u.]	[p.u.]	ID	Type	[p.u.]	[p.u.]	[kV]	[p.u.]	[p.u.]
1	Ref.	0.00	0.00	345.00	1.10	0.90	18	PQ	0.00	0.00	12.66	1.10	0.90
2	PQ	0.00	0.00	12.66	1.10	0.90	19	PQ	0.00	0.00	12.66	1.10	0.90
3	PQ	0.00	0.00	12.66	1.10	0.90	20	PQ	0.00	0.00	12.66	1.10	0.90
4	PQ	0.00	0.00	12.66	1.10	0.90	21	PQ	0.00	0.00	12.66	1.10	0.90
5	PQ	0.00	0.00	12.66	1.10	0.90	22	PQ	0.00	0.00	12.66	1.10	0.90
6	PQ	0.00	0.00	12.66	1.10	0.90	23	PQ	0.00	0.00	12.66	1.10	0.90
7	PQ	0.00	0.00	12.66	1.10	0.90	24	PQ	0.00	0.00	12.66	1.10	0.90
8	PQ	0.00	0.00	12.66	1.10	0.90	25	PQ	0.00	0.00	12.66	1.10	0.90
9	PQ	0.00	0.00	12.66	1.10	0.90	26	PQ	0.00	0.00	12.66	1.10	0.90
10	PQ	0.00	0.00	12.66	1.10	0.90	27	PQ	0.00	0.00	12.66	1.10	0.90
11	PQ	0.00	0.00	12.66	1.10	0.90	28	PQ	0.00	0.00	12.66	1.10	0.90
12	PQ	0.00	0.00	12.66	1.10	0.90	29	PQ	0.00	0.00	12.66	1.10	0.90
13	PQ	0.00	0.00	12.66	1.10	0.90	30	PQ	0.00	0.00	12.66	1.10	0.90
14	PQ	0.00	0.00	12.66	1.10	0.90	31	PQ	0.00	0.00	12.66	1.10	0.90
15	PQ	0.00	0.00	12.66	1.10	0.90	32	PQ	0.00	0.00	12.66	1.10	0.90
16	PQ	0.00	0.00	12.66	1.10	0.90	33	PQ	0.00	0.00	12.66	1.10	0.90
17	PQ	0.00	0.00	12.66	1.10	0.90							

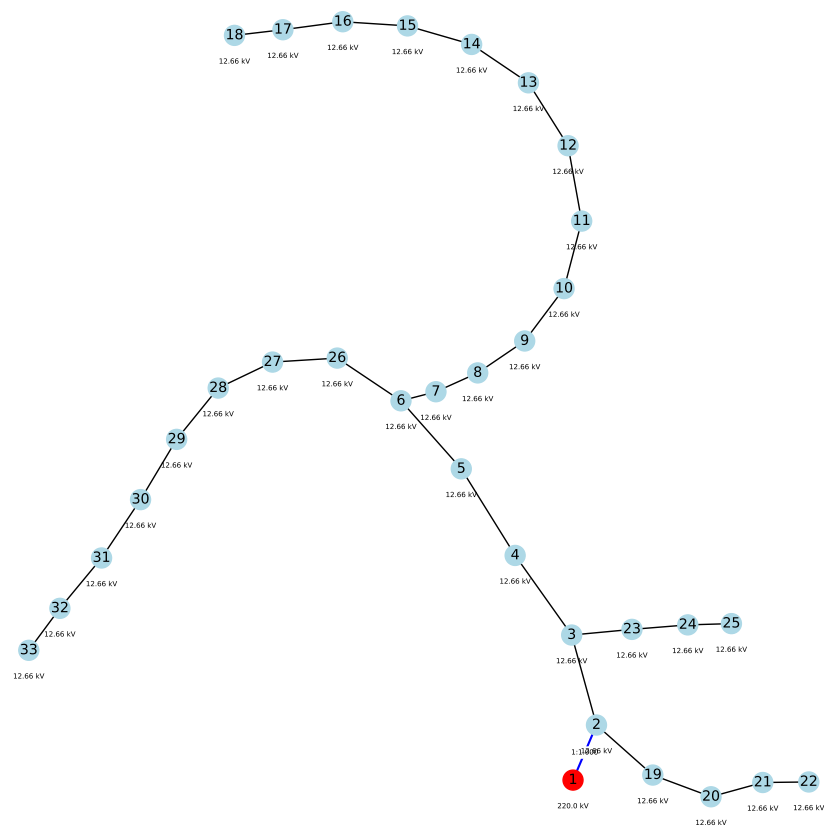


Figure A.2: IEEE 33-bus test system. Network diagram.

Table A.5: Case Study 1. IEEE 33-bus test system. Branch data.

Branch	From	To	r_{ij}	x_{ij}	b_{ij}^{Sh}	S_{ij}^{Rated}	Branch	From	To	r_{ij}	x_{ij}	b_{ij}^{Sh}	S_{ij}^{Rated}
ID	Bus ID	Bus ID	[p.u.]	[p.u.]	[p.u.]	[MVA]	ID	Bus ID	Bus ID	[p.u.]	[p.u.]	[p.u.]	[MVA]
1	1	2	0.005753	0.002932	0.00	200.00	42	6	7	0.011680	0.038608	0.00	75.00
2	2	3	0.030760	0.015667	0.00	150.00	43	7	8	0.044386	0.014668	0.00	60.00
3	3	4	0.022836	0.011630	0.00	150.00	44	8	9	0.064264	0.046170	0.00	40.00
4	4	5	0.023778	0.012110	0.00	125.00	45	9	10	0.065138	0.046170	0.00	40.00
5	5	6	0.051099	0.044112	0.00	125.00	46	10	11	0.012266	0.004056	0.00	40.00
6	6	7	0.011680	0.038608	0.00	100.00	47	11	12	0.023360	0.007724	0.00	40.00
7	7	8	0.044386	0.014668	0.00	75.00	48	12	13	0.091592	0.072063	0.00	30.00
8	8	9	0.064264	0.046170	0.00	75.00	49	13	14	0.033792	0.044480	0.00	25.00
9	9	10	0.065138	0.046170	0.00	50.00	50	14	15	0.036874	0.032818	0.00	15.00
10	10	11	0.012266	0.004056	0.00	50.00	51	15	16	0.046564	0.034004	0.00	10.00
11	11	12	0.023360	0.007724	0.00	50.00	52	16	17	0.080424	0.107378	0.00	5.00
12	12	13	0.091592	0.072063	0.00	50.00	53	17	18	0.045671	0.035813	0.00	5.00
13	13	14	0.033792	0.044480	0.00	40.00	54	6	26	0.012666	0.006451	0.00	50.00
14	14	15	0.036874	0.032818	0.00	40.00	55	26	27	0.017732	0.009028	0.00	50.00
15	15	16	0.046564	0.034004	0.00	40.00	56	27	28	0.066074	0.058256	0.00	50.00
16	16	17	0.080424	0.107378	0.00	40.00	57	28	29	0.050176	0.043712	0.00	50.00
17	17	18	0.045671	0.035813	0.00	40.00	58	29	30	0.031664	0.016128	0.00	50.00
18	2	19	0.010232	0.009764	0.00	50.00	59	30	31	0.060795	0.060084	0.00	25.00
19	19	20	0.093851	0.084567	0.00	40.00	60	31	32	0.019373	0.022580	0.00	25.00
20	20	21	0.025550	0.029849	0.00	40.00	61	32	33	0.021276	0.033081	0.00	15.00
21	21	22	0.044230	0.058481	0.00	40.00	62	21	8	0.124785	0.124785	0.00	3.00
22	3	23	0.028152	0.019236	0.00	75.00	63	9	15	0.124785	0.124785	0.00	3.00
23	23	24	0.056028	0.044243	0.00	60.00	64	12	22	0.124785	0.124785	0.00	3.00
24	24	25	0.055904	0.043743	0.00	50.00	65	18	33	0.031196	0.031196	0.00	3.00
25	6	26	0.012666	0.006451	0.00	100.00	66	25	29	0.031196	0.031196	0.00	3.00
26	26	27	0.017732	0.009028	0.00	100.00	67	2	3	0.030760	0.015667	0.00	125.00
27	27	28	0.066074	0.058256	0.00	75.00	68	3	4	0.022836	0.011630	0.00	100.00
28	28	29	0.050176	0.043712	0.00	75.00	69	4	5	0.023778	0.012110	0.00	100.00
29	29	30	0.031664	0.016128	0.00	75.00	70	5	6	0.051099	0.044112	0.00	100.00
30	30	31	0.060795	0.060084	0.00	50.00	71	6	7	0.011680	0.038608	0.00	75.00
31	31	32	0.019373	0.022580	0.00	50.00	72	7	8	0.044386	0.014668	0.00	60.00
32	32	33	0.021276	0.033081	0.00	50.00	73	8	9	0.064264	0.046170	0.00	40.00
33	21	8	0.124785	0.124785	0.00	3.00	74	9	10	0.065138	0.046170	0.00	40.00
34	9	15	0.124785	0.124785	0.00	3.00	75	10	11	0.012266	0.004056	0.00	40.00
35	12	22	0.124785	0.124785	0.00	3.00	76	11	12	0.023360	0.007724	0.00	40.00
36	18	33	0.031196	0.031196	0.00	3.00	77	12	13	0.091592	0.072063	0.00	30.00
37	25	29	0.031196	0.031196	0.00	3.00	78	13	14	0.033792	0.044480	0.00	25.00
38	2	3	0.030760	0.015667	0.00	125.00	79	14	15	0.036874	0.032818	0.00	15.00
39	3	4	0.022836	0.011630	0.00	100.00	80	15	16	0.046564	0.034004	0.00	10.00
40	4	5	0.023778	0.012110	0.00	100.00	81	16	17	0.080424	0.107378	0.00	5.00
41	5	6	0.051099	0.044112	0.00	100.00	82	17	18	0.045671	0.035813	0.00	5.00

Table A.6: Case Study 1. IEEE 33-bus test system. Connection with TN

Generator	Node	$P_g^{G,\max}$	$P_g^{G,\min}$	$Q_g^{G,\max}$	$Q_g^{G,\min}$	V_g^S
ID	ID	[MW]	[MW]	[MVar]	[MVar]	[p.u.]
1	1	250.00	-250.00	250.00	-250.00	1.00

Table A.7: Case Study 1. IEEE 33-bus test system. Load data.

Load	Bus	FL Ratio	Load	Bus	FL Ratio	Load	Bus	FL Ratio
ID	ID	[%]	ID	ID	[%]	ID	ID	[%]
1	2	2.69%	12	13	1.62%	23	24	11.31%
2	3	2.42%	13	14	3.23%	24	25	11.31%
3	4	3.23%	14	15	1.62%	25	26	1.62%
4	5	1.62%	15	16	1.62%	26	27	1.62%
5	6	1.62%	16	17	1.62%	27	28	1.62%
6	7	5.38%	17	18	2.42%	28	29	3.23%
7	8	5.38%	18	19	2.42%	29	30	5.38%
8	9	1.62%	19	20	2.42%	30	31	4.04%
9	10	1.62%	20	21	2.42%	31	32	5.65%
10	11	1.21%	21	22	2.42%	32	33	1.62%
11	12	1.62%	22	23	2.42%			

Appendix B

Case Study 2

This appendix provides the detailed data and modeling assumptions associated with the TSO–DSO coordinated operational planning case study presented in Section 7.2 of Chapter 7. The TN and DNs adopted in this case study are based on standard IEEE test systems, which were appropriately modified to reflect the characteristics and requirements of the proposed coordination framework.

Section B.1 describes the TN adopted in this case study, including its topology and generation portfolio. Section B.2 details the ADNs connected to the transmission system, highlighting their structural characteristics and levels of RES integration. Section B.3 presents the wholesale energy and flexibility market data considered in the simulations. Finally, Section B.4 reports additional results that complement those discussed in the main body of the chapter.

B.1 Transmission Network

The TN adopted in this case study is based on the IEEE 57-bus test system (Zimmerman et al., 2011). All network parameters are expressed on a common power base of $S^{\text{Base}} = 100.00$ MVA. Figure 7.13, presented in Section 7.2, illustrates the single-line diagram of the adopted test system.

In the network diagram, the reference (slack) bus is shown in red, PV buses (corresponding to conventional generator locations) are shown in green, and PQ buses are shown in light blue. Table B.1 summarizes the bus data of the TN, including voltage limits and base voltage levels. Table B.2 reports the electrical parameters and thermal ratings of the transmission branches (lines and transformers). The characteristics of the conventional generators connected to the TN are provided in Table B.3, while Table B.4 details the aggregated loads connected at the transmission level.

To capture seasonal variability in operating conditions, representative load and RES generation scenarios were defined for different seasons of the year. Figures B.1, B.2, and B.3 present the TN-level load and RES generation profiles adopted for the Summer,

Table B.1: Case Study 2. IEEE 57-bus test system. Bus data.

Bus	Bus	g_i	b_i	V_i^{Base}	V_i^{max}	V_i^{min}	Bus	Bus	g_i	b_i	V_i^{Base}	V_i^{max}	V_i^{min}
ID	Type	[p.u.]	[p.u.]	[kV]	[p.u.]	[p.u.]	ID	Type	[p.u.]	[p.u.]	[kV]	[p.u.]	[p.u.]
1	Ref.	0.00	0.00	220.00	1.06	0.94	30	PQ	0.00	0.00	220.00	1.06	0.94
2	PV	0.00	0.00	220.00	1.06	0.94	31	PQ	0.00	0.00	220.00	1.06	0.94
3	PV	0.00	0.00	220.00	1.06	0.94	32	PQ	0.00	0.00	220.00	1.06	0.94
4	PQ	0.00	0.00	220.00	1.06	0.94	33	PQ	0.00	0.00	220.00	1.06	0.94
5	PQ	0.00	0.00	220.00	1.06	0.94	34	PQ	0.00	0.00	220.00	1.06	0.94
6	PV	0.00	0.00	220.00	1.06	0.94	35	PQ	0.00	0.00	220.00	1.06	0.94
7	PQ	0.00	0.00	220.00	1.06	0.94	36	PQ	0.00	0.00	220.00	1.06	0.94
8	PV	0.00	0.00	220.00	1.06	0.94	37	PQ	0.00	0.00	220.00	1.06	0.94
9	PV	0.00	0.00	220.00	1.06	0.94	38	PQ	0.00	0.00	220.00	1.06	0.94
10	PQ	0.00	0.00	220.00	1.06	0.94	39	PQ	0.00	0.00	220.00	1.06	0.94
11	PQ	0.00	0.00	220.00	1.06	0.94	40	PQ	0.00	0.00	220.00	1.06	0.94
12	PV	0.00	0.00	220.00	1.06	0.94	41	PQ	0.00	0.00	220.00	1.06	0.94
13	PQ	0.00	0.00	220.00	1.06	0.94	42	PQ	0.00	0.00	220.00	1.06	0.94
14	PQ	0.00	0.00	220.00	1.06	0.94	43	PQ	0.00	0.00	220.00	1.06	0.94
15	PQ	0.00	0.00	220.00	1.06	0.94	44	PQ	0.00	0.00	220.00	1.06	0.94
16	PQ	0.00	0.00	220.00	1.06	0.94	45	PQ	0.00	0.00	220.00	1.06	0.94
17	PQ	0.00	0.00	220.00	1.06	0.94	46	PQ	0.00	0.00	220.00	1.06	0.94
18	PQ	0.00	10.00	220.00	1.06	0.94	47	PQ	0.00	0.00	220.00	1.06	0.94
19	PQ	0.00	0.00	220.00	1.06	0.94	48	PQ	0.00	0.00	220.00	1.06	0.94
20	PQ	0.00	0.00	220.00	1.06	0.94	49	PQ	0.00	0.00	220.00	1.06	0.94
21	PQ	0.00	0.00	220.00	1.06	0.94	50	PQ	0.00	0.00	220.00	1.06	0.94
22	PQ	0.00	0.00	220.00	1.06	0.94	51	PQ	0.00	0.00	220.00	1.06	0.94
23	PQ	0.00	0.00	220.00	1.06	0.94	52	PQ	0.00	0.00	220.00	1.06	0.94
24	PQ	0.00	0.00	220.00	1.06	0.94	53	PQ	0.00	6.30	220.00	1.06	0.94
25	PQ	0.00	5.90	220.00	1.06	0.94	54	PQ	0.00	0.00	220.00	1.06	0.94
26	PQ	0.00	0.00	220.00	1.06	0.94	55	PQ	0.00	0.00	220.00	1.06	0.94
27	PQ	0.00	0.00	220.00	1.06	0.94	56	PQ	0.00	0.00	220.00	1.06	0.94
28	PQ	0.00	0.00	220.00	1.06	0.94	57	PQ	0.00	0.00	220.00	1.06	0.94
29	PQ	0.00	0.00	220.00	1.06	0.94							

Table B.2: Case Study 2. IEEE 57-bus test system. Branch data.

Branch	From	To	r_{ij}	x_{ij}	b_{ij}^{Sh}	S_{ij}^{Rated}	Branch	From	To	r_{ij}	x_{ij}	b_{ij}^{Sh}	S_{ij}^{Rated}
ID	Node ID	Node ID	[p.u.]	[p.u.]	[p.u.]	[MVA]	ID	Node ID	Node ID	[p.u.]	[p.u.]	[p.u.]	[MVA]
1	1	2	0.0083	0.0280	0.1290	125.00	41	7	29	0.0000	0.0648	0.0000	250.00
2	2	3	0.0298	0.0850	0.0818	125.00	42	25	30	0.1350	0.2020	0.0000	100.00
3	3	4	0.0112	0.0366	0.0380	150.00	43	30	31	0.3260	0.4970	0.0000	50.00
4	4	5	0.0625	0.1320	0.0258	65.00	44	31	32	0.5070	0.7550	0.0000	40.00
5	4	6	0.0430	0.1480	0.0348	65.00	45	32	33	0.0392	0.0360	0.0000	65.00
6	6	7	0.0200	0.1020	0.0276	125.00	46	34	32	0.0000	0.9530	0.0000	65.00
7	6	8	0.0339	0.1730	0.0470	125.00	47	34	35	0.0520	0.0780	0.0032	150.00
8	8	9	0.0099	0.0505	0.0548	200.00	48	35	36	0.0430	0.0537	0.0016	200.00
9	9	10	0.0369	0.1679	0.0440	50.00	49	36	37	0.0290	0.0366	0.0000	200.00
10	9	11	0.0258	0.0848	0.0218	175.00	50	37	38	0.0651	0.1009	0.0020	250.00
11	9	12	0.0648	0.2950	0.0772	50.00	51	37	39	0.0239	0.0379	0.0000	100.00
12	9	13	0.0481	0.1580	0.0406	50.00	52	36	40	0.0300	0.0466	0.0000	100.00
13	13	14	0.0132	0.0434	0.0110	150.00	53	22	38	0.0192	0.0295	0.0000	175.00
14	13	15	0.0269	0.0869	0.0230	50.00	54	11	41	0.0000	0.7490	0.0000	100.00
15	1	15	0.0178	0.0910	0.0988	150.00	55	41	42	0.2070	0.3520	0.0000	75.00
16	1	16	0.0454	0.2060	0.0546	50.00	56	41	43	0.0000	0.4120	0.0000	125.00
17	1	17	0.0238	0.1080	0.0286	75.00	57	38	44	0.0289	0.0585	0.0020	125.00
18	3	15	0.0162	0.0530	0.0544	100.00	58	15	45	0.0000	0.1042	0.0000	125.00
19	4	18	0.0000	0.5550	0.0000	80.00	59	14	46	0.0000	0.0735	0.0000	200.00
20	4	18	0.0000	0.4300	0.0000	60.00	60	46	47	0.0230	0.0680	0.0032	100.00
21	5	6	0.0302	0.0641	0.0124	75.00	61	47	48	0.0182	0.0233	0.0000	100.00
22	7	8	0.0139	0.0712	0.0194	175.00	62	48	49	0.0834	0.1290	0.0048	125.00
23	10	12	0.0277	0.1262	0.0328	125.00	63	49	50	0.0801	0.1280	0.0000	100.00
24	11	13	0.0223	0.0732	0.0188	175.00	64	50	51	0.1386	0.2200	0.0000	50.00
25	12	13	0.0178	0.0580	0.0604	175.00	65	10	51	0.0000	0.0712	0.0000	75.00
26	12	16	0.0180	0.0813	0.0216	125.00	66	13	49	0.0000	0.1910	0.0000	65.00
27	12	17	0.0397	0.1790	0.0476	125.00	67	29	52	0.1442	0.1870	0.0000	35.00
28	14	15	0.0171	0.0547	0.0148	175.00	68	52	53	0.0762	0.0984	0.0000	85.00
29	18	19	0.4610	0.6850	0.0000	75.00	69	53	54	0.1878	0.2320	0.0000	35.00
30	19	20	0.2830	0.4340	0.0000	30.00	70	54	55	0.1732	0.2265	0.0000	35.00
31	21	20	0.0000	0.7767	0.0000	65.00	71	11	43	0.0000	0.1530	0.0000	200.00
32	21	22	0.0736	0.1170	0.0000	175.00	72	44	45	0.0624	0.1242	0.0040	75.00
33	22	23	0.0099	0.0152	0.0000	60.00	73	40	56	0.0000	1.1950	0.0000	50.00
34	23	24	0.1660	0.2560	0.0084	75.00	74	56	41	0.5530	0.5490	0.0000	35.00
35	24	25	0.0000	1.1820	0.0000	35.00	75	56	42	0.2125	0.3540	0.0000	35.00
36	24	25	0.0000	1.2300	0.0000	75.00	76	39	57	0.0000	1.3550	0.0000	50.00
37	24	26	0.0000	0.0473	0.0000	75.00	77	57	56	0.1740	0.2600	0.0000	50.00
38	26	27	0.1650	0.2540	0.0000	75.00	78	38	49	0.1150	0.1770	0.0030	85.00
39	27	28	0.0618	0.0954	0.0000	100.00	79	38	48	0.0312	0.0482	0.0000	125.00
40	28	29	0.0418	0.0587	0.0000	175.00	80	9	55	0.0000	0.1205	0.0000	250.00

Table B.3: Case Study 2. IEEE 57-bus test system. Conventional generators data.

Generator	Bus	$P_g^{G,max}$	$P_g^{G,min}$	$Q_g^{G,max}$	$Q_g^{G,min}$	V_g^S
ID	ID	[MW]	[MW]	[MVA]	[MVA]	[p.u.]
1	1	550.00	0.00	200.00	-140.00	1.04
2	2	100.00	0.00	50.00	-17.00	1.01
3	3	140.00	0.00	60.00	-10.00	0.99
4	6	100.00	0.00	25.00	-8.00	0.98
5	8	550.00	0.00	200.00	-140.00	1.01
6	9	100.00	0.00	9.00	-3.00	0.98
7	12	410.00	0.00	155.00	-150.00	1.02

Table B.4: Case Study 2. IEEE 57-bus test system. Load data.

Load	Bus	FL Ratio	Load	Bus	FL Ratio	Load	Bus	FL Ratio
ID	ID	[%]	ID	ID	[%]	ID	ID	[%]
1	1	6.92%	15	18	3.42%	29	41	0.79%
2	2	0.38%	16	19	0.42%	30	42	0.89%
3	3	5.16%	17	20	0.29%	31	43	0.25%
4	5	1.64%	18	23	0.79%	32	44	1.51%
5	6	9.44%	19	25	0.79%	33	47	3.74%
6	8	6.29%	20	27	1.17%	34	49	2.26%
7	9	7.80%	21	28	0.58%	35	50	2.64%
8	10	0.63%	22	29	2.14%	36	51	2.26%
9	12	10.07%	23	30	0.45%	37	52	0.62%
10	13	2.26%	24	31	0.73%	38	53	2.52%
11	14	1.32%	25	32	0.20%	39	54	0.52%
12	15	2.77%	26	33	0.48%	40	55	0.86%
13	16	5.41%	27	35	0.75%	41	56	0.96%
14	17	5.28%	28	38	1.76%	42	57	0.84%

Autumn, and Winter representative days, respectively. The corresponding data for the Spring representative day are reported directly in Section 7.2, where the full case study setup is described.

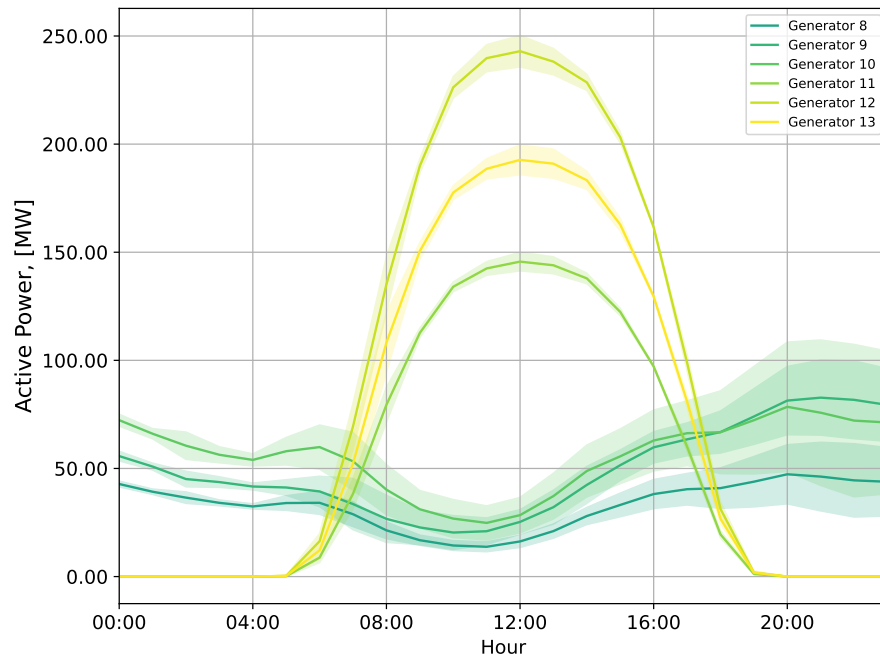
B.2 Distribution Networks

This section describes the **DNs** data adopted in Case Study 2, presented in Section 7.2. All **DNs** considered in this case study are based on standard **IEEE** test systems, which were adapted to include **RES** generation and representative load profiles.

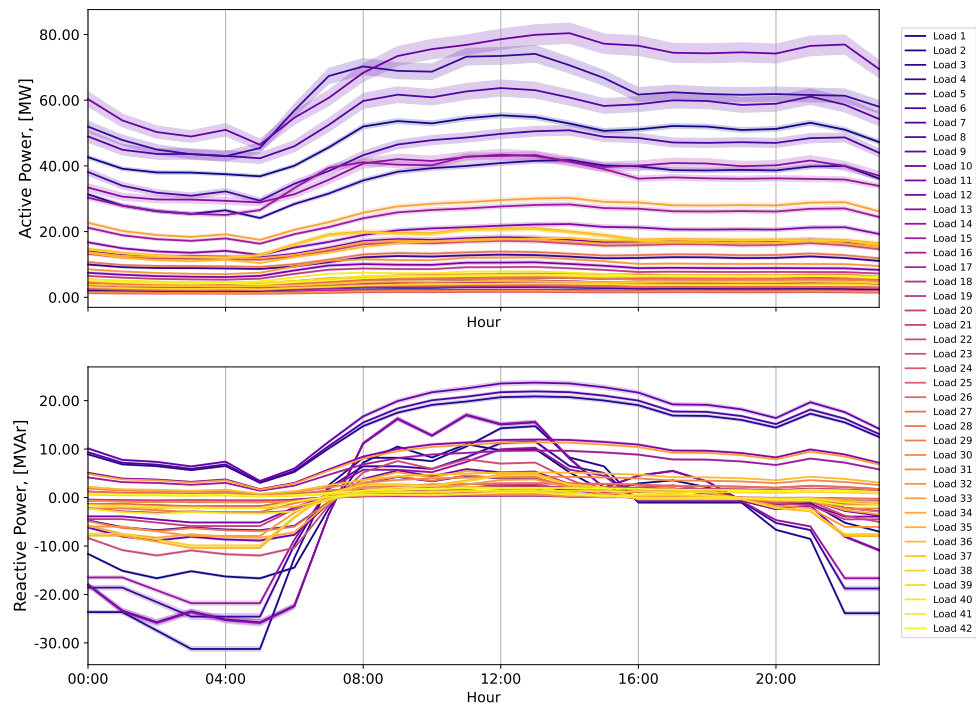
The adopted test systems, together with the corresponding load and **RES** generation scenarios, are detailed in the following subsections. Subsection B.2.1 presents the topological data of the selected distribution networks. Subsections B.2.2–B.2.10 describe the operating scenarios for each **ADN**, including load, **RES** generation, and flexibility profiles for the representative days.

B.2.1 Topological Data

This subsection summarizes the topological data of the **DNs** adopted in Case Study 2. Three different **IEEE**-based test systems were used, namely the 18-bus, 22-bus, and 33-bus distribution networks, selected to represent heterogeneous distribution system characteristics. Table 7.7 in Section 7.2 specifies the test system assigned to each of the nine **ADNs** participating in the coordinated operation framework.

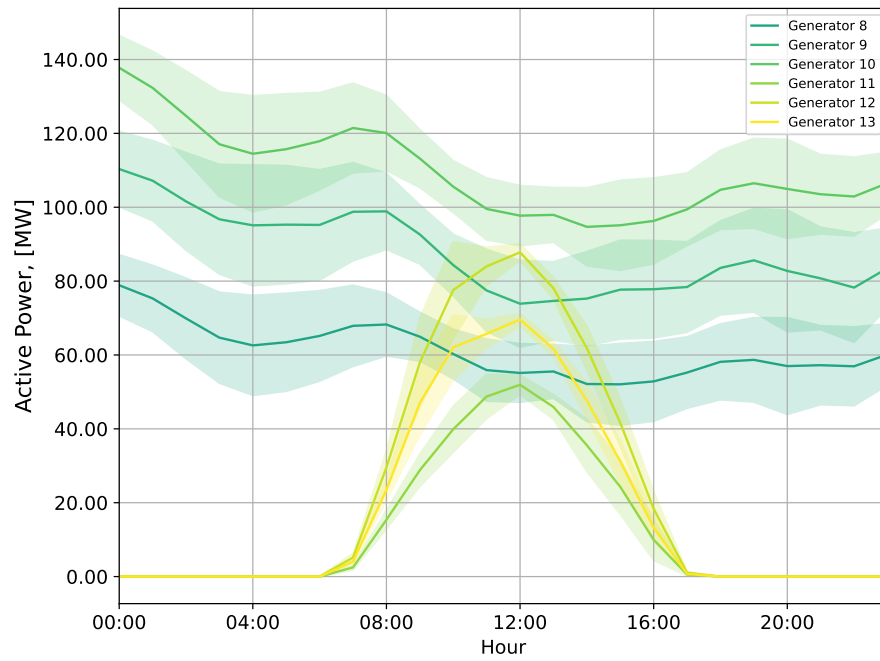


(a) RES generation profiles.

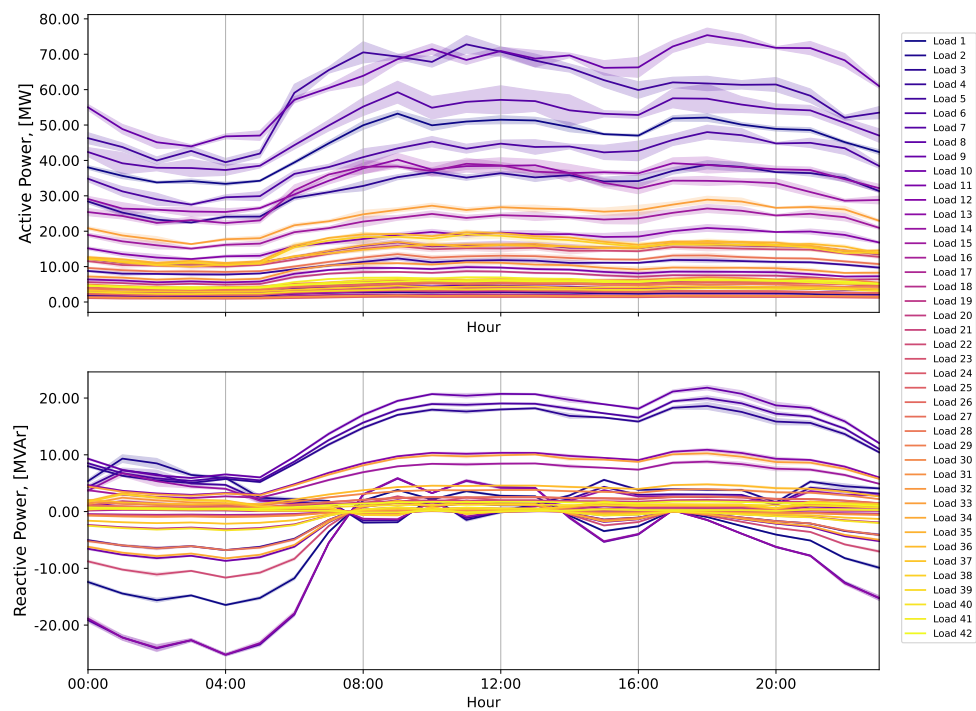


(b) Load profiles (active and reactive power).

Figure B.1: Case Study 2. TN. RES generation and load scenarios. Summer.

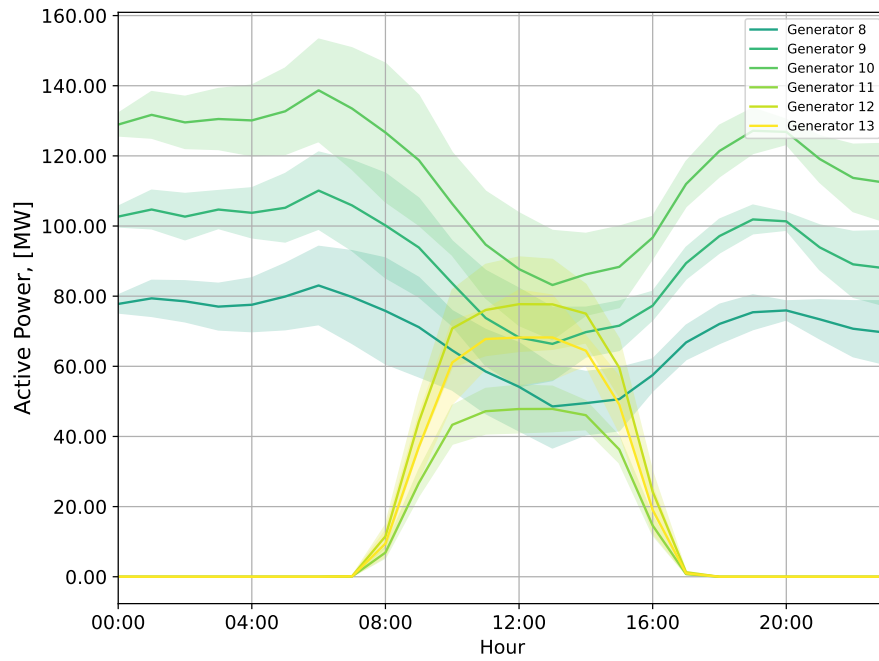


(a) RES generation profiles.

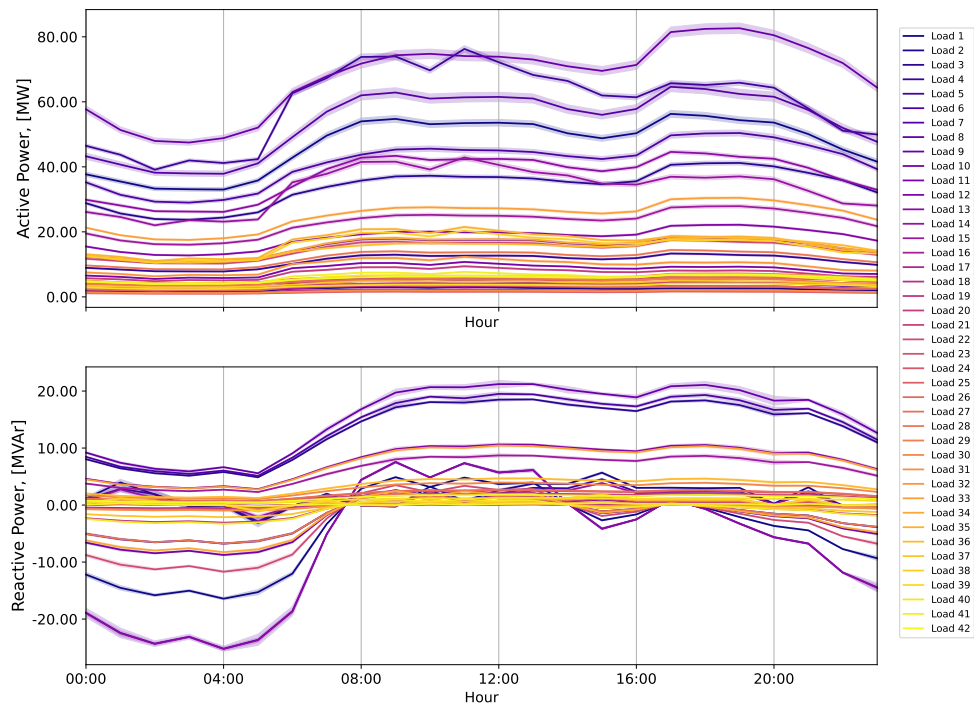


(b) Load profiles (active and reactive power).

Figure B.2: Case Study 2. TN. RES generation and load scenarios. Autumn.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure B.3: Case Study 2. TN. RES generation and load scenarios. Winter.

B.2.1.1 IEEE 18-Bus Test System

The IEEE 18-bus test system was originally developed by Grady et al. (1992). The data used in this thesis were gathered from the MATPOWER package (Zimmerman et al., 2011). Figure B.4 shows the single-line diagram of the IEEE 18-bus test system. The system's base is $S^{\text{Base}} = 10.00$ MVA. Table B.5 lists the bus data; Table B.6 describes the branch data; Table B.7 characterizes the connection with the TN; and Table B.8 characterizes the loads.

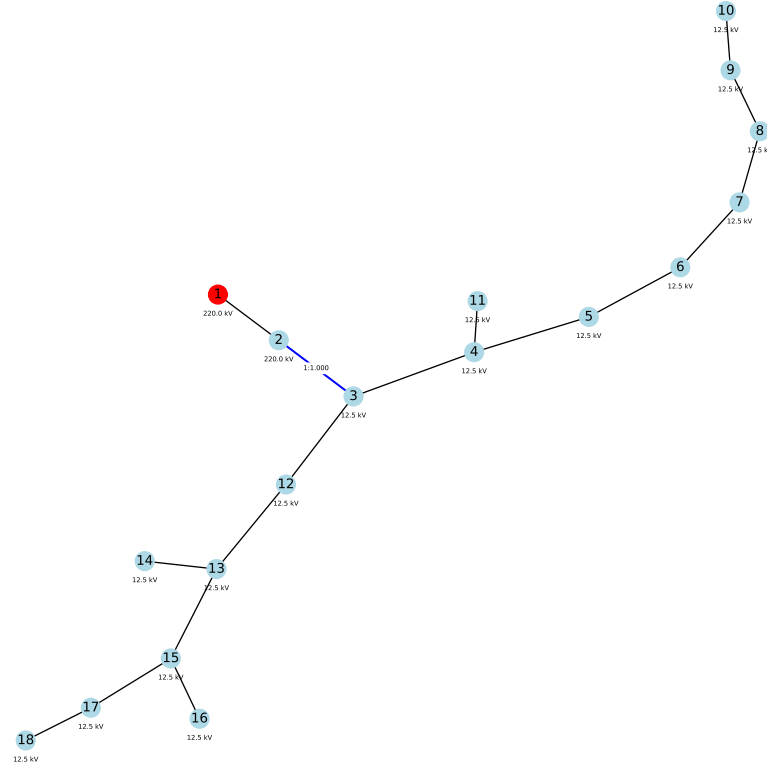


Figure B.4: Case Study 2. IEEE 18-bus test system. Single-line diagram.

B.2.1.2 IEEE 22-Bus Test System

The IEEE 22-bus test system was originally developed by Ramalinga Raju et al. (2012). The data used in this thesis were gathered from the MATPOWER package (Zimmerman et al., 2011). Figure B.5 shows the single-line diagram of the IEEE 22-bus test system. The system's base is $S^{\text{Base}} = 10.00$ MVA. Table B.9 lists the bus data; Table B.10 describes the branch data; Table B.11 characterizes the connection with the TN; and Table B.12 characterizes the loads.

Table B.5: Case Study 2. IEEE 18-bus test system. Bus data.

Bus	Bus	g_i	b_i	V_i^{Base}	V_i^{max}	V_i^{min}	Bus	Bus	g_i	b_i	V_i^{Base}	V_i^{max}	V_i^{min}
ID	Type	[p.u.]	[p.u.]	[kV]	[p.u.]	[p.u.]	ID	Type	[p.u.]	[p.u.]	[kV]	[p.u.]	[p.u.]
1	Ref.	0.00	0.00	220.00	1.10	0.90	10	PQ	0.00	0.00	12.50	1.10	0.90
2	PQ	0.00	1.20	220.00	1.10	0.90	11	PQ	0.00	0.00	12.50	1.10	0.90
3	PQ	0.00	0.00	12.50	1.10	0.90	12	PQ	0.00	0.60	12.50	1.10	0.90
4	PQ	0.00	1.05	12.50	1.10	0.90	13	PQ	0.00	1.20	12.50	1.10	0.90
5	PQ	0.00	0.60	12.50	1.10	0.90	14	PQ	0.00	0.00	12.50	1.10	0.90
6	PQ	0.00	0.60	12.50	1.10	0.90	15	PQ	0.00	0.00	12.50	1.10	0.90
7	PQ	0.00	1.80	12.50	1.10	0.90	16	PQ	0.00	1.50	12.50	1.10	0.90
8	PQ	0.00	0.00	12.50	1.10	0.90	17	PQ	0.00	0.90	12.50	1.10	0.90
9	PQ	0.00	0.60	12.50	1.10	0.90	18	PQ	0.00	0.00	12.50	1.10	0.90

Table B.6: IEEE 18-bus test system. Branch data.

Branch	From	To	r_{ij}	x_{ij}	b_{ij}^{Sh}	S_{ij}^{Rated}	Branch	From	To	r_{ij}	x_{ij}	b_{ij}^{Sh}	S_{ij}^{Rated}
ID	Bus ID	Bus ID	[p.u.]	[p.u.]	[p.u.]	[MVA]	ID	Bus ID	Bus ID	[p.u.]	[p.u.]	[p.u.]	[MVA]
1	2	3	0.003120	0.067530	0.00	50.00	10	3	12	0.029100	0.037680	0.00	20.00
2	3	4	0.004310	0.012040	0.00	30.00	11	12	13	0.022220	0.028770	0.00	15.00
3	4	5	0.006010	0.016770	0.00	30.00	12	13	14	0.048030	0.062180	0.00	15.00
4	5	6	0.003160	0.008820	0.00	30.00	13	13	15	0.039850	0.051600	0.00	15.00
5	6	7	0.008960	0.025020	0.00	30.00	14	15	16	0.029100	0.037680	0.00	15.00
6	7	8	0.002950	0.008240	0.00	20.00	15	15	17	0.037270	0.045930	0.00	10.00
7	8	9	0.017200	0.021200	0.00	20.00	16	17	18	0.011040	0.013600	0.00	10.00
8	9	10	0.040700	0.030530	0.00	15.00	17	2	1	0.000500	0.003440	0.00	50.00
9	4	11	0.017060	0.022090	0.00	15.00							

Table B.7: Case Study 2. IEEE 18-bus test system. Connection with TN.

Generator	Node	$P_g^{G,\text{max}}$	$P_g^{G,\text{min}}$	$Q_g^{G,\text{max}}$	$Q_g^{G,\text{min}}$	V_g^S
ID	ID	[MW]	[MW]	[MVar]	[MVar]	[p.u.]
1	1	80.00	-80.00	80.00	-80.00	1.00

Table B.8: Case Study 2. IEEE 18-bus test system. Load data.

Load	Bus	FL Ratio	Load	Bus	FL Ratio	Load	Bus	FL Ratio
ID	ID	[%]	ID	ID	[%]	ID	ID	[%]
1	4	1.89%	6	9	1.89%	11	14	1.89%
2	5	3.77%	7	10	9.43%	12	15	7.55%
3	6	14.15%	8	11	4.72%	13	16	4.72%
4	7	18.87%	9	12	9.43%	14	17	9.43%
5	8	7.55%	10	13	2.83%	15	18	1.89%

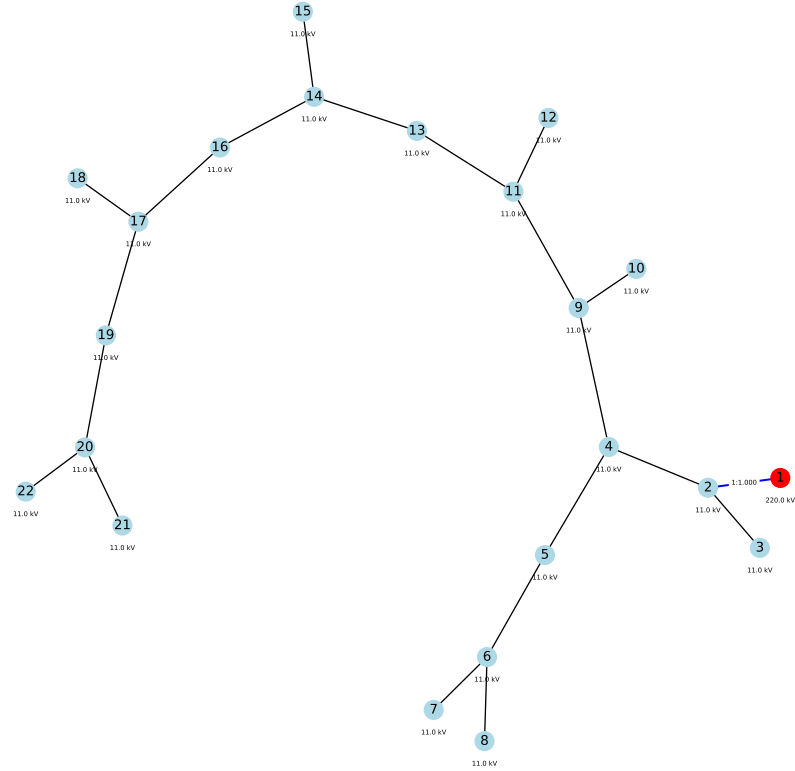


Figure B.5: Case Study 2. IEEE 22-bus test system. Single-line diagram.

Table B.9: Case Study 2. IEEE 22-bus test system. Bus data.

Bus	Bus	g_i	b_i	V_i^{Base}	V_i^{max}	V_i^{min}	Bus	Bus	g_i	b_i	V_i^{Base}	V_i^{max}	V_i^{min}
ID	Type	[p.u.]	[p.u.]	[kV]	[p.u.]	[p.u.]	ID	Type	[p.u.]	[p.u.]	[kV]	[p.u.]	[p.u.]
1	Ref.	0.00	0.00	220.00	1.10	0.90	12	PQ	0.00	0.00	11.00	1.10	0.90
2	PQ	0.00	0.00	11.00	1.10	0.90	13	PQ	0.00	0.00	11.00	1.10	0.90
3	PQ	0.00	0.00	11.00	1.10	0.90	14	PQ	0.00	0.00	11.00	1.10	0.90
4	PQ	0.00	0.00	11.00	1.10	0.90	15	PQ	0.00	0.00	11.00	1.10	0.90
5	PQ	0.00	0.00	11.00	1.10	0.90	16	PQ	0.00	0.00	11.00	1.10	0.90
6	PQ	0.00	0.00	11.00	1.10	0.90	17	PQ	0.00	0.00	11.00	1.10	0.90
7	PQ	0.00	0.00	11.00	1.10	0.90	18	PQ	0.00	0.00	11.00	1.10	0.90
8	PQ	0.00	0.00	11.00	1.10	0.90	19	PQ	0.00	0.00	11.00	1.10	0.90
9	PQ	0.00	0.00	11.00	1.10	0.90	20	PQ	0.00	0.00	11.00	1.10	0.90
10	PQ	0.00	0.00	11.00	1.10	0.90	21	PQ	0.00	0.00	11.00	1.10	0.90
11	PQ	0.00	0.00	11.00	1.10	0.90	22	PQ	0.00	0.00	11.00	1.10	0.90

Table B.10: IEEE 22-bus test system. Branch data.

Branch	From	To	r_{ij}	x_{ij}	b_{ij}^{Sh}	S_{ij}^{Rated}	Branch	From	To	r_{ij}	x_{ij}	b_{ij}^{Sh}	S_{ij}^{Rated}
ID	Bus ID	Bus ID	[p.u.]	[p.u.]	[p.u.]	[MVA]	ID	Bus ID	Bus ID	[p.u.]	[p.u.]	[p.u.]	[MVA]
1	1	2	0.003028	0.001493	0.00	10.00	12	11	13	0.003258	0.001678	0.00	5.00
2	2	3	0.000452	0.000233	0.00	1.00	13	13	14	0.008645	0.004453	0.00	5.00
3	2	4	0.004476	0.002305	0.00	10.00	14	14	15	0.000182	0.000096	0.00	1.00
4	4	5	0.001595	0.000818	0.00	3.00	15	14	16	0.000452	0.000233	0.00	3.00
5	4	9	0.006141	0.003163	0.00	3.00	16	16	17	0.002655	0.001367	0.00	3.00
6	5	6	0.010835	0.005580	0.00	2.00	17	17	18	0.000784	0.000403	0.00	1.00
7	6	7	0.000494	0.000255	0.00	1.00	18	17	19	0.004744	0.002445	0.00	2.00
8	6	8	0.002401	0.001236	0.00	1.00	19	19	20	0.001068	0.000545	0.00	1.00
9	9	10	0.000452	0.000233	0.00	1.00	20	20	21	0.000720	0.000372	0.00	1.00
10	9	11	0.005579	0.002877	0.00	5.00	21	20	22	0.004404	0.002268	0.00	1.00
11	11	12	0.000452	0.000233	0.00	1.00							

Table B.11: Case Study 2. IEEE 22-bus test system. Connection with TN.

Generator	Node	$P_g^{G,max}$	$P_g^{G,min}$	$Q_g^{G,max}$	$Q_g^{G,min}$	V_g^S
ID	ID	[MW]	[MW]	[MVA]	[MVA]	[p.u.]
1	1	10.00	-10.00	10.00	-10.00	1.00

Table B.12: Case Study 2. IEEE 22-bus test system. Load data.

Load	Bus	FL Ratio	Load	Bus	FL Ratio	Load	Bus	FL Ratio
ID	ID	[%]	ID	ID	[%]	ID	ID	[%]
1	2	2.53%	8	9	2.92%	15	16	12.13%
2	3	2.53%	9	10	2.17%	16	17	7.49%
3	4	5.10%	10	11	2.46%	17	18	7.49%
4	5	2.20%	11	12	2.46%	18	19	6.61%
5	6	1.58%	12	13	12.40%	19	20	5.63%
6	7	1.33%	13	14	5.24%	20	21	5.63%
7	8	2.17%	14	15	5.24%	21	22	4.68%

B.2.1.3 IEEE 33-Bus Test System

The IEEE 33-bus test system were originally developed by Baran and Wu (1989). The data used in this thesis was gathered from the MATPOWER package (Zimmerman et al., 2011). Figure B.6 shows the single-line diagram of the IEEE 33-bus test system. The system's base is $S^{\text{Base}} = 100.00$ MVA. Table B.13 lists the bus data; Table B.14 describes the branch data; Table B.15 characterizes the connection with the TN; and Table B.16 characterizes the loads.

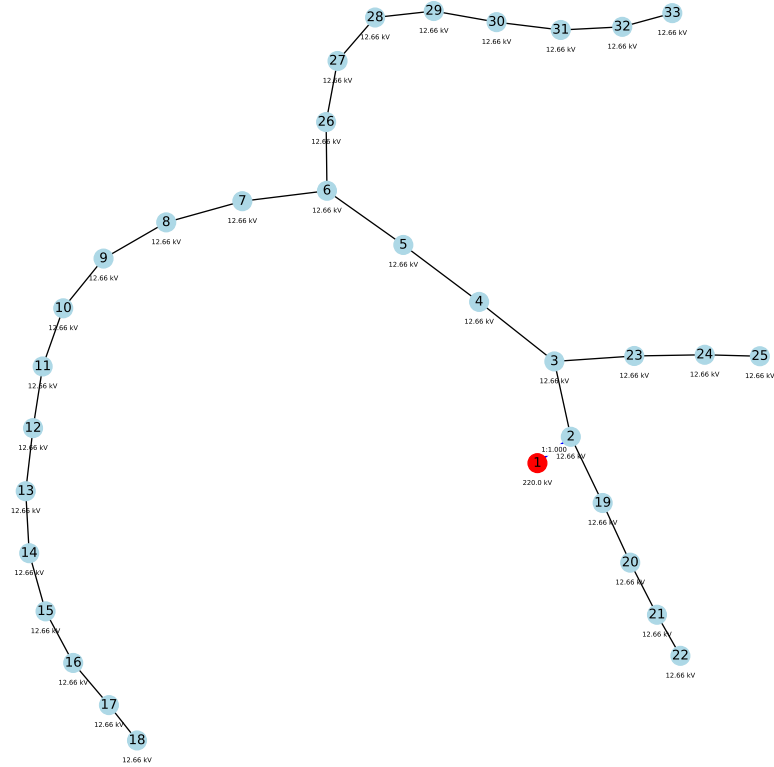


Figure B.6: Case Study 2. IEEE 33-bus test system. Single-line diagram.

B.2.2 ADN Connected to Node 2 of the TN

The ADN connected to node 2 of the TN is based on the IEEE 33-bus distribution test system (Baran and Wu, 1989). The corresponding network topology is described in Section B.2.1.3, and the single-line diagram is shown in Figure B.6. Detailed bus, branch, and interface generator data are reported in Tables B.13–B.15.

The original test system was extended to include RES generators, whose technical characteristics are summarized in Table 7.10. Figures B.7–B.9 present the load and RES generation profiles for the representative days.

Table B.13: Case Study 2. IEEE 33-bus test system. Bus data.

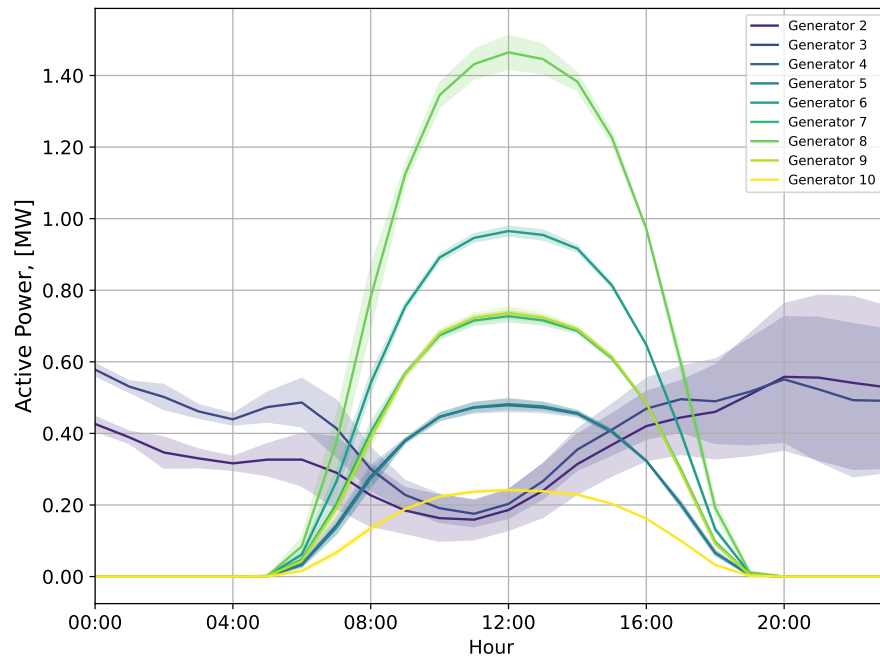
Bus	Bus	g_i	b_i	V_i^{Base}	V_i^{max}	V_i^{min}	Bus	Bus	g_i	b_i	V_i^{Base}	V_i^{max}	V_i^{min}
ID	Type	[p.u.]	[p.u.]	[kV]	[p.u.]	[p.u.]	ID	Type	[p.u.]	[p.u.]	[kV]	[p.u.]	[p.u.]
1	Ref.	0.00	0.00	220.00	1.10	0.90	18	PQ	0.00	0.00	12.66	1.10	0.90
2	PQ	0.00	0.00	12.66	1.10	0.90	19	PQ	0.00	0.00	12.66	1.10	0.90
3	PQ	0.00	0.00	12.66	1.10	0.90	20	PQ	0.00	0.00	12.66	1.10	0.90
4	PQ	0.00	0.00	12.66	1.10	0.90	21	PQ	0.00	0.00	12.66	1.10	0.90
5	PQ	0.00	0.00	12.66	1.10	0.90	22	PQ	0.00	0.00	12.66	1.10	0.90
6	PQ	0.00	0.00	12.66	1.10	0.90	23	PQ	0.00	0.00	12.66	1.10	0.90
7	PQ	0.00	0.00	12.66	1.10	0.90	24	PQ	0.00	0.00	12.66	1.10	0.90
8	PQ	0.00	0.00	12.66	1.10	0.90	25	PQ	0.00	0.00	12.66	1.10	0.90
9	PQ	0.00	0.00	12.66	1.10	0.90	26	PQ	0.00	0.00	12.66	1.10	0.90
10	PQ	0.00	0.00	12.66	1.10	0.90	27	PQ	0.00	0.00	12.66	1.10	0.90
11	PQ	0.00	0.00	12.66	1.10	0.90	28	PQ	0.00	0.00	12.66	1.10	0.90
12	PQ	0.00	0.00	12.66	1.10	0.90	29	PQ	0.00	0.00	12.66	1.10	0.90
13	PQ	0.00	0.00	12.66	1.10	0.90	30	PQ	0.00	0.00	12.66	1.10	0.90
14	PQ	0.00	0.00	12.66	1.10	0.90	31	PQ	0.00	0.00	12.66	1.10	0.90
15	PQ	0.00	0.00	12.66	1.10	0.90	32	PQ	0.00	0.00	12.66	1.10	0.90
16	PQ	0.00	0.00	12.66	1.10	0.90	33	PQ	0.00	0.00	12.66	1.10	0.90
17	PQ	0.00	0.00	12.66	1.10	0.90							

Table B.14: Case Study 2. IEEE 33-bus test system. Branch data.

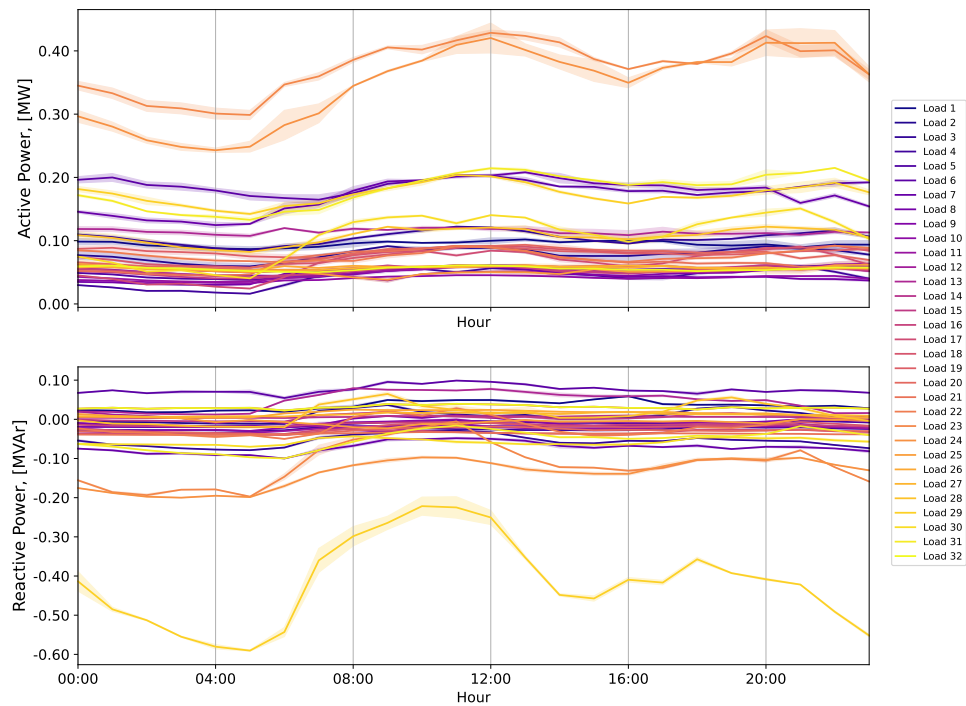
Branch	From	To	r_{ij}	x_{ij}	b_{ij}^{Sh}	S_{ij}^{Rated}	Branch	From	To	r_{ij}	x_{ij}	b_{ij}^{Sh}	S_{ij}^{Rated}
ID	Bus ID	Bus ID	[p.u.]	[p.u.]	[p.u.]	[MVA]	ID	Bus ID	Bus ID	[p.u.]	[p.u.]	[p.u.]	[MVA]
1	1	2	0.005753	0.002932	0.00	5.00	20	20	21	0.025550	0.029849	0.00	1.50
2	2	3	0.030760	0.015667	0.00	5.00	21	21	22	0.044230	0.058481	0.00	1.50
3	3	4	0.022836	0.011630	0.00	3.50	22	3	23	0.028152	0.019236	0.00	2.00
4	4	5	0.023778	0.012110	0.00	3.50	23	23	24	0.056028	0.044243	0.00	2.00
5	5	6	0.051099	0.044112	0.00	3.00	24	24	25	0.055904	0.043743	0.00	1.50
6	6	7	0.011680	0.038608	0.00	2.50	25	6	26	0.012666	0.006451	0.00	2.00
7	7	8	0.044386	0.014668	0.00	2.00	26	26	27	0.017732	0.009028	0.00	2.00
8	8	9	0.064264	0.046170	0.00	2.00	27	27	28	0.066074	0.058256	0.00	2.00
9	9	10	0.065138	0.046170	0.00	2.00	28	28	29	0.050176	0.043712	0.00	2.00
10	10	11	0.012266	0.004056	0.00	2.00	29	29	30	0.031664	0.016128	0.00	2.00
11	11	12	0.023360	0.007724	0.00	2.00	30	30	31	0.060795	0.060084	0.00	1.50
12	12	13	0.091592	0.072063	0.00	1.50	31	31	32	0.019373	0.022580	0.00	1.50
13	13	14	0.033792	0.044480	0.00	1.50	32	32	33	0.021276	0.033081	0.00	1.50
14	14	15	0.036874	0.032818	0.00	1.50	33	21	8	0.124785	0.124785	0.00	5.00
15	15	16	0.046564	0.034004	0.00	1.50	34	9	15	0.124785	0.124785	0.00	5.00
16	16	17	0.080424	0.107378	0.00	1.50	35	12	22	0.124785	0.124785	0.00	5.00
17	17	18	0.045671	0.035813	0.00	1.50	36	18	33	0.031196	0.031196	0.00	5.00
18	2	19	0.010232	0.009764	0.00	2.00	37	25	29	0.031196	0.031196	0.00	5.00
19	19	20	0.093851	0.084567	0.00	2.00							

Table B.15: Case Study 2. IEEE 33-bus test system. Connection with TN.

Generator	Node	$P_g^{G,\text{max}}$	$P_g^{G,\text{min}}$	$Q_g^{G,\text{max}}$	$Q_g^{G,\text{min}}$	V_g^S
ID	ID	[MW]	[MW]	[MVar]	[MVar]	[p.u.]
1	1	250.00	-250.00	250.00	-250.00	1.00

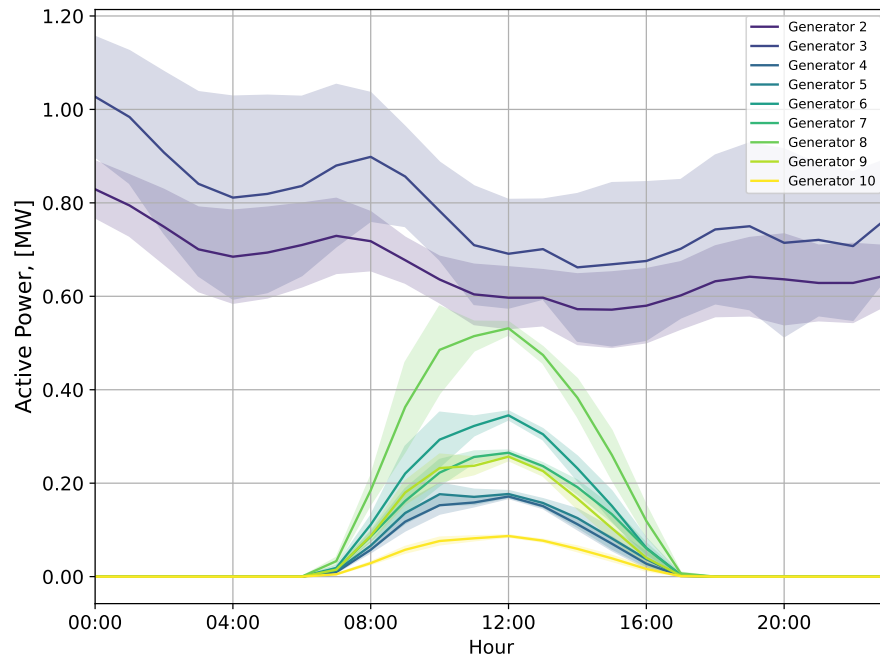


(a) RES generation profiles.

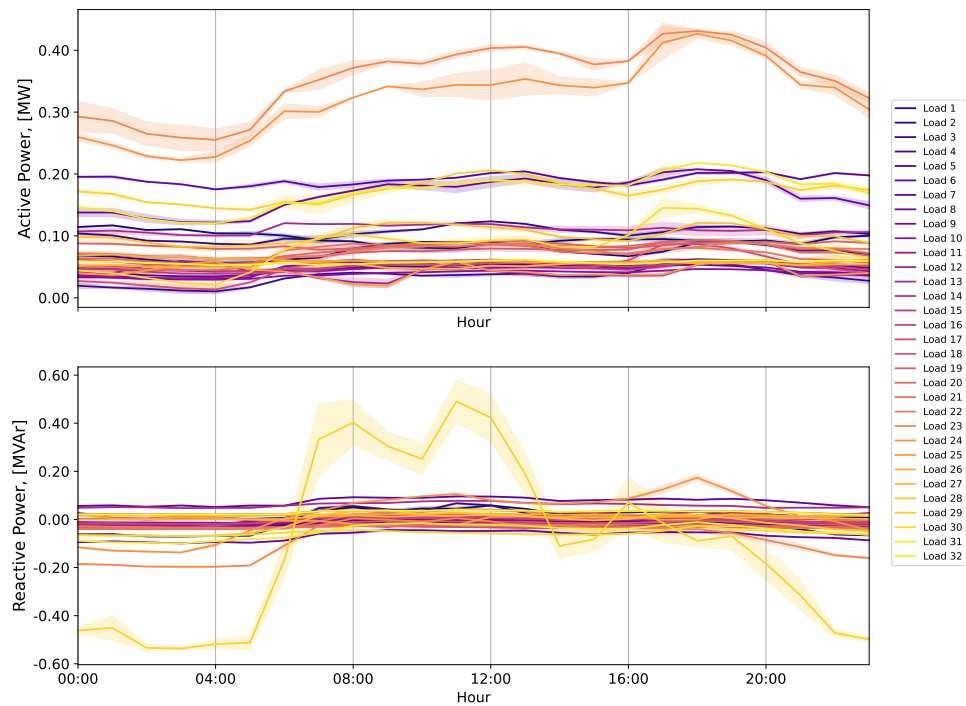


(b) Load profiles (active and reactive power).

Figure B.7: Case Study 2. ADN node 2. RES generation and load profiles. Summer.

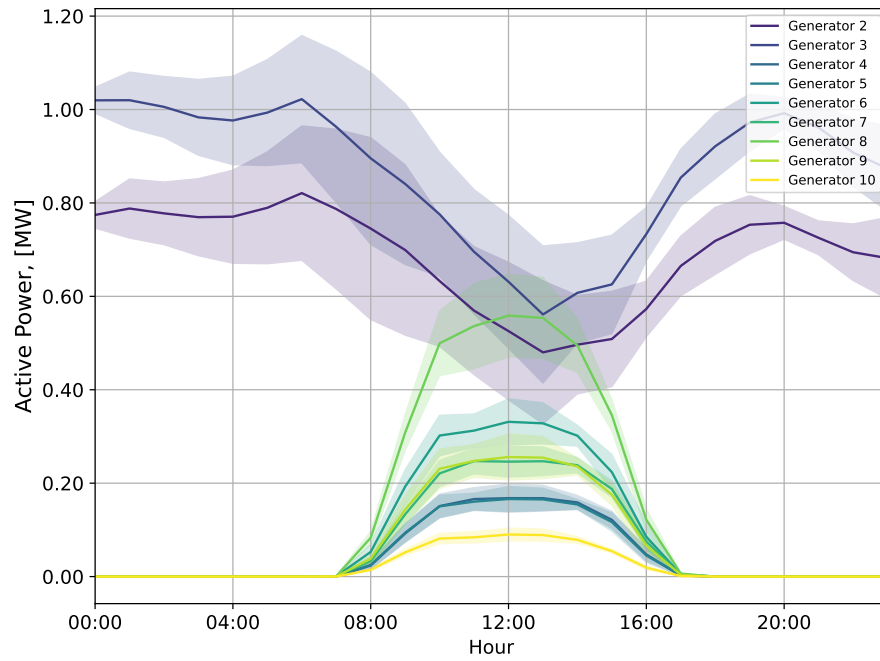


(a) RES generation profiles.

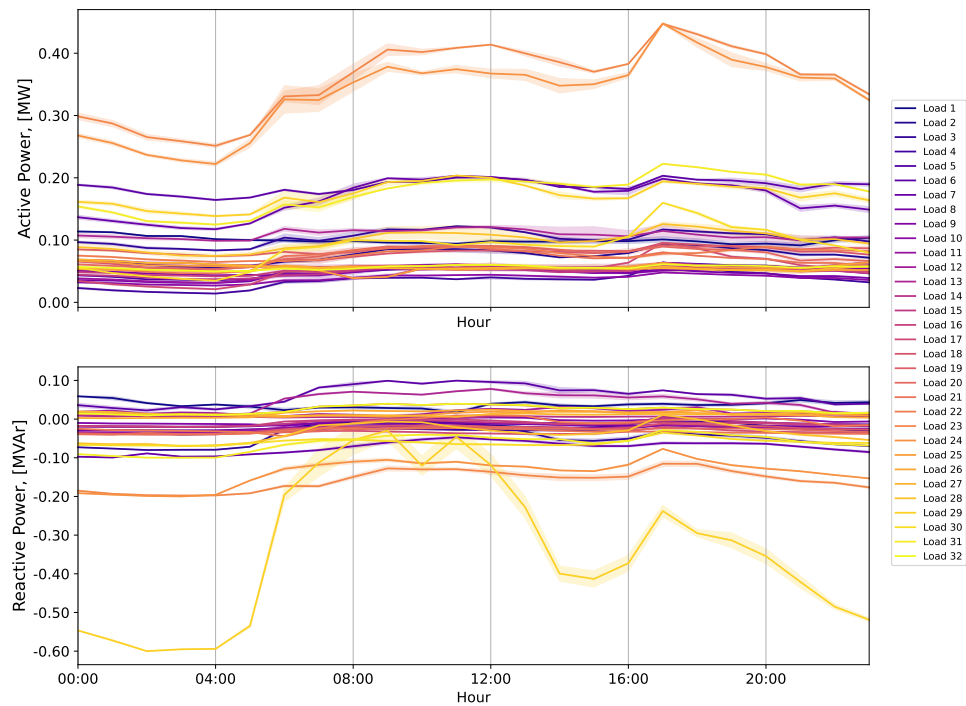


(b) Load profiles (active and reactive power).

Figure B.8: Case Study 2. ADN node 2. RES generation and load profiles. Autumn.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure B.9: Case Study 2. ADN node 2. RES generation and load profiles. Winter.

Table B.16: Case Study 2. IEEE 33-bus test system. Load data.

Load	Bus	FL Ratio	Load	Bus	FL Ratio	Load	Bus	FL Ratio
ID	ID	[%]	ID	ID	[%]	ID	ID	[%]
1	2	2.69%	12	13	1.62%	23	24	11.31%
2	3	2.42%	13	14	3.23%	24	25	11.31%
3	4	3.23%	14	15	1.62%	25	26	1.62%
4	5	1.62%	15	16	1.62%	26	27	1.62%
5	6	1.62%	16	17	1.62%	27	28	1.62%
6	7	5.38%	17	18	2.42%	28	29	3.23%
7	8	5.38%	18	19	2.42%	29	30	5.38%
8	9	1.62%	19	20	2.42%	30	31	4.04%
9	10	1.62%	20	21	2.42%	31	32	5.65%
10	11	1.21%	21	22	2.42%	32	33	1.62%
11	12	1.62%	22	23	2.42%			

B.2.3 ADN Connected to Node 18 of the TN

The **ADN** connected to node 18 of the **TN** is based on the **IEEE** 18-bus distribution test system (Grady et al., 1992). The corresponding network topology is described in Section B.2.1.1, and the single-line diagram is shown in Figure B.4. Detailed bus, branch, and interface generator data are reported in Tables B.5–B.7.

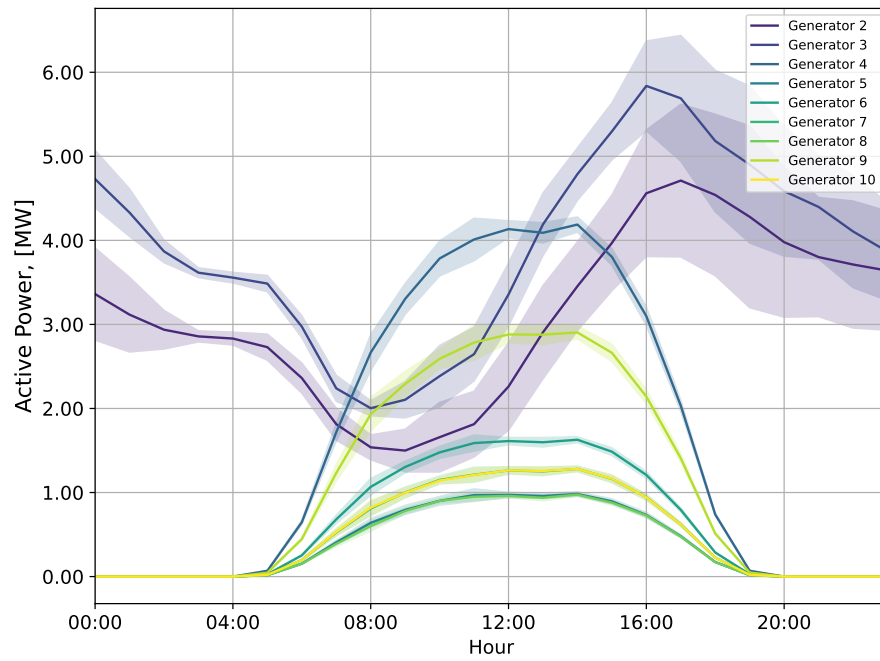
The original test system was extended to include **RES** generators, whose technical characteristics are summarized in Table B.17. Figures B.10–B.13 present the load and **RES** generation profiles for the representative days. Figure B.14 presents the flexible load profiles.

Table B.17: Case Study 2. ADN node 18. Characterization of RES generators.

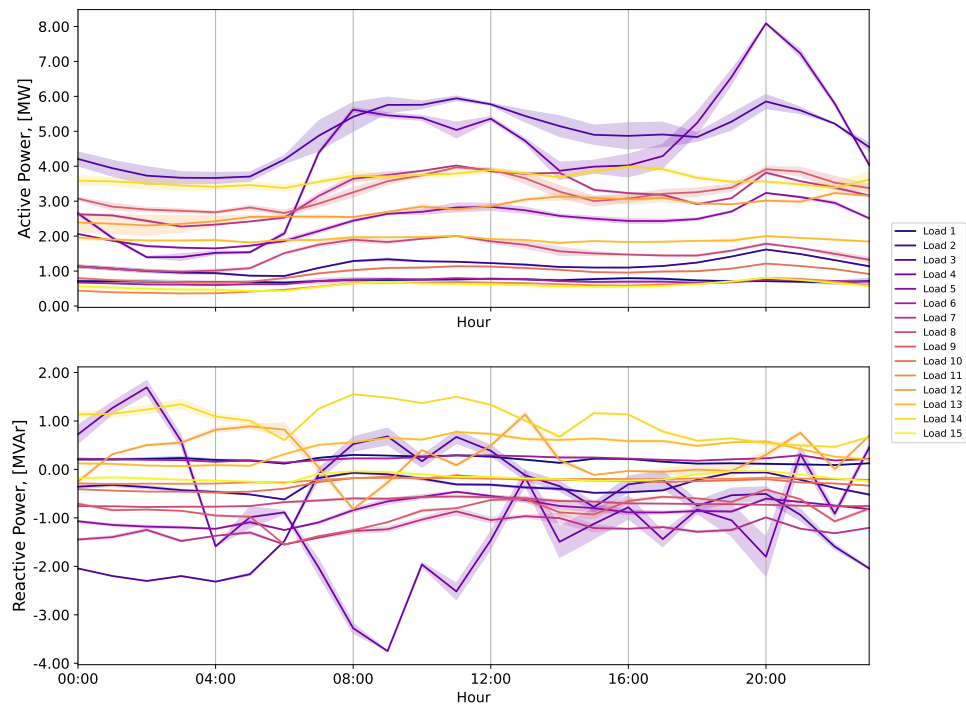
Generator	Bus	Generator	$S_g^{G,\max}$	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	ID	Type	[MVA]	[N/A]	[N/A]
2	4	Wind	12.00	-0.90	0.90
3	13	Wind	15.00	-0.90	0.90
4	15	Solar PV	6.50	-0.90	0.90
5	17	Solar PV	1.50	-0.90	0.90
6	14	Solar PV	2.50	-0.90	0.90
7	5	Solar PV	2.00	-0.90	0.90
8	7	Solar PV	1.50	-0.90	0.90
9	9	Solar PV	4.50	-0.90	0.90
10	10	Solar PV	2.00	-0.90	0.90

B.2.4 ADN Connected to Node 19 of the TN

The **ADN** connected to node 19 of the **TN** is based on the **IEEE** 33-bus distribution test system (Baran and Wu, 1989). The corresponding network topology is described in

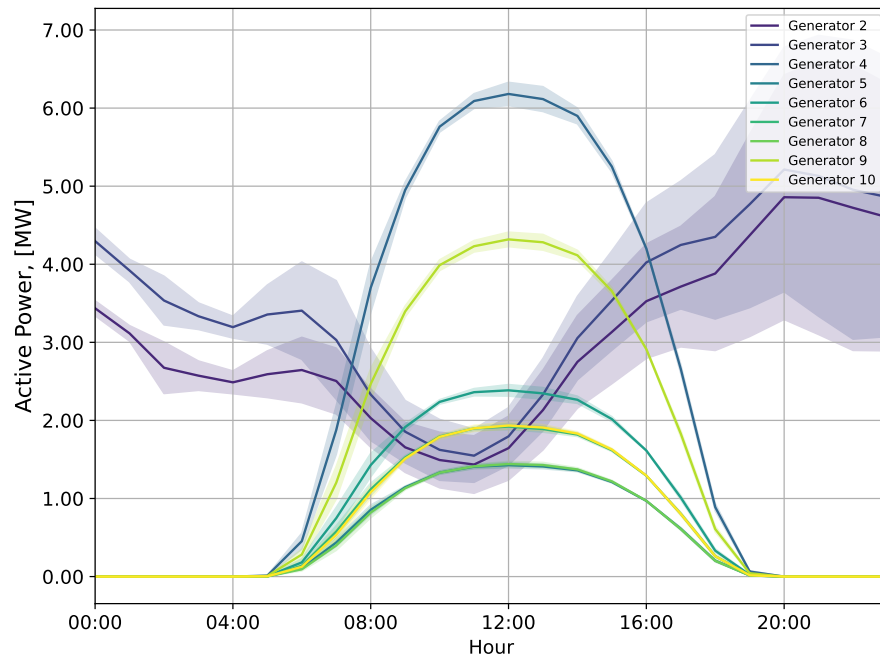


(a) RES generation profiles.

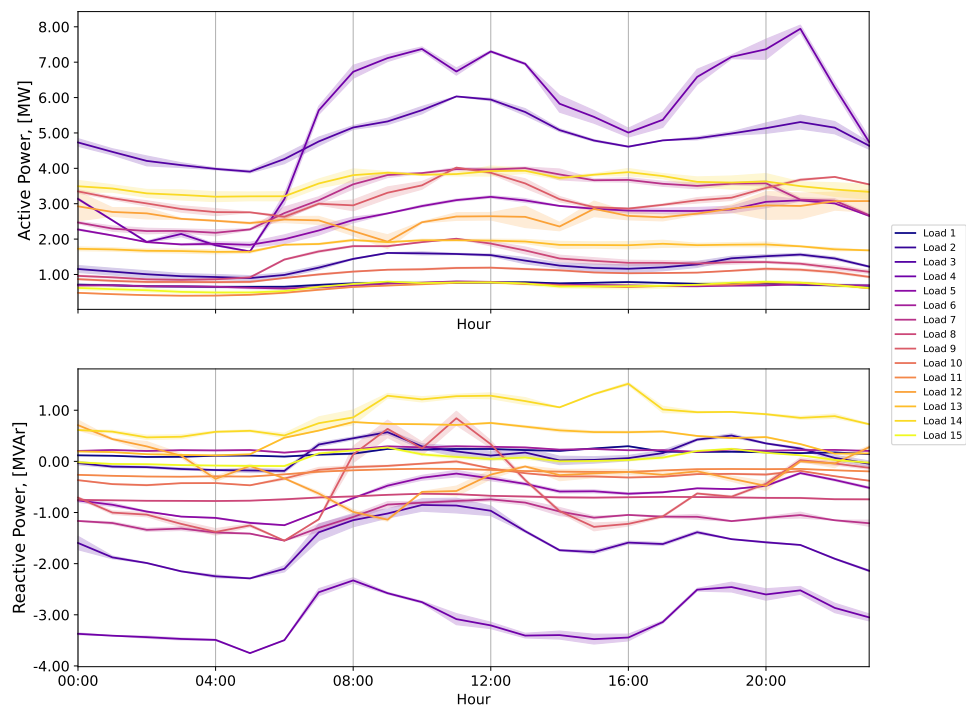


(b) Load profiles (active and reactive power).

Figure B.10: Case Study 2. ADN node 18. RES generation and load scenarios. Spring.

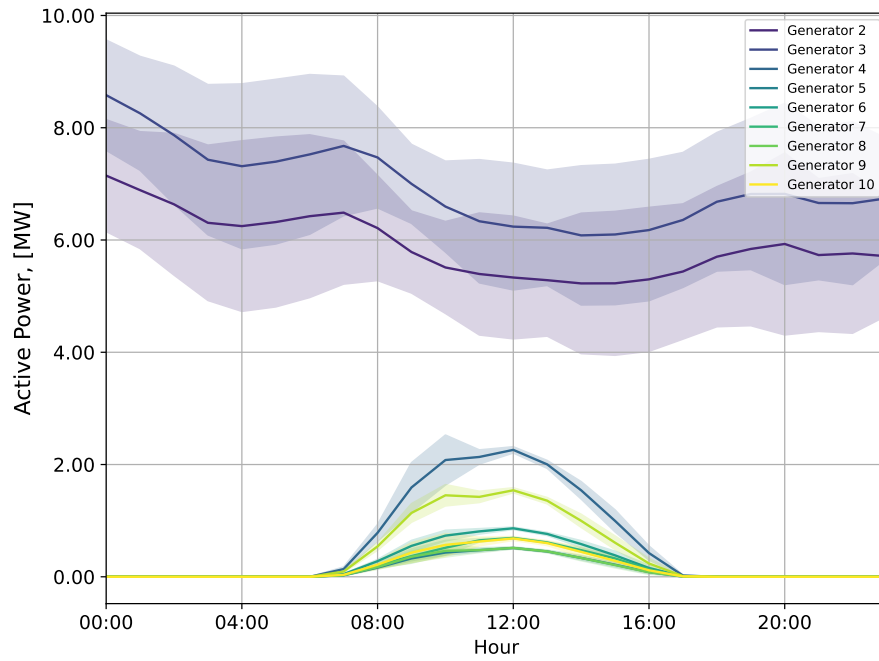


(a) RES generation profiles.

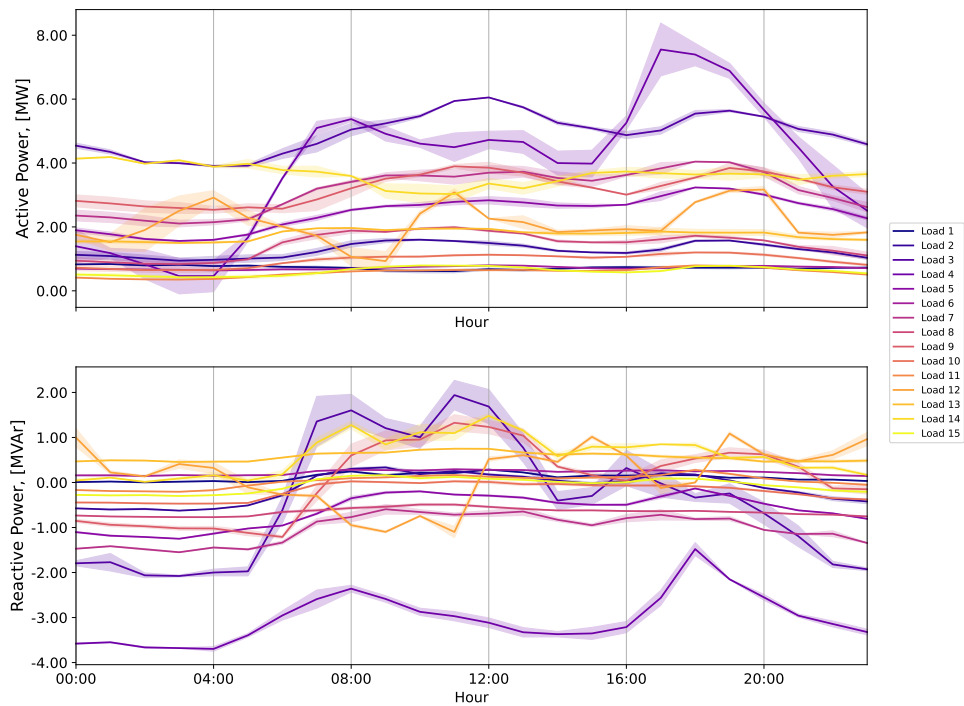


(b) Load profiles (active and reactive power).

Figure B.11: Case Study 2. ADN node 18. RES generation and load profiles. Summer.

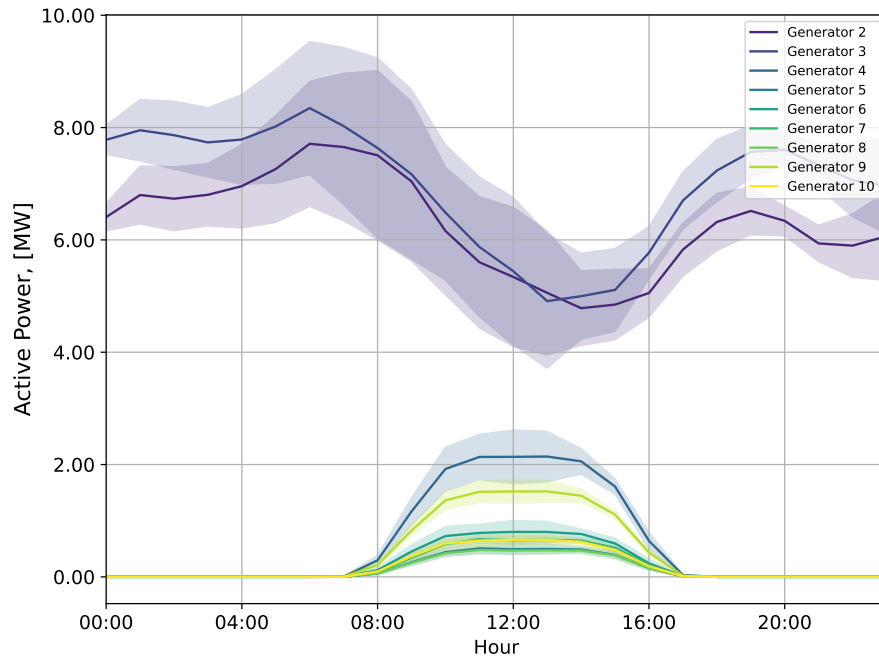


(a) RES generation profiles.

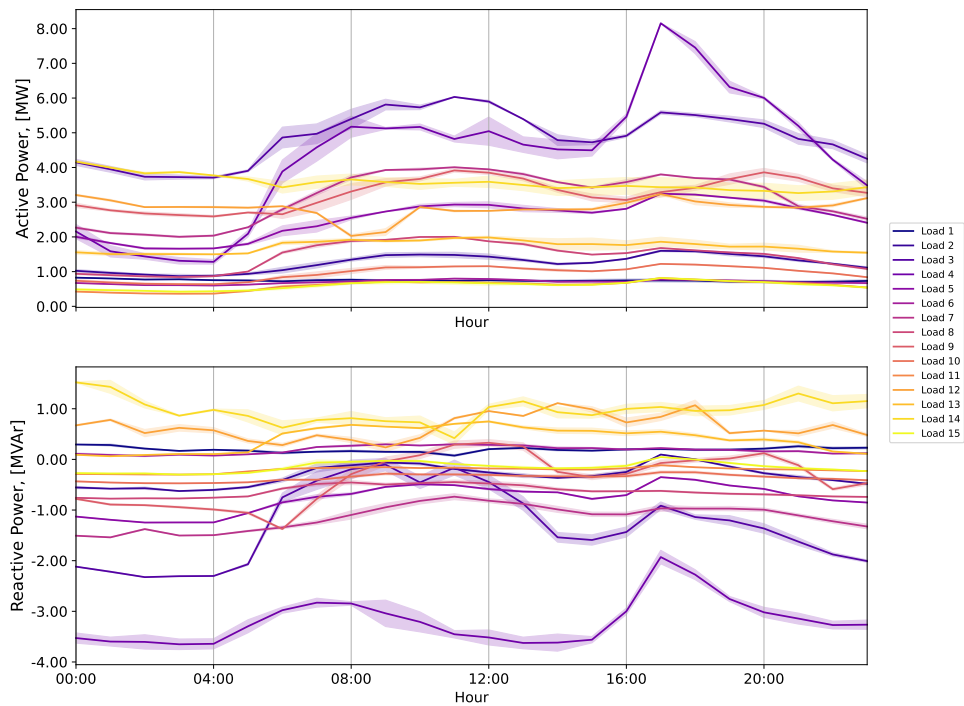


(b) Load profiles (active and reactive power).

Figure B.12: Case Study 2. ADN node 18. RES generation and load profiles. Autumn.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure B.13: Case Study 2. ADN node 18. RES generation and load profiles. Winter.

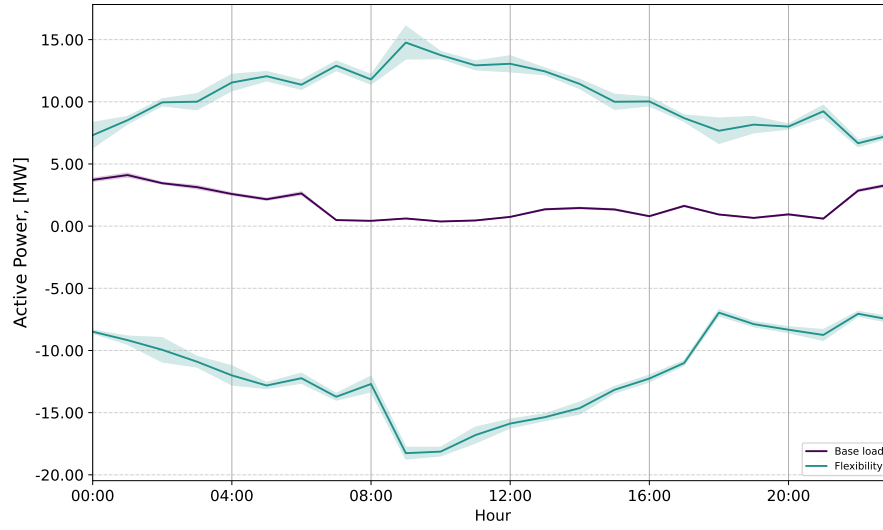


Figure B.14: Case Study 2. ADN node 18. Flexible load profiles.

Section B.2.1.3, and the single-line diagram is shown in Figure B.6. Detailed bus, branch, and interface generator data are reported in Tables B.13–B.15.

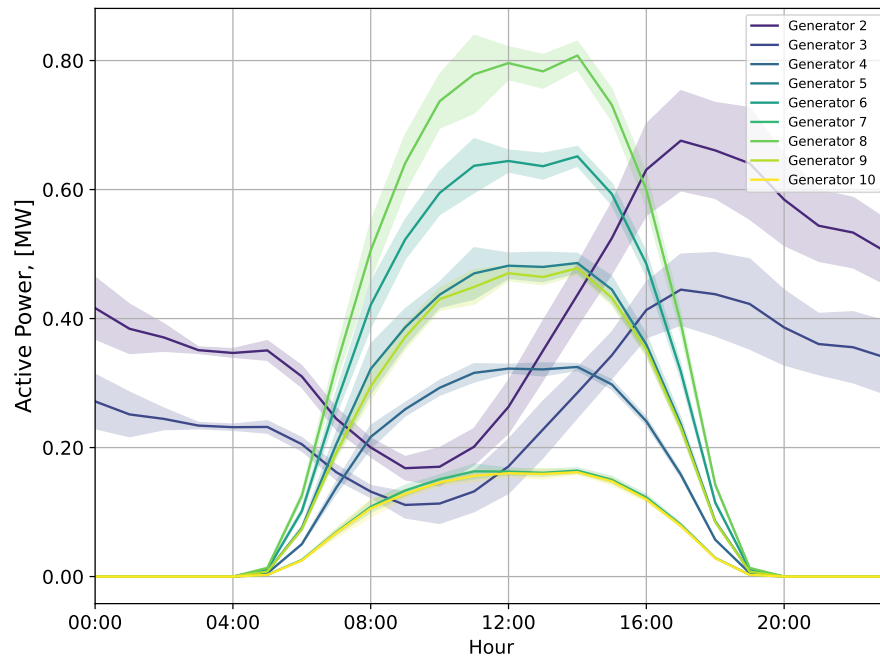
The original test system was extended to include RES generators, whose technical characteristics are summarized in Table B.18. Figures B.15–B.18 present the load and RES generation profiles for the representative days. Figure B.19 presents the flexible load profiles.

Table B.18: Case Study 2. ADN node 19. Characterization of RES generators.

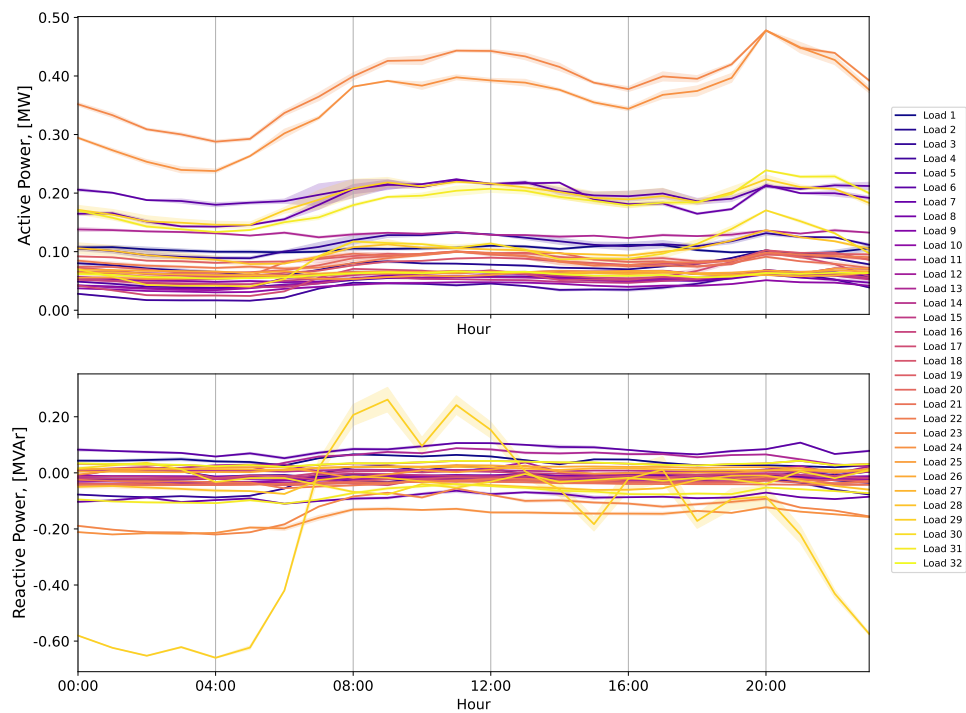
Generator	Bus	Generator	$S_g^{G,\max}$	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	ID	Type	[MVA]	[N/A]	[N/A]
2	20	Wind	1.50	-0.90	0.90
3	22	Wind	1.00	-0.90	0.90
4	3	Solar PV	0.50	-0.90	0.90
5	25	Solar PV	0.75	-0.90	0.90
6	6	Solar PV	1.00	-0.90	0.90
7	28	Solar PV	0.25	-0.90	0.90
8	33	Solar PV	1.25	-0.90	0.90
9	9	Solar PV	0.75	-0.90	0.90
10	18	Solar PV	0.25	-0.90	0.90

B.2.5 ADN Connected to Node 20 of the TN

The ADN connected to node 20 of the TN is based on the IEEE 33-bus distribution test system (Baran and Wu, 1989). The corresponding network topology is described in

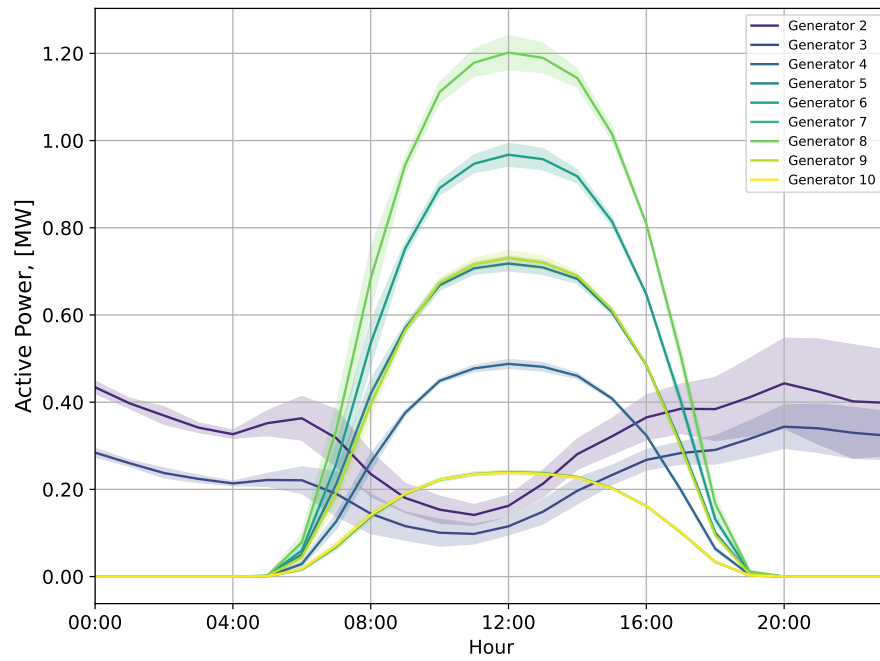


(a) RES generation profiles.

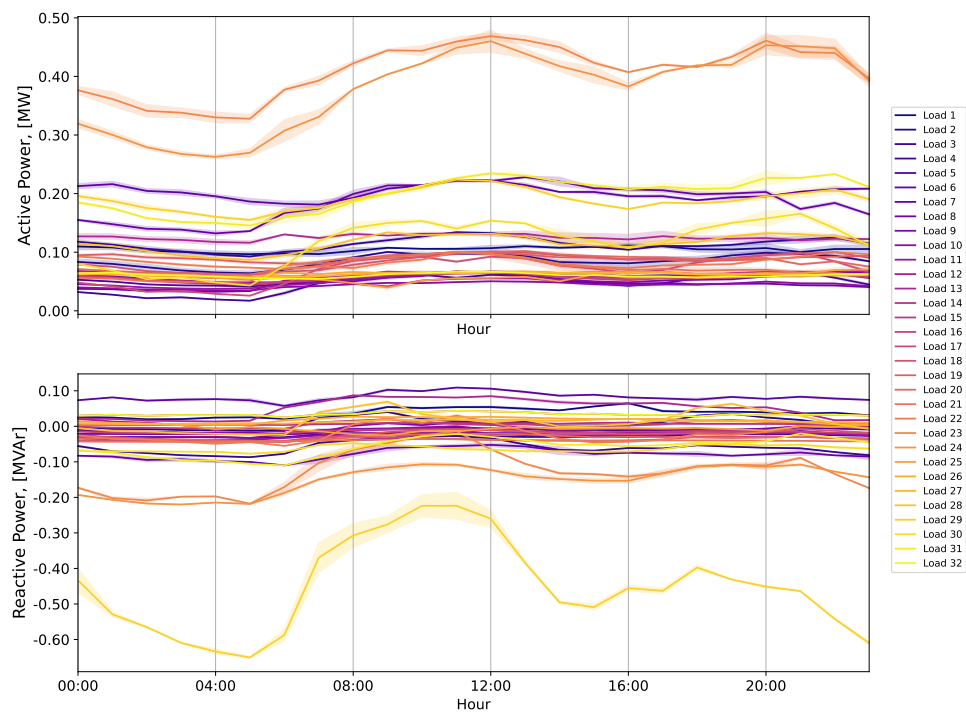


(b) Load profiles (active and reactive power).

Figure B.15: Case Study 2. ADN node 19. RES generation and load scenarios. Spring.

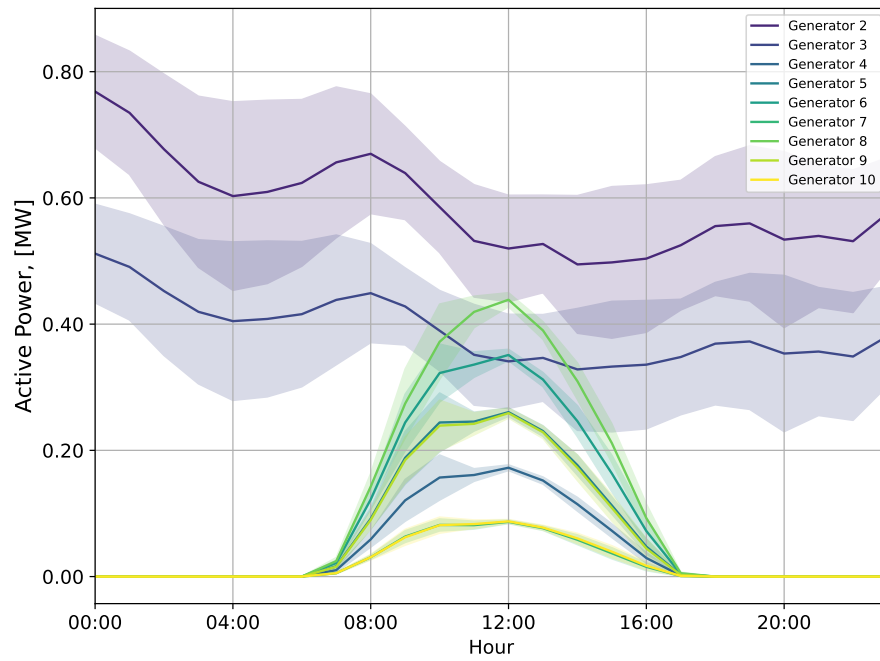


(a) RES generation profiles.

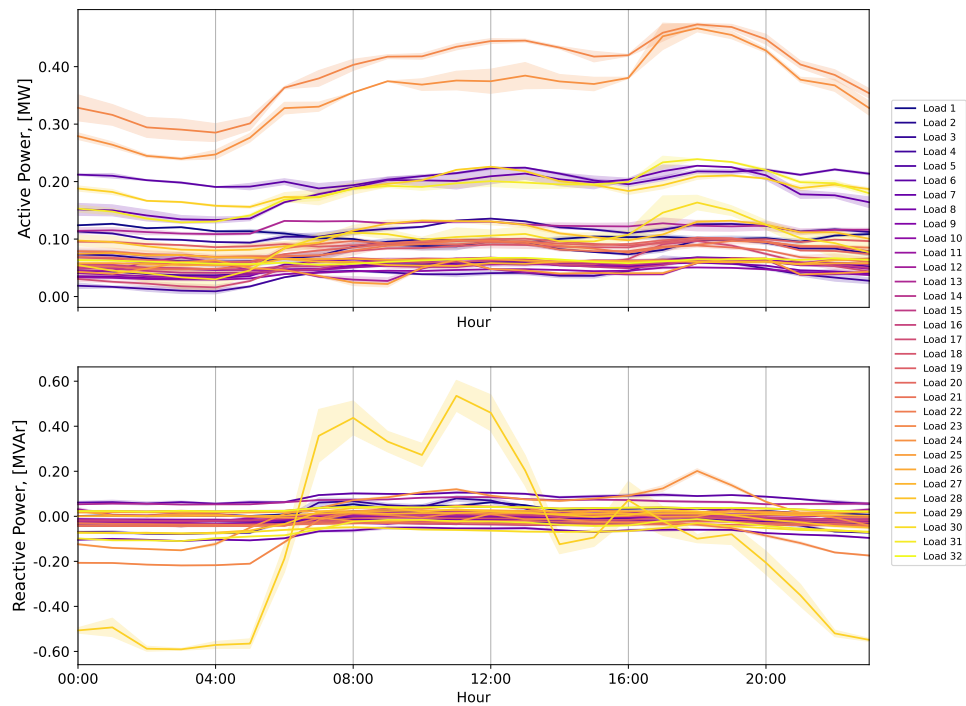


(b) Load profiles (active and reactive power).

Figure B.16: Case Study 2. ADN node 19. RES generation and load profiles. Summer.

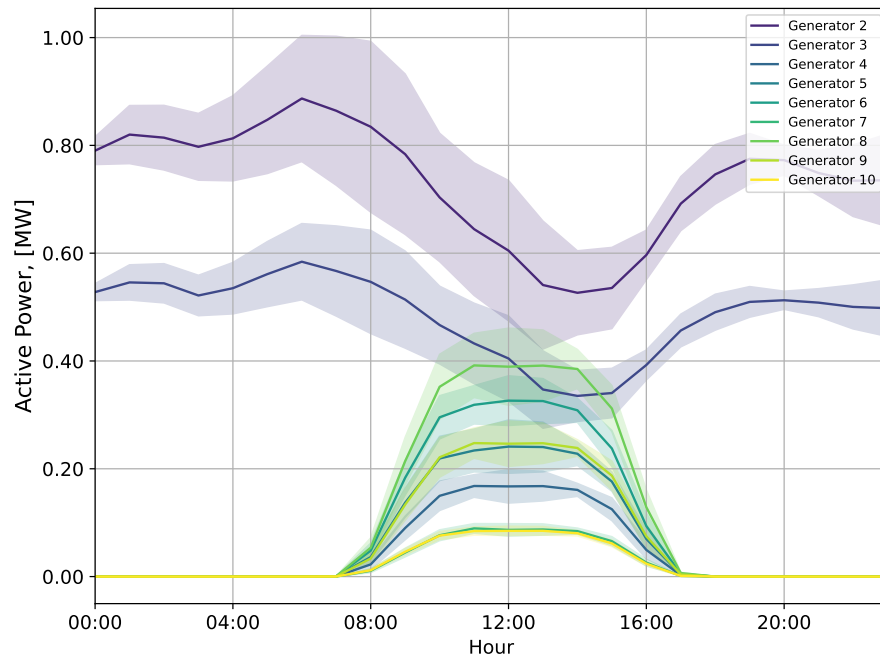


(a) RES generation profiles.

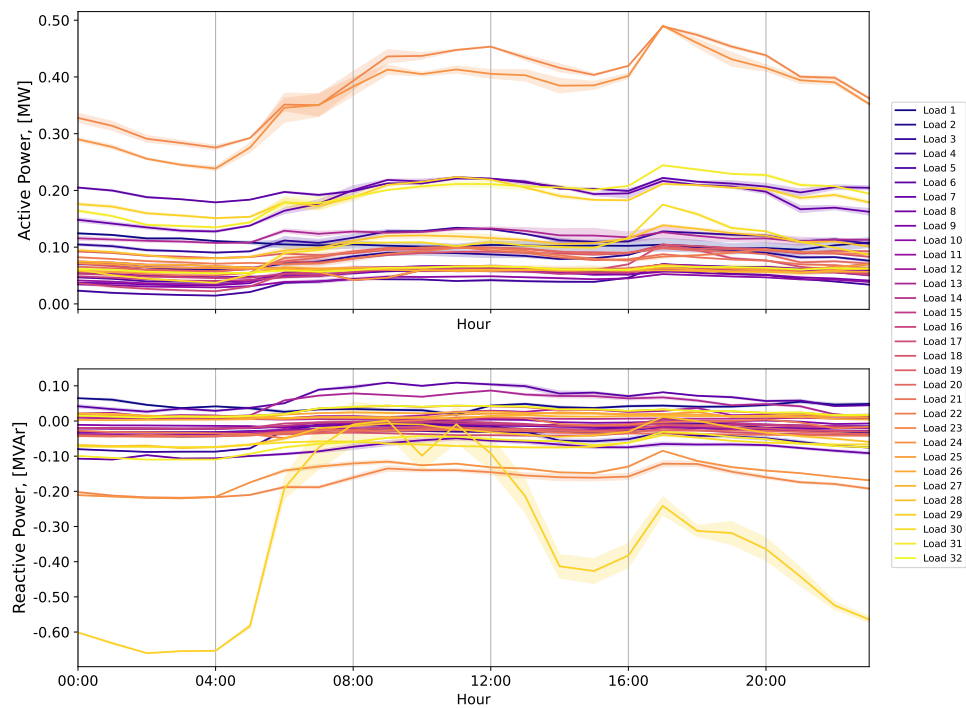


(b) Load profiles (active and reactive power).

Figure B.17: Case Study 2. ADN node 19. RES generation and load profiles. Autumn.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure B.18: Case Study 2. ADN node 19. RES generation and load profiles. Winter.

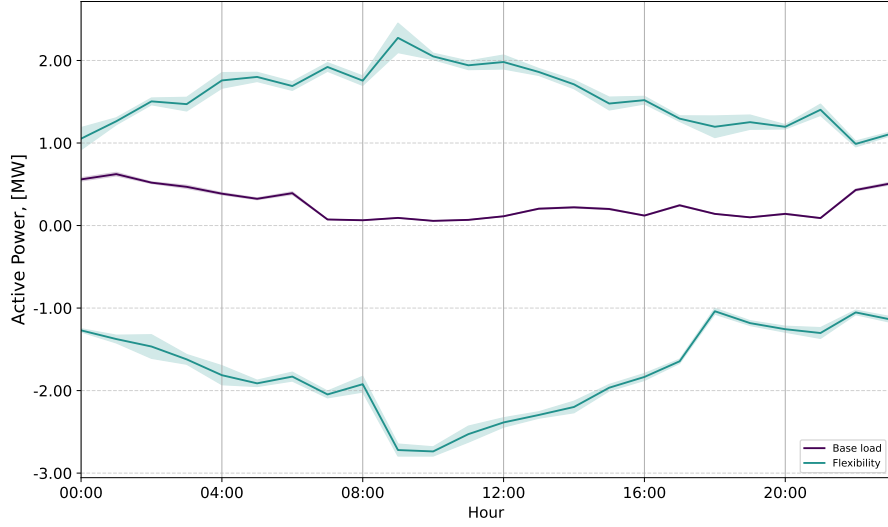


Figure B.19: Case Study 2. ADN node 19. Flexible load profiles.

Section B.2.1.3, and the single-line diagram is shown in Figure B.6. Detailed bus, branch, and interface generator data are reported in Tables B.13–B.15.

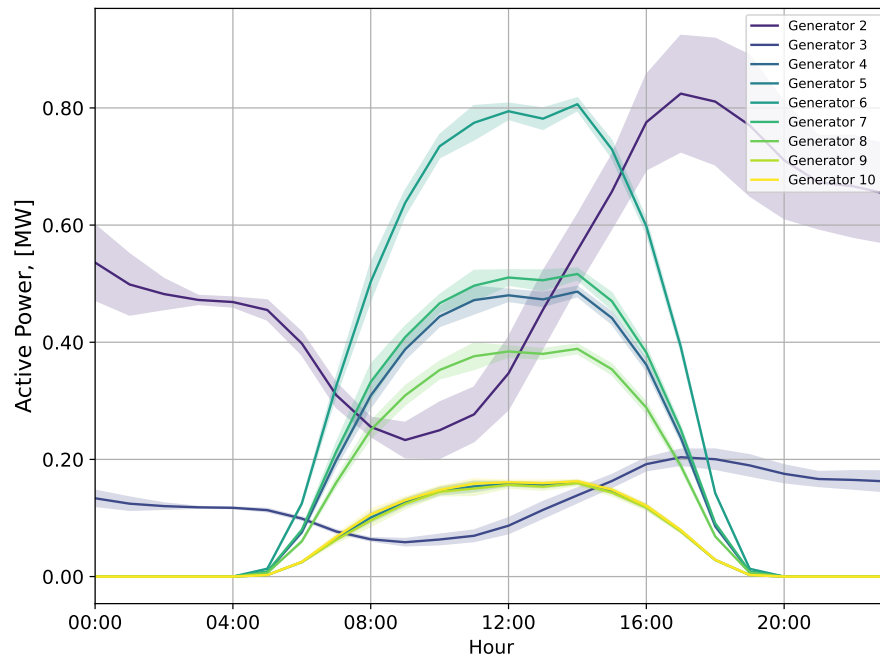
The original test system was extended to include RES generators, whose technical characteristics are summarized in Table B.19. Figures B.20–B.23 present the load and RES generation profiles for the representative days. Figure B.24 presents the flexible load profiles.

Table B.19: Case Study 2. ADN node 20. Characterization of RES generators.

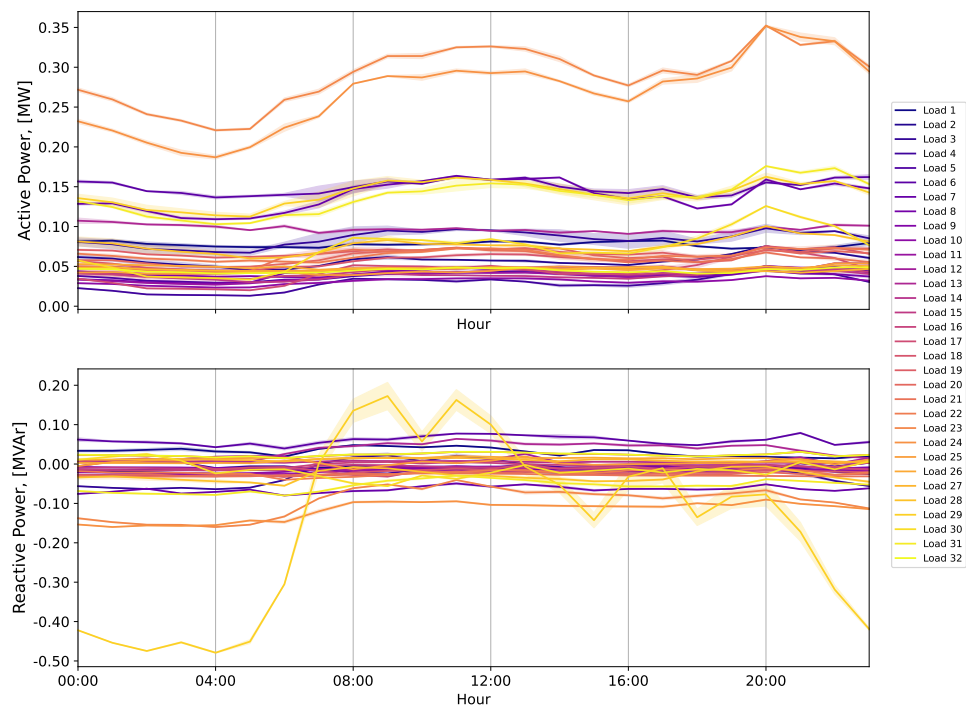
Generator	Bus	Generator	$S_g^{G,\max}$	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	ID	Type	[MVA]	[N/A]	[N/A]
2	20	Wind	2.00	-0.90	0.90
3	22	Wind	0.50	-0.90	0.90
4	3	Solar PV	0.75	-0.90	0.90
5	25	Solar PV	0.25	-0.90	0.90
6	6	Solar PV	1.25	-0.90	0.90
7	28	Solar PV	0.80	-0.90	0.90
8	33	Solar PV	0.60	-0.90	0.90
9	9	Solar PV	0.25	-0.90	0.90
10	18	Solar PV	0.25	-0.90	0.90

B.2.6 ADN Connected to Node 30 of the TN

The ADN connected to node 30 of the TN is based on the IEEE 33-bus distribution test system (Baran and Wu, 1989). The corresponding network topology is described in

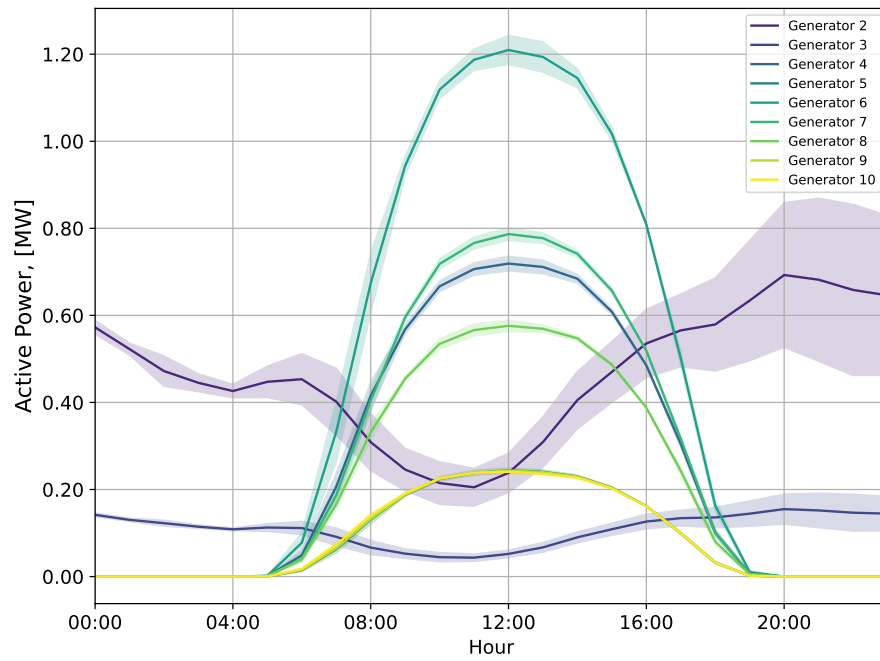


(a) RES generation profiles.

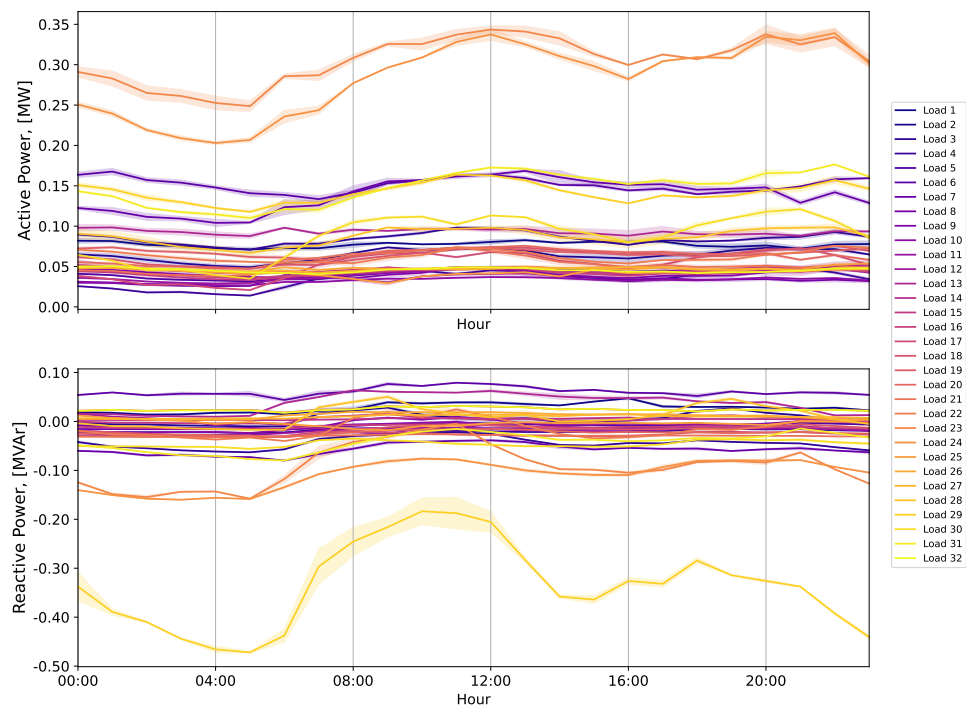


(b) Load profiles (active and reactive power).

Figure B.20: Case Study 2. ADN node 20. RES generation and load scenarios. Spring.

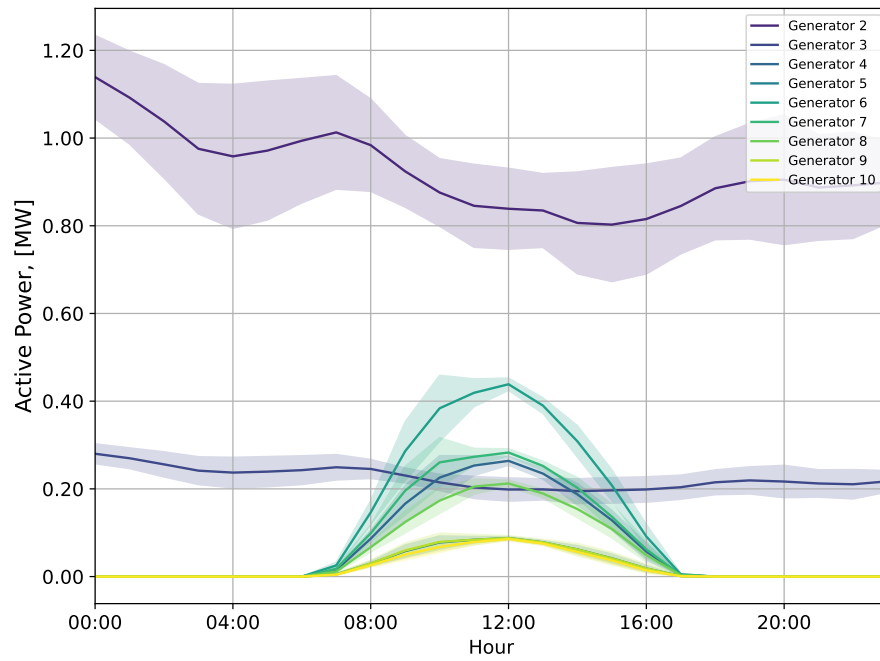


(a) RES generation profiles.

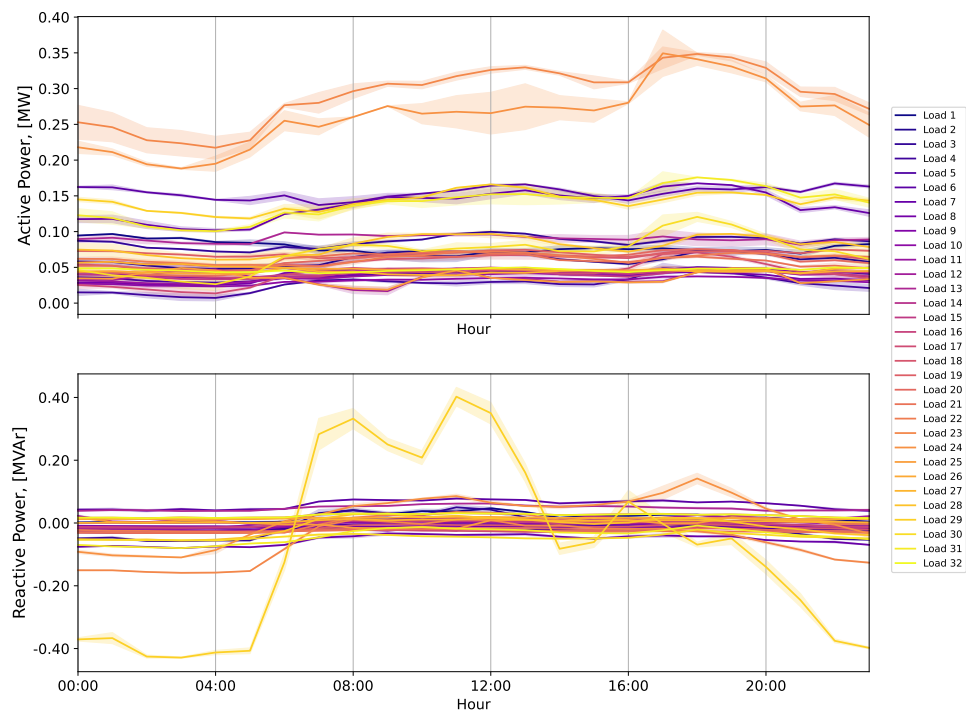


(b) Load profiles (active and reactive power).

Figure B.21: Case Study 2. ADN node 20. RES generation and load profiles. Summer.

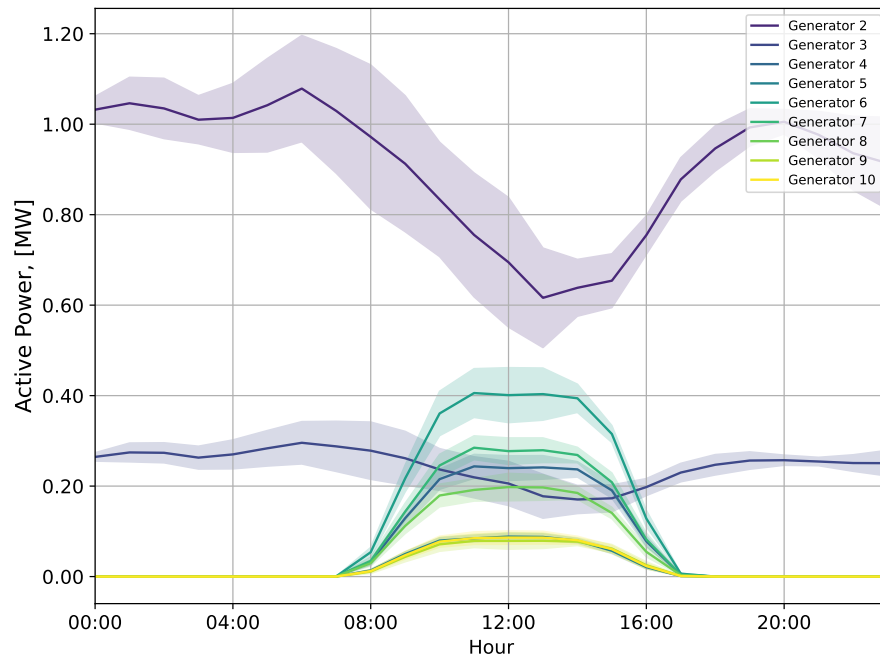


(a) RES generation profiles.

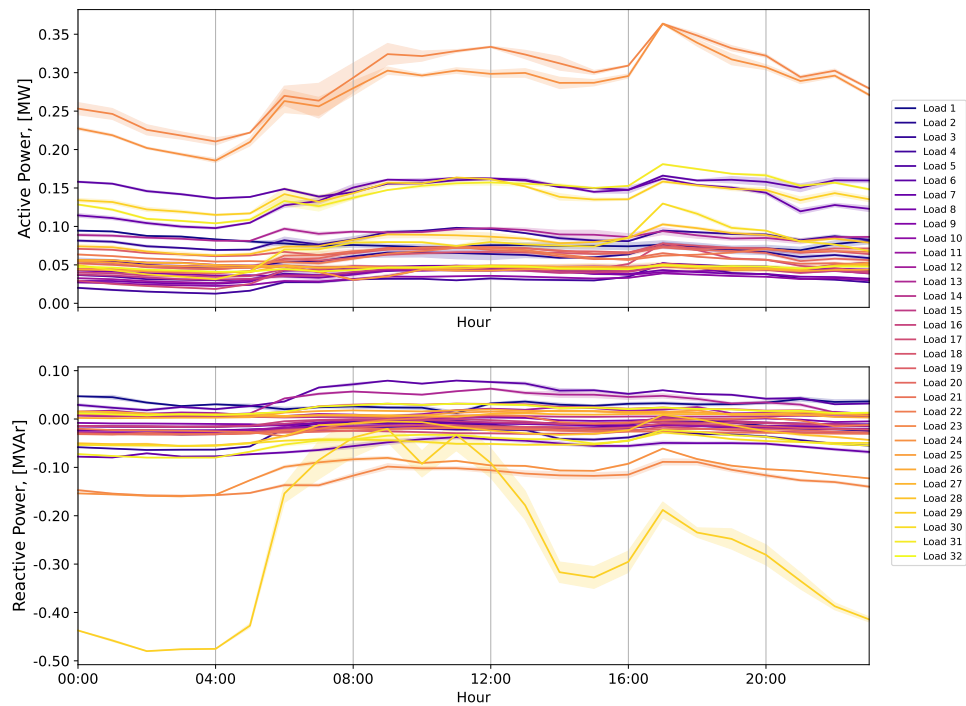


(b) Load profiles (active and reactive power).

Figure B.22: Case Study 2. ADN node 20. RES generation and load profiles. Autumn.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure B.23: Case Study 2. ADN node 20. RES generation and load profiles. Winter.

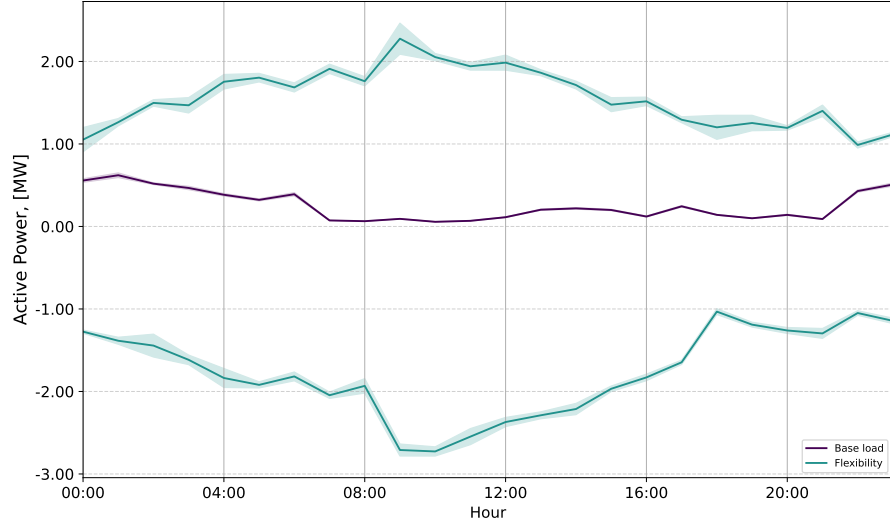


Figure B.24: Case Study 2. ADN node 20. Flexible load profiles.

Section B.2.1.3, and the single-line diagram is shown in Figure B.6. Detailed bus, branch, and interface generator data are reported in Tables B.13–B.15.

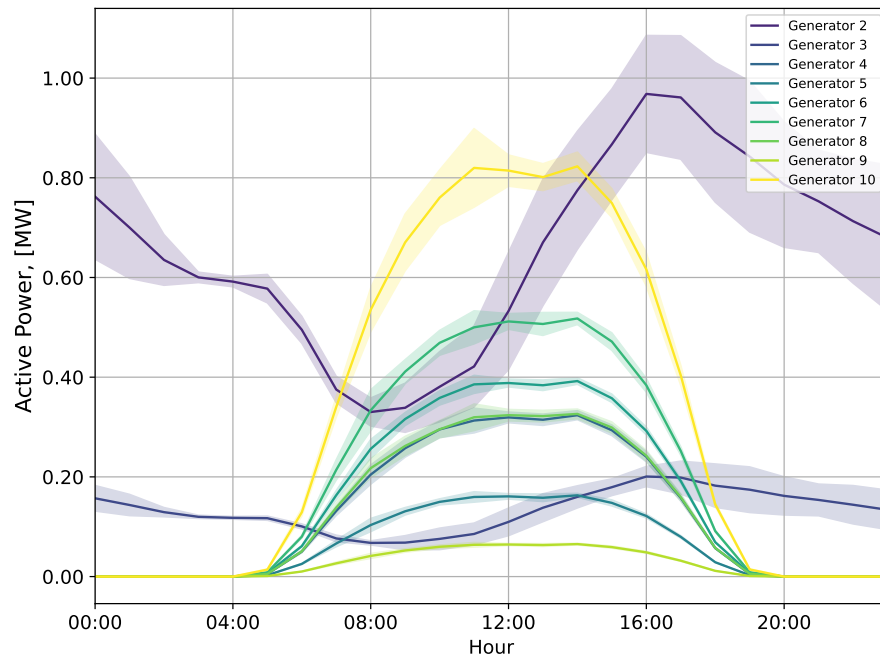
The original test system was extended to include RES generators, whose technical characteristics are summarized in Table B.20. Figures B.25–B.28 present the load and RES generation profiles for the representative days. Figure B.29 presents the flexible load profiles.

Table B.20: Case Study 2. ADN node 30. Characterization of RES generators.

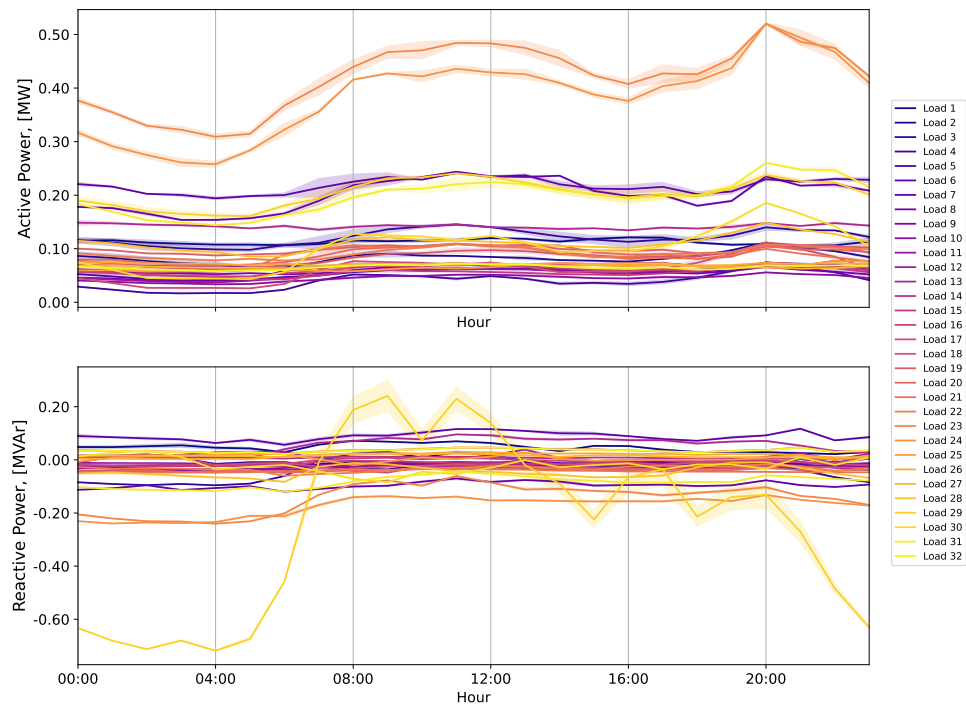
Generator	Bus	Generator	$S_g^{G,\max}$	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	ID	Type	[MVA]	[N/A]	[N/A]
2	20	Wind	2.50	-0.90	0.90
3	22	Wind	0.50	-0.90	0.90
4	3	Solar PV	0.50	-0.90	0.90
5	25	Solar PV	0.25	-0.90	0.90
6	6	Solar PV	0.60	-0.90	0.90
7	28	Solar PV	0.80	-0.90	0.90
8	33	Solar PV	0.50	-0.90	0.90
9	9	Solar PV	0.10	-0.90	0.90
10	18	Solar PV	1.25	-0.90	0.90

B.2.7 ADN Connected to Node 32 of the TN

The ADN connected to node 32 of the TN is based on the IEEE 22-bus distribution test system (Ramalinga Raju et al., 2012). The corresponding network topology is described in

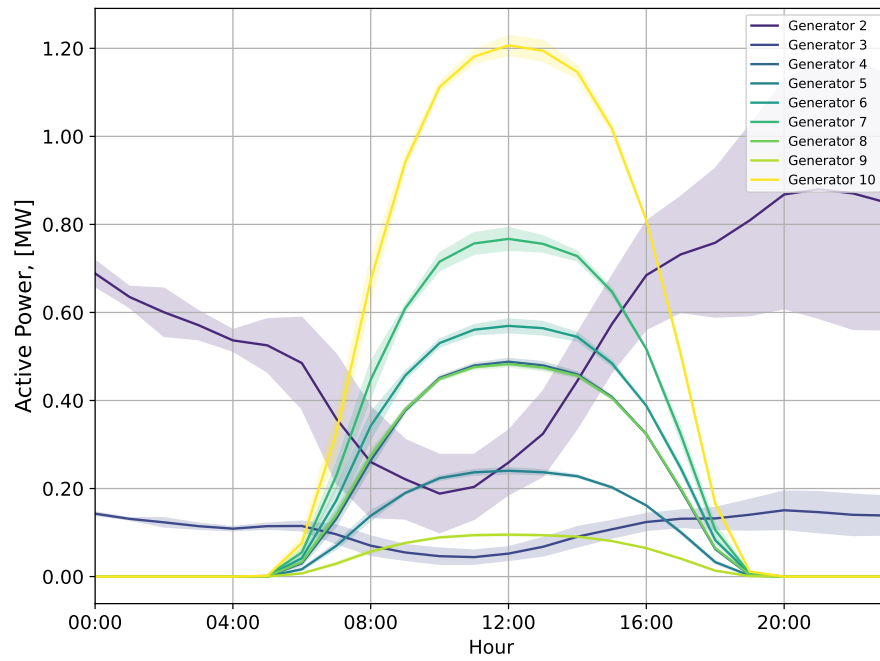


(a) RES generation profiles.

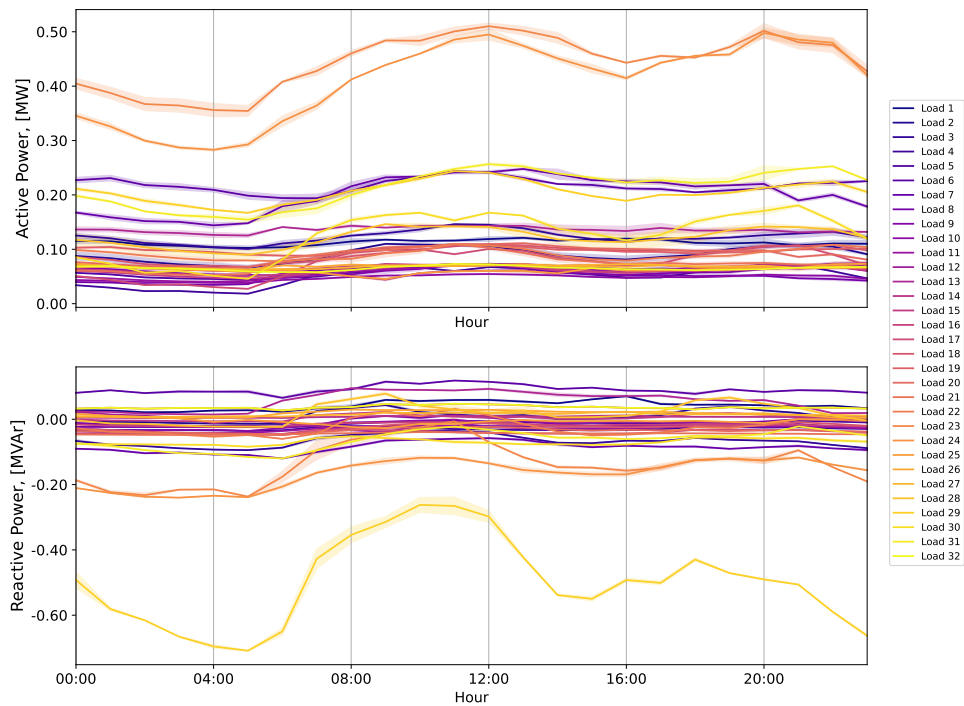


(b) Load profiles (active and reactive power).

Figure B.25: Case Study 2. ADN node 30. RES generation and load scenarios. Spring.

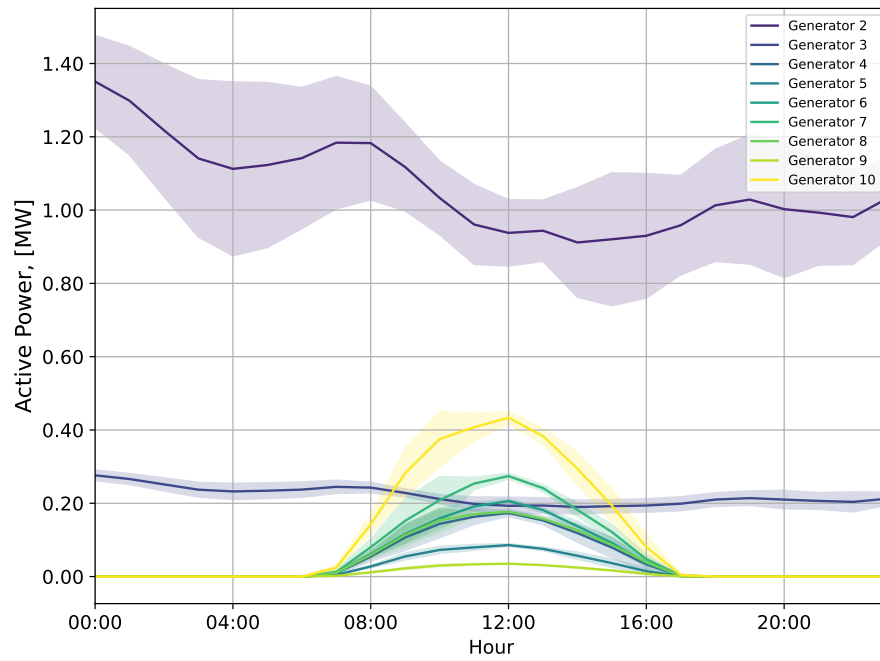


(a) RES generation profiles.

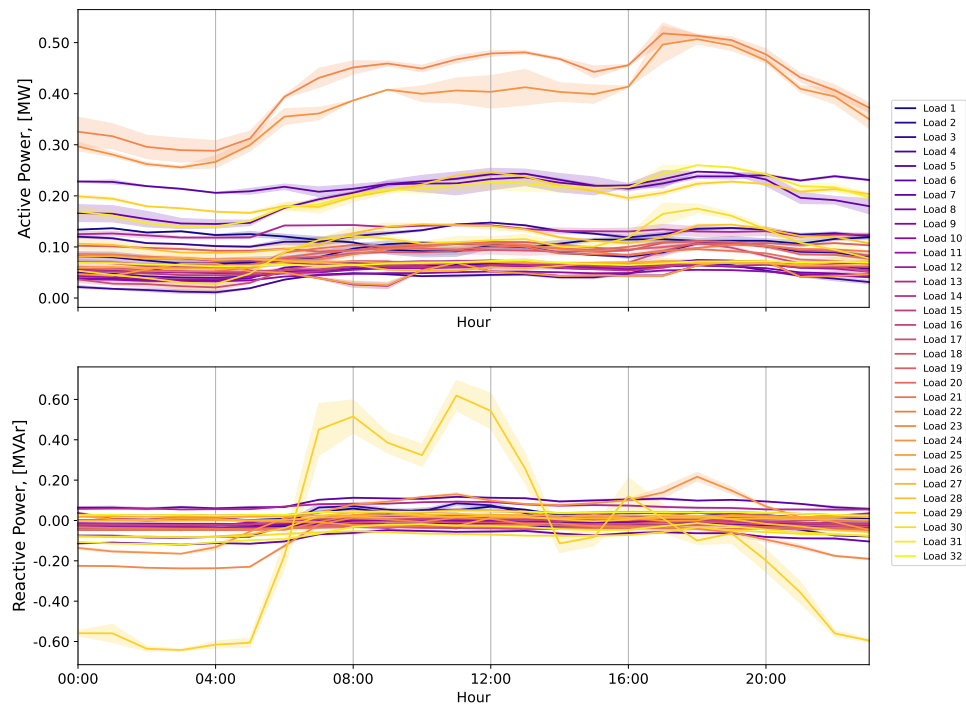


(b) Load profiles (active and reactive power).

Figure B.26: Case Study 2. ADN node 30. RES generation and load profiles. Summer.

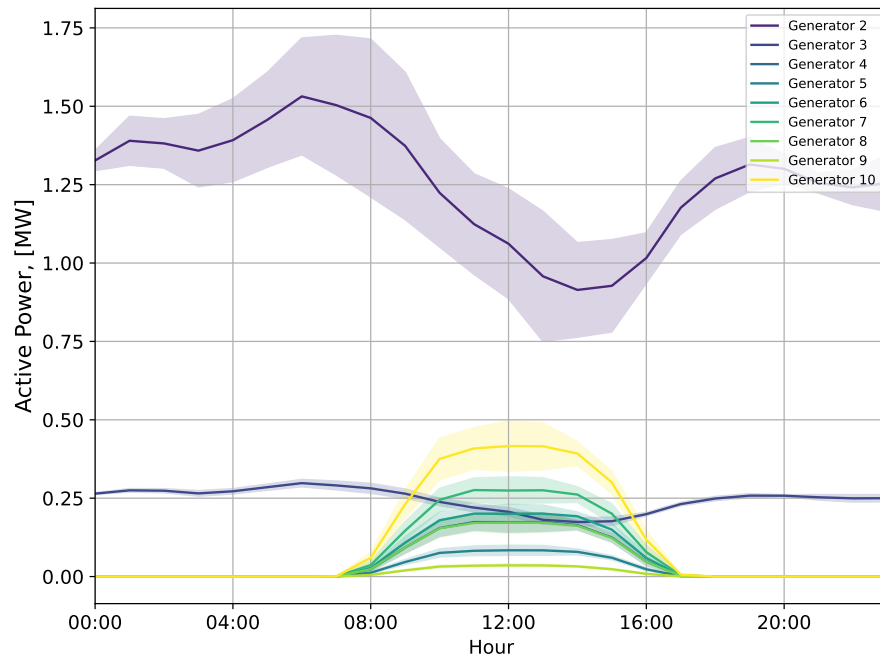


(a) RES generation profiles.

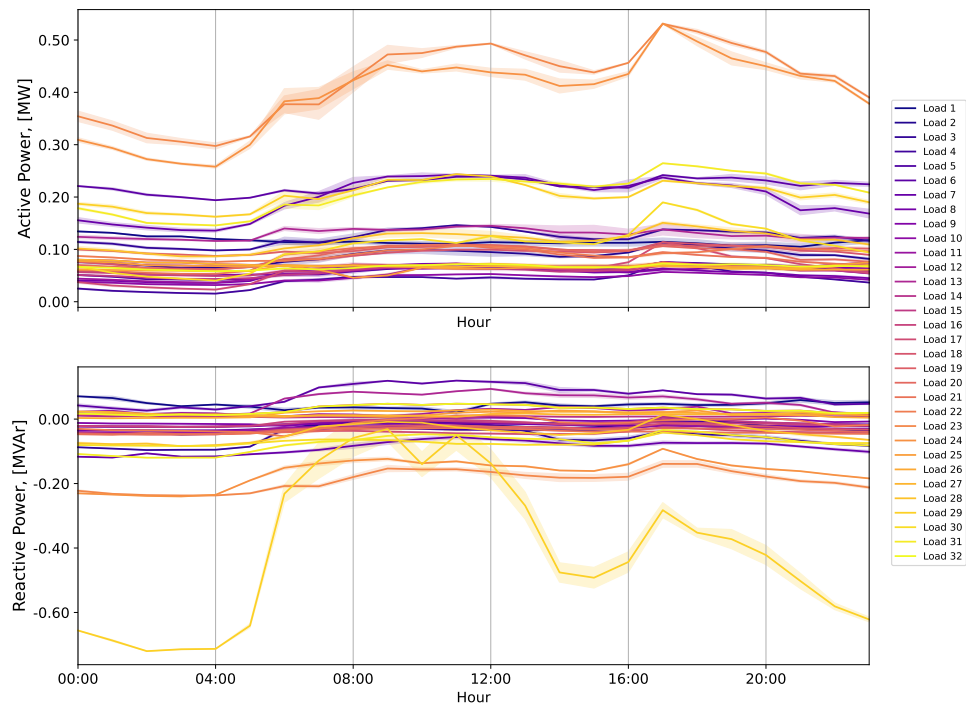


(b) Load profiles (active and reactive power).

Figure B.27: Case Study 2. ADN node 30. RES generation and load profiles. Autumn.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure B.28: Case Study 2. ADN node 30. RES generation and load profiles. Winter.

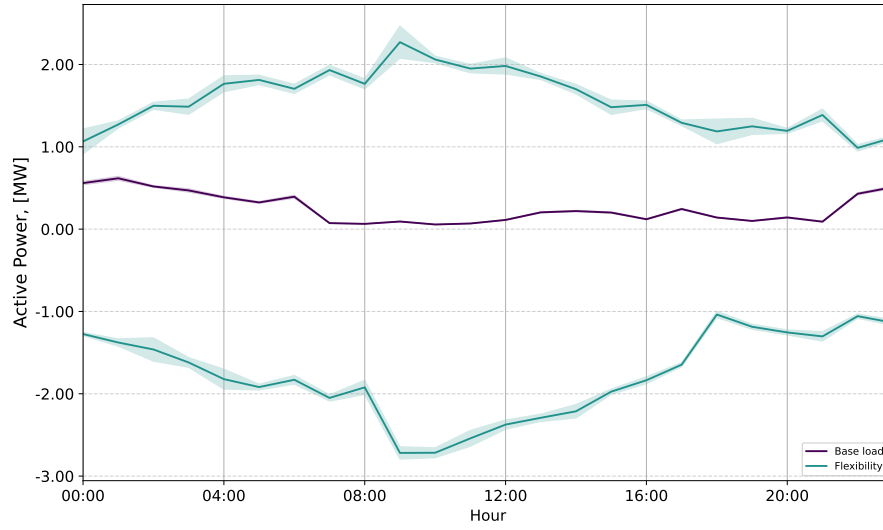


Figure B.29: Case Study 2. ADN node 30. Flexible load profiles.

Section B.2.1.2, and the single-line diagram is shown in Figure B.5. Detailed bus, branch, and interface generator data are reported in Tables B.9–B.11.

The original test system was extended to include RES generators, whose technical characteristics are summarized in Table B.21. Figures B.30–B.33 present the load and RES generation profiles for the representative days. Figure B.34 presents the flexible load profiles.

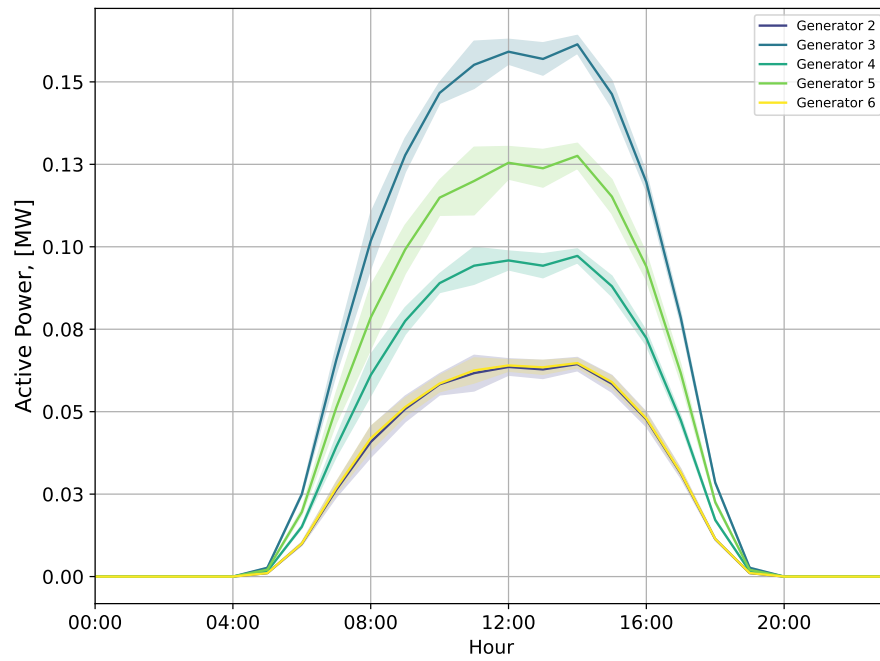
Table B.21: Case Study 2. ADN node 32. Characterization of RES generators.

Generator	Bus	Generator	$S_g^{G,\max}$	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	ID	Type	[MVA]	[N/A]	[N/A]
2	3	Solar PV	0.10	-0.90	0.90
3	7	Solar PV	0.25	-0.90	0.90
4	12	Solar PV	0.15	-0.90	0.90
5	18	Solar PV	0.20	-0.90	0.90
6	22	Solar PV	0.10	-0.90	0.90

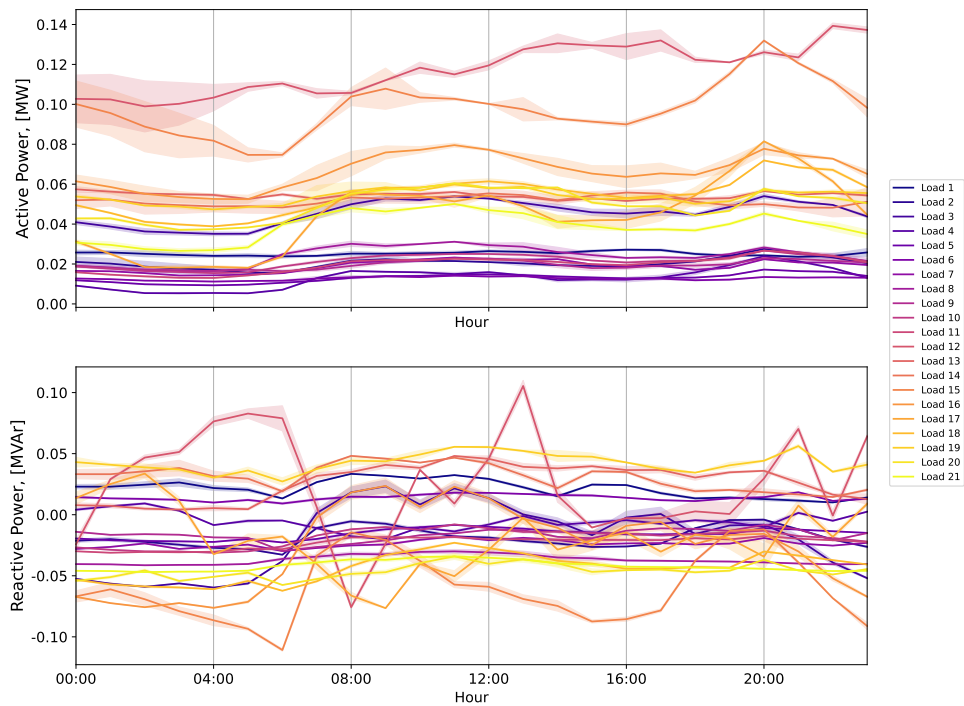
B.2.8 ADN Connected to Node 33 of the TN

The ADN connected to node 33 of the TN is based on the IEEE 33-bus distribution test system (Baran and Wu, 1989). The corresponding network topology is described in Section B.2.1.3, and the single-line diagram is shown in Figure B.6. Detailed bus, branch, and interface generator data are reported in Tables B.13–B.15.

The original test system was extended to include RES generators, whose technical characteristics are summarized in Table B.22. Figures B.35–B.38 present the load and

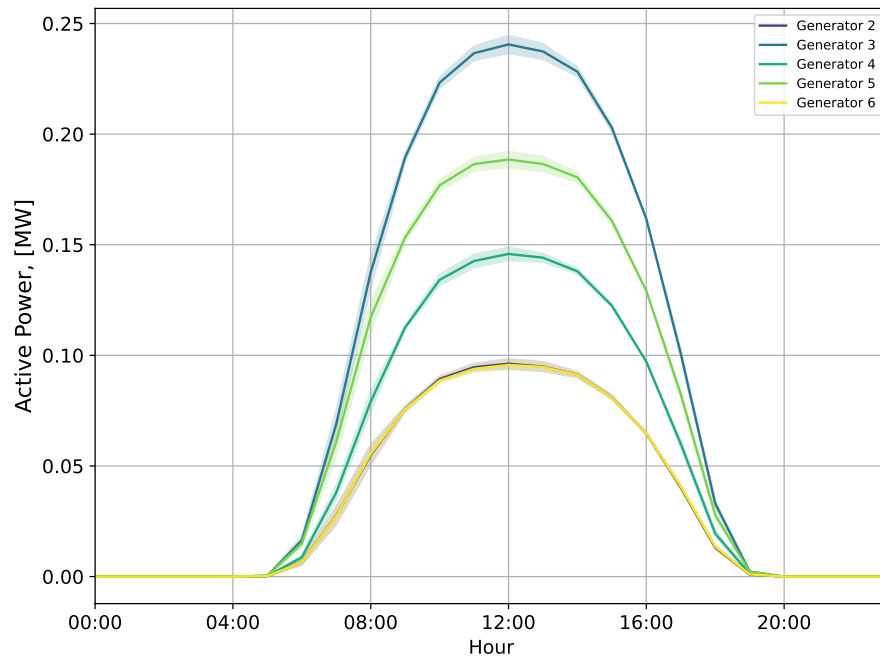


(a) RES generation profiles.

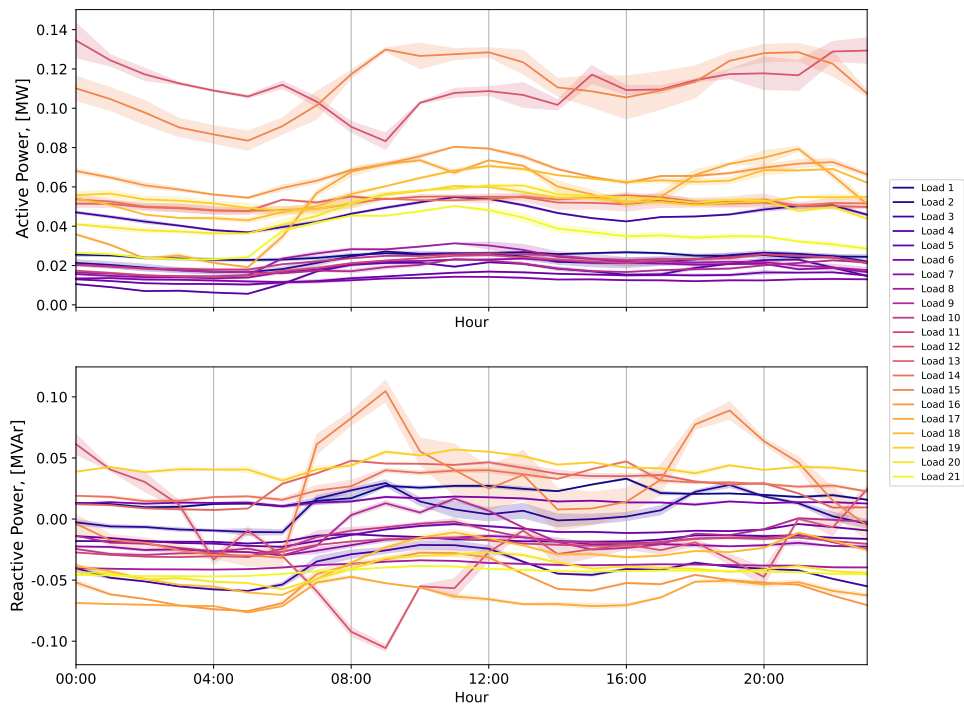


(b) Load profiles (active and reactive power).

Figure B.30: Case Study 2. ADN node 32. RES generation and load scenarios. Spring.

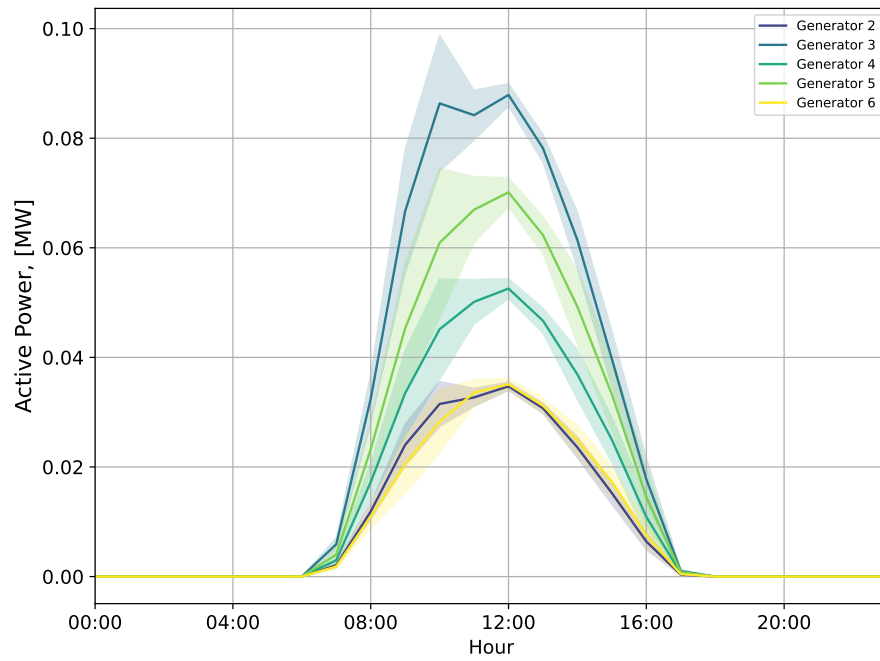


(a) RES generation profiles.

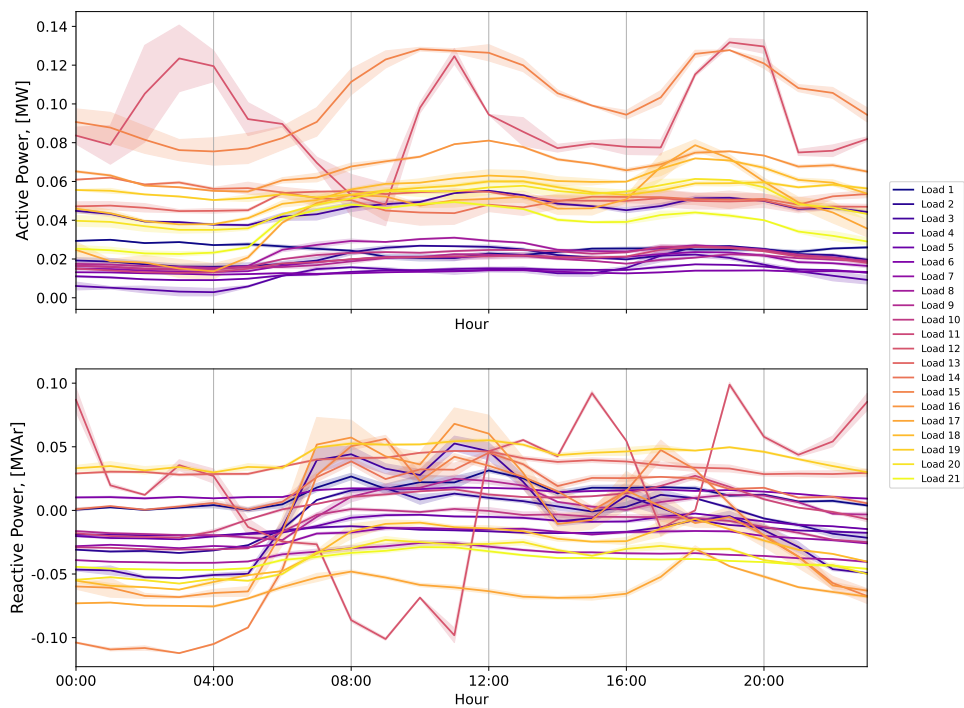


(b) Load profiles (active and reactive power).

Figure B.31: Case Study 2. ADN node 32. RES generation and load profiles. Summer.

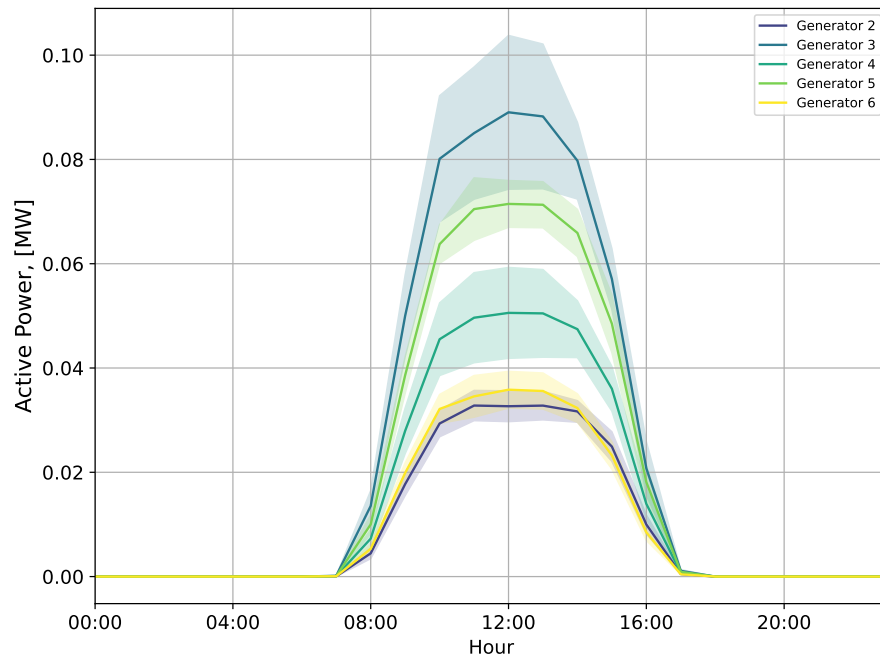


(a) RES generation profiles.

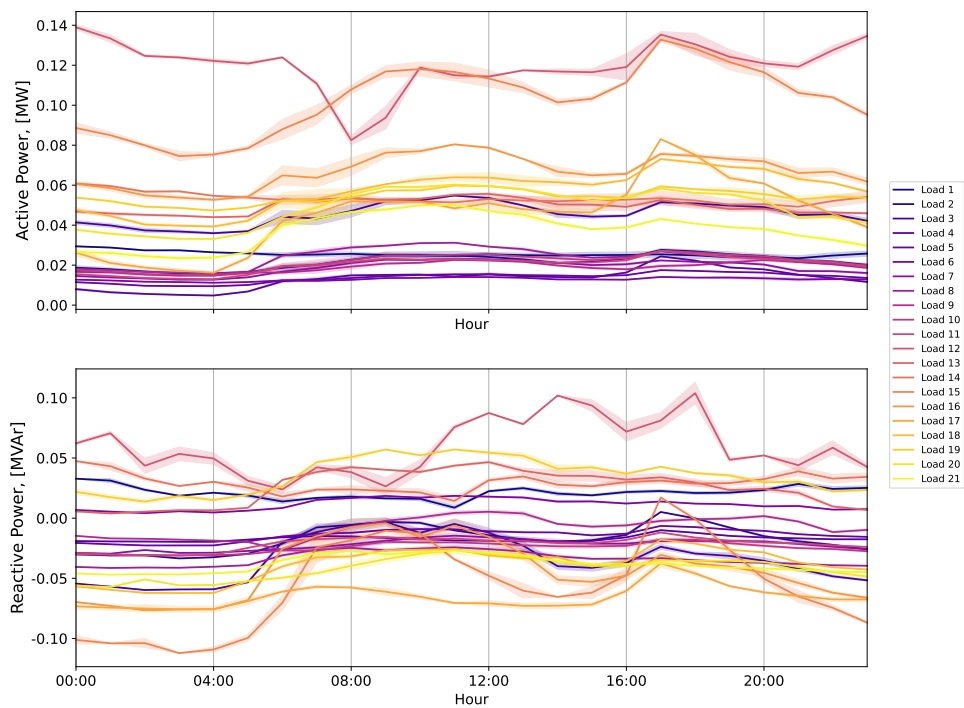


(b) Load profiles (active and reactive power).

Figure B.32: Case Study 2. ADN node 32. RES generation and load profiles. Autumn.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure B.33: Case Study 2. ADN node 32. RES generation and load profiles. Winter.

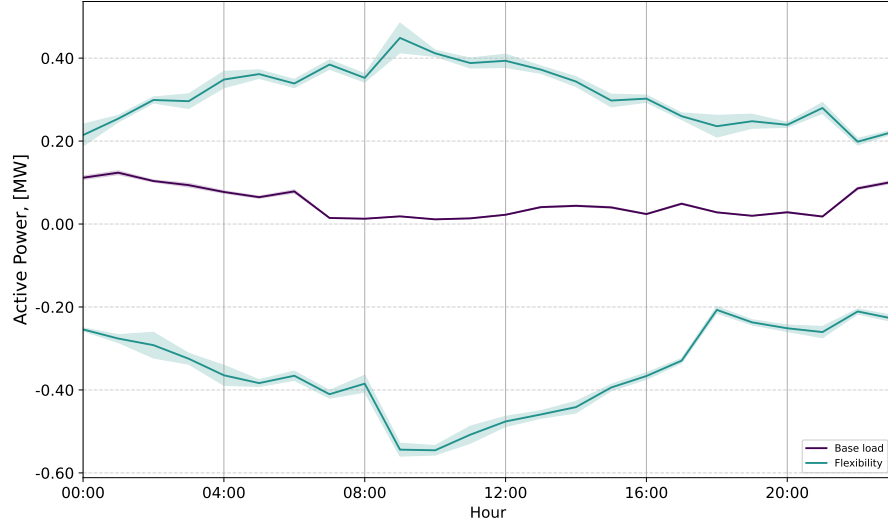


Figure B.34: Case Study 2. ADN node 32. Flexible load profiles.

RES generation profiles for the representative days. Figure B.39 presents the flexible load profiles.

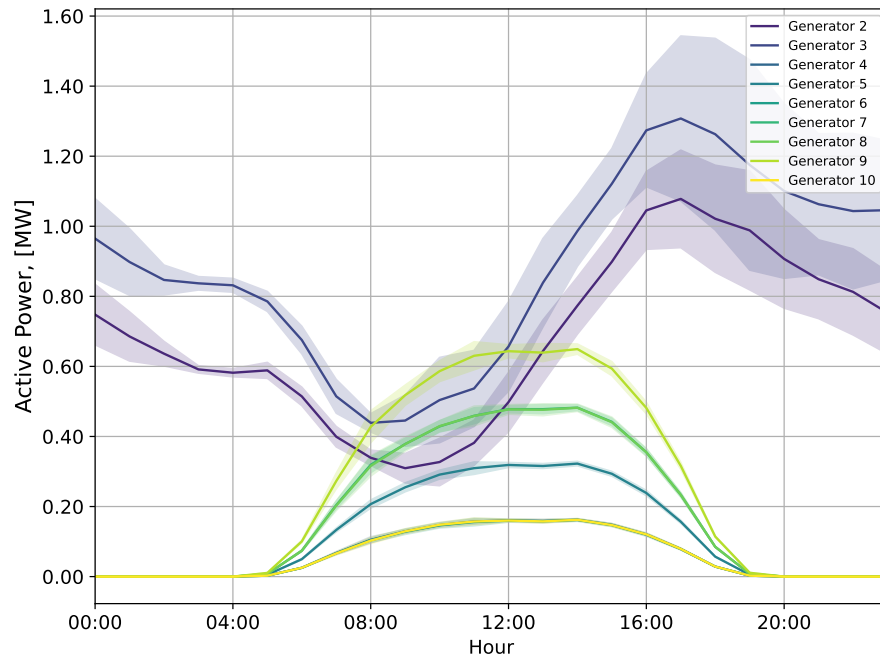
Table B.22: Case Study 2. ADN node 33. Characterization of RES generators.

Generator	Bus	Generator	$S_g^{G,\max}$	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	ID	Type	[MVA]	[N/A]	[N/A]
2	20	Wind	2.50	-0.90	0.90
3	22	Wind	3.50	-0.90	0.90
4	3	Solar PV	0.25	-0.90	0.90
5	25	Solar PV	0.50	-0.90	0.90
6	6	Solar PV	0.25	-0.90	0.90
7	28	Solar PV	0.75	-0.90	0.90
8	33	Solar PV	0.75	-0.90	0.90
9	9	Solar PV	1.00	-0.90	0.90
10	18	Solar PV	0.25	-0.90	0.90

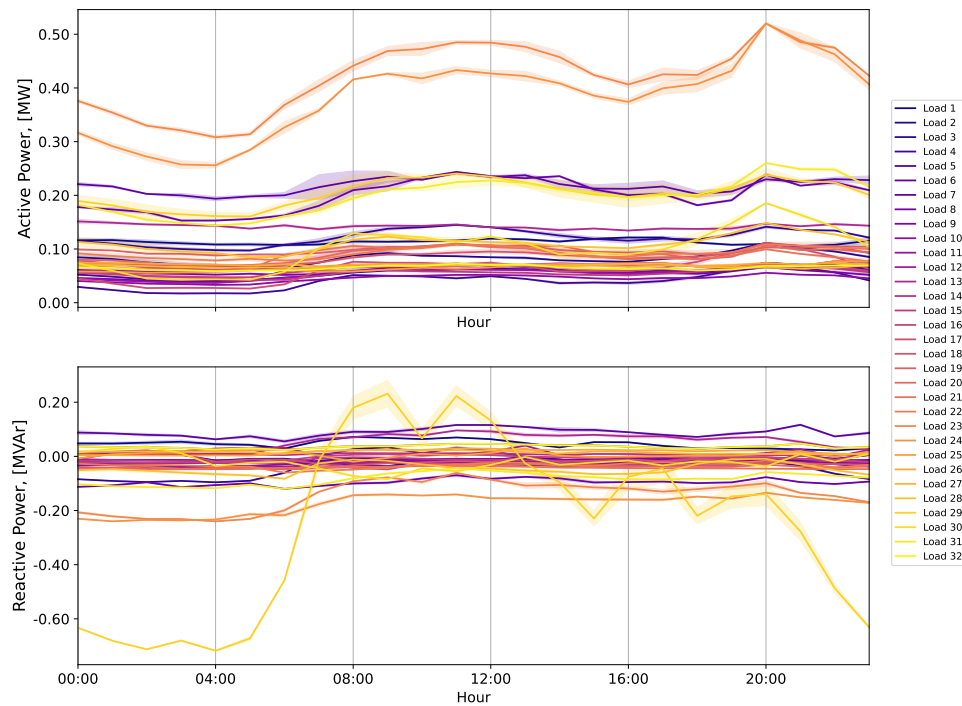
B.2.9 ADN Connected to Node 43 of the TN

The ADN connected to node 43 of the TN is based on the IEEE 22-bus distribution test system (Ramalinga Raju et al., 2012). The corresponding network topology is described in Section B.2.1.2, and the single-line diagram is shown in Figure B.5. Detailed bus, branch, and interface generator data are reported in Tables B.9–B.11.

The original test system was extended to include RES generators, whose technical characteristics are summarized in Table B.23. Figures B.40–B.43 present the load and

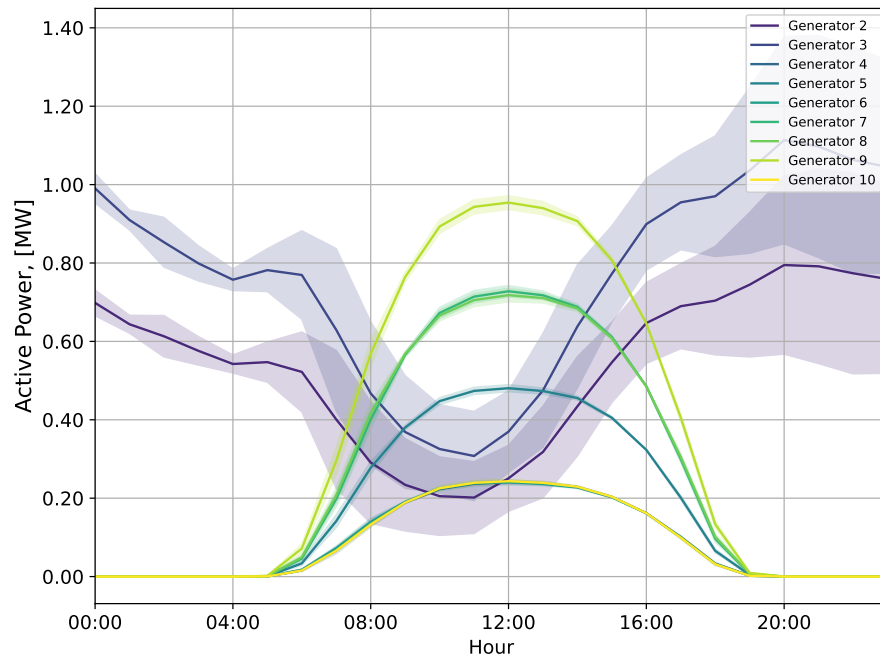


(a) RES generation profiles.

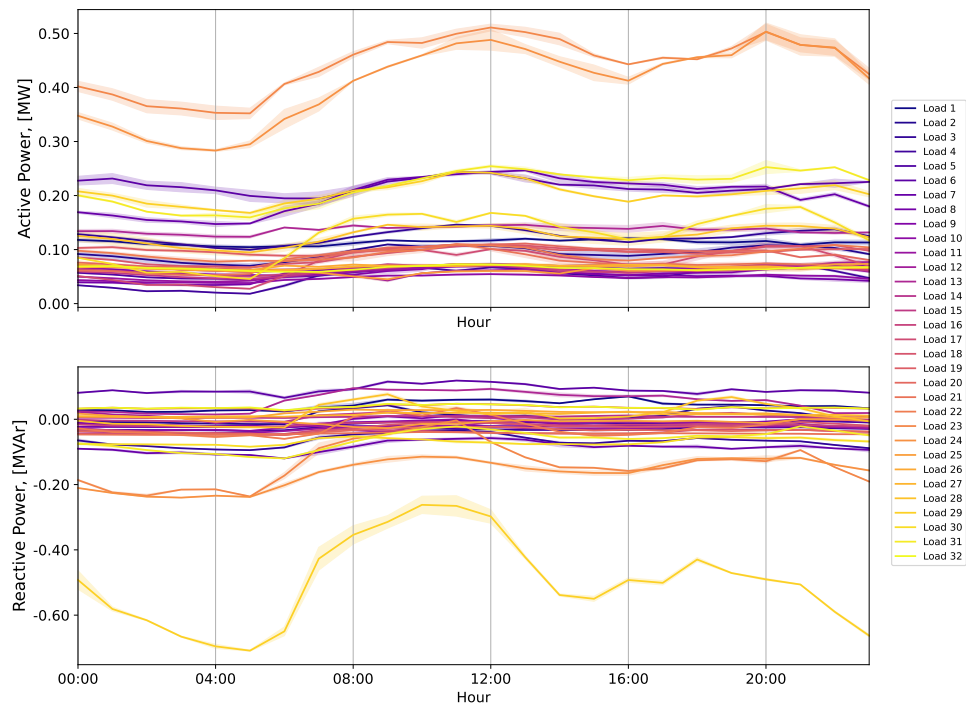


(b) Load profiles (active and reactive power).

Figure B.35: Case Study 2. ADN node 33. RES generation and load scenarios. Spring.

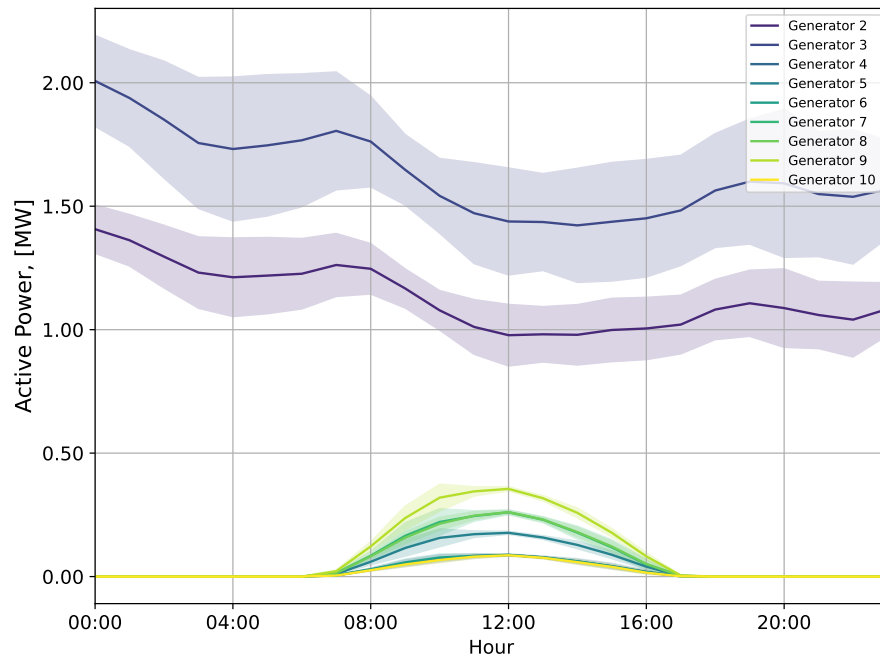


(a) RES generation profiles.

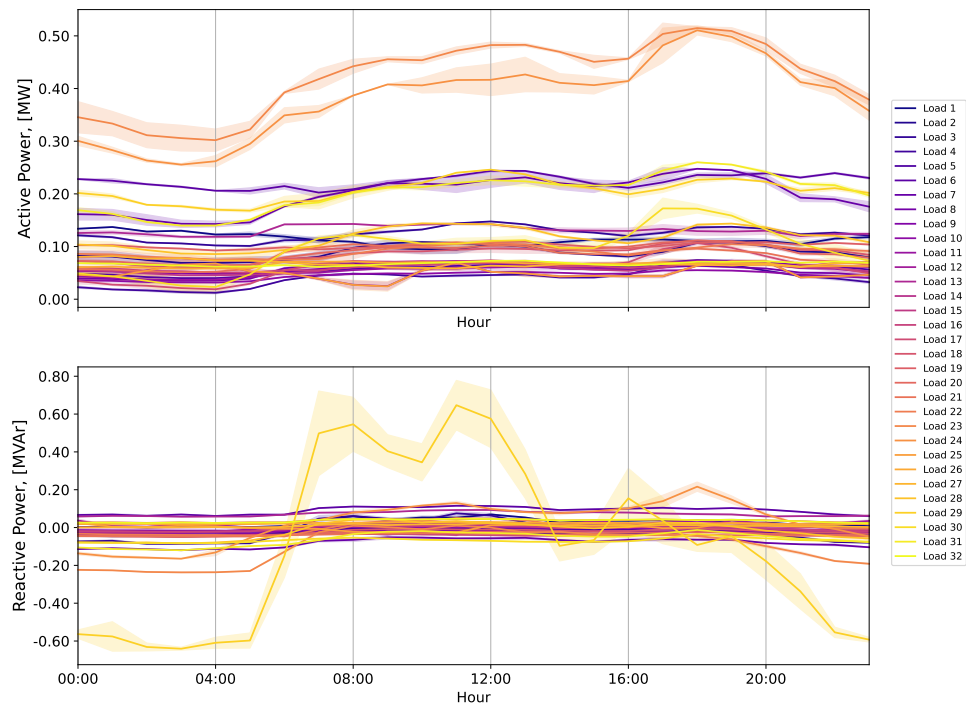


(b) Load profiles (active and reactive power).

Figure B.36: Case Study 2. ADN node 33. RES generation and load profiles. Summer.

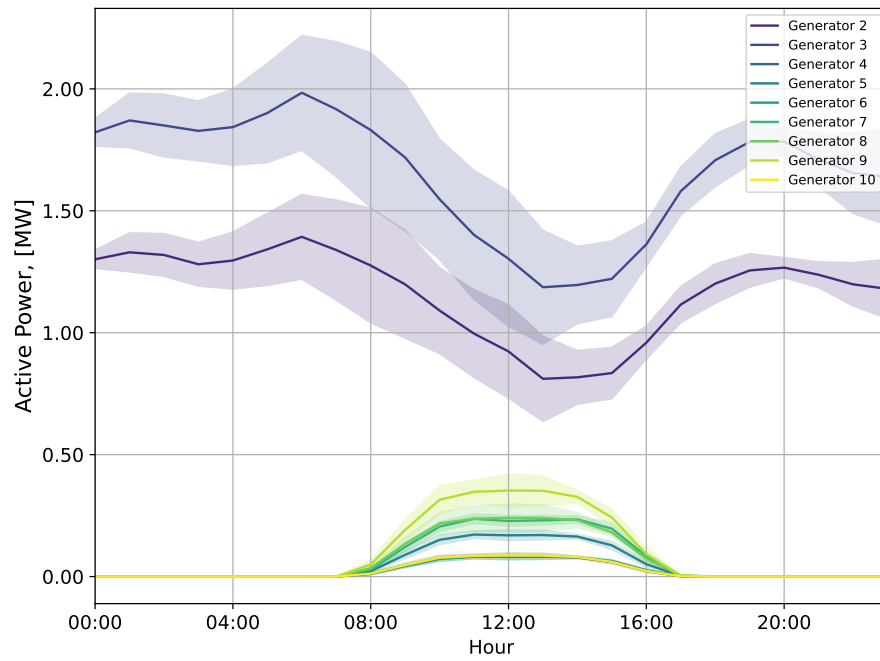


(a) RES generation profiles.

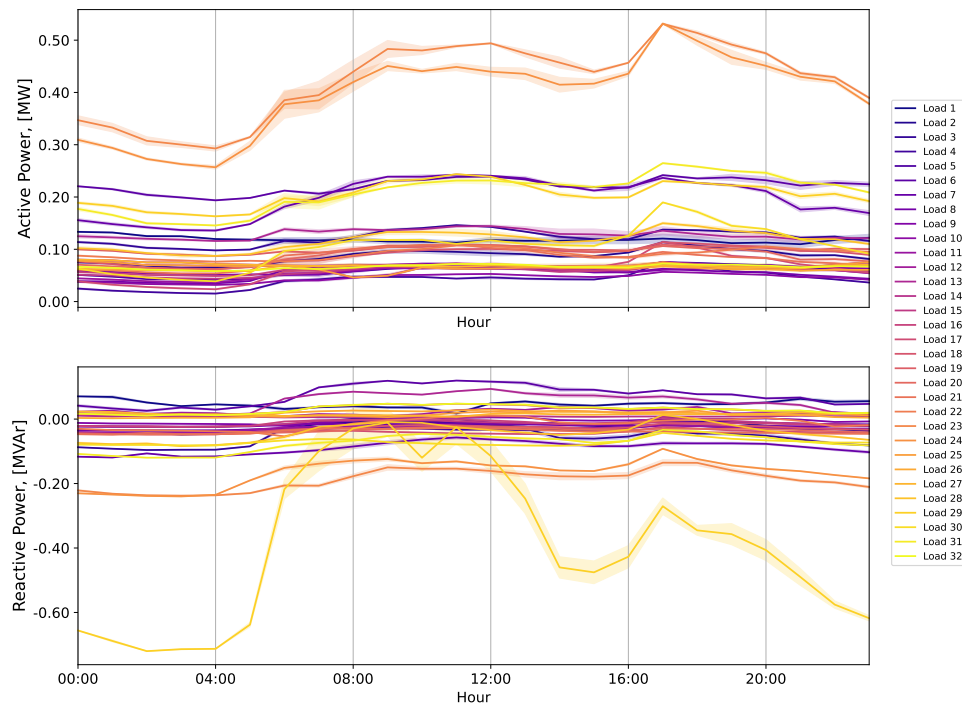


(b) Load profiles (active and reactive power).

Figure B.37: Case Study 2. ADN node 33. RES generation and load profiles. Autumn.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure B.38: Case Study 2. ADN node 33. RES generation and load profiles. Winter.

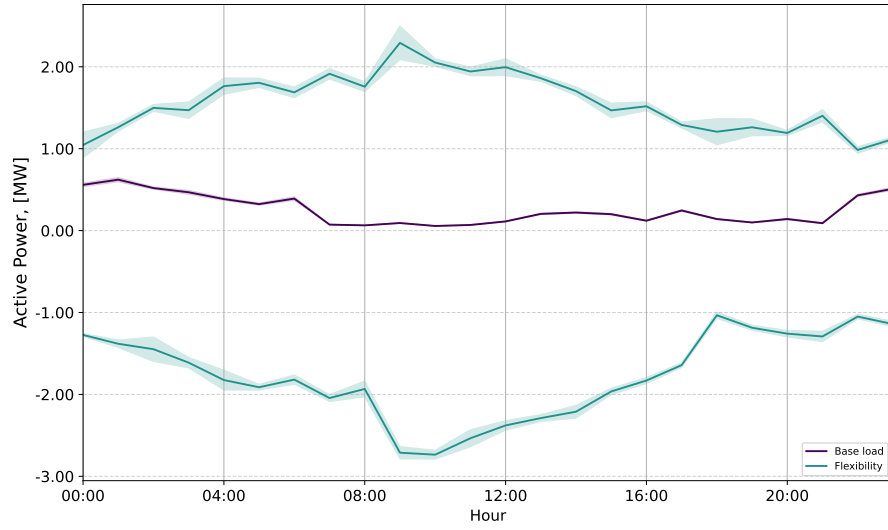


Figure B.39: Case Study 2. ADN node 33. Flexible load profiles.

RES generation profiles for the representative days. Figure B.44 presents the flexible load profiles.

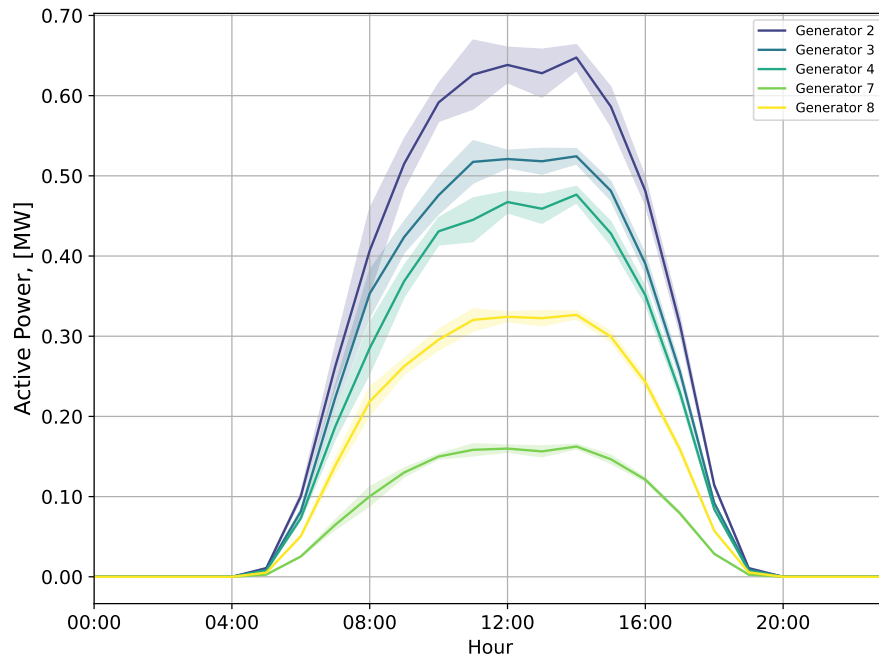
Table B.23: Case Study 2. ADN node 43. Characterization of RES generators.

Generator	Bus	Generator	$S_g^{G,\max}$	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	ID	Type	[MVA]	[N/A]	[N/A]
2	3	Solar PV	1.00	-0.90	0.90
3	7	Solar PV	0.80	-0.90	0.90
4	8	Solar PV	0.75	-0.90	0.90
7	15	Solar PV	0.25	-0.90	0.90
8	18	Solar PV	0.50	-0.90	0.90

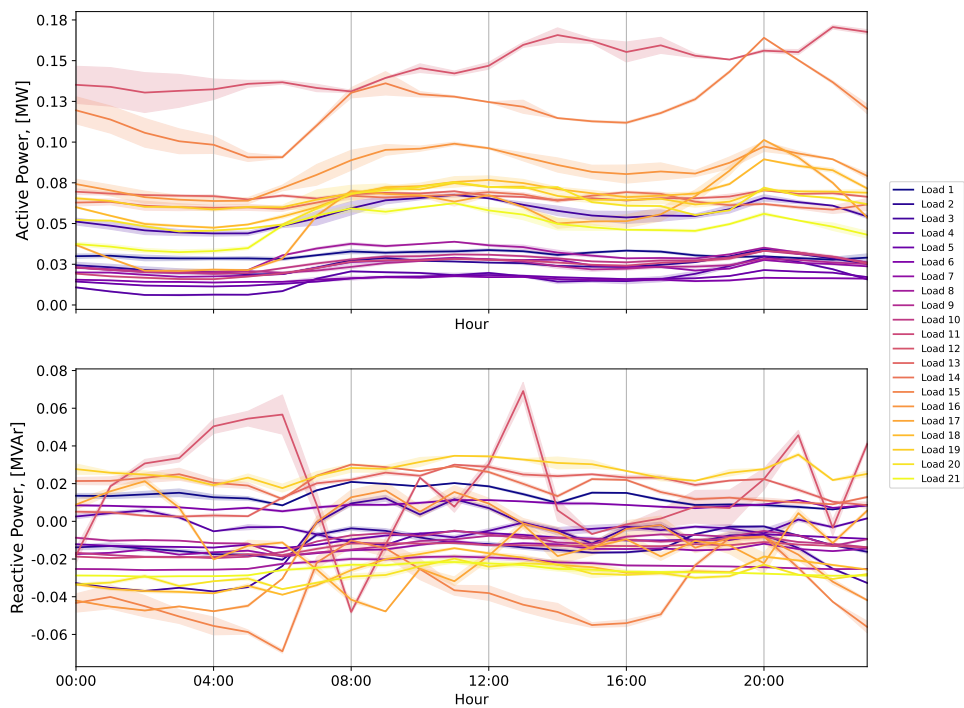
B.2.10 ADN Connected to Node 47 of the TN

The ADN connected to node 47 of the TN is based on the IEEE 18-bus distribution test system (Grady et al., 1992). The corresponding network topology is described in Section B.2.1.1, and the single-line diagram is shown in Figure B.4. Detailed bus, branch, and interface generator data are reported in Tables B.5–B.7.

The original test system was extended to include RES generators, whose technical characteristics are summarized in Table B.24. Figures B.45–B.48 present the load and RES generation profiles for the representative days. Figure B.49 presents the flexible load profiles.

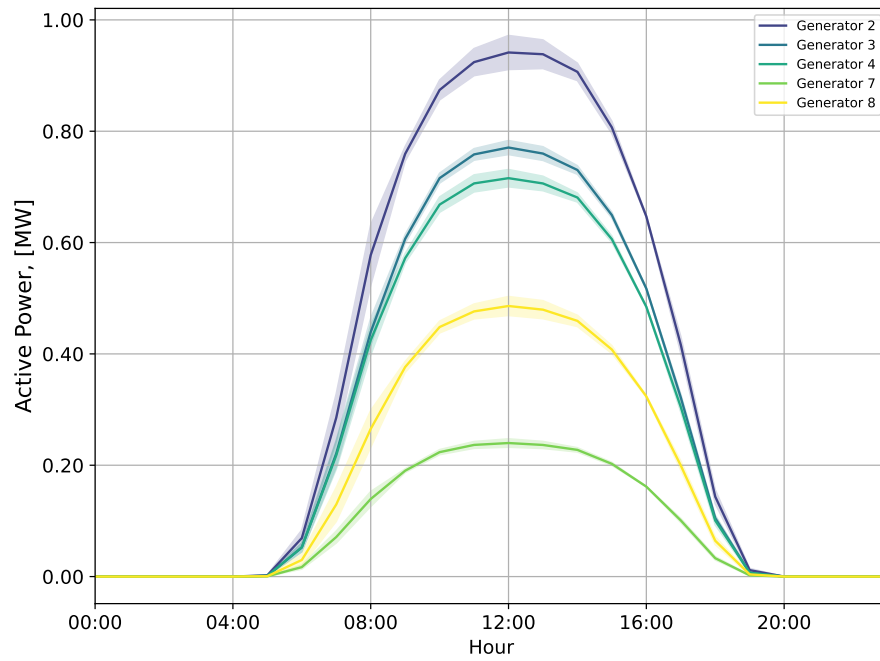


(a) RES generation profiles.

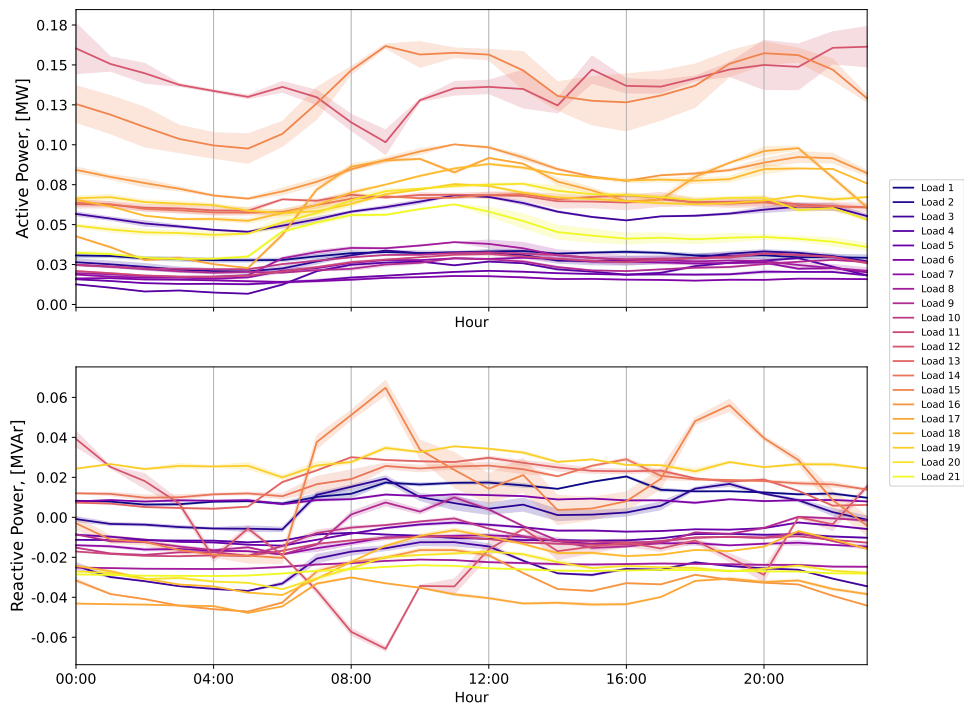


(b) Load profiles (active and reactive power).

Figure B.40: Case Study 2. ADN node 43. RES generation and load scenarios. Spring.

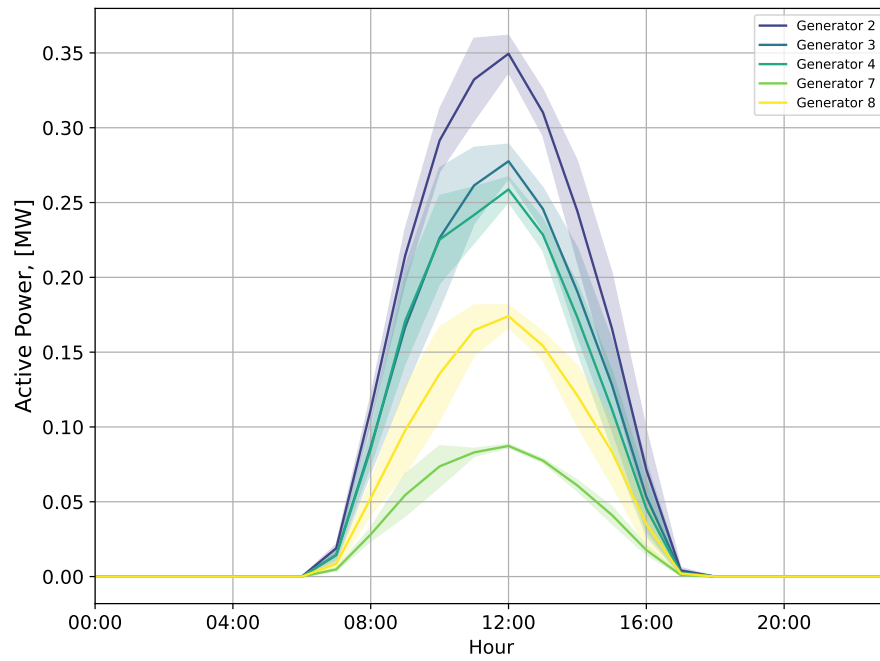


(a) RES generation profiles.

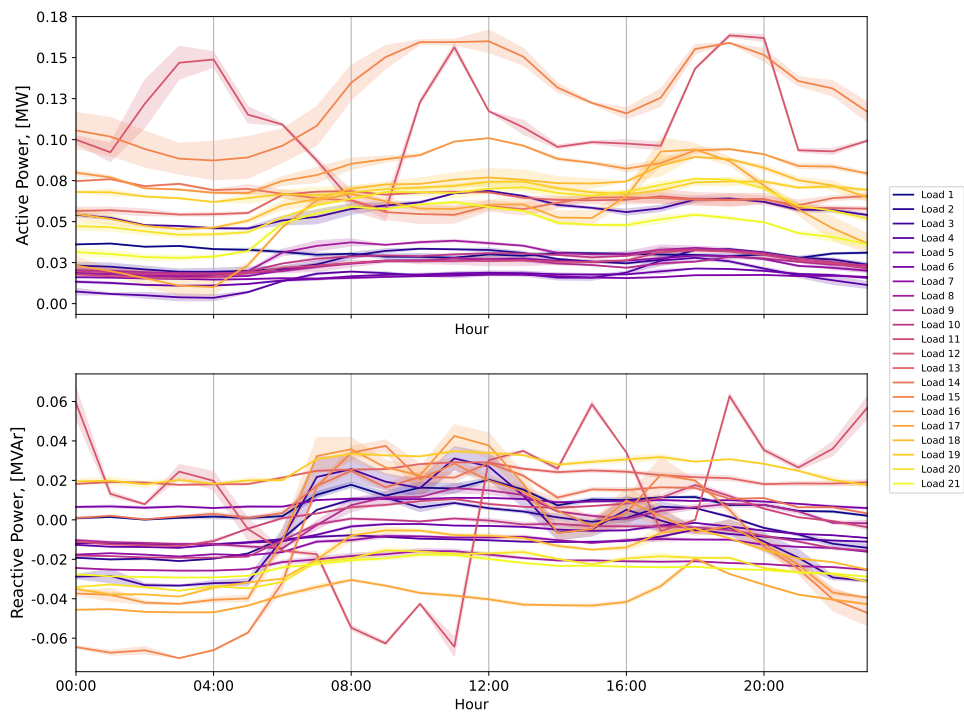


(b) Load profiles (active and reactive power).

Figure B.41: Case Study 2. ADN node 43. RES generation and load profiles. Summer.

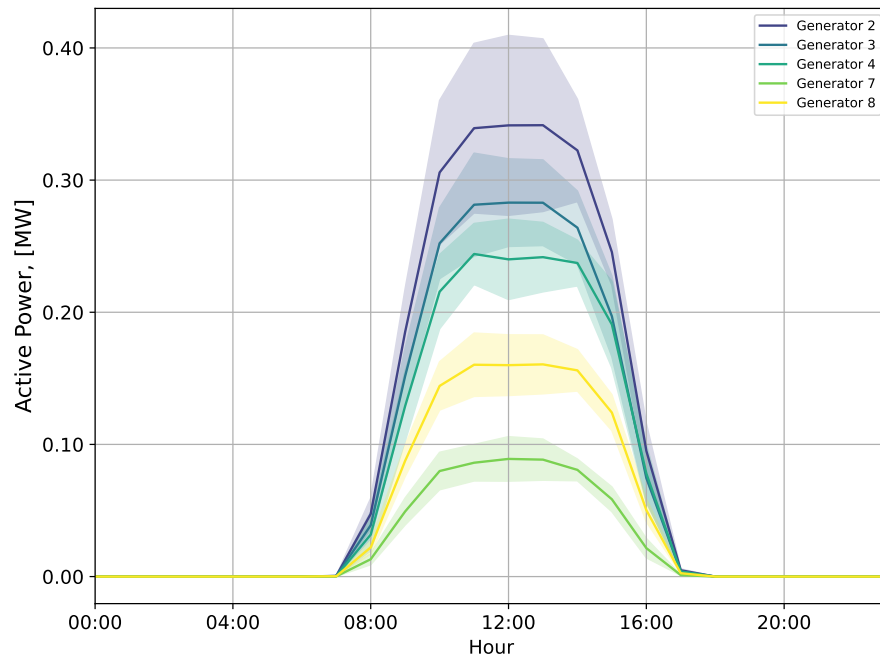


(a) RES generation profiles.

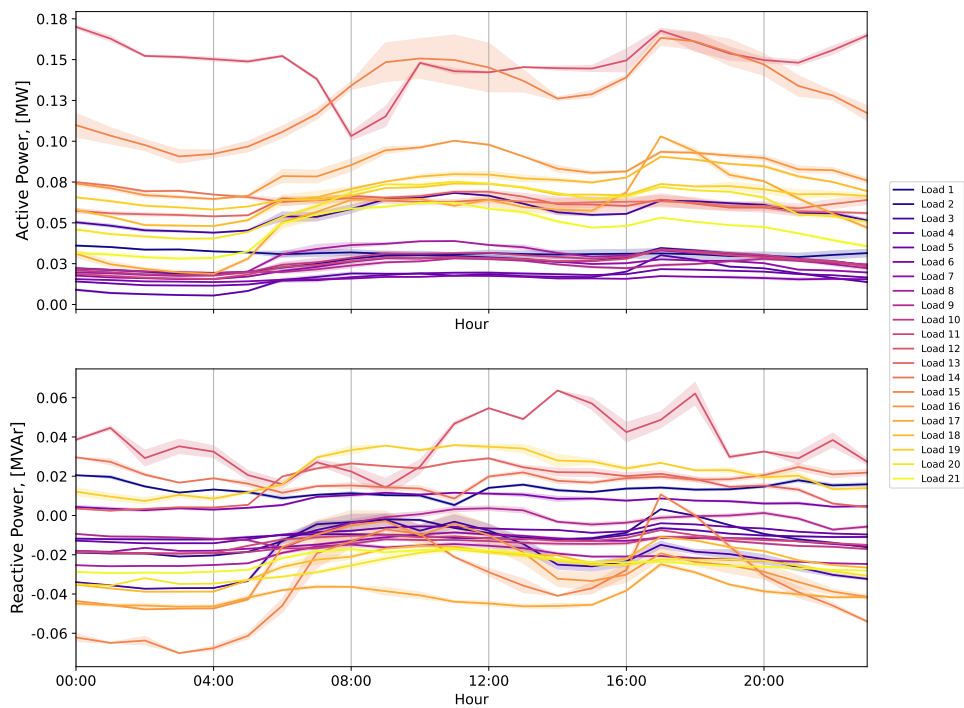


(b) Load profiles (active and reactive power).

Figure B.42: Case Study 2. ADN node 43. RES generation and load profiles. Autumn.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure B.43: Case Study 2. ADN node 43. RES generation and load profiles. Winter.

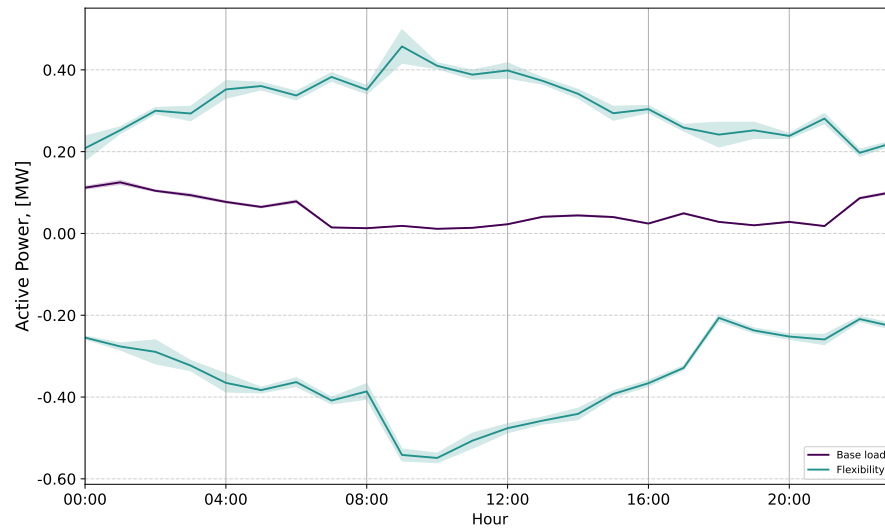
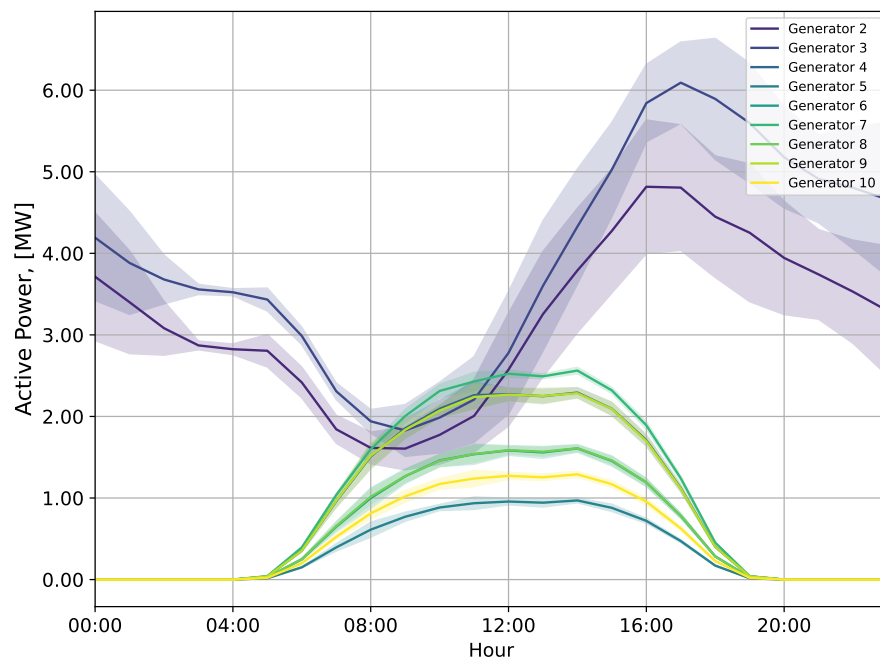


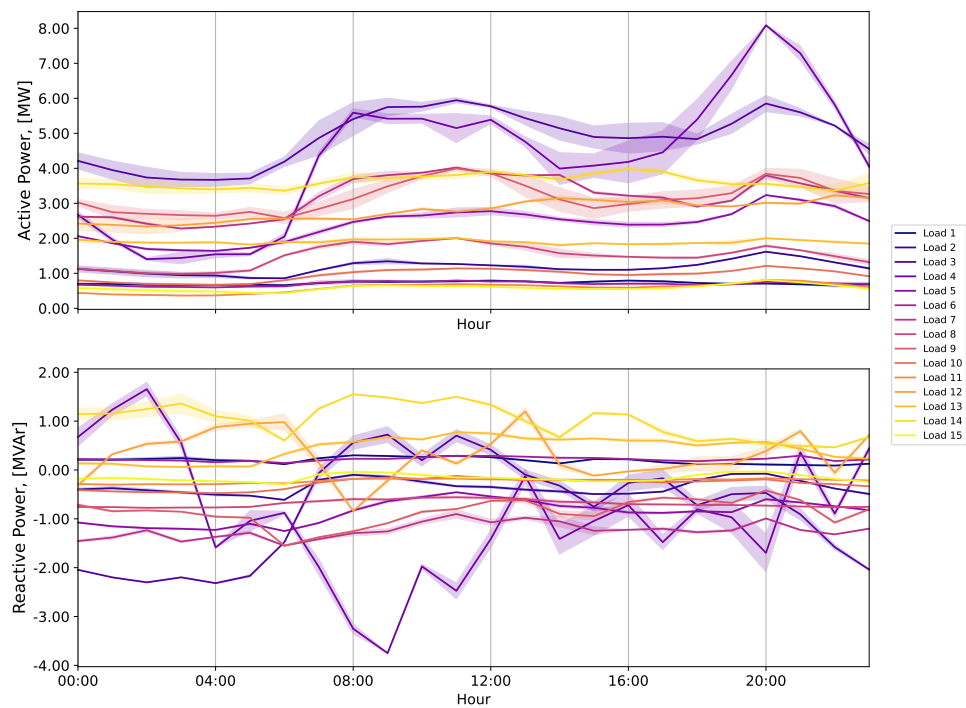
Figure B.44: Case Study 2. ADN node 43. Flexible load profiles.

Table B.24: Case Study 2. ADN node 47. Characterization of RES generators.

Generator	Bus	Generator	$S_g^{G,\max}$	$\cos(\varphi_g^{G,\min})$	$\cos(\varphi_g^{G,\max})$
ID	ID	Type	[MVA]	[N/A]	[N/A]
2	4	Wind	12.00	-0.90	0.90
3	13	Wind	15.00	-0.90	0.90
4	15	Solar PV	3.50	-0.90	0.90
5	17	Solar PV	1.50	-0.90	0.90
6	14	Solar PV	2.50	-0.90	0.90
7	5	Solar PV	4.00	-0.90	0.90
8	7	Solar PV	2.50	-0.90	0.90
9	9	Solar PV	3.50	-0.90	0.90
10	10	Solar PV	2.00	-0.90	0.90

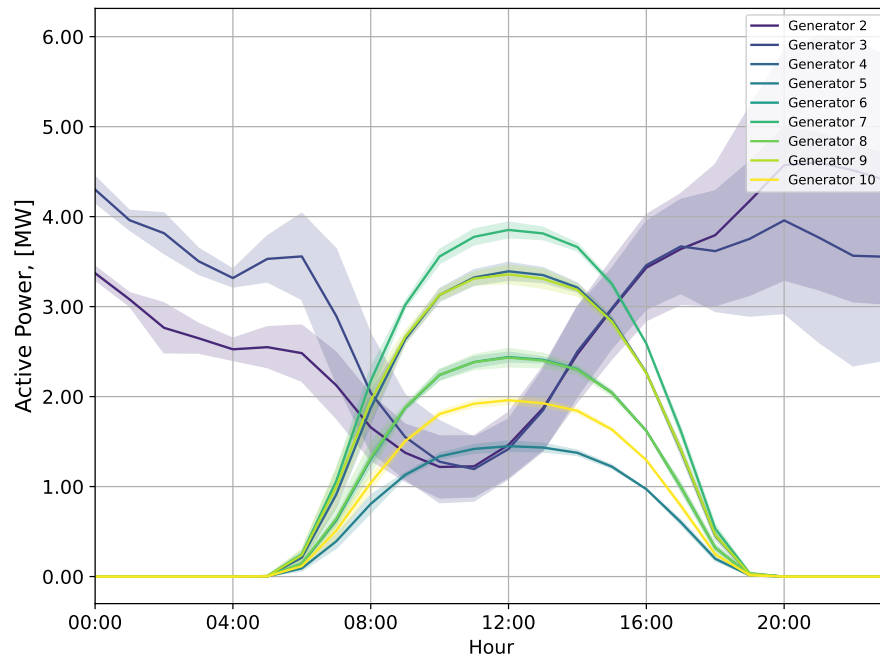


(a) RES generation profiles.

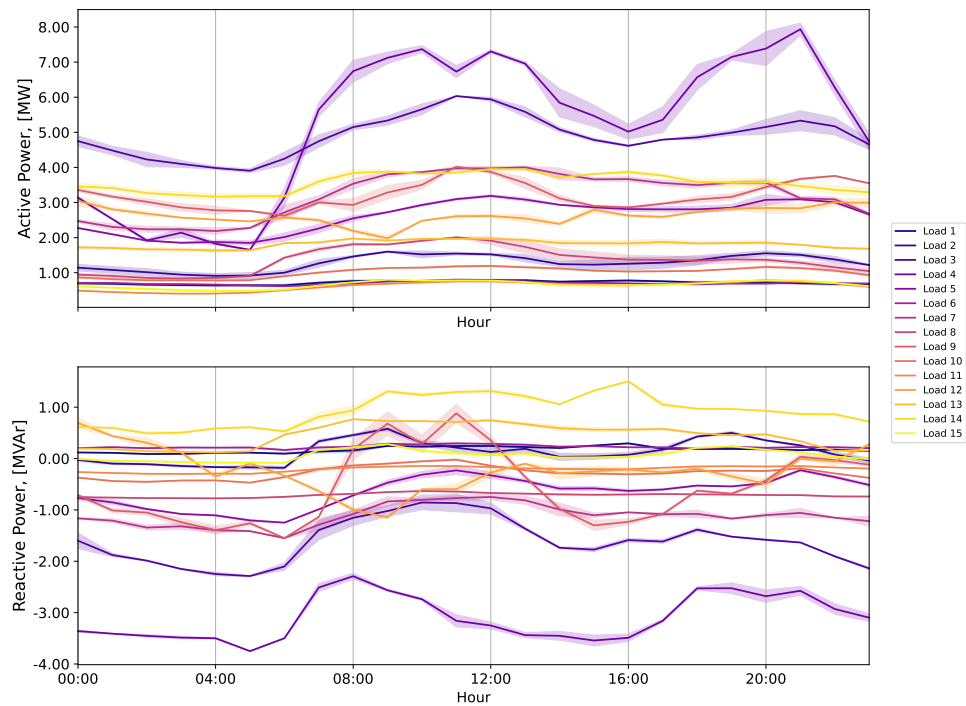


(b) Load profiles (active and reactive power).

Figure B.45: Case Study 2. ADN node 47. RES generation and load scenarios. Spring.

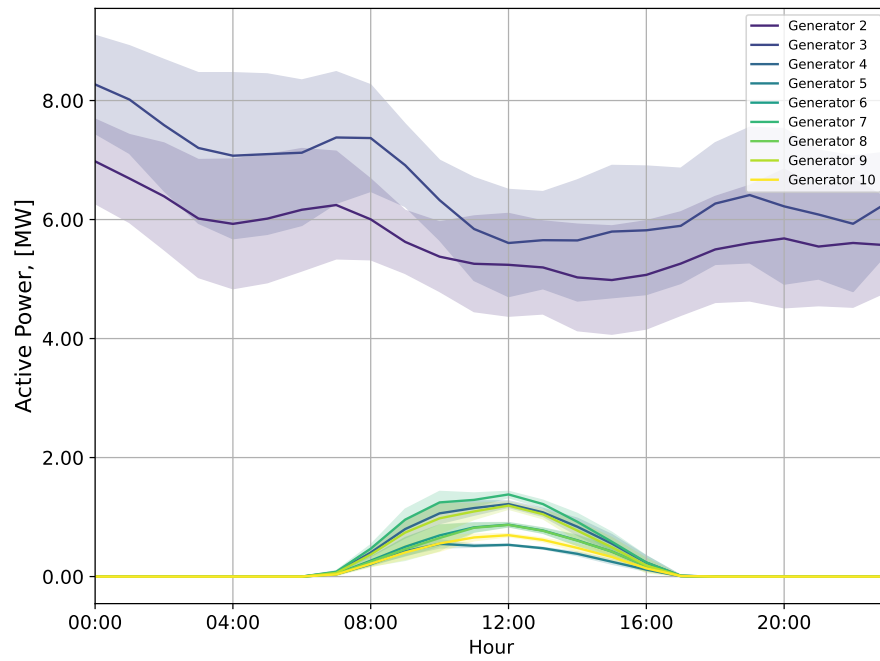


(a) RES generation profiles.

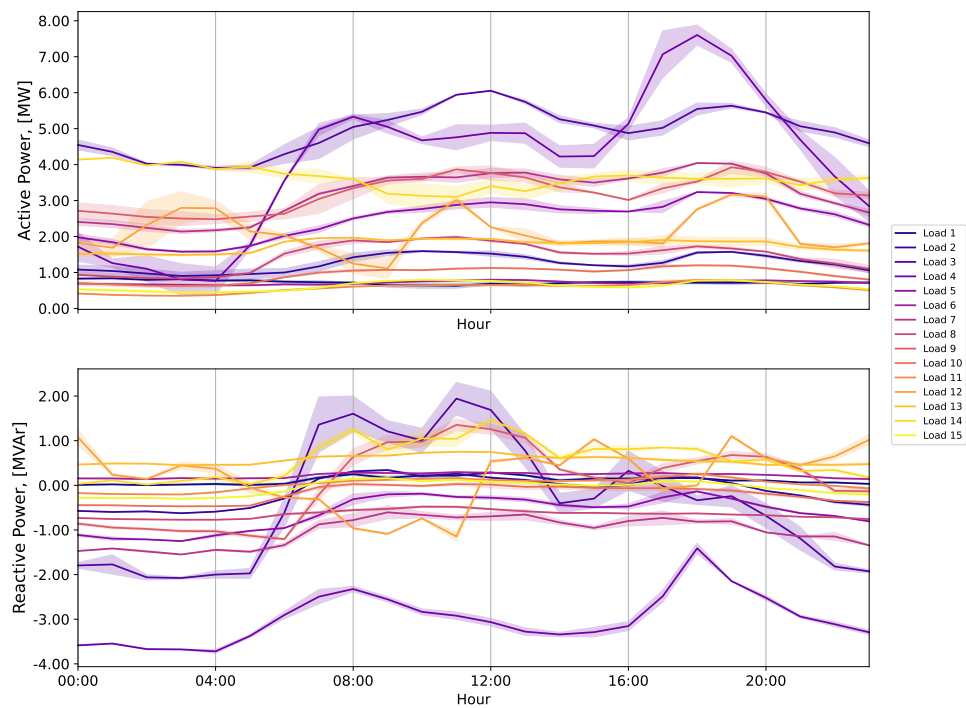


(b) Load profiles (active and reactive power).

Figure B.46: Case Study 2. ADN node 47. RES generation and load profiles. Summer.

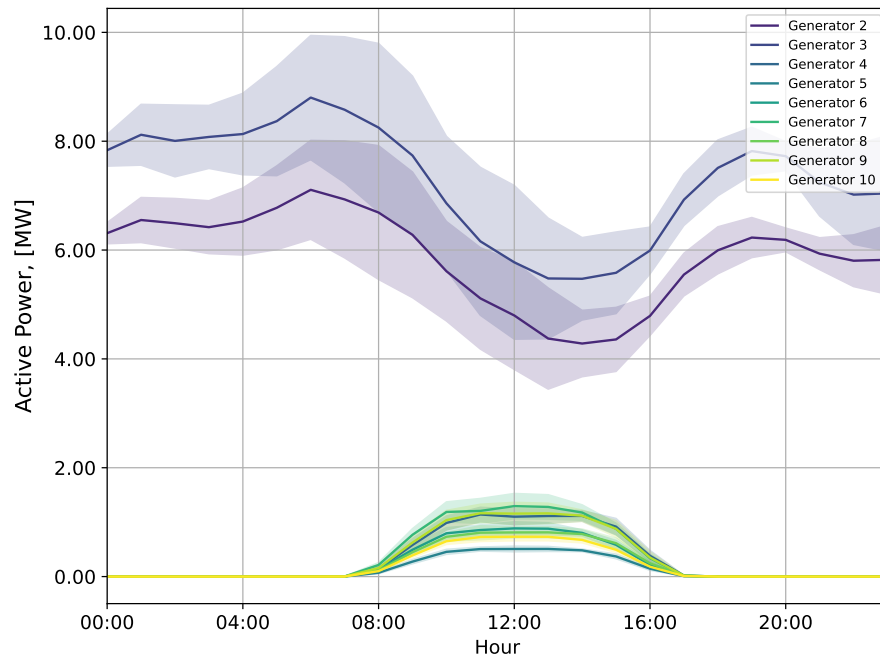


(a) RES generation profiles.

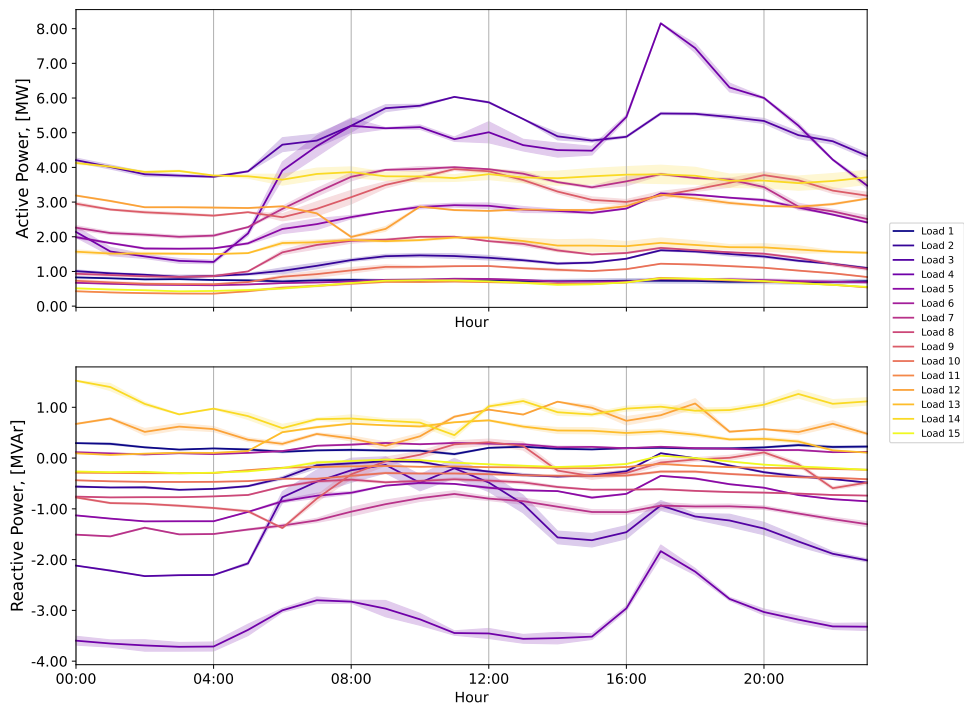


(b) Load profiles (active and reactive power).

Figure B.47: Case Study 2. ADN node 47. RES generation and load profiles. Autumn.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure B.48: Case Study 2. ADN node 47. RES generation and load profiles. Winter.

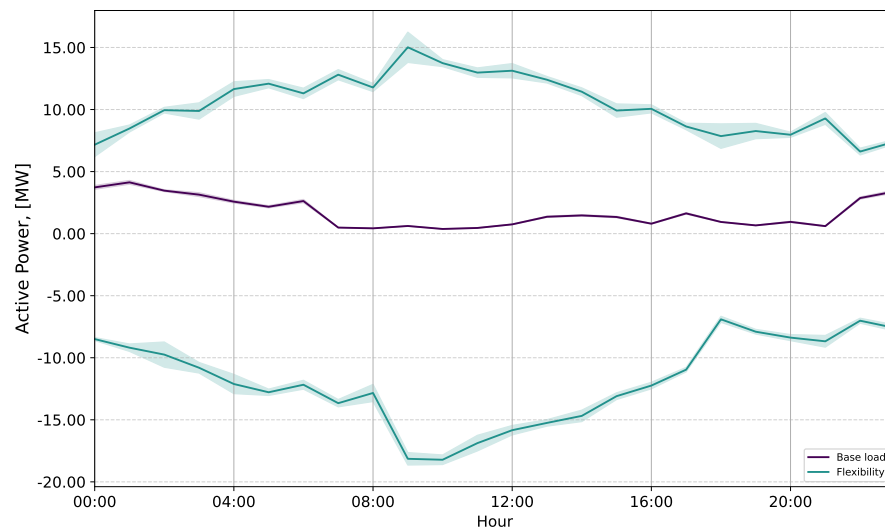


Figure B.49: Case Study 2. ADN node 47. Flexible load profiles.

B.3 Market Data

This section presents the wholesale energy and flexibility market data adopted in Case Study 2, as described in Section 7.2.

Figures B.50–B.52 illustrate the hourly wholesale energy and flexibility market prices for the Summer, Autumn, and Winter representative days. Market price data for the Spring representative day are presented in the corresponding subsection (Figure 7.12).

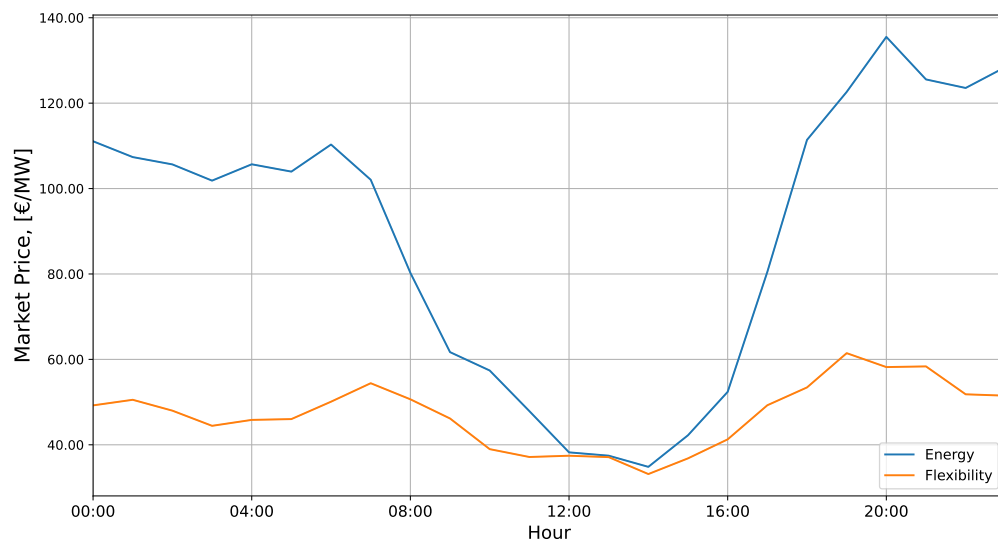


Figure B.50: Case Study 2. Wholesale energy and flexibility market prices. Summer.

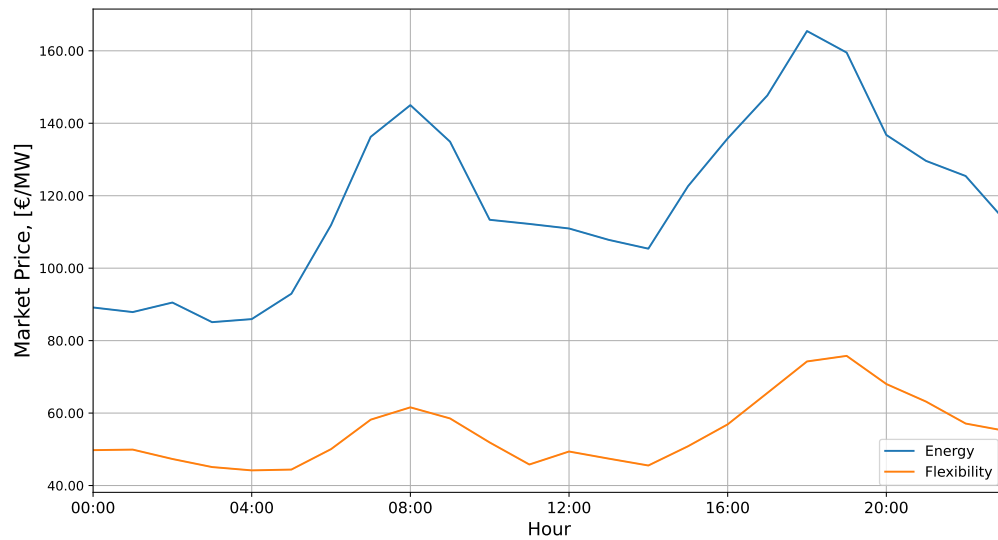


Figure B.51: Case Study 2. Wholesale energy and flexibility market prices. Autumn.

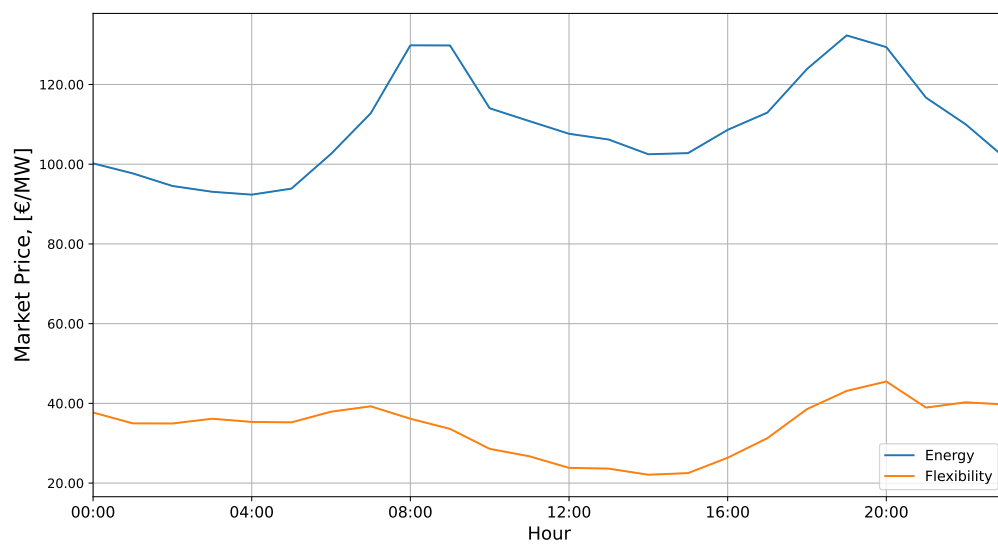


Figure B.52: Case Study 2. Wholesale energy and flexibility market prices. Winter.

B.4 Results

In addition to the results presented in Section 7.2, this section presents additional results obtained for Case Study 2, focusing on the convergence behavior of the distributed coordination algorithm, the impact of coordination on transmission–distribution interface variables, and the operation of shared ESSs under coordinated control.

B.4.1 Convergence Characteristic

Figures B.53–B.55 illustrate the primal residual evolution of the distributed coordination algorithm for the Summer, Autumn, and Winter representative days. The primal residual evolution for the Spring representative day is presented in the corresponding subsection (Figure 7.22).

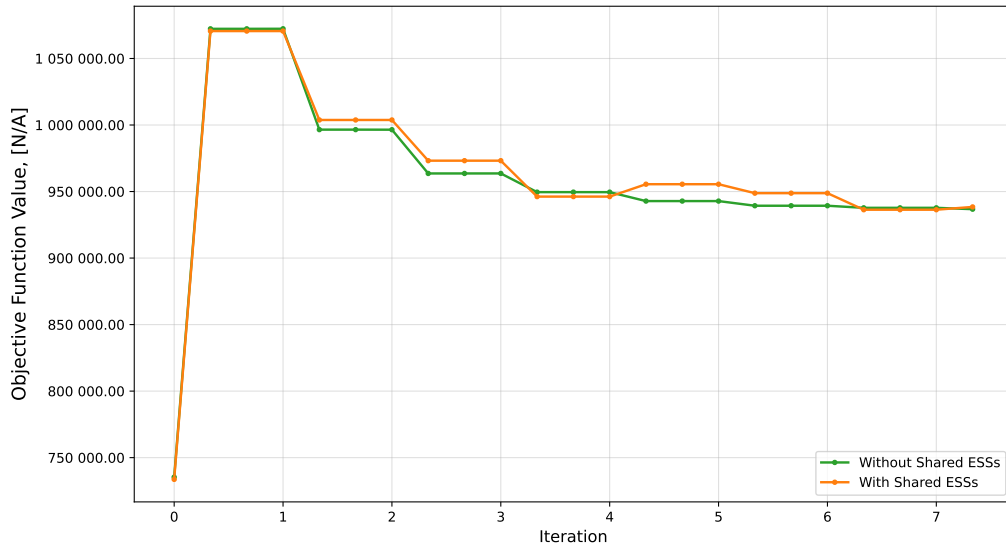


Figure B.53: Case Study 2. Primal evolution. Summer representative day.

B.4.2 Interface Voltage Magnitude and Power Flows

This subsection analyzes the impact of coordinated TSO-DSO operation on voltage magnitudes and active and reactive power exchanges at interface nodes with ADNs participating in the coordination procedure.

B.4.2.1 Node 19

Figure B.56 presents the voltage magnitude and the active and reactive power exchanges at the interface between the TN and the ADN connected to transmission bus 19, for the three operational strategies considered, for the Spring representative day.

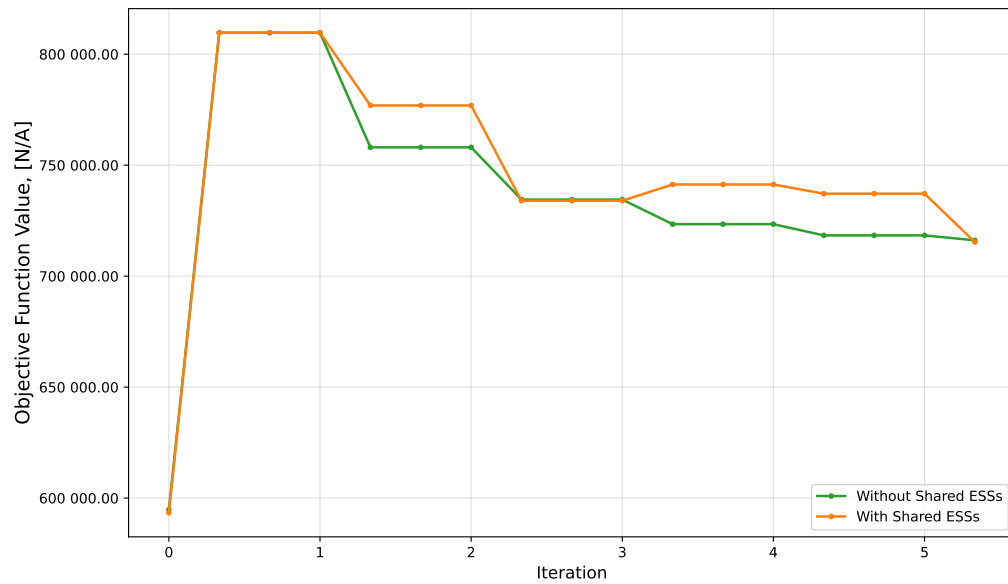


Figure B.54: Case Study 2. Primal evolution. Autumn representative day.

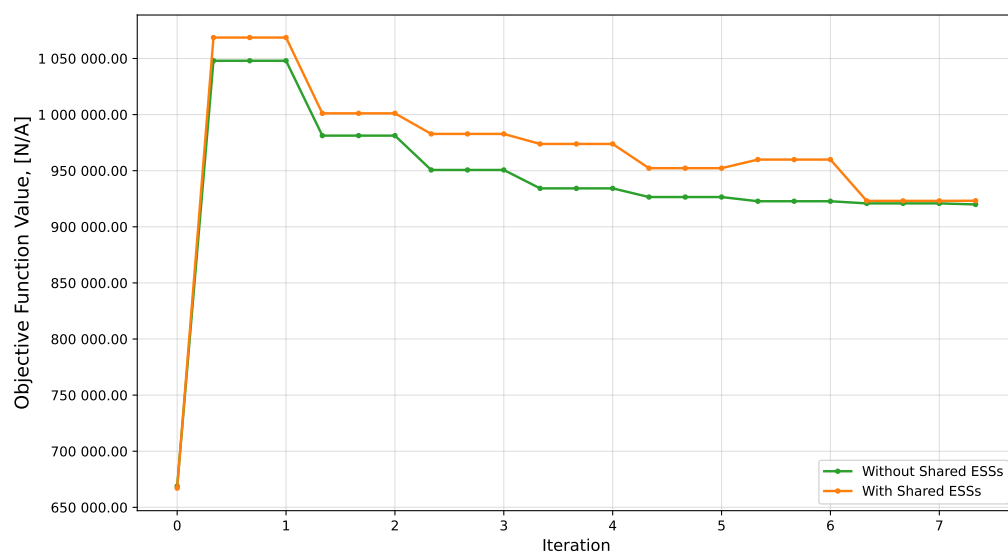
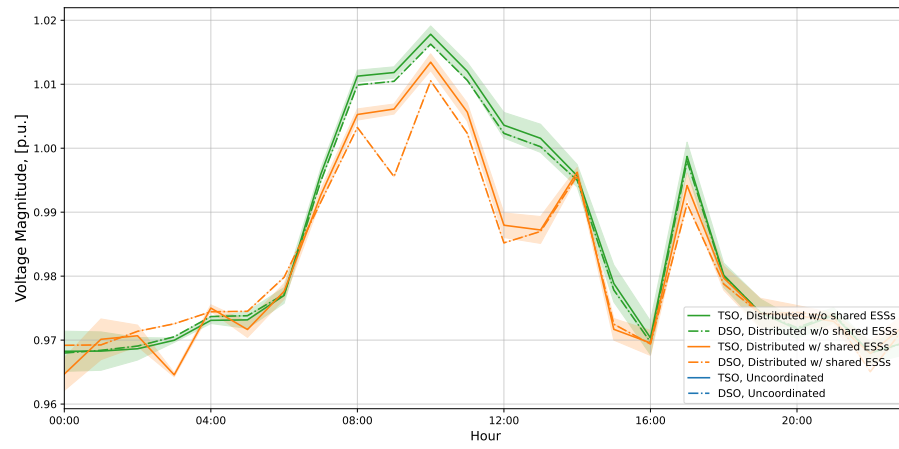
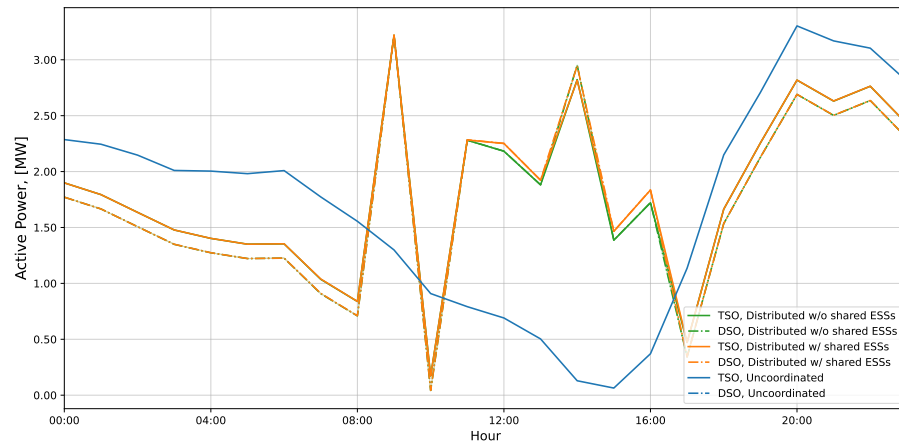


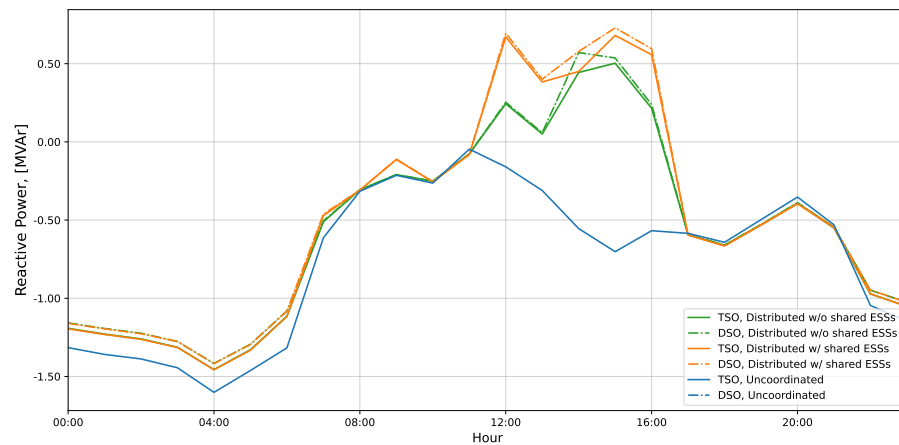
Figure B.55: Case Study 2. Primal evolution. Winter representative day.



(a) Voltage magnitude.



(b) Active power.



(c) Reactive power.

Figure B.56: Case Study 2. ADN node 19. Comparison of interface voltage magnitude and power flows for the three test cases analyzed. Spring representative day.

B.4.2.2 Node 20

Figure B.57 presents the voltage magnitude and the active and reactive power exchanges at the interface between the TN and the ADN connected to transmission bus 20, for the three operational strategies considered, for the Spring representative day.

B.4.2.3 Node 30

Figure B.58 presents the voltage magnitude and the active and reactive power exchanges at the interface between the TN and the ADN connected to transmission bus 30, for the three operational strategies considered, for the Spring representative day.

B.4.2.4 Node 32

Figure B.59 presents the voltage magnitude and the active and reactive power exchanges at the interface between the TN and the ADN connected to transmission bus 32, for the three operational strategies considered, for the Spring representative day.

B.4.2.5 Node 33

Figure B.60 presents the voltage magnitude and the active and reactive power exchanges at the interface between the TN and the ADN connected to transmission bus 33, for the three operational strategies considered, for the Spring representative day.

B.4.2.6 Node 43

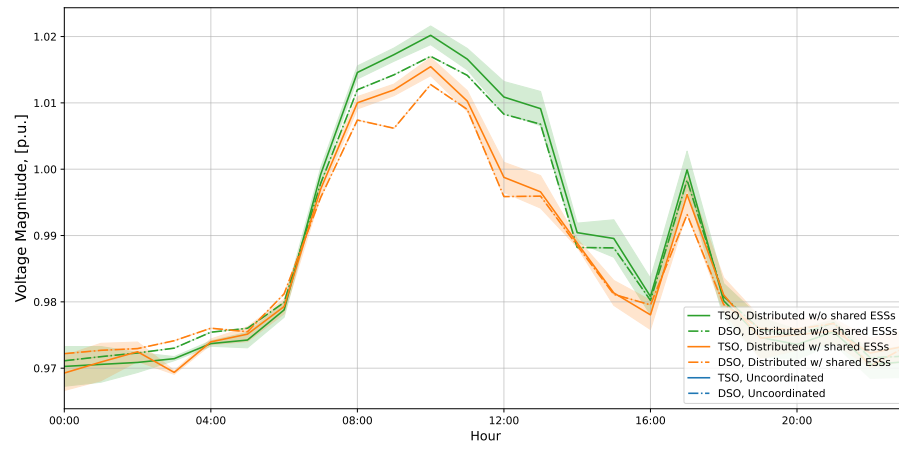
Figure B.61 presents the voltage magnitude and the active and reactive power exchanges at the interface between the TN and the ADN connected to transmission bus 43, for the three operational strategies considered, for the Spring representative day.

B.4.2.7 Node 47

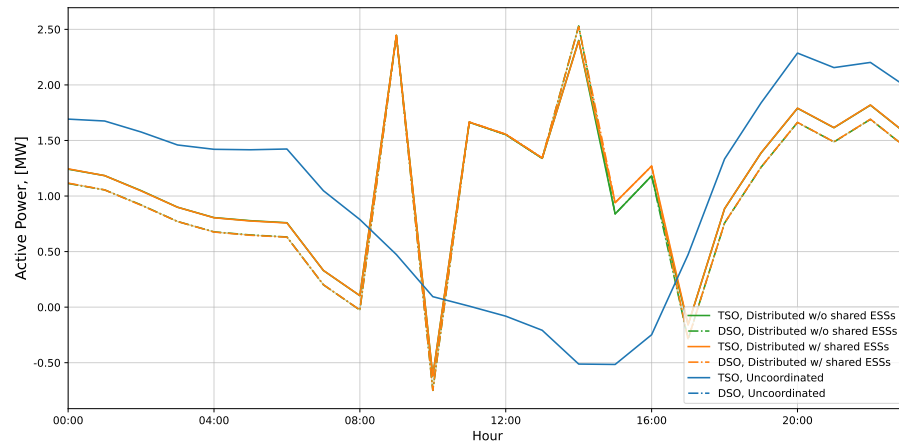
Figure B.62 presents the voltage magnitude and the active and reactive power exchanges at the interface between the TN and the ADN connected to transmission bus 47, for the three operational strategies considered, for the Spring representative day.

B.4.3 Shared ESS Power Profiles

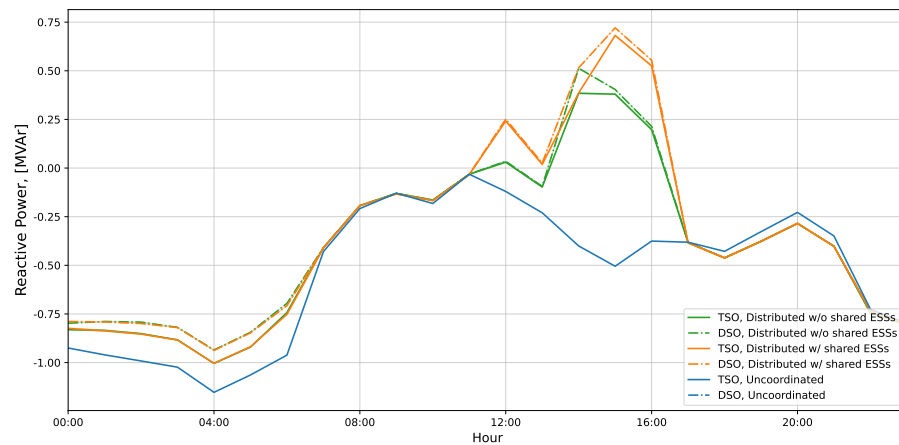
This subsection analyzes the impact of coordinated TSO–DSO operation on the active and reactive power profiles of the shared ESSs considered in these simulations, installed at the TN–DN interface and connected to transmission buses 18 and 47.



(a) Voltage magnitude.

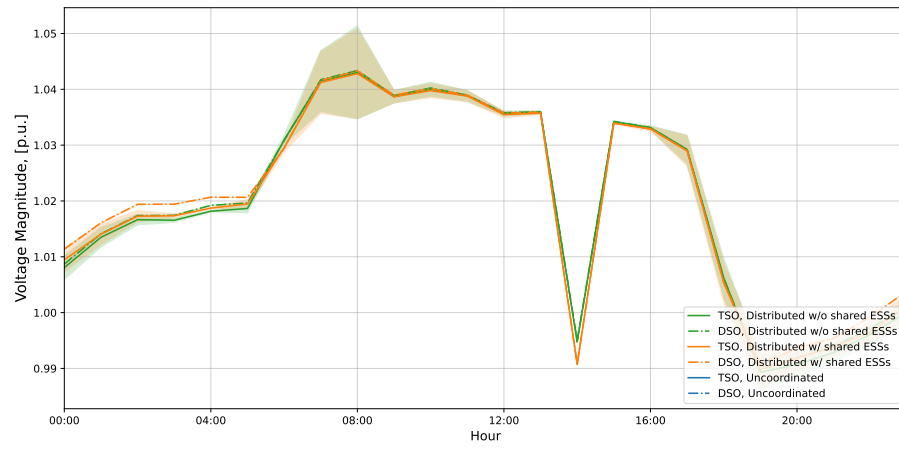


(b) Active power.

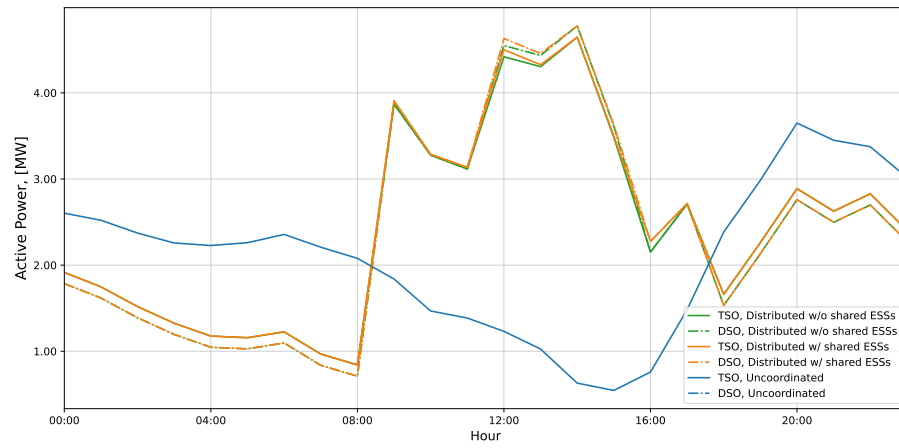


(c) Reactive power.

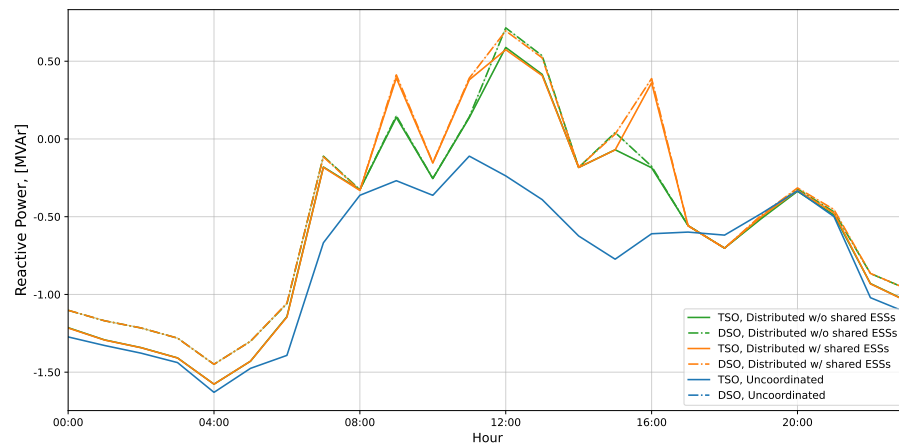
Figure B.57: Case Study 2. ADN node 20. Comparison of interface voltage magnitude and power flows for the three test cases analyzed. Spring representative day.



(a) Voltage magnitude.

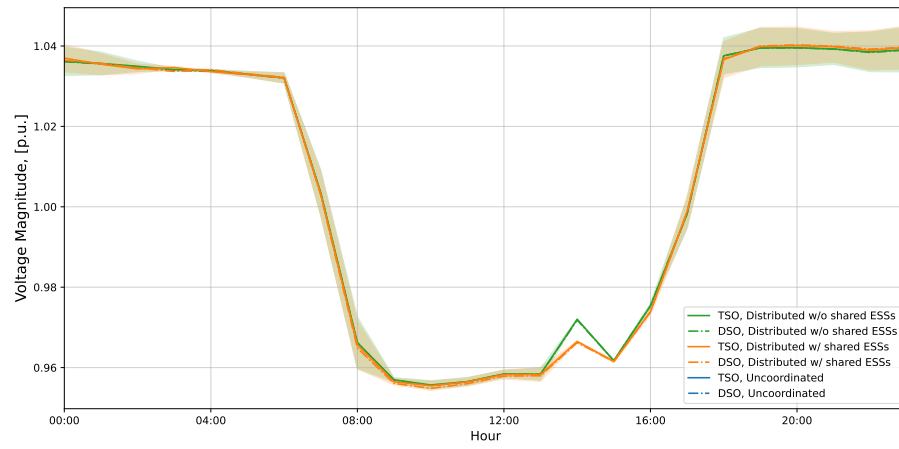


(b) Active power.

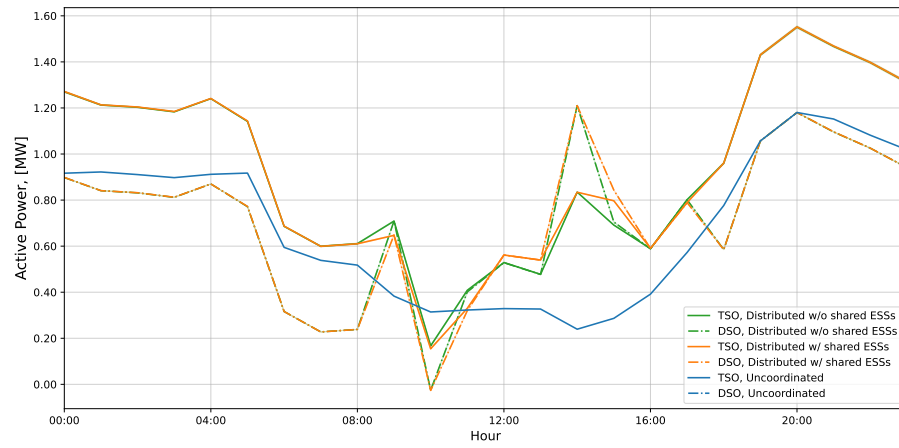


(c) Reactive power.

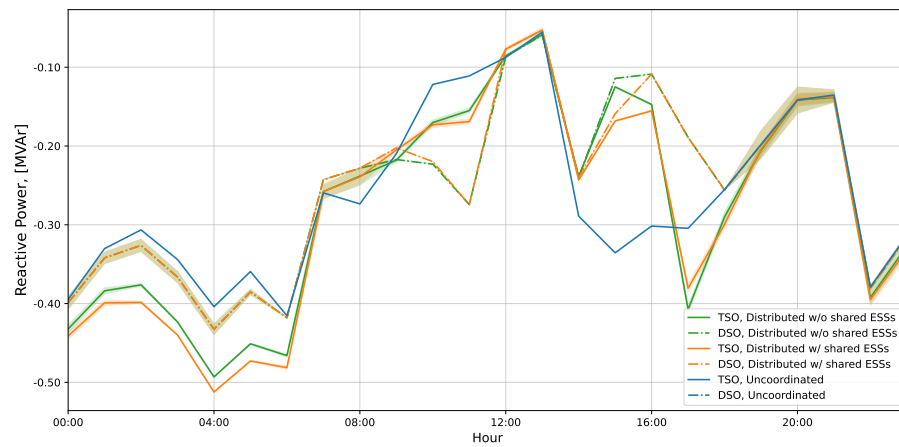
Figure B.58: Case Study 2. ADN node 30. Comparison of interface voltage magnitude and power flows for the three test cases analyzed. Spring representative day.



(a) Voltage magnitude.

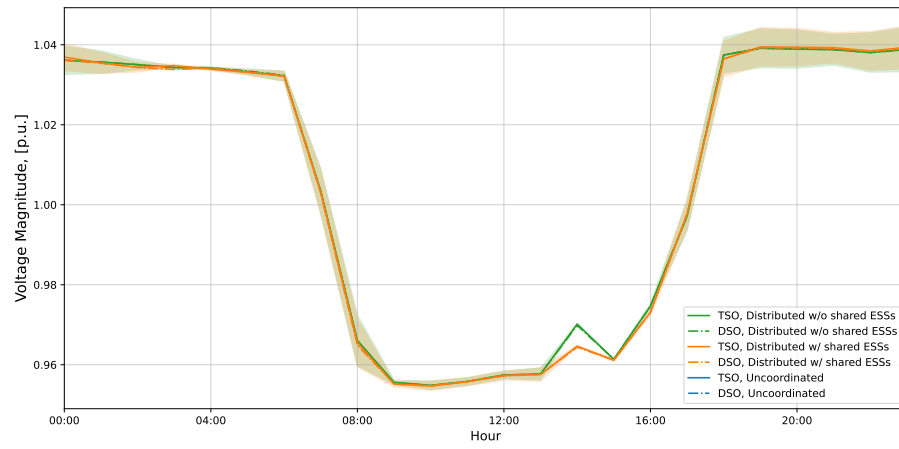


(b) Active power.

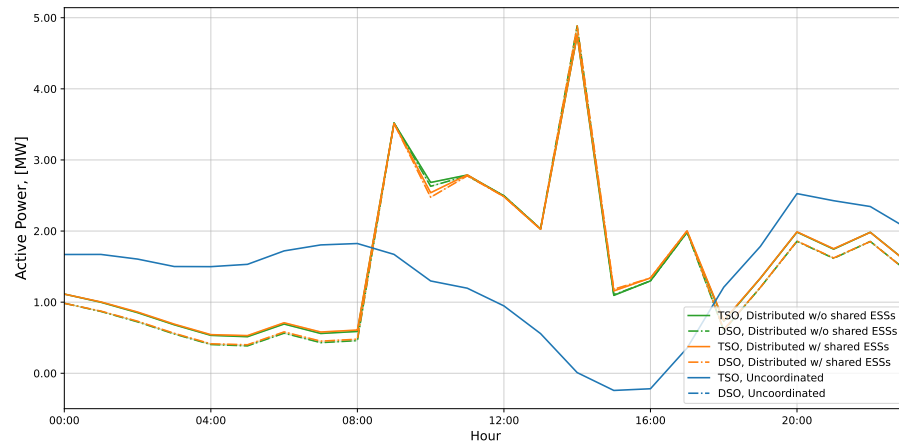


(c) Reactive power.

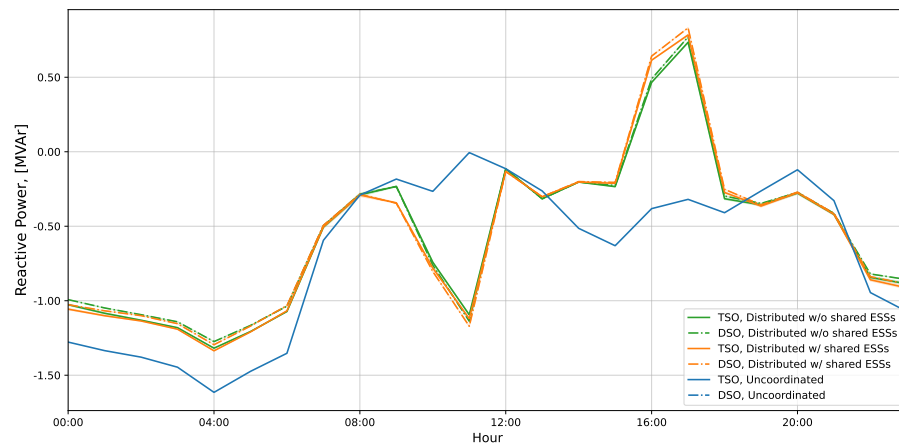
Figure B.59: Case Study 2. ADN node 32. Comparison of interface voltage magnitude and power flows for the three test cases analyzed. Spring representative day.



(a) Voltage magnitude.

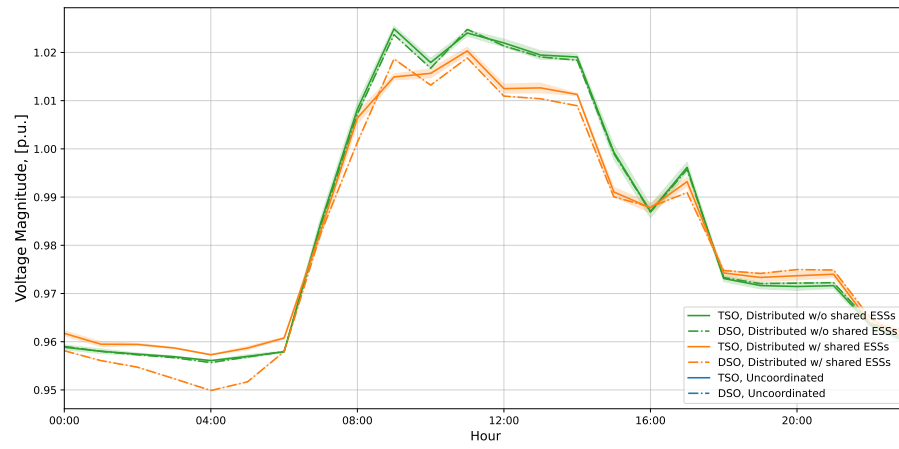


(b) Active power.

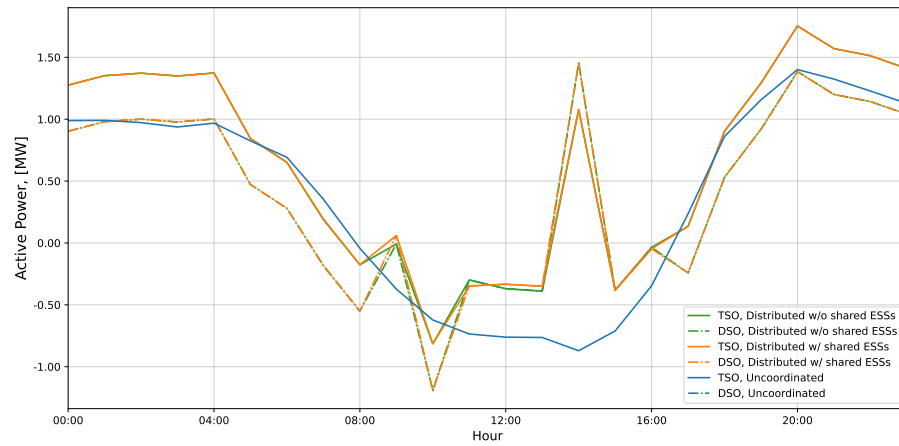


(c) Reactive power.

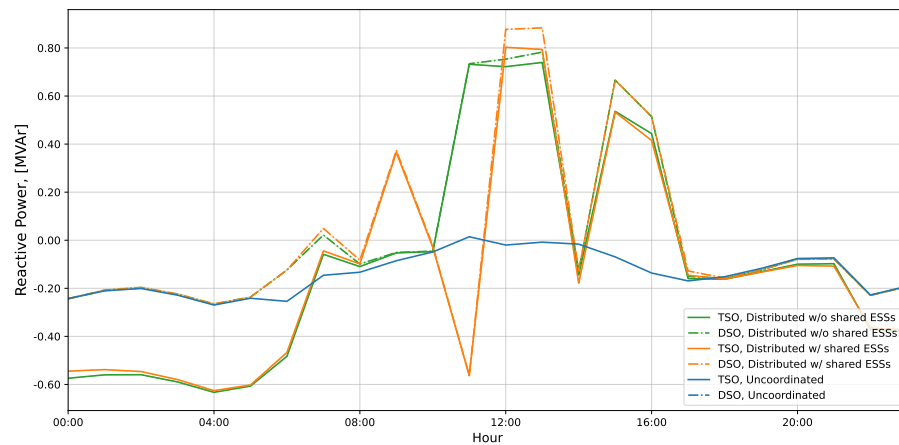
Figure B.60: Case Study 2. ADN node 33. Comparison of interface voltage magnitude and power flows for the three test cases analyzed. Spring representative day.



(a) Voltage magnitude.

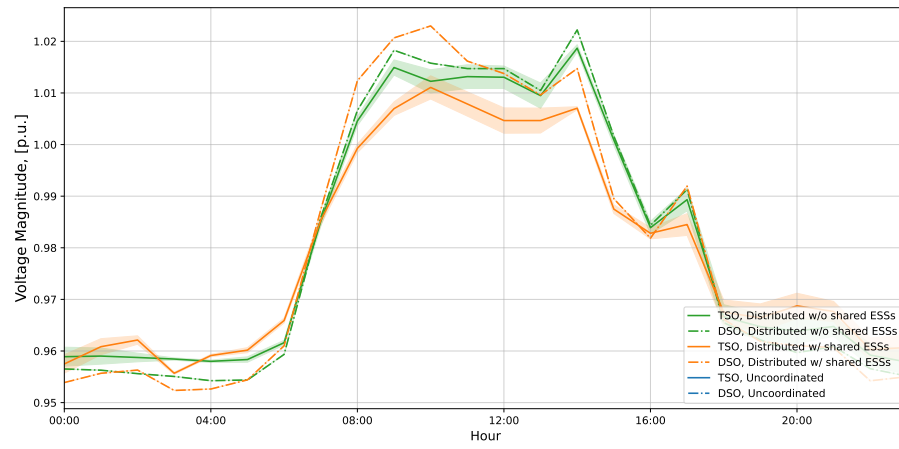


(b) Active power.

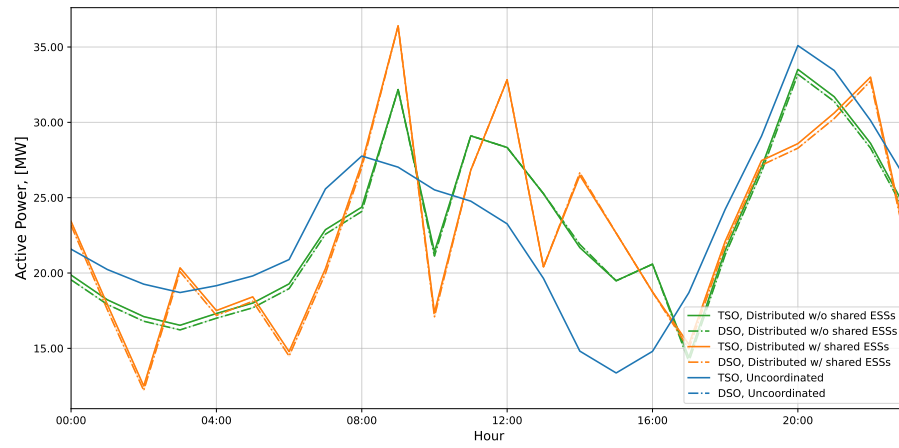


(c) Reactive power.

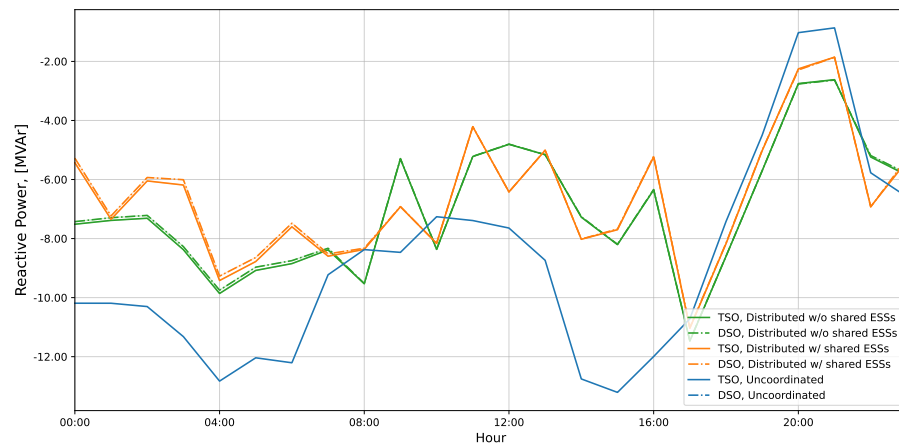
Figure B.61: Case Study 2. ADN node 43. Comparison of interface voltage magnitude and power flows for the three test cases analyzed. Spring representative day.



(a) Voltage magnitude.



(b) Active power.



(c) Reactive power.

Figure B.62: Case Study 2. ADN node 47. Comparison of interface voltage magnitude and power flows for the three test cases analyzed. Spring representative day.

B.4.3.1 Node 18

Figures B.63–B.65 illustrate the active and reactive power profiles of the shared ESS installed at transmission bus 18 for the Summer, Autumn, and Winter representative days, respectively. The corresponding profiles for the Spring representative day are shown in Figure 7.25.

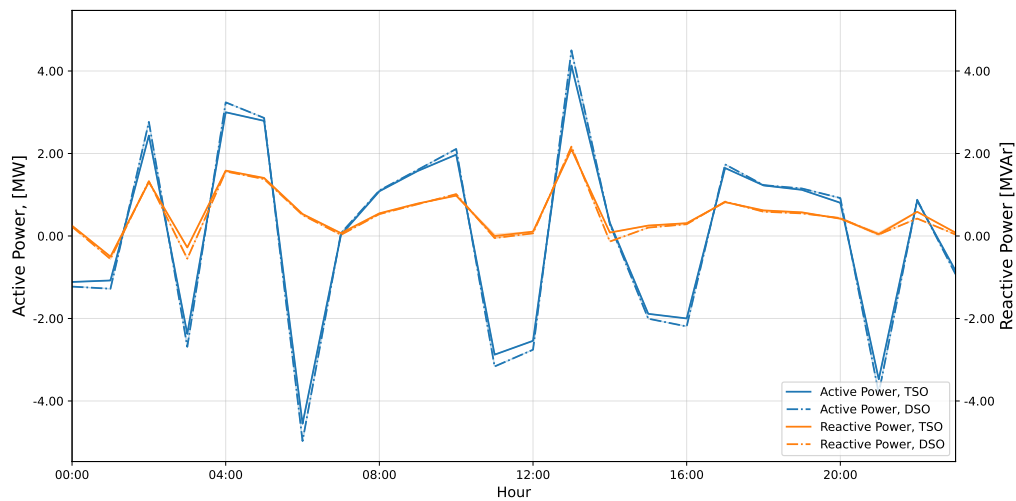


Figure B.63: Case Study 2. ADN node 18. Comparison of shared ESS's active and reactive power profiles. Summer representative day.

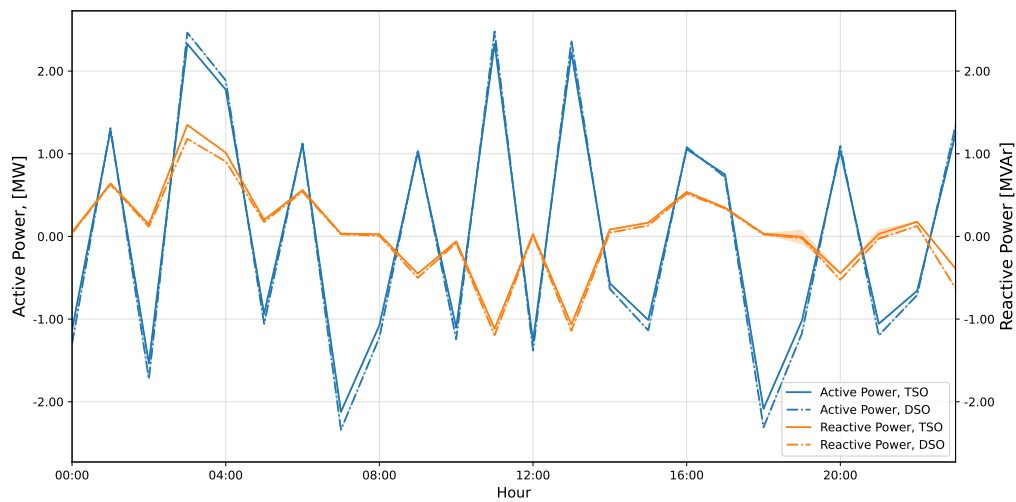


Figure B.64: Case Study 2. ADN node 18. Comparison of shared ESS's active and reactive power profiles. Autumn representative day.

B.4.3.2 Node 47

Figures B.66–B.69 illustrate the active and reactive power profiles of the shared ESS installed at transmission bus 47 for the Spring, Summer, Autumn, and Winter representative

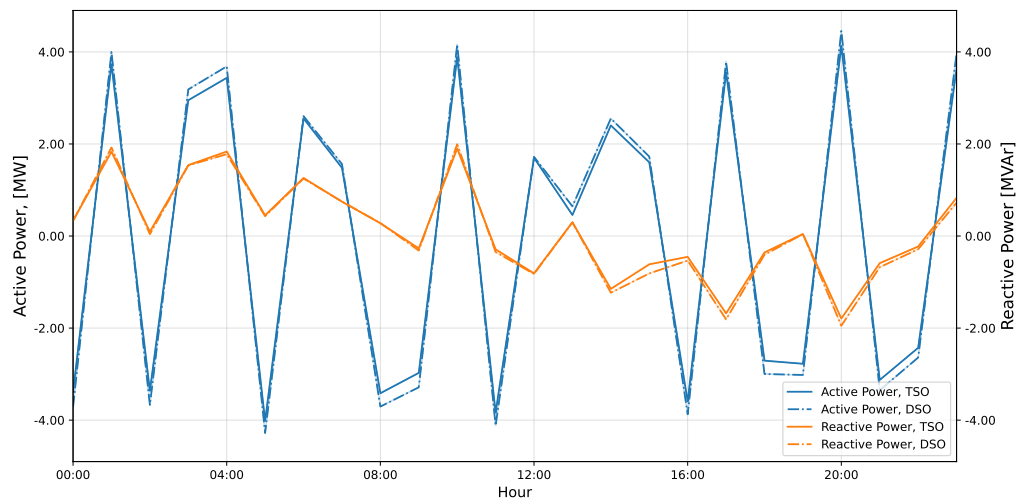


Figure B.65: Case Study 2. ADN node 18. Comparison of shared ESS's active and reactive power profiles. Winter representative day.

days, respectively.

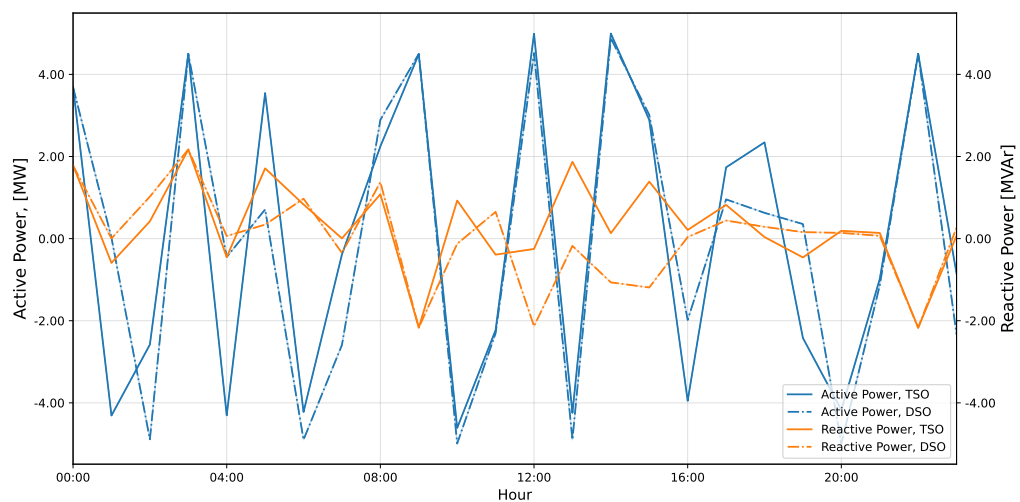


Figure B.66: Case Study 2. ADN node 47. Comparison of shared ESSs active and reactive power profiles. Spring representative day.

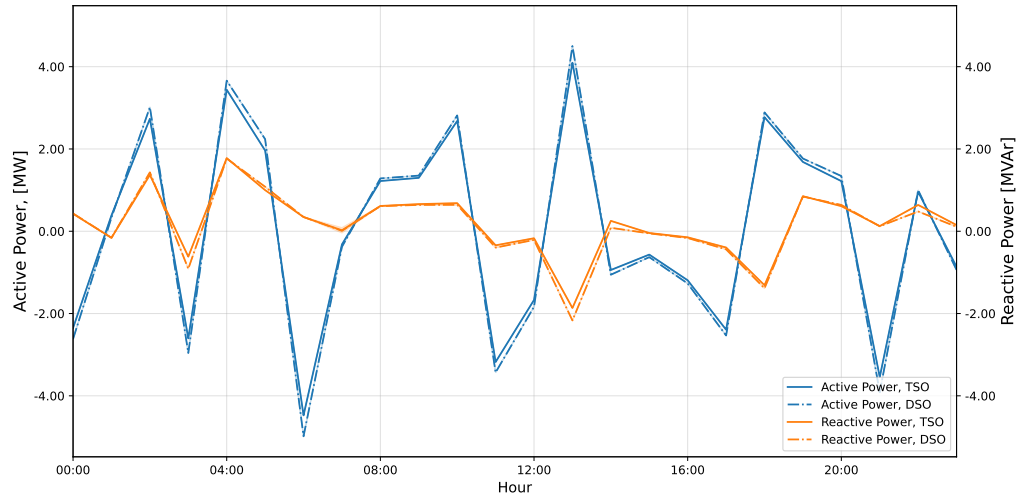


Figure B.67: Case Study 2. ADN node 47. Comparison of shared ESS's active and reactive power profiles. Summer representative day.

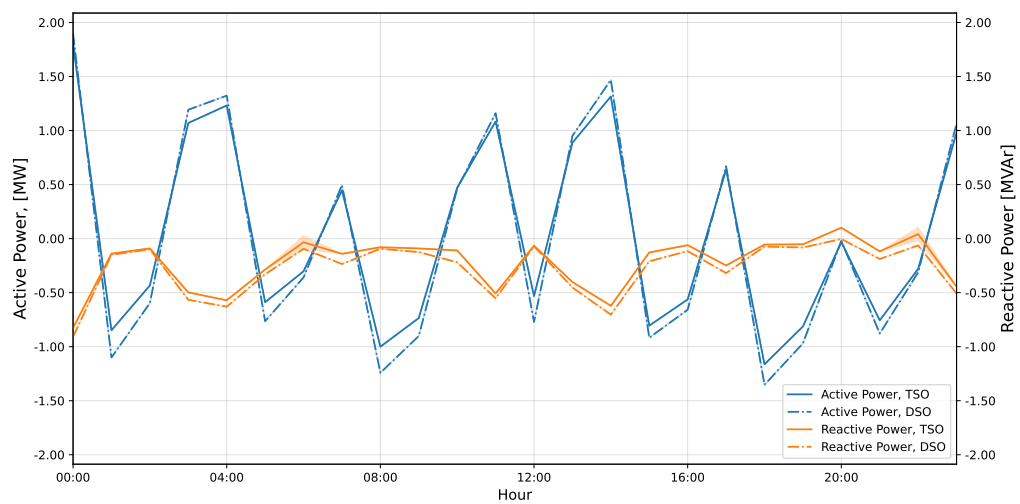


Figure B.68: Case Study 2. ADN node 47. Comparison of shared ESS's active and reactive power profiles. Autumn representative day.

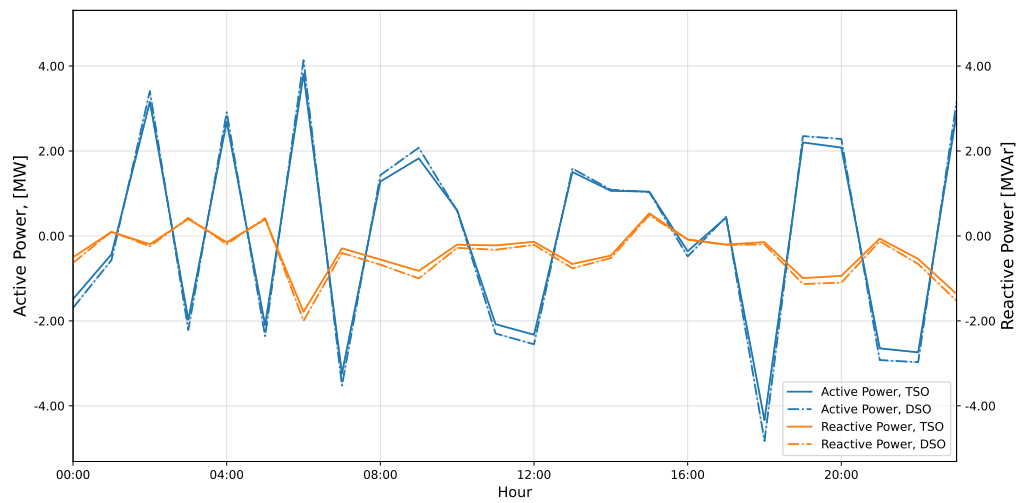


Figure B.69: Case Study 2. ADN node 47. Comparison of shared ESS's active and reactive power profiles. Winter representative day.

Appendix C

Case Study 3

This appendix details the data associated with the shared resources planning case study presented in Section 7.3 of the simulations chapter. The networks adopted in this case study are based on IEEE standard test systems, which were suitably modified to meet the specific requirements of the proposed framework.

Section C.1 describes the TN considered in this case study, while Section C.2 presents the corresponding DNs. Section C.3 introduces the wholesale energy and flexibility market data adopted in the simulations. Finally, Section C.4 reports complementary results that extend those discussed in the main body of the chapter.

C.1 Transmission Network

As described in Section 7.3, the TN adopted in Case Study 3 is similar to the network described in Section A.1. Figure A.1 presents the single-line diagram of the TN considered. Detailed data for buses, branches, and conventional generators are provided in Tables A.1, A.2, A.3, respectively.

Figure C.1–C.3 illustrate RES generation profiles adopted in this case study for the Summer, Autumn, and Winter representative days of 2025, respectively. Data related to the Spring representative day is presented in Figure 7.27 of Section 7.3.

C.2 Distribution Networks

This section describes the DNs data adopted in Case Study 3, presented in Section 7.3. All DNs considered in this case study are based on standard IEEE test systems, which were suitably adapted to include RES generation and representative load profiles.

The topological data of the selected DNs are presented in Section A.2. Detailed bus, branch, and interface generator data are reported in Tables A.4–A.6.

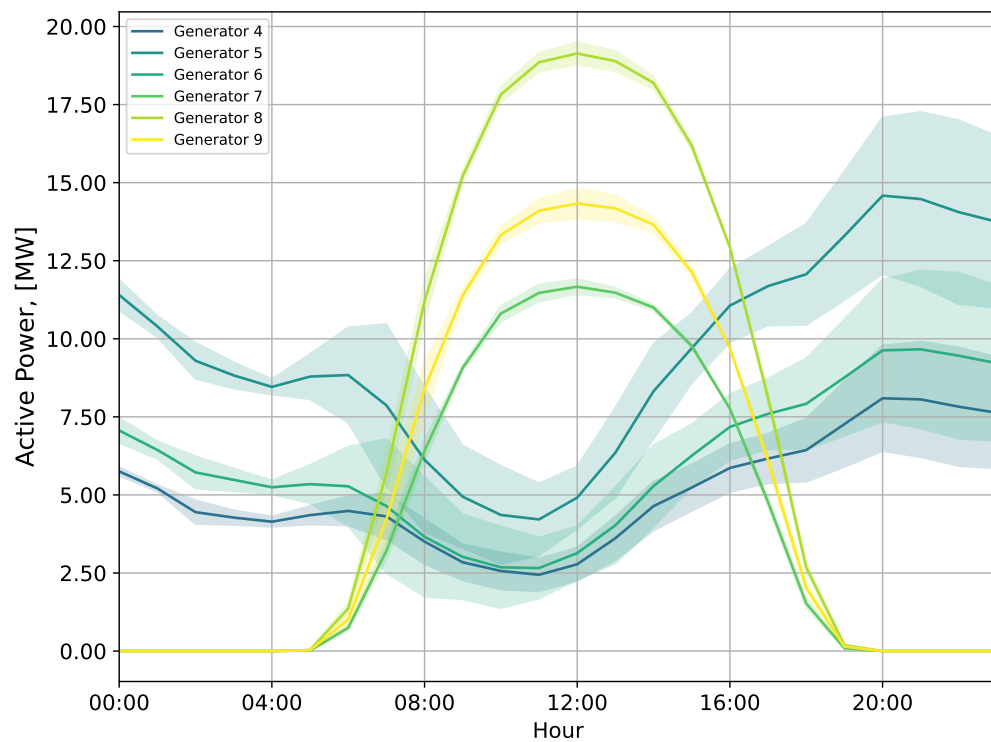


Figure C.1: Case Study 3. TN RES generation profiles. Summer 2025.

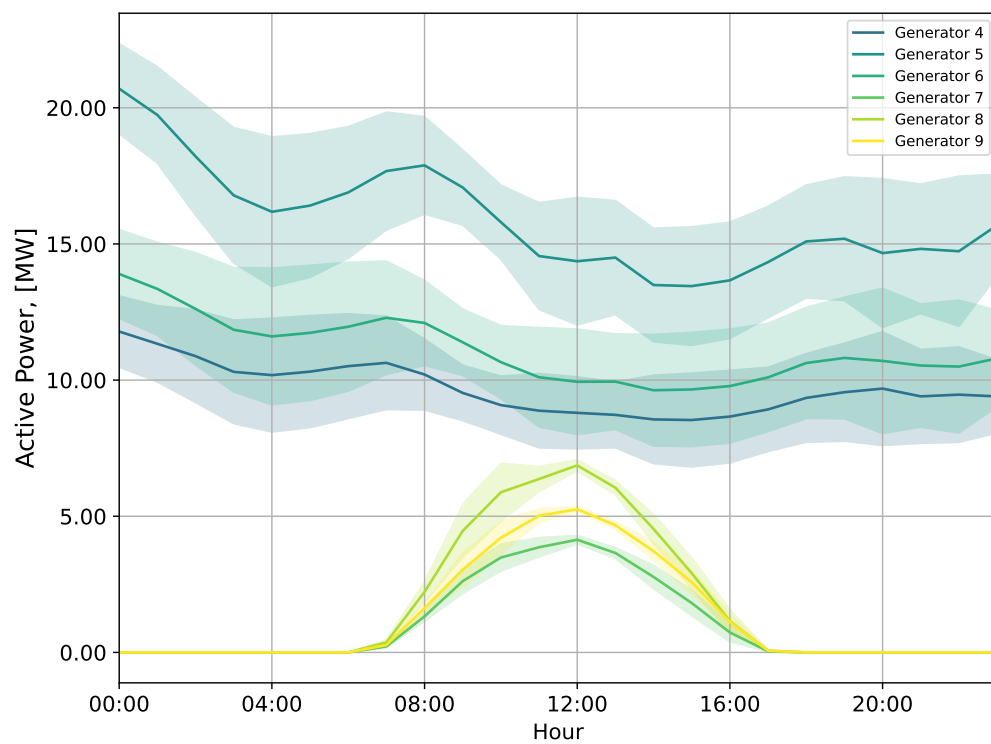


Figure C.2: Case Study 3. TN RES generation profiles. Autumn 2025.

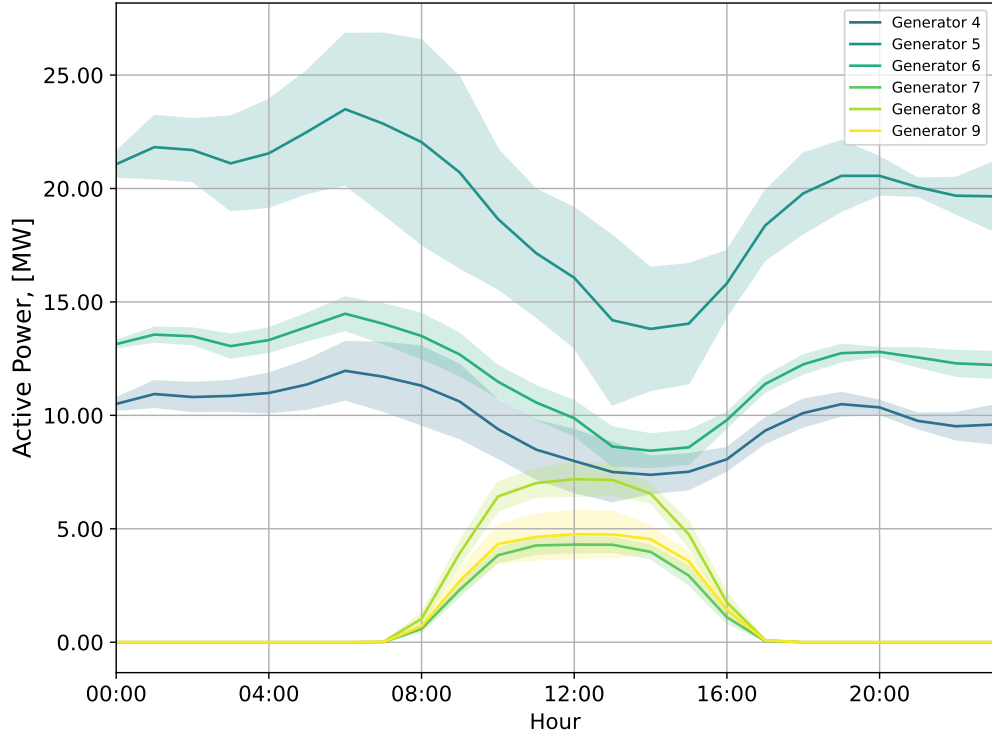


Figure C.3: Case Study 3. TN RES generation profiles. Winter 2025.

C.2.1 ADN Connected to Node 5 of the TN

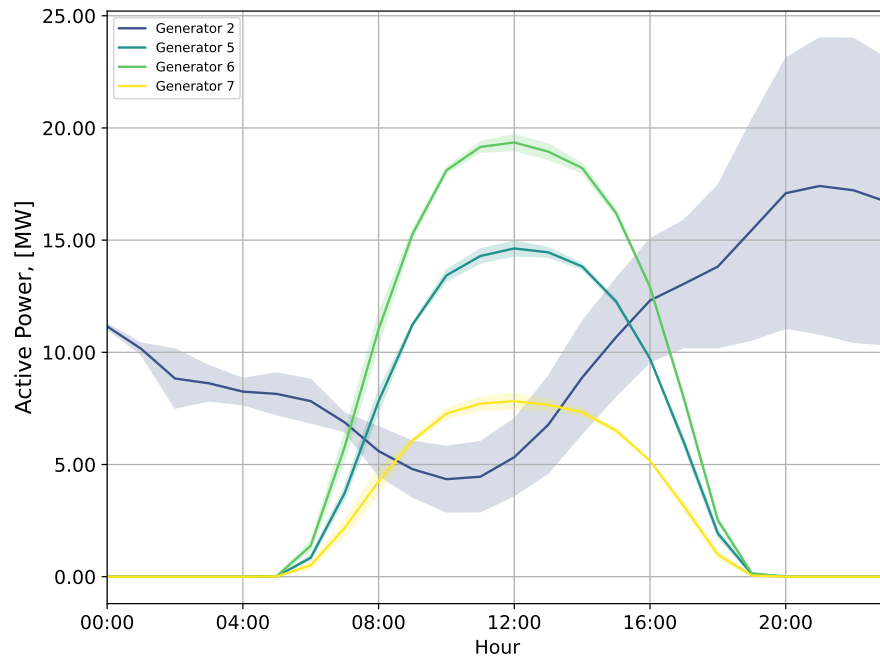
The ADN connected to node 5 of the TN is based on the IEEE 33-bus distribution test system (Baran and Wu, 1989). The corresponding network topology is described in Section A.2, and the single-line diagram is shown in Figure A.2. Detailed bus, branch, and interface generator data are reported in Tables A.4–A.6.

Figures C.4–C.6 show the load and RES generation profiles for the Summer, Autumn, and Winter representative days of 2025. Data corresponding to the Spring representative day are presented in Section 7.3.

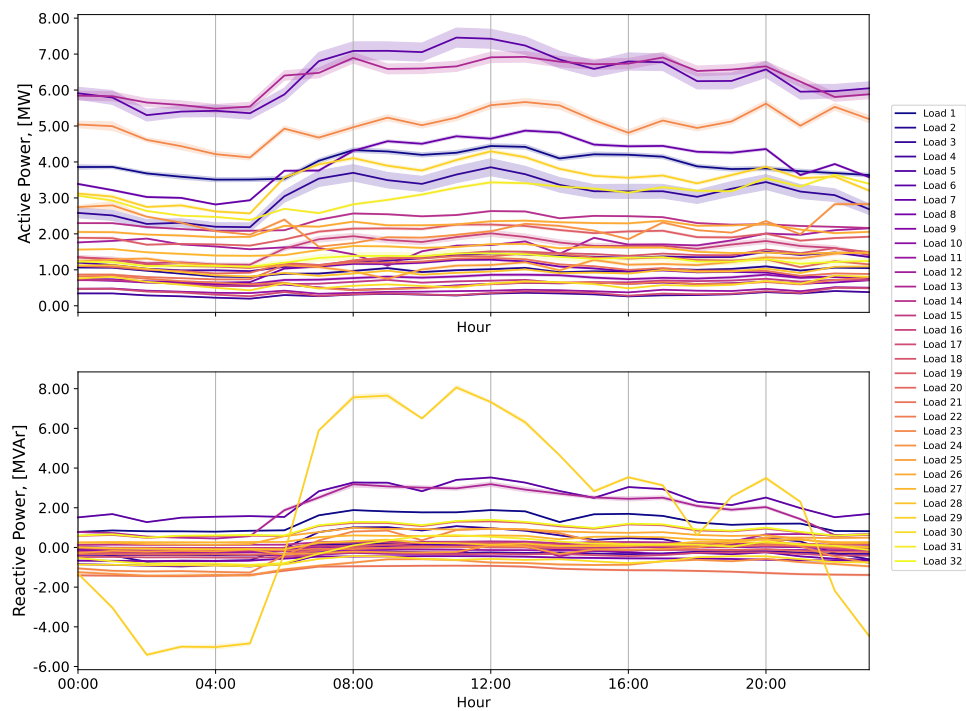
C.2.2 ADN Connected to Node 7 of the TN

The ADN connected to node 7 of the TN is based on the IEEE 33-bus distribution test system (Baran and Wu, 1989). The corresponding network topology is described in Section A.2, and the single-line diagram is shown in Figure A.2. Detailed bus, branch, and interface generator data are reported in Tables A.4–A.6.

Figures C.7–C.9 show the load and RES generation profiles for the Summer, Autumn, and Winter representative days of 2025. Data corresponding to the Spring representative day are presented in Figure 7.30 of Section 7.3.

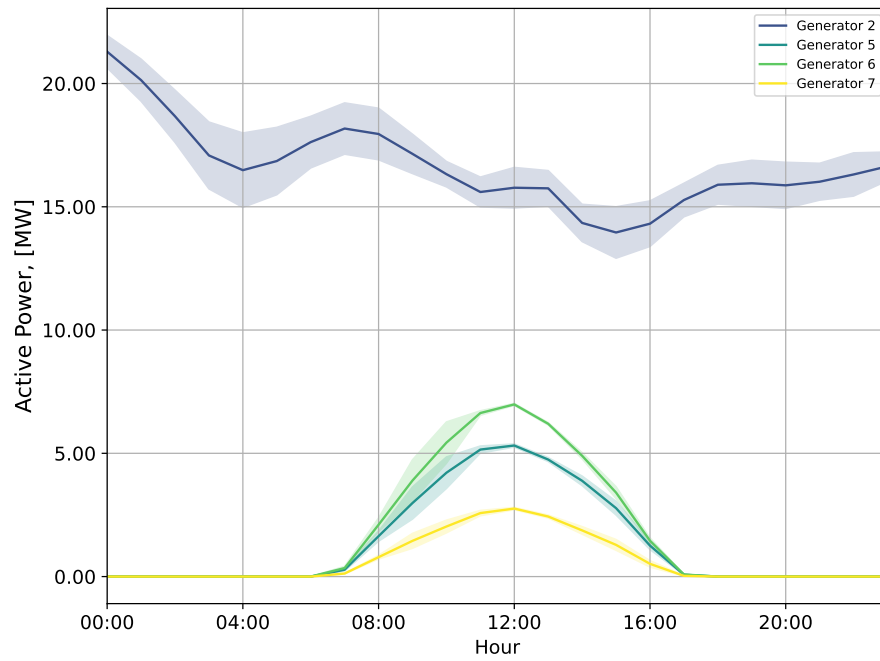


(a) RES generation profiles.

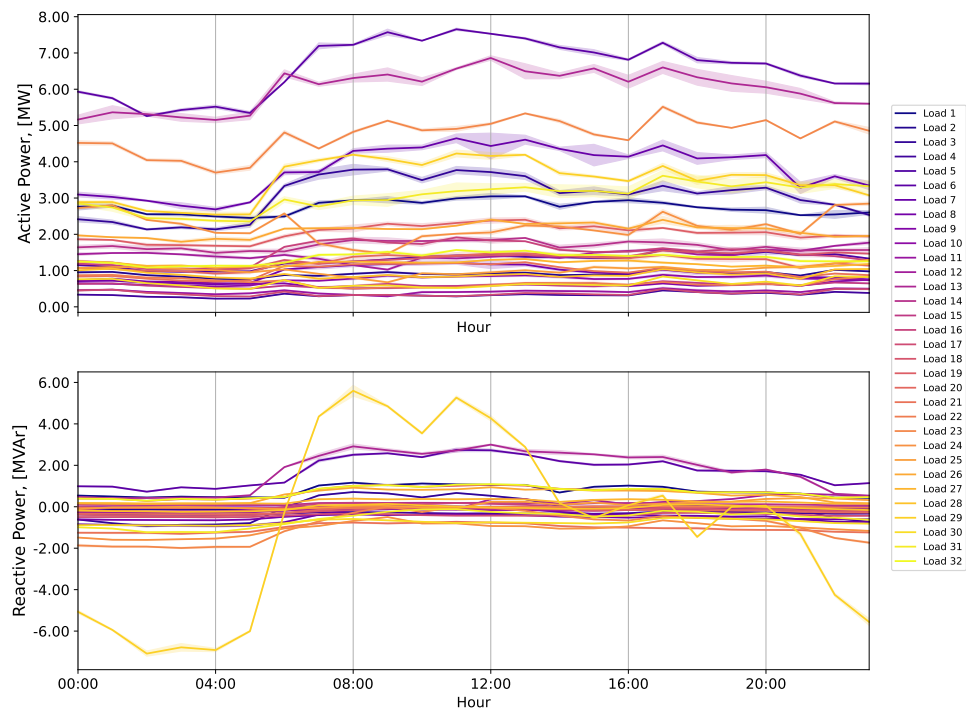


(b) Load profiles (active and reactive power).

Figure C.4: Case Study 3. ADN node 5. RES generation and load profiles. Summer 2025.

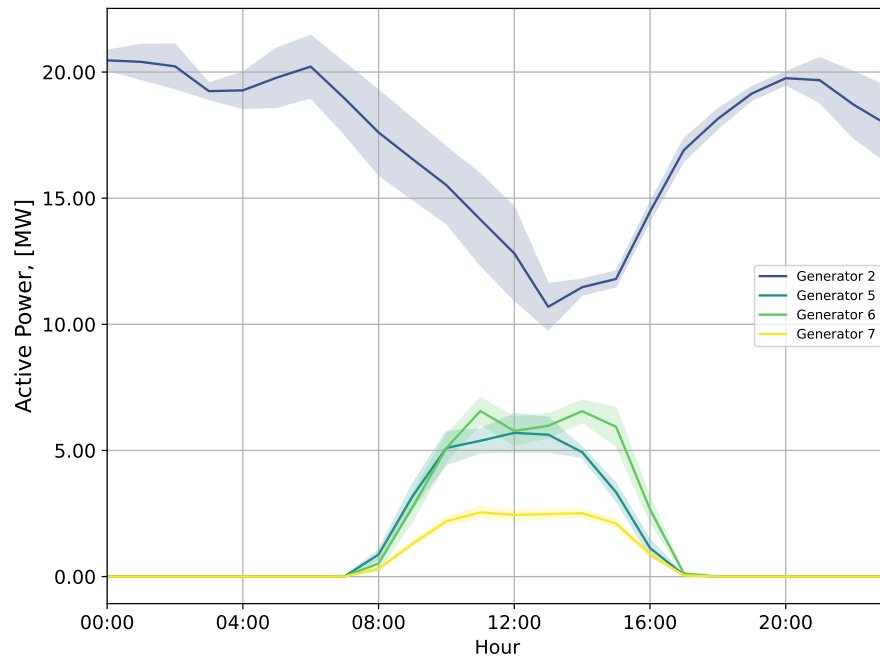


(a) RES generation profiles.

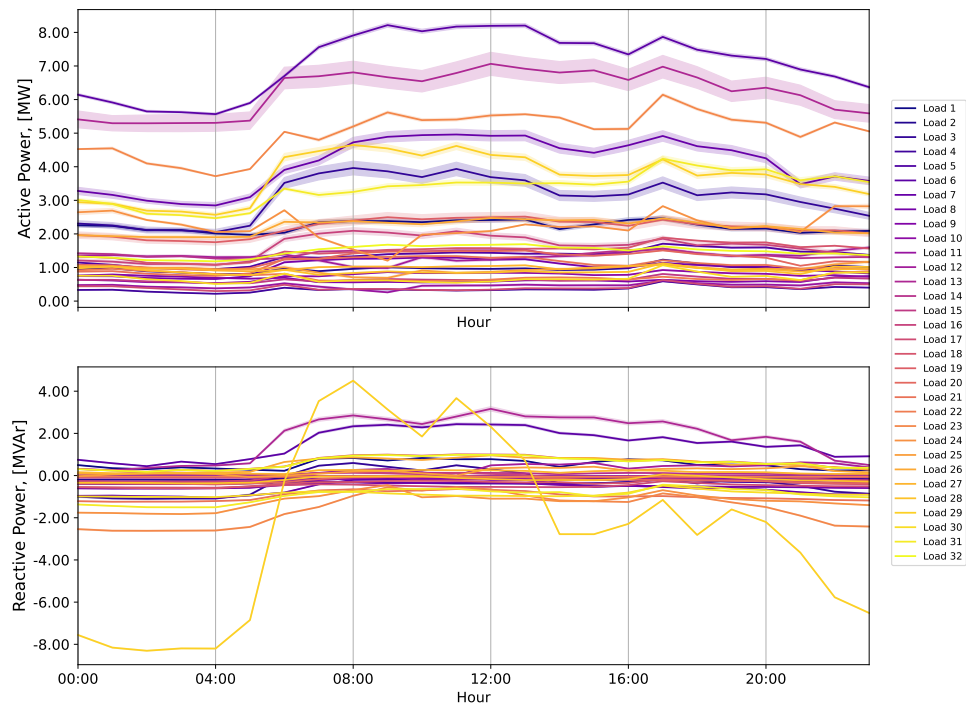


(b) Load profiles (active and reactive power).

Figure C.5: Case Study 3. ADN node 5. RES generation and load profiles. Autumn 2025.

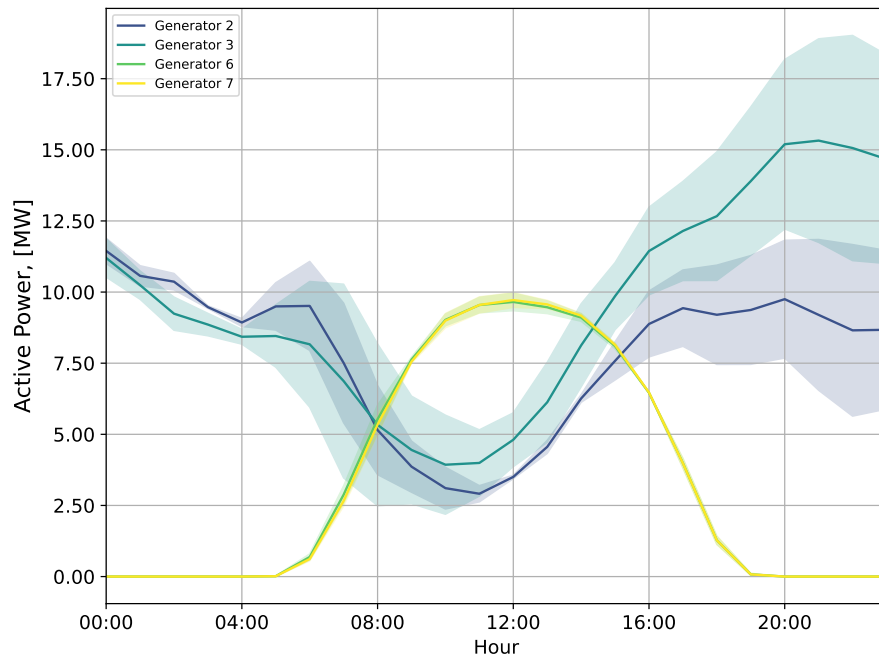


(a) RES generation profiles.

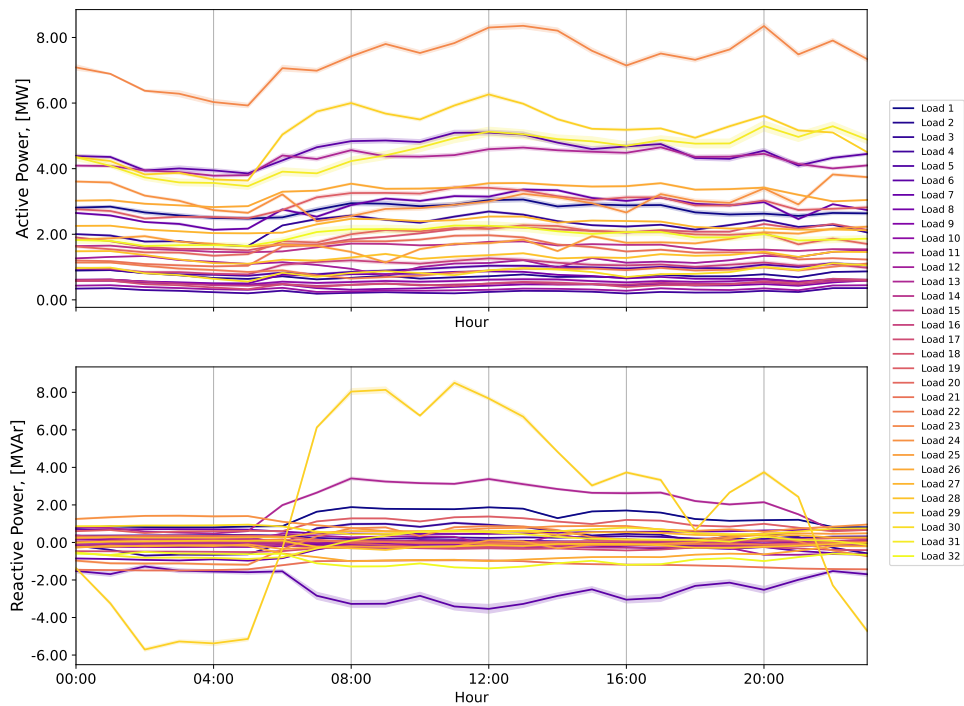


(b) Load profiles (active and reactive power).

Figure C.6: Case Study 3. ADN node 5. RES generation and load profiles. Winter 2025.

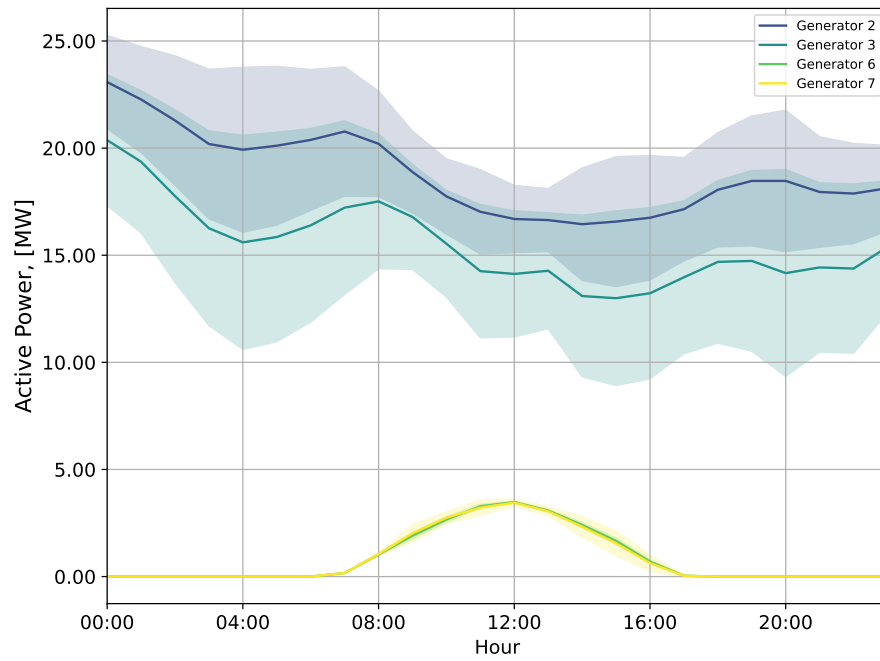


(a) RES generation profiles.

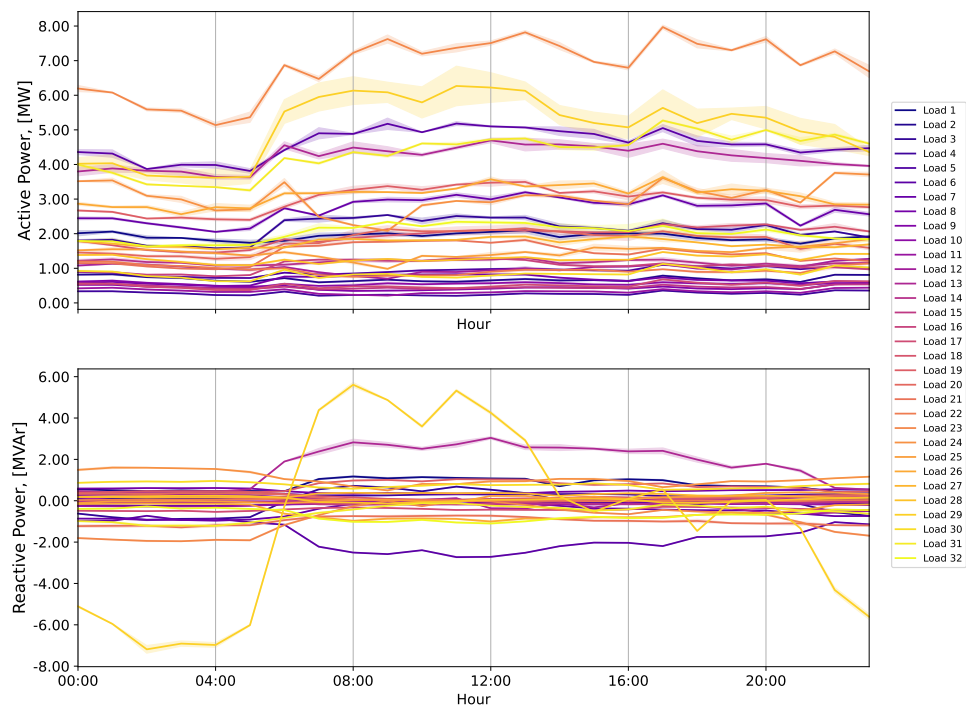


(b) Load profiles (active and reactive power).

Figure C.7: Case Study 3. ADN node 7. RES generation and load profiles. Summer 2025.

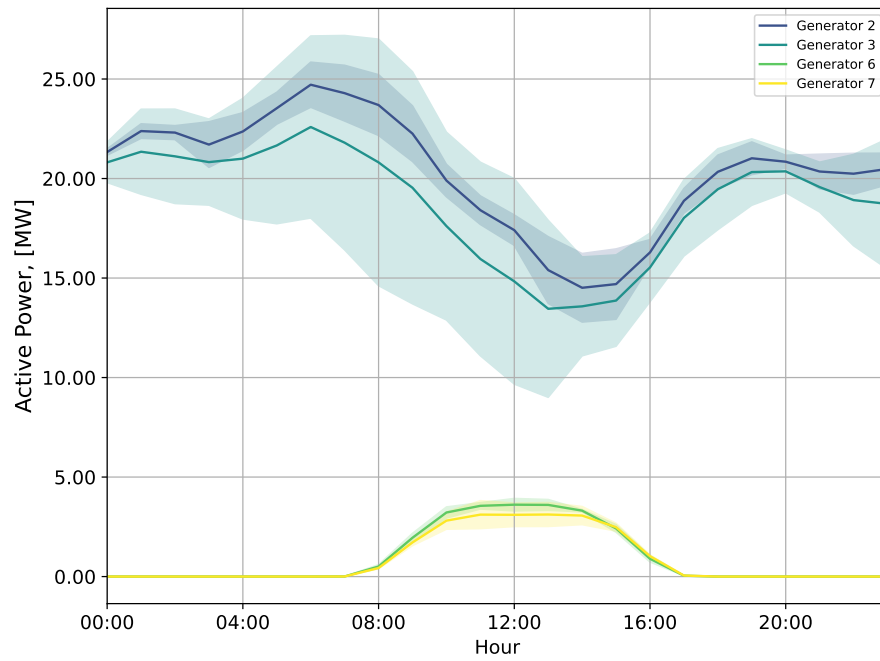


(a) RES generation profiles.

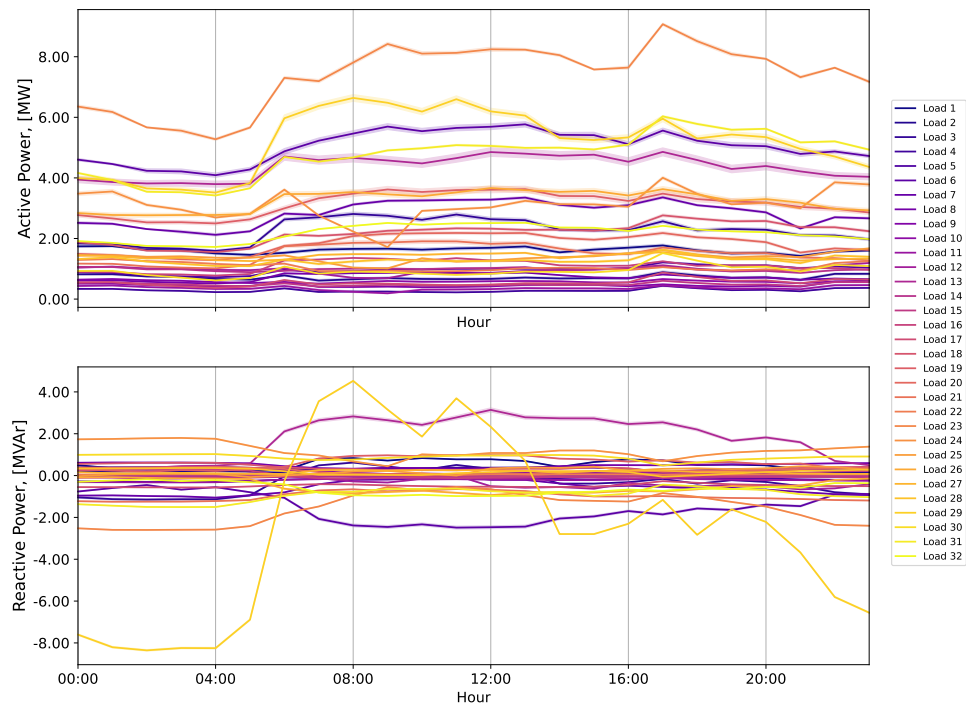


(b) Load profiles (active and reactive power).

Figure C.8: Case Study 3. ADN node 7. RES generation and load profiles. Autumn 2025.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure C.9: Case Study 3. ADN node 7. RES generation and load profiles. Winter 2025.

C.2.3 ADN Connected to Node 9 of the TN

The **ADN** connected to node 9 of the **TN** is based on the **IEEE** 33-bus distribution test system (Baran and Wu, 1989). The corresponding network topology is described in Section A.2, and the single-line diagram is shown in Figure A.2. Detailed bus, branch, and interface generator data are reported in Tables A.4–A.6.

Figures C.10–C.12 show the load and **RES** generation profiles for the Summer, Autumn, and Winter representative days of 2025. Data corresponding to the Spring representative day are presented in Figure 7.32 of Section 7.3.

C.3 Market Data

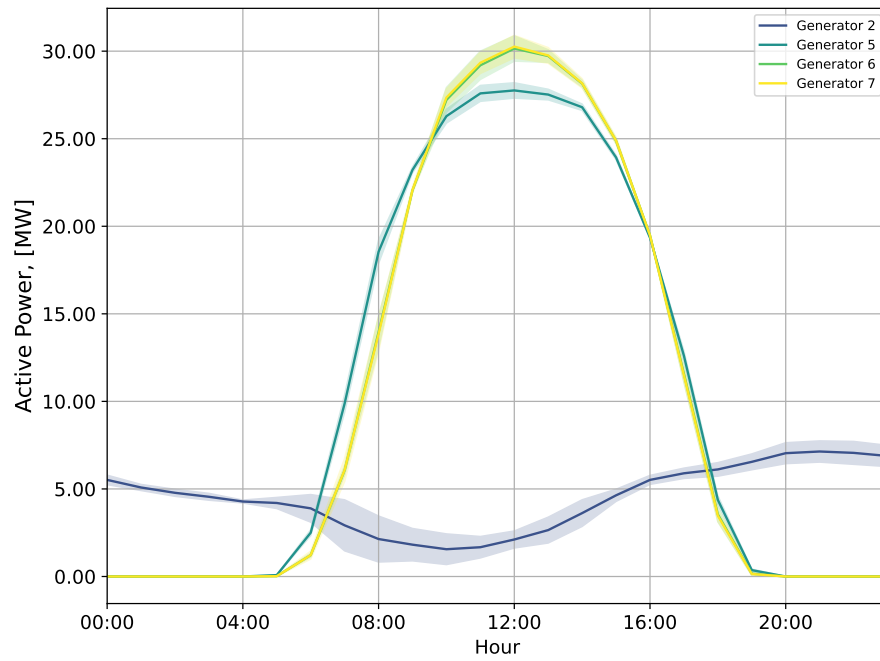
This section presents the wholesale energy and flexibility market data adopted in Case Study 3, which serve as economic inputs to the shared resources planning framework described in Section 7.3.

Figures C.13–C.15 illustrate the hourly wholesale energy and flexibility market prices for the Summer, Autumn, and Winter representative days of 2025. Market price data for the Spring representative day are presented in the corresponding subsection (Figure 7.26).

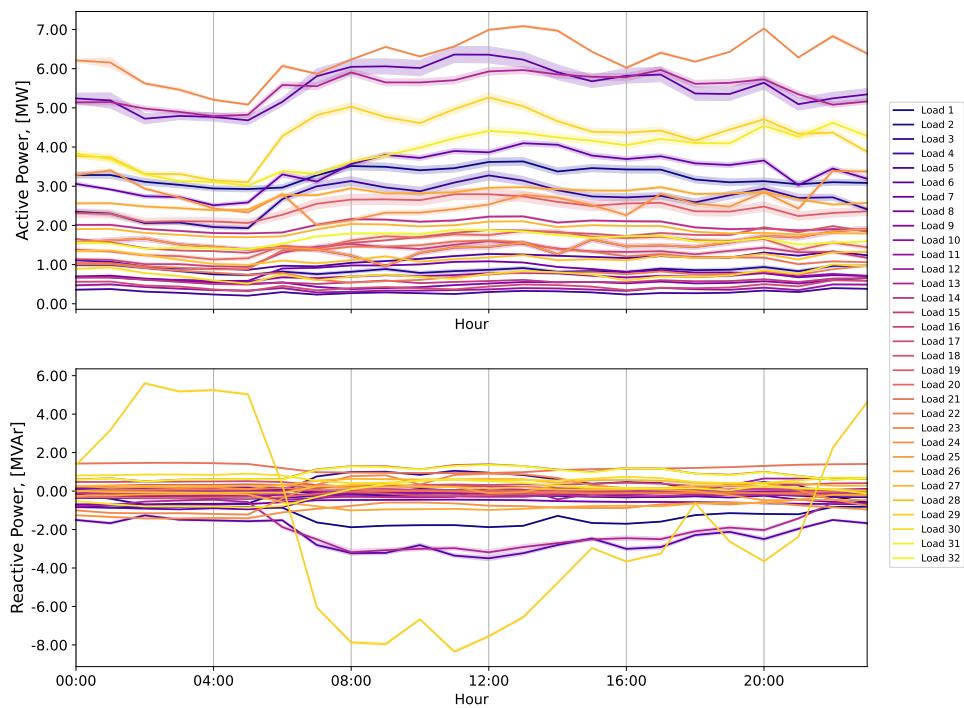
C.4 Results

This section presents the main operational results obtained in Case Study 3, organized by representative year and representative day, as described in Section 7.3.

Table C.1 summarizes the key performance indicators analyzed, including operational costs (non-discounted), total **RES** generation, and **RES** curtailment, for the three test cases considered across all representative years and seasonal days. All values reported correspond to daily average quantities for the respective representative day.

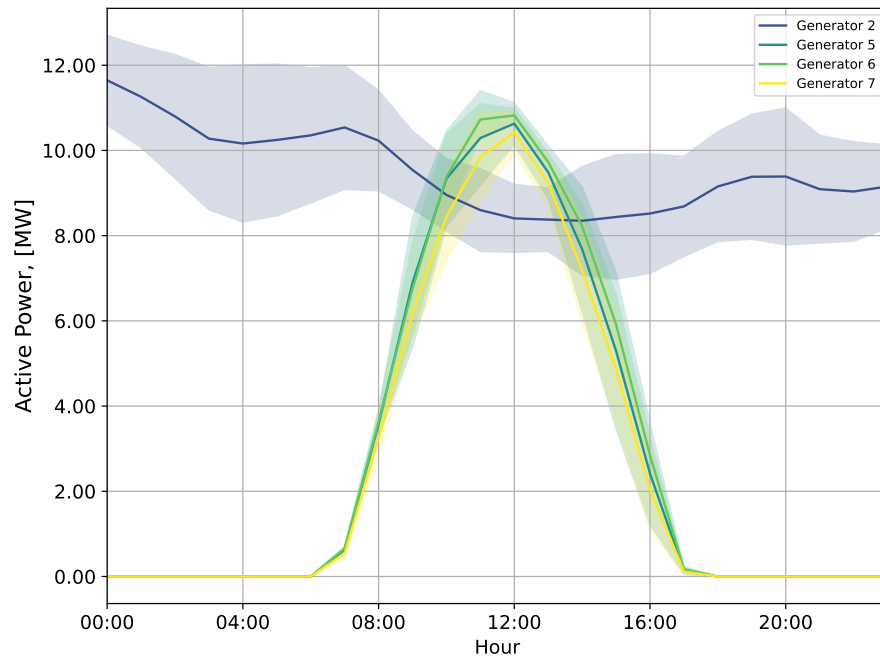


(a) RES generation profiles.

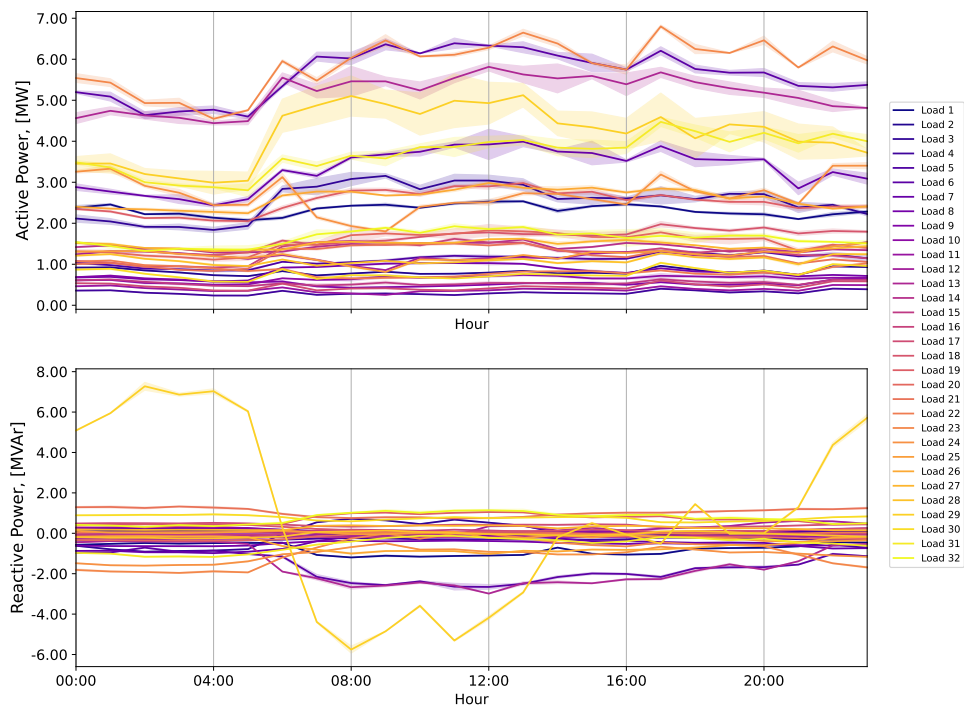


(b) Load profiles (active and reactive power).

Figure C.10: Case Study 3. ADN node 9. RES generation and load profiles. Summer 2025.

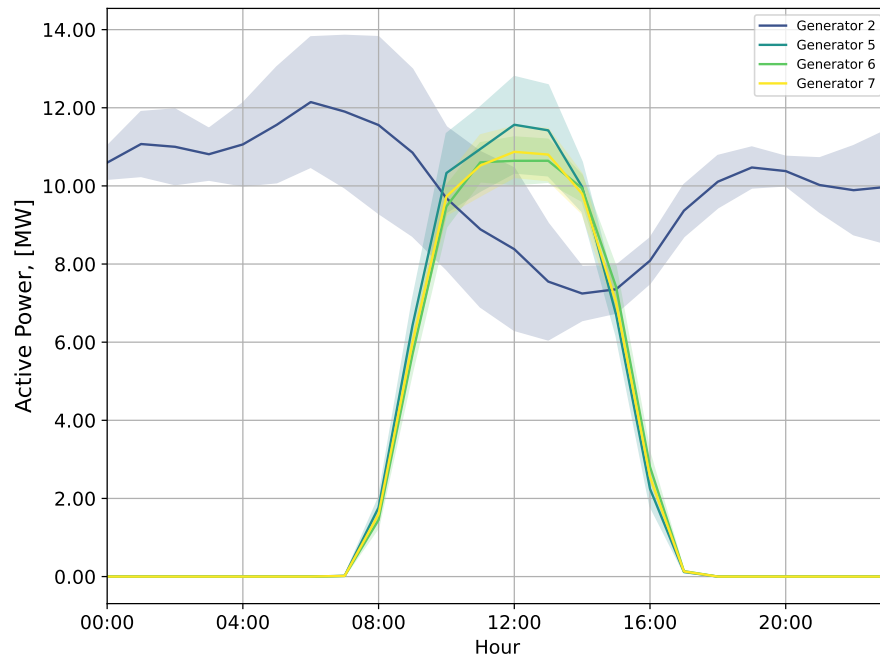


(a) RES generation profiles.

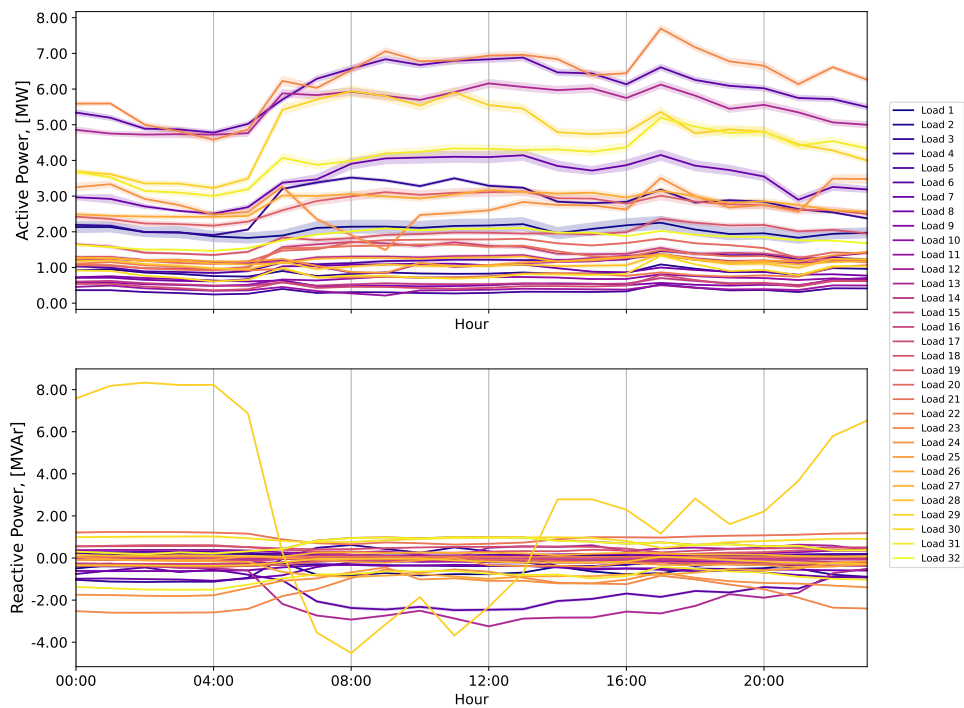


(b) Load profiles (active and reactive power).

Figure C.11: Case Study 3. ADN node 9. RES generation and load profiles. Autumn 2025.



(a) RES generation profiles.



(b) Load profiles (active and reactive power).

Figure C.12: Case Study 3. ADN node 9. RES generation and load profiles. Winter 2025.

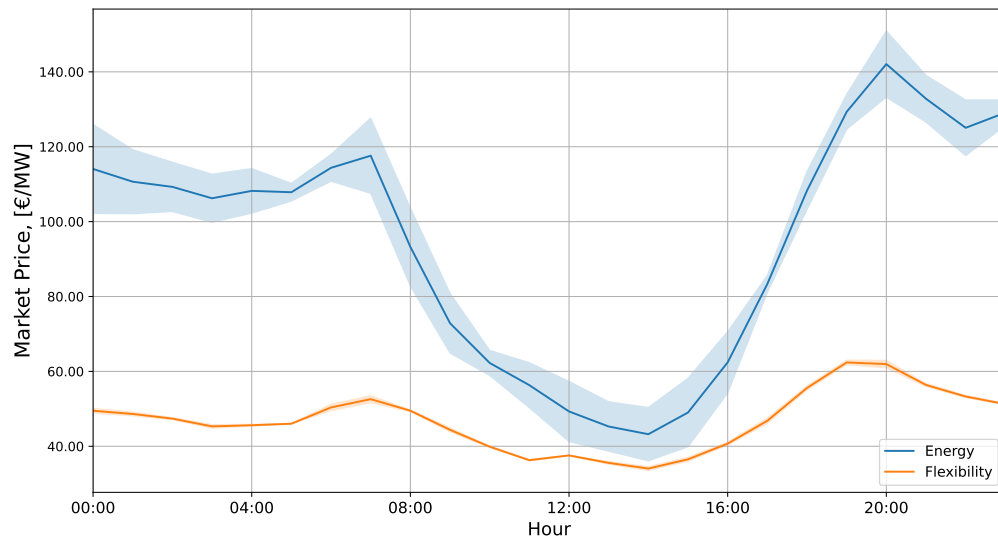


Figure C.13: Case Study 3. Wholesale energy and flexibility market prices. Summer 2025.

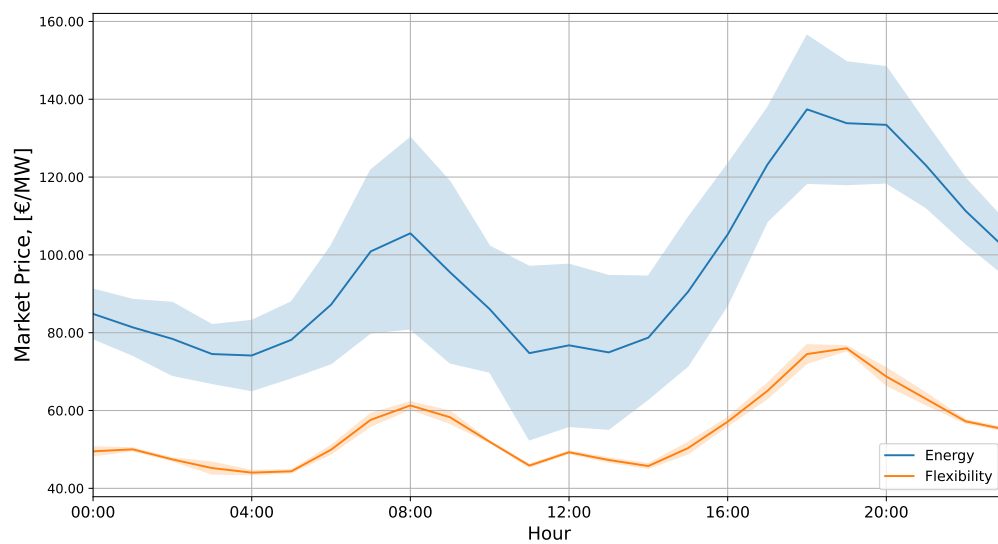


Figure C.14: Case Study 3. Wholesale energy and flexibility market prices. Autumn 2025.

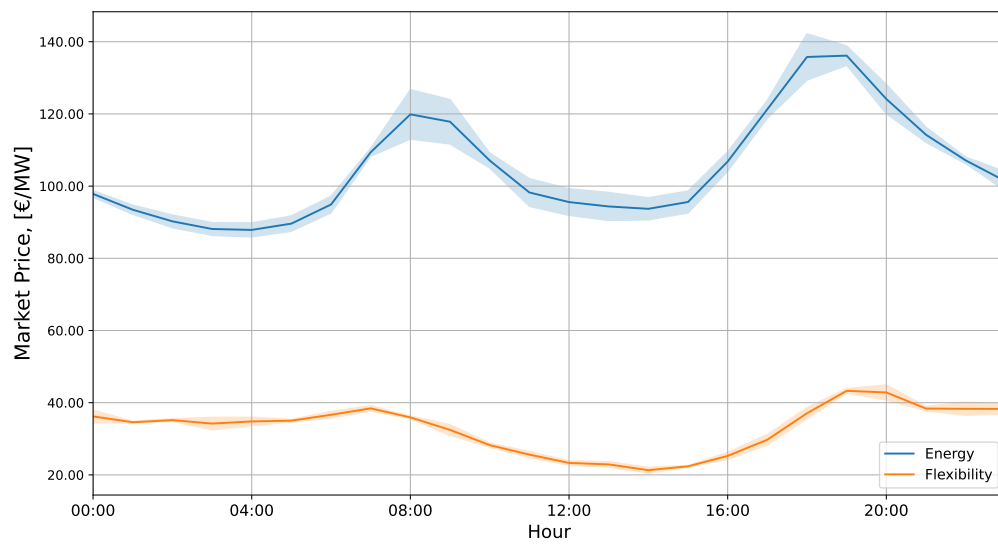


Figure C.15: Case Study 3. Wholesale energy and flexibility market prices. Winter 2025.

