



Universidade do Porto

Faculdade de Engenharia

DYNAMIC SECURITY OF POWER SYSTEMS
WITH HIGH RES PENETRATION: OPTIMAL PLACEMENT
OF GFM CONVERTERS AND INTERPRETABLE DYNAMIC
SECURITY ASSESSMENT TOOLS

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fulfilment of the requirements for the degree of Doctor of Philosophy

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"In many ways, the work of a critic is easy. We risk very little, yet enjoy a position over those who offer up their work and their selves to our judgment. We thrive on negative criticism, which is fun to write and to read. But the bitter truth we critics must face, is that in the grand scheme of things, the average piece of junk is probably more meaningful than our criticism designating it so.

But there are times when a critic truly risks something, and that is in the discovery and defence of the new. The world is often unkind to new talent, new creations. The new needs friends.

Last night, I experienced something new: an extraordinary meal from a singularly unexpected source. To say that both the meal and its maker have challenged my preconceptions about fine cooking is a gross understatement. They have rocked me to my core. In the past, I have made no secret of my disdain for Chef Gusteau's famous motto, "Anyone can cook". But I realise, only now do I truly understand what he meant. Not everyone can become a great artist; but a great artist can come from anywhere."

Anton Ego, *Ratatouille*, 2007

Acknowledgments

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The logo for TwinEU, featuring the word "TwinEU" in a bold, blue, sans-serif font. The letter "i" in "Twin" has a small white star above it.The logo for INESC TEC, consisting of a blue square icon with a white circuit-like pattern on the left, followed by the text "INESCTEC" in a bold, blue, sans-serif font.

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Abstract

The large-scale integration of renewable energy sources (RES), marked by the replacement of conventional power plants with converter-based generation, is leading the power system into operating conditions of reduced dynamic security margins.

In this context, Grid-forming (GFM) controlled converters are seen as a promising solution to avoid the continuous degradation of dynamic security due to their unique control characteristics that can greatly support the system stability. However, the widespread use of GFMs is still constrained by the cost of energy storage systems and the over-current capabilities of switching devices. Hence, maximising the stability benefits of introducing GFMs through careful consideration of their size and location in the grid is crucial to efficient system planning.

To address this planning challenge, this work proposes a robust methodology for the location and sizing of GFM converters that simultaneously considers the solution costs and the security gains while accounting for the TSO cost-security preferences. Such methodology formulates the placement problem as a multi-criteria decision support problem and uses a solution-seeking algorithm based on Bayesian Optimisation to determine the solution. A modified version of the IEEE 39 Test System is used as a case study for both the method's explanation and application example. The results show that the proposed method is successful in finding solutions with physical meaning and that respect the decision agent's preferences.

On the other hand, diagnosing system security has also become more complex, particularly in an online setting. This complexity arises from increased system instability, a greater number of interacting DER, and a larger number of scenarios to evaluate in real-time due to the variability of RES. This increased complexity and the prevalence of power electronics lead to extensive state models that turn online dynamic security assessment (DSA) into a problem too large to be solved using traditional model-based techniques. While data-driven solutions have long been seen as promising solutions, their adaptation to the current regulatory framework for AI in Europe is still an open task. This calls for the development of interpretable AI models that humans can easily understand and integrate with their domain knowledge, providing TSOs with DSA tools that respect the pillars of human-centric and trustworthy AI.

That being said, this work proposes a novel methodology, the Evolving Symbolic Model (ESM), for generating highly interpretable data-driven models for the DSA, namely in system security classification and the definition of preventive actions. The ESM uses simulated annealing for a data-driven evolution of a symbolic model template, enabling different cooperative learning schemes between humans and AI. The Madeira Island power system is used to validate the application of the ESM concept in DSA. The results show that ESM has classification accuracy comparable to pruned decision trees, higher global interpretability, and outperforms an operator-defined expert system and an artificial neural network in defining preventive actions.

Resumo

A integração em larga escala de fontes de energia renovável (RES), marcada pela substituição de centrais elétricas convencionais por geração baseada em conversores, está a conduzir o sistema elétrico a condições de operação com margens de segurança dinâmica reduzidas.

Neste contexto, devido às suas características de controlo únicas, os conversores controlados em modo Grid-forming (GFM) são vistos como uma solução promissora para evitar a degradação contínua da segurança dinâmica. O uso generalizado de GFMs é, no entanto, ainda limitado pelo custo dos sistemas de armazenamento de energia e pela capacidade de sobre-corrente dos dispositivos de comutação. Assim, para um planeamento eficiente do sistema, é fundamental maximizar os benefícios da introdução dos GFMs na estabilidade do sistema, através do seu dimensionamento e posicionamento na rede.

Posto isto, esta tese propõe uma metodologia robusta para a localização e dimensionamento de conversores GFM, que considera os custos da solução, a melhoria da segurança e as preferências do operador do sistema. Tal metodologia formula o problema como um problema de decisão multicritério e utiliza depois um algoritmo de procura de soluções baseado em Otimização Bayesiana. Para ilustrar a aplicação do método, uma versão modificada do Sistema de Teste IEEE39 é utilizada como caso de estudo. Os resultados mostram que o método permite encontrar soluções com significado físico e que respeitam as preferências do agente de decisão.

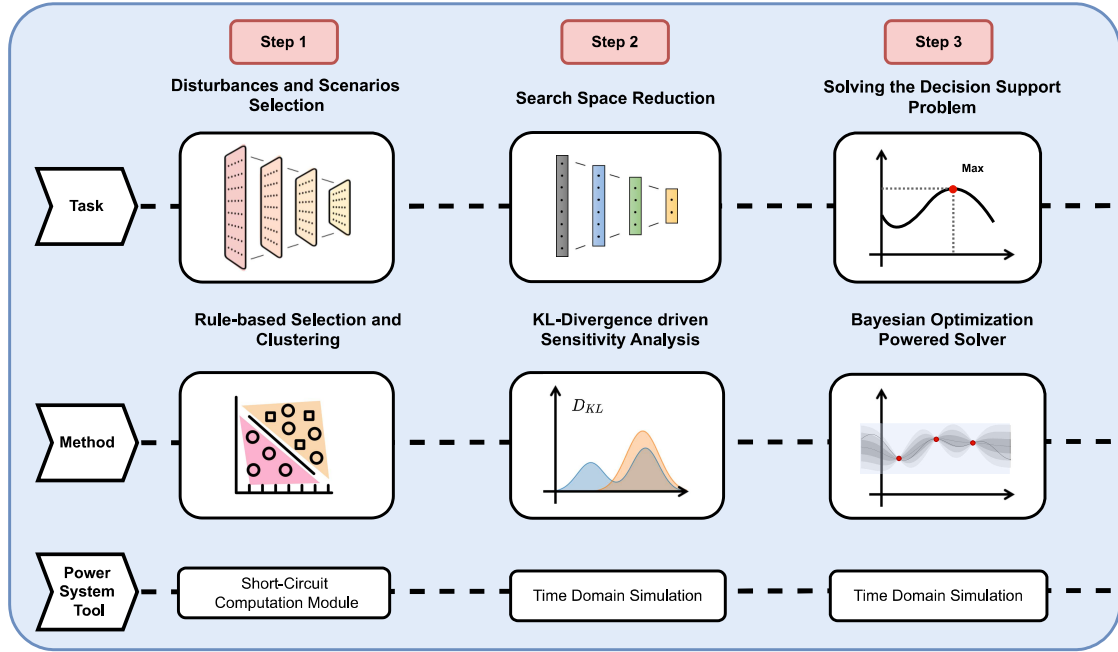
Por outro lado, diagnosticar em tempo real a segurança do sistema tornou-se também mais complexo, devido ao aumento da instabilidade, ao maior número de recursos distribuídos e ao maior número de cenários a avaliar em tempo real. Esta complexidade e a prevalência da eletrónica de potência resultam em extensos modelos de estado que tornam a avaliação dinâmica da segurança em tempo real (oDSA) um problema muito grande para ser resolvido usando técnicas clássicas baseadas em modelos físicos. Embora as soluções baseadas em dados serem há muito vistas como soluções promissoras, a sua adaptação ao atual quadro regulamentar para a IA na Europa está ainda em aberto. Assim, importa desenvolver modelos de IA interpretáveis que os humanos possam compreender e integrar com o seu conhecimento, fornecendo aos operadores ferramentas de DSA de confiança e centradas no humano.

Assim, esta tese propõe uma metodologia, os Modelos Simbólicos Evolutivos (ESMs), para a geração de modelos interpretáveis com recurso a dados para o DSA, nomeadamente para classificação da segurança e definição de ações preventivas. Os ESMs utilizam o Simulated Annealing para evoluir um modelo simbólico e permitem ainda diferentes esquemas de aprendizagem cooperativa. O sistema da ilha da Madeira é utilizado para validar a aplicação do conceito ao DSA. Os resultados mostram que os ESMs têm uma performance comparável à das árvores de decisão podadas mas maior interpretabilidade global, superando ainda um sistema especializado definido por um operador e uma rede neural na definição de ações preventivas.

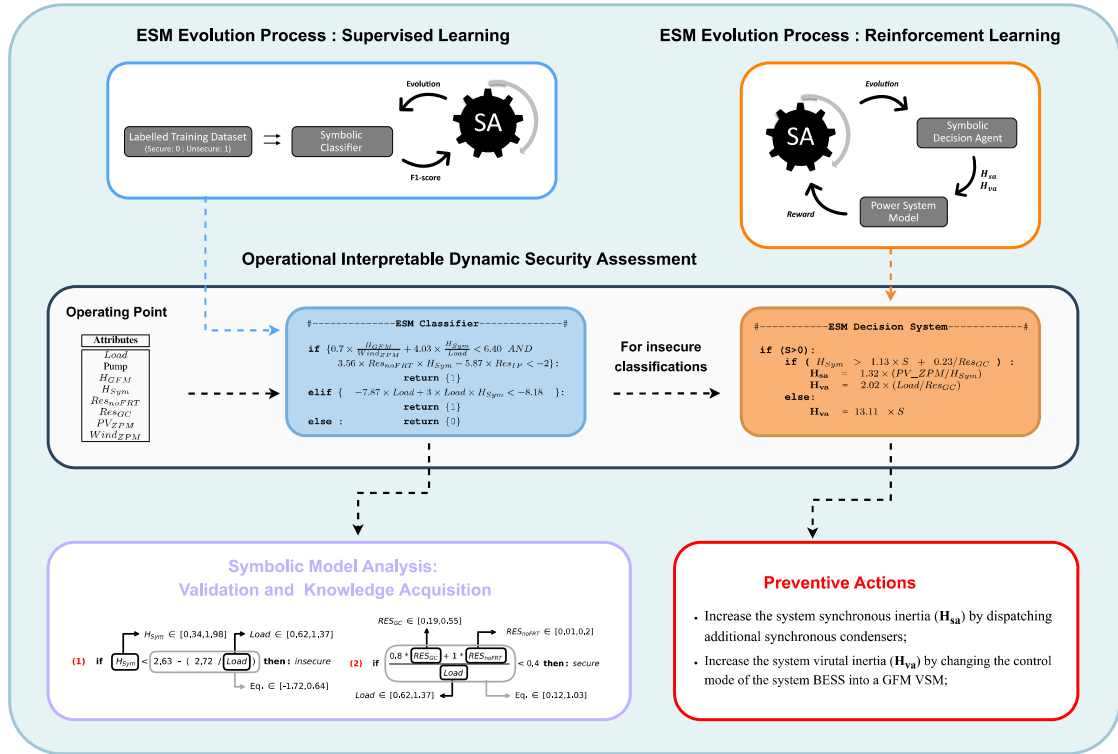
Graphical Abstract

Dynamic Security of Power Systems with high RES Penetration

Optimal Placement and Sizing of GFM Converters



Evolving Symbolic Models



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List of Acronyms and Symbols

Acronyms

AC	Alternating Current
AEMO	Australian Energy Market Operator
AI	Artificial Intelligence
ANN	Artificial Neural Network
AVR	Automatic Voltage Regulator
BESS	Battery Energy Storage System
BO	Bayesian Optimisation
CIG	Converter Interface Generation
CoI	Center of Inertia
CSA	Current Saturation Algorithm
DC	Direct Current
DE	Differential Evolution
DER	Distributed Energy Sources
DM	Decision Maker
DS	Decision Support
DSA	Dynamic Security Assessment
DSL	Domain-Specific Language
DT	Decision Trees
EEM	Empresa de Eletricidade da Madeira
EPO	European Patent Office

Acronyms

EPSO	Evolutionary Particle Swarm Optimisation
ES	Expert System
ESM	Evolving Symbolic Model
FACTS	Flexible Alternating Current Transmission System
FIS	Fuzzy Interference System
FRT	Fault Ride Through
GFL	Grid Following
GFM	Grid Forming
GPL	General-Purpose Programming Language
GPR	Gaussian Process Regressor
gSCR	Generalised Short Circuit Ratio
HVDC	High Voltage Direct Current
IBR	Inverter Based Resources
IEEE	Institute of Electrical and Electronics Engineers
INESC TEC	Instituto de Engenharia de Sistemas e Computadores, Tecnologia e Ciência
KL	Kullback-Leibler
L-BFGS	Limited-memory Broyden-Fletcher-Goldfarb-Shanno
MI	Mutual Information
MISO	Midcontinent Independent System Operator
ML	Machine Learning
NEMMCO	National Electricity Market Management Company Limited
NERC	North American Electric Reliability Corporation
ONS	Operador Nacional do Sistema Elétrico
OP	Operation Point
OS	Operating Scenarios
PC	Preventive Control
PCC	Point of Common Coupling
PINN	Physics Informed Neural Networks

Symbols

PLL	Phase-Locked Loop
PMU	Phase Measurement Unit
PSS	Power System Stabiliser
PV	Photovoltaic
PWM	Pulse Width Modulation
RBF	Radial Basis Function
RES	Renewable Energy Sources
RL	Reinforcement Learning
RMS	Root Mean Square
RoCoF	Rate of Change of Frequency
SA	Simulated Annealing
SC	Security Classification
SCADA	Supervisory Control and Data Acquisition
SCR	Short Circuit Ratio
SM	Symbolic Model
TEPCO	Tokyo Electric Power Company
TSO	Transmission System Operator
VSC	Voltage Source Converter
VSM	Virtual Synchronous Machine
WECC	Western Electricity Coordinating Council
XAI	Explainable Artificial Intelligence

Symbols

a	Cost in $M\$/MW$ of the BESS, with a power converter designed without overcurrent capacity
AE	Absolute error
A_{init}	Array of Initial $A(X)$ values used in the first Gaussian Process Regressor
$A_S(X)$	Surrogate model of $A(X)$
$A(X)$	Adaptation function
$\tilde{A}(X)$	Statistical surrogate model of $A(X)$

Symbols

b	Tunable parameter of individual value function of security
C_{a_i}	Normalised cost of additional inertia for Operating Point i
$CQPD_{PLL}$	Cumulative quadratic phase deviation of the PLL
CVD	Cumulative voltage deviation
$\overline{C_X}$	Normalised cost of solution X
C_X	Cost of Solution X
δ	Rotor angle
$\Delta\delta_{coi}$	Rotor angle deviation in regard to the centre of inertia
$\overline{\Delta\delta_{coi}}$	Maximum rotor angle deviation in regards to the centre of inertia, found among all the system's synchronous machines
$\overline{\overline{\Delta\delta_{coi}^{T_{sc}}}}$	Value of $\overline{\overline{\Delta\delta_{coi}}}$, when the time interval of analysis is T_{sc}
$\overline{\overline{\hat{\Delta\delta_{coi}^{T_{sc}}}}}$	Estimate of $\overline{\overline{\Delta\delta_{coi}^{T_{sc}}}}$
$\overline{\Delta f}$	Maximum deviation of the frequency curve $f(t)$ from its nominal value
$\mathcal{D}$	Distribution of the $\Delta\delta_{coi}$ values of all system synchronous machines for all disturbances and scenarios
$\mathcal{D}_X$	Distribution of the $\Delta\delta_{coi}$ values of all system synchronous machines for all disturbances and scenarios, when the solution X is adopted.
ε	Security index
ε_{lim}	Limit value of the security index
ε_{Max}	Maximum value of the security index
ε_{Min}	Minimum value of the security index
$\overline{\varepsilon_X}$	Normalised security index for solution X
ε_{Spec}	Specific value of the security index ε
$\hat{\varepsilon}_X$	Estimate of ε_X
ε_X	Value of security index for solution X
f	Cost in $M\$/A$ of the converters overcurrent capacity
f_{ele}	Electrical frequency
$F_M(X)$	Fitness function that aggregates the composite stability indicators formulated using a max-based formulation
Δf_{SM}	Maximum deviation of the synchronous machine frequency
$F_S(X)$	Fitness function that aggregates the composite stability indicators formulated using a sum-based formulation
$\mathcal{F}_i$	Fitness of the symbolic model SM_i to perform the task of interest

Symbols

$\mathcal{F}_n$	Fitness of the symbolic model SM_i to perform the task of interest
H	Inertia constant
H_{sa}	Additional synchronous inertia
H_{va}	Additional virtual inertia
i_k	Overcurrent capacity of the k GFM-controlled converter
I_{Max}	Fixed value of the overcurrent capacity for all GFM converters
I_T	Number of iterations at temperature T
I_X	Overcurrent capacities of the GFM converters that are to be placed according to solution X
K_b	Virtual Boltzmann constant
K_H	Trade-off between the cost of additional inertia and the enhanced system security
K_{μ_j}	Numerical weight that traduces the importance of the stability class expressed by the stability variable μ_j
K_p	Weight of the individual value function of security
k_{pen}	Penalising constant
K_w	Weight of the individual value function of cost
L	Location of GFM converters
l_k	Bus location of the k GFM-controlled converter
L_X	Location of the GFM converters that are to be placed according to solution X
$Max\ CQPD_{PLL}$	Maximum CQPD found among the phases of the PLLs of all the system's GFL converters
$Max\ CVD$	Maximum cumulative voltage deviation of the system
$Max\ \Delta f$	Maximum frequency deviation found among a set of maximum frequency deviations
$Max\ \Delta f_{SM}$	Maximum frequency deviation found among the frequencies of all the system's synchronous machines
$Max Rocof_{SM} $	Maximum absolute value of the Rocof found among the frequencies of all the system's synchronous machines
m_j	Mutation
$M_{\mu_j}(X)$	Max-based composite stability indicator, associated with the stability variable μ_j when evaluating a particular solution X .

Symbols

μ	Generic security variable
N_g	Maximum number of GFM that can be placed
N_{it}	Number of iterations
ω	Rotor speed
Ω_b	Set of all system buses
Ω_b^{init}	Set of bus locations used to define the initial points of the bayesian optimisation algorithm
Ω_b^{LG}	Set of all system buses with load or generation
Ω_b^o	Set of optimisation relevant bus locations
Ω_{comb}^{init}	Set of combinations of bus locations used fo
Ω_d	Set of disturbances
Ω_d^o	Set of optimisation relevant disturbances
Ω_{GFL}	Set of all system converters with grid following control.
Ω_m^o	Set of optimisation relevant scenarios
Ω_{sm}	Set of all system synchronous machines
Pa	Probability of accepting each mutation
P_a	Accelerating power
$p(C_X)$	Individual value function of cost
$P(X)$	Penalising function
R	Cumulative reward function
R_i	Environment reward for Operating Point i
$Rocof$	Time derivative of the frequency curve $f(t)$
$ Rocof $	Maximum absolute value of the Rocof of the frequency curve $f(t)$
S	Nominal capacities of the GFM converters
ΔS	Marginal GFM capacity
S_i	Environment stability indicator for Operating Point i
σ_s	Cost of an extra unit of synchronous inertia
σ_v	Cost of an extra unit of virtual inertia
s_k	Nominal capacity of the k GFM-controlled converter
s_{max}	Maximum value of the nominal capacity that can be sized for each converter
SM_i	Current symbolic model
SM_n	Neighbouring symbolic model

$S_{u_j}(X)$	Sum-based composite stability indicator, associated with the stability variable μ_j when evaluating a particular solution X .
St_X	Total nominal capacity of GFM converters in solution X
S_X	Nominal capacities of the GFM converters that are to be placed according to solution X
T	Temperature of the simulated annealing cooling scheme
T_0	Initial temperature of the simulated annealing cooling scheme
T_f	Final temperature of the simulated annealing cooling scheme
T_{sc}	Time interval between the fault inception and the fault clearance instances
Θ_0	Generic symbolic model 0
Θ_1	Generic symbolic model 1
TMO	Total number of mental operations
v_{Nom}	Nominal voltage of the converters
$V(X)$	Value function
$w(\varepsilon_X)$	Individual value function of security
X	State variable array of the placement Problem
X_0	Elementary Solution of the placement problem, where no additional GFM is considered
X_{init}	Array of initial points used in the first gaussian process regressor

Introduction

1.1 Context (Panorama)

Prominent issues like climate change, global warming, and the increasing environmental awareness of Western societies have long led major governmental entities to prioritise the decarbonisation of the economy in their strategic policies. Since then, significant strides have been made in advancing decarbonisation, particularly through the expanded integration of renewable energy sources (RES) and the electrification of the economy (see Figure 1.2). Key initiatives - such as replacing carbon-intensive technologies like coal power plants with large-scale RES, increasing RES self-consumption among industrial, domestic, and transportation sectors, and electrifying vehicle fleets [1] - have played a crucial role in driving this transformation. A visual illustration of this key initiatives is depicted in Figure 1.1.

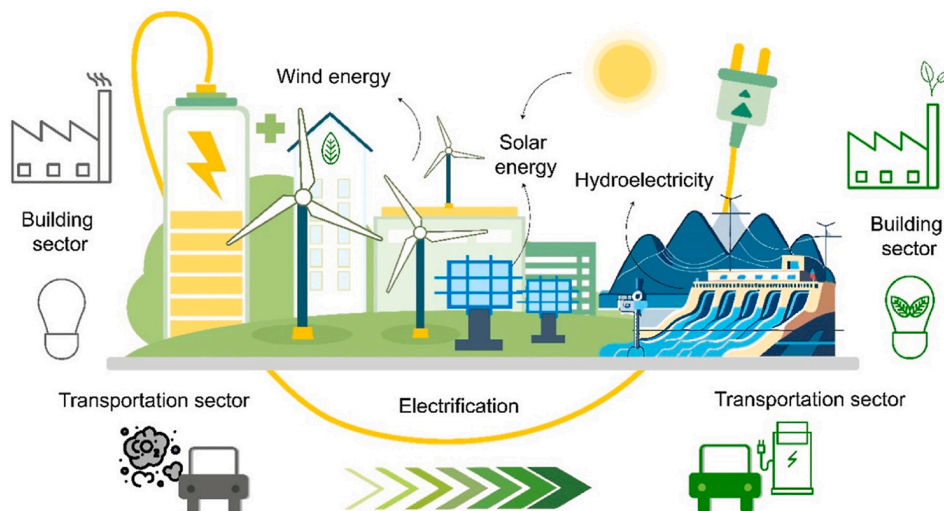


Figure 1.1: Decarbonisation through electrification and increased integration of RES [2].

1.1. Context (Panorama)

In Europe, most member states took significant steps towards achieving decarbonisation goals, leading to a notable increase in the installed capacity and share of RES in the energy mix [3]. This ongoing shift, which has already transformed certain aspects of power system operations, is expected to accelerate due to several key factors:

- **New Decarbonisation Targets:** The European Commission has set intermediate emission reduction goals, leading to new capacity targets for various RES. This is evident in initiatives such as the Fit for 55 package [4] and the REPowerEU plan [5].
- **Energy Security:** Recent events, including the COVID-19 pandemic and the conflict in Ukraine, have prompted member states to prioritise energy independence. Wind and solar energy, as distributed resources, are seen as potential solutions.
- **Financial Benefits:** Given the advanced technology maturity of wind and solar generation, the volatility of natural gas prices, and the value of CO₂ emission bonds, converter-based generation provides today not only the cheapest electricity price but also the most attractive investment option [6].

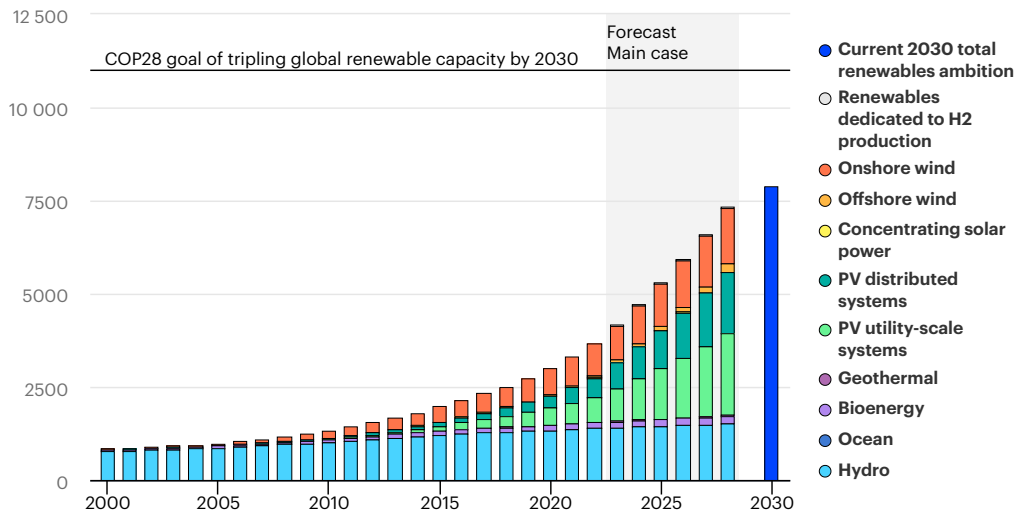


Figure 1.2: Installed renewable energy capacity in the world, by technology type [7].

Simultaneously, a large digital transformation of the power system has been taking place [8]. Initially driven by the placement of smart meters and now, due to recent advancements in Internet of Things and cloud technology, digitalisation is expanding beyond the electrical infrastructure to encompass grid users and service providers, including those from related sectors like mobility [9]. Concepts like digital twins, energy data spaces, and the internet of energy are emerging, with several pilot projects currently in progress, meaning a shift towards a more connected and intelligent landscape [9]. This transformation, which has multiplied the amount of readily accessible data and facilitated the remote control of widespread system

1.1. Context (Panorama)

elements, has brought the perfect conditions for a total system disruption driven by the spread of modern artificial intelligence (AI).

Due to this new digital environment and the recent advancements in AI (e.g., increased performance and decreasing hardware costs, advances in deep learning for areas such as computer vision or natural language processing, etc.), the interest in applying AI technology in power systems has skyrocketed. An interest that later translated into the adoption of the AI technology in diverse real-world tasks, such as RES/Load Forecasting, Steady State Risk Assessment, and Asset Monitoring [10]. Furthermore, researchers continue to propose new applications to harness AI's capabilities in processing large volumes of data and performing fast decision-making. These applications encompass tasks such as contingency management, dynamic security assessment, reporting assistance using generative AI, and their numbers are increasing rapidly.

The aforementioned advantages of AI, however, have been shadowed by the "black-box" nature of many AI techniques that instil algorithmic aversion in human operators and prevent their real-world application in high-risk tasks. Both the White Paper titled "Artificial Intelligence: a European Approach to Excellence and Trust" [11] and the "Artificial Intelligence Act" [12] recognise the energy sector as a high-risk sector for AI applications due to its reliance on critical infrastructures. This designation as a high-risk sector means that the requirements established by the Commission in the AI Act, specifically requirements of transparency and explainability, must be adhered to.

<u>ANNEX III</u>	
<u>HIGH-RISK AI SYSTEMS REFERRED TO IN ARTICLE 6(2)</u>	
High-risk AI systems pursuant to Article 6(2) are the AI systems listed in any of the following areas:	
1.	Biometric identification and categorisation of natural persons:
(a)	AI systems intended to be used for the 'real-time' and 'post' remote biometric identification of natural persons;
2.	Management and operation of critical infrastructure:
(a)	AI systems intended to be used as safety components in the management and operation of road traffic and the supply of water, gas, heating and electricity .

Figure 1.3: Definition of the use of AI in the electricity sector as high-risk (AI-Act annexe III).

Hence, developing fully interpretable AI solutions that align with trustworthy and human-centric pillars is now a growing need for tasks such as power system security assessment and security of supply verification, among others [13]. This will not only require a re-evaluation of the AI algorithms used, potentially shifting towards more symbolic or neuro-symbolic approaches, but will also demand rethinking the interface between the operator and intelligent systems to the extent that humans can be involved in the AI learning process [14].

1.2 Motivation

The aforementioned large-scale transformation is leading the power system towards operating conditions characterised by large penetration of converter-interfaced generation, an increasing number of distributed energy resources (DER), and high temporal variability of both demand and generation. These changes further hinder the already difficult role of the operator in ensuring a safe and reliable system operation and require more anticipation, coordination, and automation in real-time [14].

On the one hand, the simultaneous decommissioning of conventional power plants and their replacement with converter-based RES generation have significantly altered system dynamics. This shift is primarily driven by the removal of synchronous machines and their associated controls, such as power system stabilisers, which substantially reduce synchronous inertia, short-circuit power and damping (a variable that evolves at a different rate due to concurrent changes on the demand side). Due to their inherent physical and electrical characteristics, power converters cannot fully replicate these stabilising contributions of synchronous machines [15].

Furthermore, due to the distinct nature of power converters and their control mechanisms, various dynamic phenomena emerge, including interactions with the electromechanical dynamics of existing machines, the electromagnetic dynamics of the network, and with other converters. As a result, not only can classical power systems stability issues — such as rotor angle, frequency, and voltage stability — become more pronounced, but entirely new categories of stability challenges, including converter-driven and resonance-related instabilities, may also arise [16]. Figure 1.4 illustrates the different stability categories relevant in this new power system panorama.

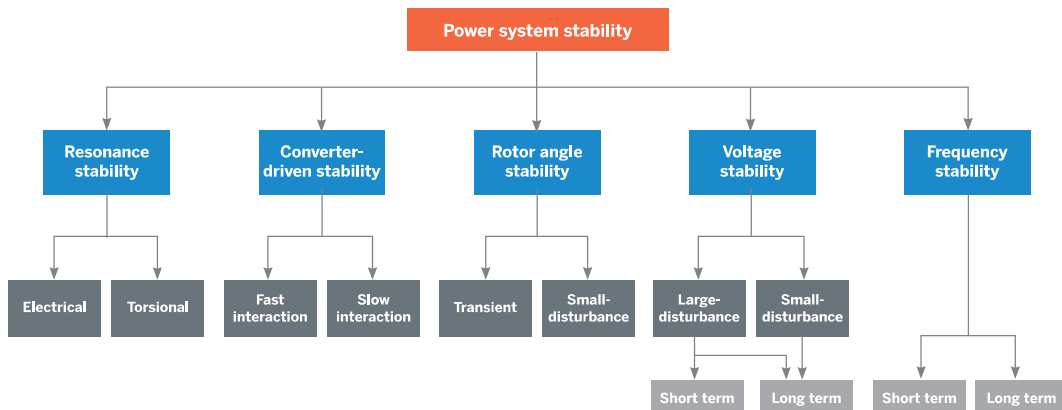


Figure 1.4: Schematic of Power System stability classes/categories [16].

In this new panorama, the need for essential system stability functions such as frequency con-

1.2. Motivation

trol, voltage control, damping, and synchronisation, traditionally provided by conventional thermal power plants, has led to exploring new solutions. Various approaches have been proposed, including advanced inverter control methods (such as synthetic inertia and fast frequency response), synchronous condensers, grid-forming (GFM) capable solutions, and hybrid alternatives [17, 16, 18, 19]. Among these options, GFM converters stood out as particularly intriguing to the industry since they provide a fast grid-supporting response, work in grids without minimum system strength requirements, and provide additional damping to the system [20, 19]. Hence, as depicted in Figure 1.5, they can play a fundamental role in achieving 100% penetration of inverter-based resources (IBRs) contrary to other technologies.

However, the widespread use of GFM converters is currently hindered by cost limitations associated with energy storage systems, the overcurrent capabilities of switching devices, and the mechanical wear on the primary energy source [16, 21]. Therefore, it is crucial to maximise the stability benefits of introducing GFM converters, which demands careful consideration of multiple factors such as device location and size [16, 18, 21], areas that still require further examination.

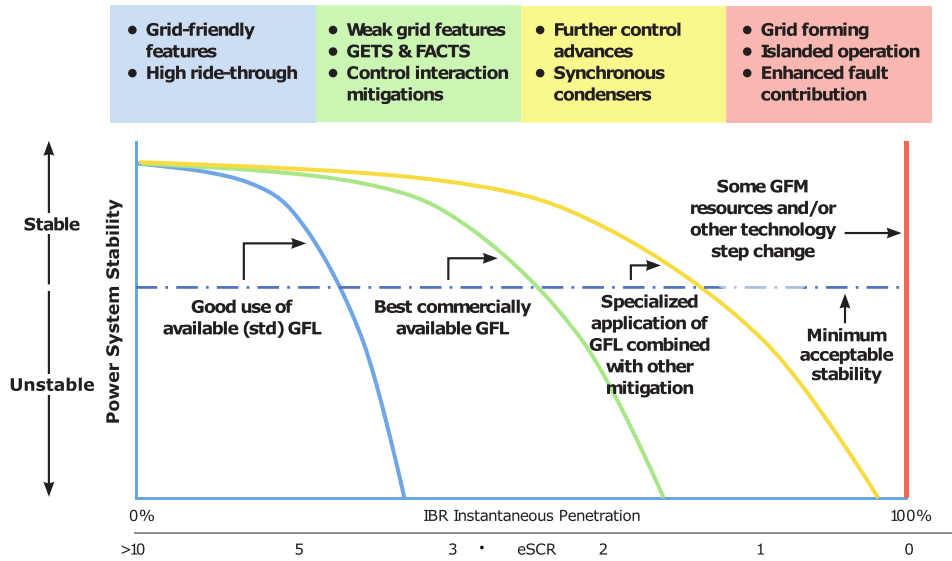


Figure 1.5: *Technology Enablers to Promote the Shift to a 100 % Renewable Future* [16]

On the other hand, diagnosing system security has also become more complex, particularly in an online setting. This complexity arises for several reasons: (1) the system is more prone to instability, (2) it includes a greater number of interacting DER-type elements [14], whose behaviour depends on both the primary energy source (e.g., wind, solar) and the control methodology (grid-following or grid-forming), and (3) the number of scenarios that must be evaluated in real time has increased due to the variability and uncertainty of RES [22].

This increased complexity and the widespread presence of power electronics lead to large and

1.3. Research Questions, Objectives and Contributions

complex state models that turn online dynamic security assessment (DSA) into a problem too large to be solved using the conventional model-based techniques [23]. While data-driven methods have long been seen as a promising solution to this problem, their adaptation to the current regulatory framework for AI is still an open task. This calls for the development of inherently interpretable AI models that humans can easily understand and integrate with their domain knowledge, providing TSOs with DSA tools that are ethically aligned with the commission's view, meaning human-centric and trustworthy.

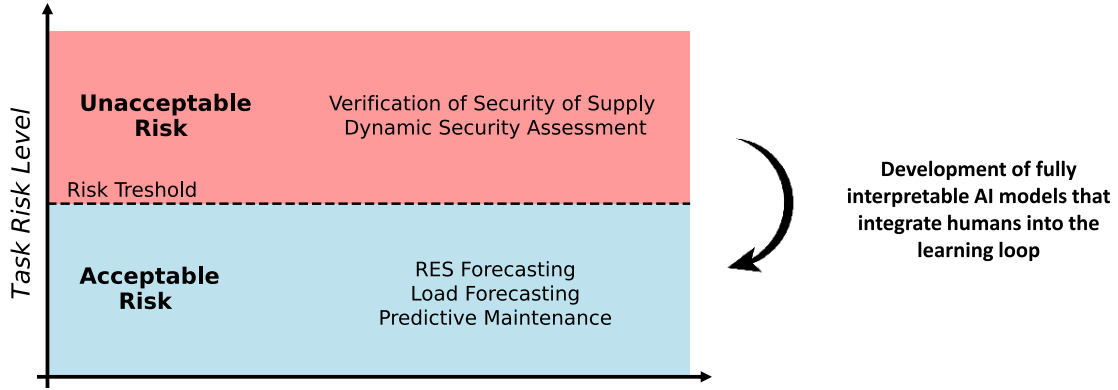


Figure 1.6: Reducing the risk level of AI tools in DSA through the development of transparent machine learning (ML) models (inspired in [23]).

1.3 Research Questions, Objectives and Contributions

The overarching objective of this thesis is to improve the security-related planning and operation of power systems with large penetrations of converter-based generation. Three research gaps that relate to pressing issues in the area of power system dynamic security were identified. These motivate the following objectives and contributions:

Objective 1. To Evaluate the Effect of GFM Converter Placement on the Stability

Improvement resulting from their Integration.

Research question: How does the location of GFM-controlled converters affect the system stability?

Contributions:

- 1– Index-based Multi-class stability assessment of the location of a single GFM converter.
- 2– Analysis of the GFM location's role in preventing the loss of synchronism for different stability phenomena.

1.3. Research Questions, Objectives and Contributions

Objective 2. To Develop a Methodology to Optimally Place and Size Grid-Forming Converters.

Research question: *Is it possible to optimally place and size GFM converters for dynamic security purposes within the context of large disturbances while owning the cost of the solution as a fundamental criterion?*

Contributions: 1– Development of an algorithm solution to optimally place and size GFM converters for dynamic security during large system disturbances. This approach includes several innovative aspects, such as: a) Considering the complex TSO cost-security preferences in the formulation of the GFM placement problem. b) Simultaneously incorporating the converter’s nominal and overcurrent capacity in the formulation of the GFM placement problem.

2– Development of a wise methodology for the placement problem that accounts for the impact of the GFM-controlled resources on different stability classes

Objective 3. To Develop Interpretable Dynamic Security Assessment Tools for Power Systems with high penetration of Converter-Based Generation.

Research question: *Can purely interpretable DSA tools be created to support the human operator in assessing the security of the power system in real-time and defining preventive actions?*

Contributions: Development of methodology for generating highly interpretable data-driven models for DSA in converter-dominated power systems, namely in system security classification and the definition of preventive actions. This methodology distinguishes itself by its ability to consider the user in the learning loop, leveraging in this way existing human knowledge.

While the motivation and empirical evaluation of the thesis is on Power System Dynamic Security, some of the contributions could be applied to other areas. Evolving Symbolic Models (ESM), in particular, can be applied to any area where new, fully interpretable decision systems are needed or to improve the behaviour of existing expert systems. Among its possible applications, a few are highlighted next:

- **Power System Protections:** Traditional protection systems rely on predefined rules and parameters derived from domain knowledge, physical equations, and trial-and-error practices. ESMs can enhance these systems by introducing adaptability and self-learning

1.4. Structure of the Thesis

capabilities, allowing them to handle new and challenging operating conditions effectively.

- **Power System Controllers:** Conventional controller design is grounded in established control engineering principles and researcher creativity. By extending the concept of evolving symbolic models to evolving graphs, the proposed methodology can explore the vast design space, enabling the discovery of innovative and optimised control structures.
- **Rule-Based Diagnosis Systems:** Nearly all rule-based diagnostic systems can be modelled as symbolic frameworks and refined using the proposed methodology. This applies to decision systems across various domains, such as healthcare and manufacturing, where improvements can significantly enhance their performance.

1.4 Structure of the Thesis

As shown in Figure 1.7, this PhD thesis is organised into eight main chapters. This chapter serves as the introduction, which includes the contextualisation of the theme and its relevance, the clearly defined goals, an outline of the document's structure, and a summary of the publications produced during the course of the thesis.

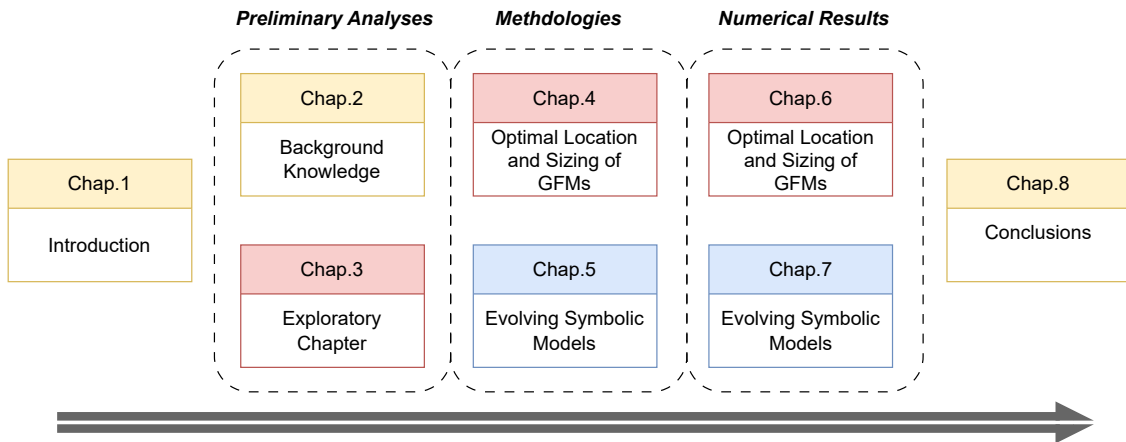


Figure 1.7: Visual representation of thesis structure.

Chapter 2 introduces the key concepts necessary to understand the problem statements and the corresponding state of the art. This includes fundamental ideas related to dynamic security, dynamic security assessment, issues concerning GFM control, and the placement of GFM-controlled converters. Following this, Chapter 3 serves as an exploratory section aimed at better understanding the impact of the GFM location on system stability and offering suggestions for optimally positioning GFM converters.

1.5. Publications

Afterwards, Chapter 4 and Chapter 5 present the methodological part of this thesis. Chapter 4 introduces a robust methodology for the optimal placement and sizing of GFM converters, outlining the problem formulation and the techniques employed to address it. Additionally, it discusses the placement of GFM converters with a focus on stability considerations across multiple stability classes. In its turn, Chapter 5 introduces a novel methodology for developing interpretable data-driven models for dynamic security assessment, referred to as the Evolving Symbolic Model. This chapter covers the fundamental principles of ESMs, their evolutionary process, their application in security classification and in the definitions of preventive control actions.

In Chapters 6 and 7, the numerical results derived from the application of the previously introduced methodologies to various case studies are presented and thoroughly discussed. Chapter 6 assesses the effectiveness of the proposed methodologies for the placement and sizing of GFM converters, specifically through their application to the modified version of the IEEE 39 Test System. Chapter 7 validates the use of the ESM methodology for dynamic security assessment, utilising the Madeira Power System as a test case.

The thesis is then closed with Chapter 8, where the main outcomes that resulted from this work are outlined, the research questions are answered, and the related future work is described.

This thesis comprehensively explores the dynamic security of power systems with a significant integration of renewable energy sources. Certain chapters specifically focus on the optimal location of grid-forming resources, while others delve into the topic of interpretable online dynamic security assessment. In Figure 1.7, where the structure of this thesis is outlined, chapters addressing both themes are highlighted in yellow, those focusing on optimal location are marked in red, and chapters dedicated to online DSA are represented in blue. Although this visual representation aims to facilitate the reader's navigation through the thesis, it is important to recognise that the thesis is a cohesive and continuous body of work, to be understood as such.

Three appendices complement the main document. Appendix AA outlines the parametrisation and structure of several dynamic models utilised in this work. Appendix B details the mathematical derivation employed to define the damping constant of the virtual synchronous machine, presented in Chapter 3. Appendix C provides a comprehensive illustration of one of the decision trees used as a benchmark in Chapter 7.

1.5 Publications

The work conducted during this PhD thesis has led to numerous publications in reputable Q1/Q2 journals and reference conferences within the field of power system stability. A list

1.5. Publications

of these publications is provided below. Additionally, throughout the course of this thesis, parallel research was also undertaken in both power system stability and symbolic learning. The resulting publications are also detailed below.

Journal Publications:

- F. S. Fernandes, R. J. Bessa, J. P. Lopes, Evolving symbolic model for dynamic security assessment in power systems, *Journal of Modern Power Systems and Clean Energy* (2025).
- F. Fernandes, J. P. Lopes, C. Moreira, Multi-criteria Placement and Sizing of Utility-Scale Grid Forming Converters, *International Journal of Electrical Power & Energy Systems* (2025).
- F. Fernandes, J. P. Lopes, C. Moreira, Location of grid forming converters when dealing with multi-class stability problems, *IET Generation, Transmission & Distribution* (2025).
- Lucas Bost, Francisco S. Fernandes, Ricardo J. Bessa, AI-assistant for intelligent design of controllers in power systems, *Sustainable Energy, Grids and Networks* (2025).
- F. J. Ribeiro, J. A. P. Lopes, F. S. Fernandes, F. J. Soares, A. G. Madureira, The role of hydrogen electrolyzers in frequency related ancillary services: A case study in the Iberian peninsula up to 2040, *Sustainable Energy, Grids and Networks* (2023).

Conference Publications:

- F. Fernandes, J. P. Lopes, C. Moreira, Multi-class stability analysis of the grid-forming placement problem, in: *2023 IEEE Belgrade PowerTech*, IEEE, 2023, pp. 1-6.
- F. Fernandes, J. P. Lopes, C. Moreira, Combining batteries and synchronous condensers: the case study of Madeira island, in: *8th International Hybrid Power Plants & Systems Workshop (HYB 2024)*, Vol. 2024, IET, 2024, pp.58-64.
- F. Fernandes, J. P. Lopes, Assessment of frequency stability behaviour regarding inertia reduction due to high renewable integration in the Iberian system, in: *11th Bulk Power Systems Dynamics and Control Symposium (IREP 2022)*, arXiv preprint arXiv:2301.06360 (2023).
- L. Bost, F. Fernandes, R.J. Bessa, AI-assistant for intelligent design of controllers in power systems, *IREP 2025*.
- F. J. Ribeiro, J. A. P. Lopes, F. S. Fernandes, F. J. Soares, A. G. Madureira, The role of hydrogen electrolyzers in the frequency containment reserve: A case study in the Iberian

1.5. Publications

peninsula up to 2040, in: 2022 International Conference on Smart Energy Systems and Technologies (SEST), IEEE, 2022, pp. 1-6.

- R. J. Bessa, F. Lobo, F. Fernandes, B. Silva, Data augmented rule-based expert system to control a hybrid storage system, in: 2024 IEEE 22nd Mediterranean Electrotechnical Conference (MELECON), IEEE, 2024, pp. 814-819.

In addition to these publications, a patent was also submitted to the European Patent Office (EPO) in 04.02.2025, related to the evolving symbolic model method for dynamic security assessment (proposed in Chapter 5).

- Patent Application (P1696.4 PP). Method for providing a dynamic security assessment of stability of a power network and model thereof. Public Inventors: F. Fernandes, R. J. Bessa, J. P. Lopes; Provisional Patent Application (PPP) no. PT 119668, 30.08.2024, Instituto Nacional da Propriedade Industrial (INPI). European Patent Application (EP) no. EP 25155896.1, 04.02.2025, European Patent Office (EPO).

Background Knowledge on Dynamic Security and Grid-Forming Control

The main goal of the present chapter is to review the most important concepts essential to the scientific and technical contextualisation of the thesis theme.

The first section begins with a concise overview of power system dynamic security and stability, outlining fundamental concepts related to security and stability, and examining how these are impacted by the ongoing large-scale energy transition.

Next, the chapter delves into grid-forming control and its counterpart, grid-following control, providing an in-depth discussion of their methodologies, implementations and real-world applications. Following this, the focus shifts to a review of existing research on the placement of GFM converters, exploring various assessments and methods for their optimal location and sizing.

The third section addresses dynamic security assessment, detailing its definition, traditional implementations, the application of data-driven methods, and the necessity for interpretable DSA tools. Finally, the chapter concludes with a summary of the open research gaps that motivate this work.

2.1 Fundamental Concepts of Stability and Dynamic Security

Security of a power system refers to the degree of risk in its ability to survive imminent disturbances (contingencies) without interruption of customer service [24]. For this reason, the goal of security analysis is to assess the power system's robustness against imminent distur-

2.1. Fundamental Concepts of Stability and Dynamic Security

bances, which is influenced by both the system's operating condition and the likelihood of the disturbances. Within this context, a disturbance is considered to be an event that interrupts the normal system operation, such as load variations, generation outages, and short circuits in transmission lines.

For a power system subjected to changes — small or large — it is important that when the changes are completed, the system settles to new operating conditions such that no physical constraints are violated (e.g., branch overloads and voltage limits violation). This implies that, in addition to the next operating conditions being acceptable, the system must survive the transition between the pre-disturbance state and the post-disturbance state. The subset of security that concerns the transition between these two states is called dynamic security and has system stability as the main analysis criterion.

In addition to stability, the system's dynamic security assessment often includes various criteria that may differ based on the specific characteristics of the system being analysed. Examples of these criteria include: 1) Voltage excursions (either dips or rises) that exceed specified threshold levels and durations. 2) Frequency excursions (either dips or rises) that surpass designated threshold levels and durations. 3) Violations of relay margin criteria, if the relay margin is breached for a duration longer than a specified maximum time following a disturbance [25]. While the terms dynamic security and stability are frequently used interchangeably, it is important to note that stability represents a narrower condition and is merely one of the criteria influencing dynamic security. Therefore, this equivalence is often misleading.

To be secure, the system must be stable but must also be secure against other contingencies that would not be classified as stability problems, e.g., damage to equipment such as an explosive failure of a cable, a fall of transmission towers due to ice loading, or sabotage. As well, a system may be stable following a contingency, yet insecure due to post-fault system conditions resulting in equipment overloads or voltage violations [24]. System security can also be differentiated from stability based on its consequences. For instance, two systems may both be stable and have similar stability margins, but one may be considered more secure if the consequences of instability are less severe [24].

Power system stability is the ability of an electric power system, for a given initial operating condition, to regain a state of operating equilibrium after being subjected to a physical disturbance, with most system variables bounded so that practically the entire system remains intact [24]. This concept is illustrated in Figure 2.1 through a well-known analogy involving a small ball being flicked inside and outside a half-sphere. The distance from the centre of the half-sphere serves as the stability variable. In a stable system, when the ball is flicked, it will gradually return to its original position, which keeps the distance to the centre bounded. In contrast, in an unstable system, the ball moves further away from its initial position, leading

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to an unbounded increase in the distance from the centre.

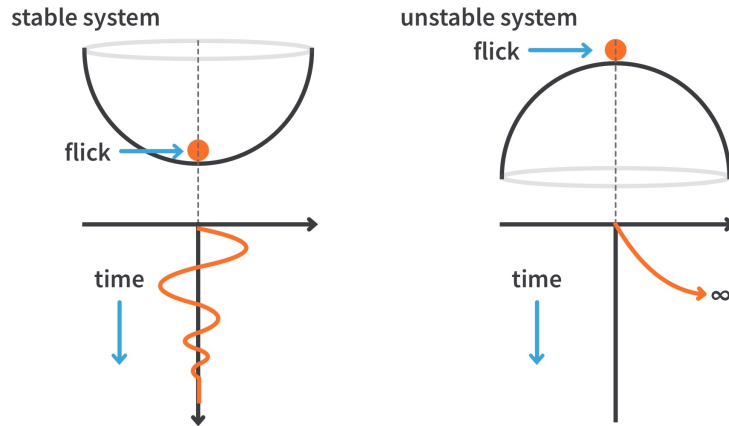


Figure 2.1: *Illustration of stability concept [26].*

While the definition provided before pertains to interconnected power systems, it is essential to acknowledge that the stability of individual system components — such as synchronous generators, converters, and loads — is also relevant [24]. Their loss of stability can occur independently of the overall system. For example, a distant generator may experience a loss of synchronism without triggering cascading instability in the main system; similarly, a motor may run down and stall without affecting the stability of the larger network. Understanding this phenomenon is fundamental to the analysis of large power systems.

2.1.1 Stability Classes

Power system stability constitutes a singular issue; however, the various forms of instability that a power system may experience cannot be fully understood or effectively managed by approaching it as a single problem. Due to the high dimensionality and complexity of stability issues, it is beneficial to adopt simplifying assumptions in order to analyse specific types of problems, utilising an appropriate level of detail in system representation and suitable analytical techniques. The analysis of stability — encompassing the identification of key factors contributing to instability and the development of methods to enhance stable operation — is significantly aided by classifying stability into relevant categories [24]. Therefore, classification is essential for a meaningful and practical analysis and resolution of power system stability challenges.

Originally [24], system stability was divided into 3 main categories: Rotor Angle Stability, Frequency Stability, and Voltage Stability. However, since the original definition, the system composition has changed significantly with the introduction of converter interface generation (CIG). The increasing share of CIGs in the power generation mix leads to new types of

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power system stability problems, which arise due to the different dynamic behaviour of CIGs compared to that of conventional synchronous generators. Practically speaking, these issues emerge due to interactions between CIG controls, reduction in total power system inertia, and limited contribution to short circuit currents from CIG during faults. Hence, two different stability classes have been introduced in [15] to account for these effects, namely converter-driven stability and resonance stability, as can be seen in Figure 2.2.

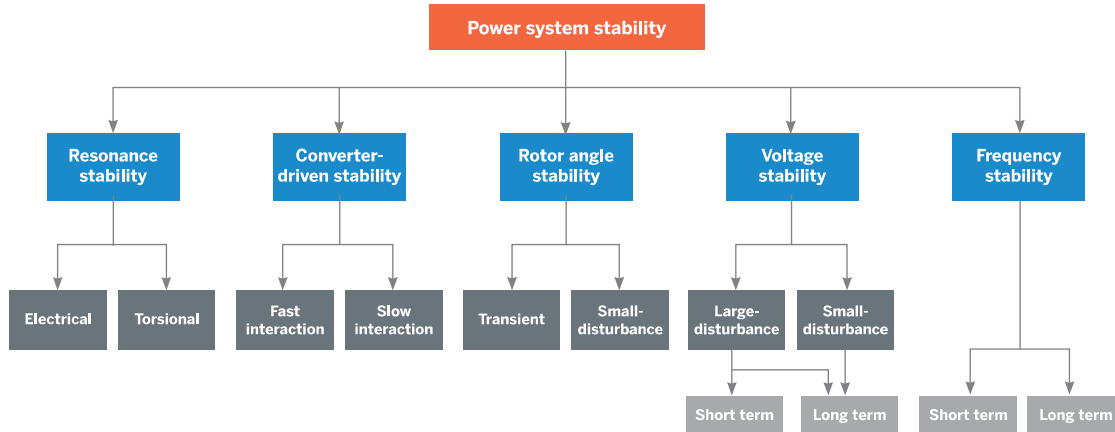


Figure 2.2: Schematic of Power System stability classes/categories [16].

Due to its importance to the work developed in this thesis, a concise definition of each stability class — highly inspired by [24] and [15] — is provided next, followed by an illustrative example of how stability loss may materialise for each category. The category of resonance stability is purposely left out as it comprises rare phenomena that fall outside of this work's scope. Still, the interested reader is referred to [27] and [28].

- **Rotor angle stability** is concerned with the ability of the interconnected synchronous machines in a power system to remain in synchronism under normal operating conditions and to regain synchronism after being subjected to a small or large disturbance.

The examination of a power system's capability to sustain synchronism under small disturbances is classified under small-disturbance (or small-signal) rotor angle stability. The resulting instability can manifest in two forms: a) an increase in rotor angle through a non-oscillatory or aperiodic mode due to insufficient synchronising torque, or b) rotor oscillations with amplitudes that progressively increase as a result of inadequate damping torque.

In contrast, the analysis of the system's ability to maintain synchronism under severe disturbances, such as a short circuit on a transmission line, falls under large-disturbance rotor angle stability or transient stability. The instability in this context is characterised

2.1. Fundamental Concepts of Stability and Dynamic Security

by increasing angular swings of certain generators, ultimately leading to their loss of synchronism with other generators. Figure 2.3 illustrates the behaviour of the rotor angle and speed of the system's synchronous machines during an event that leads to a loss of transient stability.

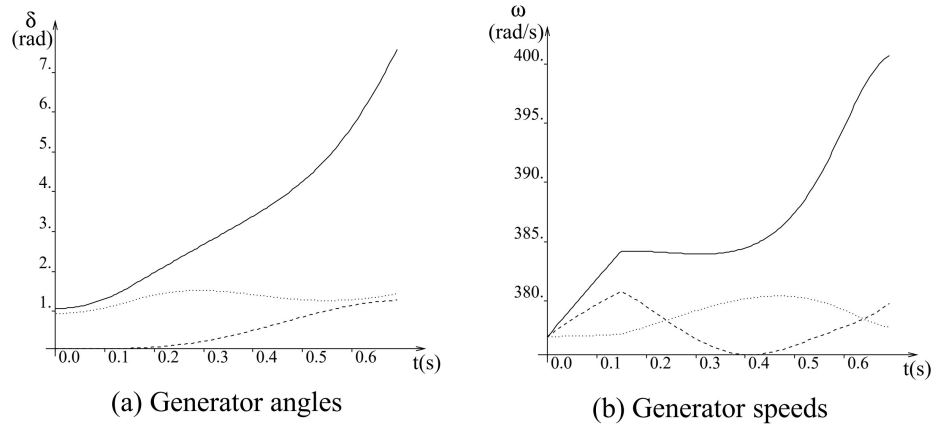


Figure 2.3: Example of transient stability (large-disturbance rotor angle stability) loss [29].

- **Frequency stability** refers to the ability of a power system to maintain a steady frequency following a severe system upset resulting in a significant imbalance between generation and load. It depends on the ability to maintain/restore equilibrium between system generation and load, with minimum unintentional loss of load. The instability that may result occurs in the form of sustained frequency swings leading to tripping of generating units and/or loads. Figure 2.4 illustrates the typical trajectories of the power system frequency after a sudden generation loss, marking a threshold for stability loss corresponding to the system load's tripping.

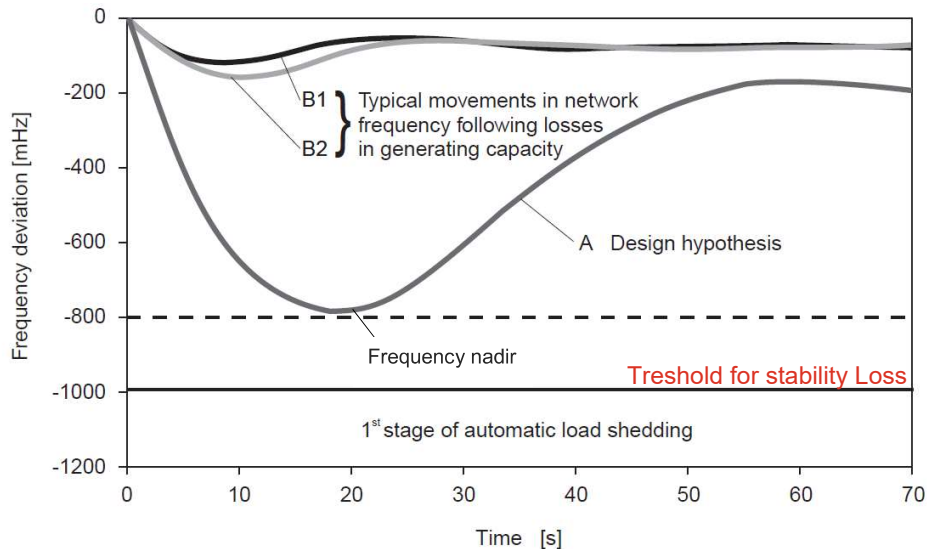


Figure 2.4: Illustration of frequency stability analysis [30].

2.1. Fundamental Concepts of Stability and Dynamic Security

- **Voltage stability** refers to the ability of a power system to maintain steady voltages close to the nominal value at all buses in the system after being subjected to a disturbance. It depends on the ability of the combined generation and transmission systems to provide the power requested by loads. This ability is constrained by the maximum power transfer to a specific set of buses and linked to the voltage drop that occurs when active and/or reactive power flows through the inductive reactances of the transmission network. The driving force for voltage instability is usually the loads.

Short-term voltage stability involves dynamics of fast-acting load components such as induction motors, electronically controlled loads, HVDC links, and inverter-based generation. The instability that may result occurs in the form of a progressive fall of the voltage or in oscillatory behaviour of constant or increasing amplitude [31, 32]. Long-term voltage stability involves slower-acting equipment such as tap-changing transformers, thermostatically controlled loads, and generator current limiters. It usually occurs in the form of a progressive reduction or increase of voltages at some network buses.

Figure 2.5 illustrates the behaviour of the system voltage near the source of instability during some of the different voltage instability phenomena that were just discussed.

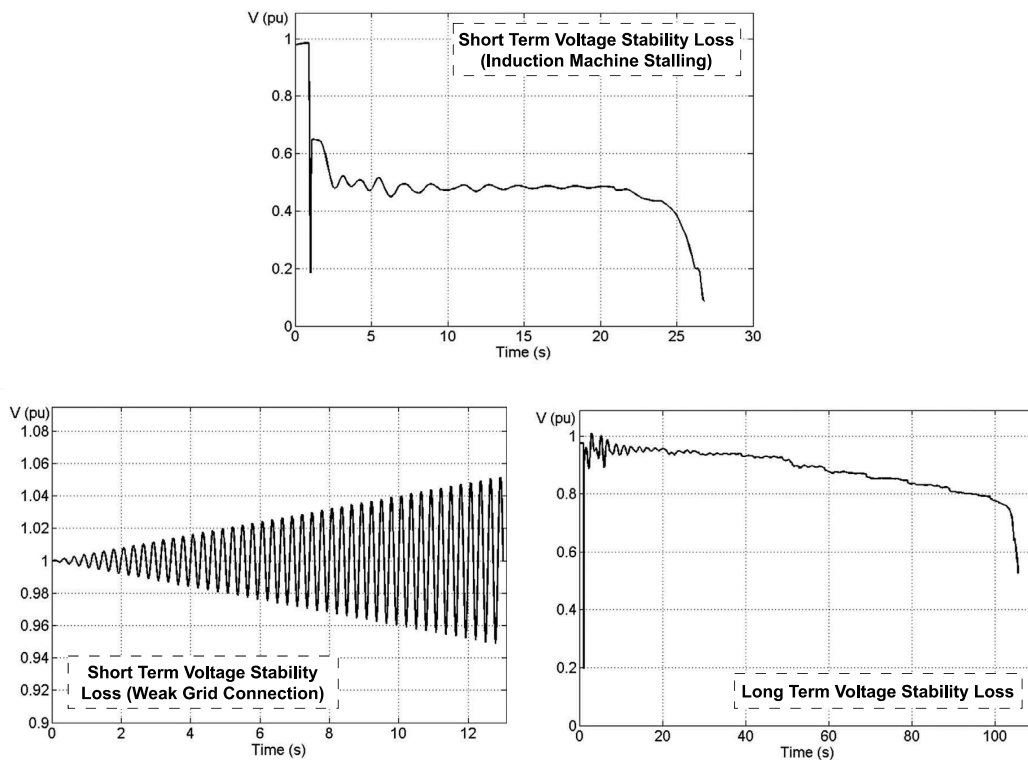


Figure 2.5: Typical manifestations of voltage instability [31].

2.1. Fundamental Concepts of Stability and Dynamic Security

- **Converter-driven Stability** is related to the cross-coupling of CIG controls with both the electromechanical dynamics of machines and the electromagnetic transients of the network, which leads to unstable power system oscillations over a wide frequency range.

Fast interaction converter-driven stability involves system-wide stability problems driven by fast dynamic interactions of the control systems of power electronic-based systems, such as CIGs, HVDC, and FACTS, with fast-response components of the power system, such as the transmission network, the stator dynamics of synchronous generators, or other power electronic-based devices. Instability arises in the form of power system oscillations with a frequency in the range of tens to hundreds of Hz and possibly into kHz.

Slow interaction involves system-wide instabilities driven by slow dynamic interactions of the control systems of power electronic-based devices with slow-response components of the power system, such as the electromechanical dynamics of synchronous generators and some generator controllers. Instability arises in the form of power system oscillations with a frequency smaller than 10 Hz. This category of converter-driven instability can be similar to voltage stability in the sense that maximum power transfer between the converter and the rest of the system, i.e., a weak system, can be the root cause of instability. The two mechanisms differ insofar as loads drive voltage instability, while converter-driven instability is associated with the power electronic converter controls.

Figure 2.6 illustrates the phase-locked loop (PLL)'s state variables behaviour during the loss of synchronism of a converter's PLL as a consequence of a terminal voltage sag. Instability phenomena that fit into the category of slow interaction converter stability.

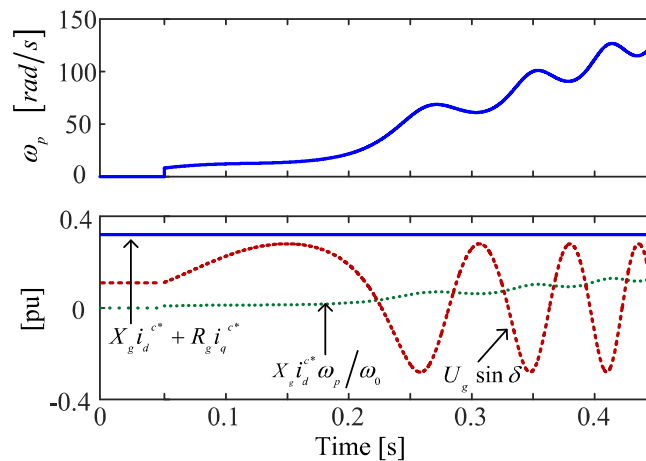


Figure 2.6: Illustrative example of loss of slow interaction converter-driven stability, namely, the loss of synchronism of the PLL of a voltage source converter (VSC) [33].

2.1. Fundamental Concepts of Stability and Dynamic Security

2.1.2 Security in the new Power System Paradigm

To ensure that a power system is sufficiently reliable, that is, that there is an acceptable probability of it operating satisfactorily over the long run, the system must be: (1) properly designed with security as a primary consideration; (2) monitored and controlled during operation to ensure sufficient security margin exists at all times; [25]

The widespread integration of converter-interfaced renewable energy sources (Wind, Solar), alongside the decommissioning of conventional fossil-fuelled power plants, is transforming traditional power systems into highly flexible and controllable networks. However, this shift has introduced significant stability challenges in systems that were initially designed with synchronous machines at their centre [16], such as the reduction of the overall synchronous inertia, damping and short-circuit currents [15, 17]. These changes greatly reduce the original system's dynamic security margins, compromising the initial design of the system, which had security as a primary concern.

For economic reasons, it is impossible to completely redesign the system, with security as a priority; hence, system operators have to adopt other intelligent ways to counterbalance the nefarious effects that the large-scale introduction of RES may bring to the system's dynamic security [14]. Often, these include the adoption of smarter and more automated operation methods and the implementation of more capable and intelligent control solutions.

Throughout the years, different control solutions have been proposed to cope with the emerging power system stability needs [16, 19], ranging from advanced inverter controls (Synthetic inertia and Fast frequency response), synchronous condensers, and grid-forming capable solutions. Due to its fast grid supporting response, ability to work in grids with no minimum system strength requirements, and voltage/frequency forming capability, grid-forming capable converters are seen by the industry as a promising solution to enhance the future system stability [20, 19]. Therefore, the grid-forming control and its traditional counterpart (grid-following) are addressed in detail in the following sections 2.2 and 2.3;

In parallel, the large-scale integration of renewable energy has also complicated the task of monitoring system security. Increased instability, a higher number of interacting DER elements, and the growing need to assess numerous real-time scenarios due to the variability and uncertainty of RES have significantly escalated the complexity of online Dynamic Security Assessment. Consequently, a comprehensive discussion on Dynamic Security Assessment and its associated challenges can be found towards the end of this chapter in Section 2.5.

2.2 IBRs Control Methodologies - Grid-following and Grid-Forming

In general, inverter-based resources can be operated under one of two control implementations [34]: grid-following (GFL), which is the most common and widely adopted in today's power grids, and grid-forming, which is better suited for operation in weak grids and has primarily been utilised in isolated power systems, such as microgrids and the networks of islands [35, 21].

The main differences between these two types of control are related to controller implementation, grid synchronisation, black start capability, and response to changes in the grid [34, 36]. Throughout this section, these two main control implementations will be discussed, and their differences will be explored.

2.2.1 Basic Principles

As the name suggests, the grid-following control rests on the idea that the IBRs are designed to follow the grid voltage [34], meaning that the converter modulated voltage is adjusted according to the grid voltage, in order to keep the IBR injected current at a set-point value [36]. The current set point value is defined according to the Active and Reactive Power that the converter is desired to inject in the grid, since that is the main objective in this type of control [34].

In the grid-forming case, the primary objective is regulating the voltage magnitude and the frequency (or voltage phase angle) of the grid [34]. Therefore, the modulated voltage is fixed freely and independently of the grid voltage [36], leveraging a power control loop to define the frequency/angle and voltage magnitude according to the measured active/reactive power [16].

Due to this control principle, a GFL-controlled IBR can be characterised as a current source in the transient domain, whereas a GFM-controlled IBR can be seen as a voltage source, as shown in Figure 2.7. This distinction arises from the current-driven control of GFL, in contrast to GFM's maintenance of an internal voltage phasor, with both magnitude and frequency determined locally [34]. This assumption holds true in the transient domain until the converter current limiting control steps into action [16], after that, the modulated voltage needs to be controlled so as to ensure the current does not pass the converter's overcurrent capacity.

2.2. IBRs Control Methodologies - Grid-following and Grid-Forming

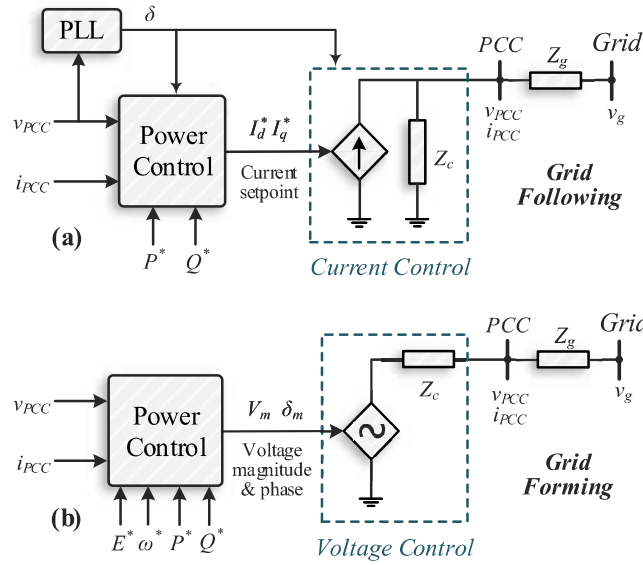


Figure 2.7: Approximation of a GFL and GFM controlled converter in the transient domain[34].

2.2.2 Synchronisation with the Grid

In [37], the author defines synchronisation as: "The process of matching a source (generator) with an existing power system, making it possible to operate these systems in parallel. During this process, the voltage, frequency, and phase angle of the generator are synchronised with the voltage, frequency, and phase angle of the power system". In the two types of controls under analysis, the synchronisation with the grid is achieved in a different way:

- In grid-following converters, the grid synchronisation is achieved using a PLL, which estimates the time domain angle of the grid voltage and the electrical frequency [36]. This will then allow for the correct calculation of the converter reference currents whose magnitude and angle with respect to the grid voltage phasor are properly modified by outer control loops so as to inject the required amount of active and reactive power. Depending on the adopted control frame (abc or dq), the PLL estimation angle may be used in the Park transform rather than in the current reference generation [36].
- In case of the grid-forming control, the way to synchronise is fundamentally different, since a self-synchronisation is achieved thanks to the power control loop, much like a synchronous generator. Here, an estimate of the grid angle is not compulsory; however, it can be used depending on the type of grid-forming control [36, 34].

2.2. IBRs Control Methodologies - Grid-following and Grid-Forming

2.2.3 Methods of GFM and GFL Control.

According to the way the power set-points are controlled, two sub-categories of the GFL control exist: grid-feeding and grid-supporting [34]. The grid feeding control was envisioned for grids where the IBR penetration was marginal; therefore, the active and reactive power could be set to remain constant, even in the case of a grid disturbance. However, as the IBR penetration grew, TSOs understood the new complications associated with voltage and frequency control and started to demand active and reactive power support from IBR [38, 39], which justified the need for the grid-supporting type of control.

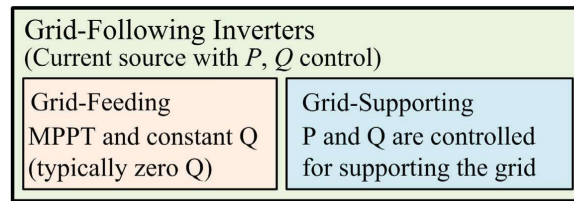


Figure 2.8: Types of grid-following controls [34].

In regard to the grid-forming control methods, multiple methodologies exist, and many others are still being studied. The ones that have been largely analysed are either based on a droop control or in a synchronous-machine based [16, 34, 35].

Droop control was first proposed in [40] and is based on the typical governor control of turbines in synchronous units. As in conventional power stations, the droop control of GFM IBRs allows for the parallel operation of multiple converters, and therefore could be suitable for large-scale system integration. Angle-based droop and frequency-based droop are the most common controls referred to in literature, for the active power control, while for the reactive power, the most common is a simple voltage magnitude droop [34].

Since droop control does not provide a significant response in the inertial time frame, other types of controls that mimic such a response of synchronous generators have been proposed. These controls, denoted in [34] as Synchronous-machine-based, enable not only a synthetic inertial response but also a damping response, which can be tuned, unlike in synchronous generators, allowing for different types of adaptive and intelligent controls [41].

In [34], the authors performed an extensive review of the main grid-forming control methods, and they presented the diagram shown in Figure 2.9 as a good representation of the state of the art.

2.2. IBRs Control Methodologies - Grid-following and Grid-Forming

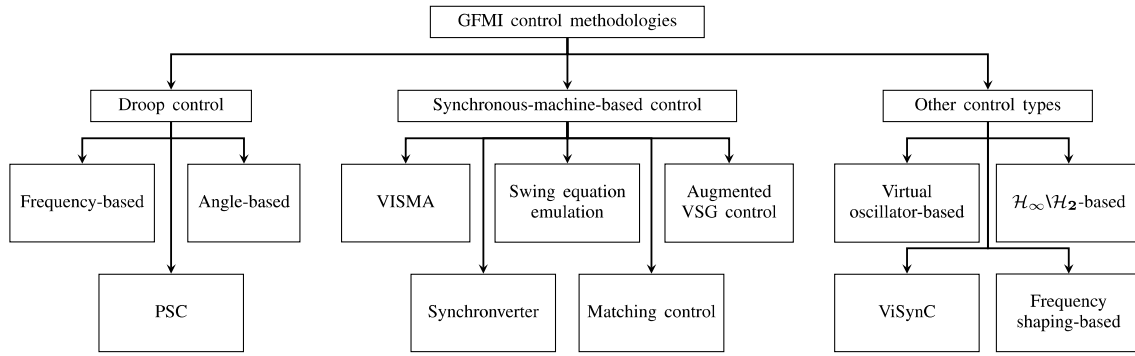


Figure 2.9: Types of grid-forming controls (based on [34]).

2.2.4 Response to Changes in the Grid.

The way GFM and GFL controlled converters react to grid disturbances is one of the major differences between them. Once a sufficiently big grid disturbance happens in the electrical surroundings of a converter, then the voltage and current at the point of common coupling (PCC) will experience changes in magnitude and frequency. A converter with grid-following capabilities of the grid supporting type will recognise these changes through voltage and current measurements, and then the power control loops will respond based on them, which will inevitably result in some form of time delays associated with the measuring and control actions [42]. Conversely, if the converter has GFM capabilities, an instantaneous power response can be achieved. This happens because the converter modulated voltage is not instantaneously changed; therefore, once the voltage angle and magnitude in the PCC changes, the transferred power will be automatically changed [34].

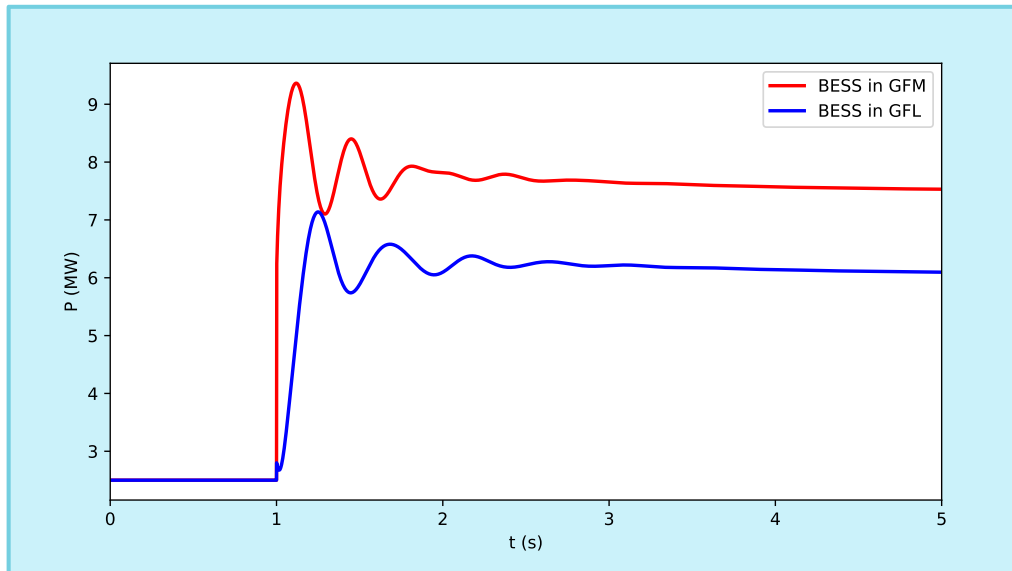


Figure 2.10: Illustrative example of the power response to a load variation of a GFM controlled converter and a GFL controlled converter [43].

2.2. IBRs Control Methodologies - Grid-following and Grid-Forming

This significant difference between the two converter controls is further demonstrated in Figure 2.10, which illustrates the power response of two battery energy storage systems (BESS) (one in GFM mode and the other in GFL mode) integrated into the network of an isolated power system, to a load variation. The GFM control is based on a simple virtual synchronous machine (VSM), while the GFL control's active power loop features a straightforward grid-supporting function utilising power/frequency droop.

2.2.5 Limitations of both Control Methodologies

As mentioned earlier, GFL inverters rely on grid voltage and angle measurements to remain synchronised to the grid [34]. Under weak grid conditions ($SCR < 3$), this method may result in small signal instability, difficulties in tracking the external grid voltage, and a lack of operation in the full power range [36, 44]. Such a problem is greatly reduced in GFMs with the possibility of self-synchronisation and the absence of dependency on grid signals for synchronous operation [21].

Independent of the type of grid-following control, the knowledge of the fundamental frequency of the grid voltage or angle is needed at any time for the correct calculation of the converter reference currents [36] or in the Park transform. Therefore, in case of a disturbance, a measurement or control time delay is always present before the power response of the converter, something that represents a limitation in the case of supporting type implementations such as the "synthetic inertia" [36].

As explained earlier, after a disturbance, a GFM will provide a faster power response when compared to the case of GFL. However, since this response may be rapid and of a significant magnitude, concerns on current limitations and stability with rapid responses need to be considered [45, 36].

Nevertheless, the GFM's ability to provide constant/committed power, inertial response, and fault currents results in the need for an energy buffer in the VSC primary [34, 16] or in a deloaded operation of the primary resource [46]. Other than the need for some type of energy storage, when a GFM control is implemented, there is also a need for an over-sizing of the converter, to allow some overcurrent capability in the switching devices [16, 34]. Both these characteristics make grid-forming converters expensive and less attractive for widespread use.

Regardless of the type of control employed, the overcurrent capacity of inverters remains a significant limitation for inverter-based resources (IBRs). Even when notably oversized (for example, at 2 p.u. [47]), IBRs still produce considerably lower fault currents [48] compared to synchronous machines, which can deliver currents in the range of 5 p.u. or larger [49]. This short-term current response is crucial for the effective operation of protection systems, partic-

2.3. Implementation of basic Grid-following and Grid-forming Control

ularly in detecting and locating faults, supplying in-rush currents during black start scenarios, and enhancing the stiffness of the system voltage [16].

2.3 Implementation of basic Grid-following and Grid-forming Control

In this section, a brief review of the most critical control loops in each type of control is performed. For that purpose, the typical control configuration of GFL-controlled converters is first discussed, and then the particularities of GFM implementations are detailed. Additionally, examples of the application of GFM technology in real transmission systems are also discussed at the end of the section.

2.3.1 Grid-Following

As can be seen in Figure 2.12, the grid-following control is typically composed of three major control blocks (ignoring low-level control and measurement loops): the PLL, the current control loop, and the power control loop, also known as outer loop controls (active and reactive power). The functions and particularities of each block are discussed next.

- **The Phase-Locked Loop (PLL):** enables the synchronisation between the converter and the AC grid [36, 50]. The PLL provides an estimation $\tilde{\omega}_g$ of the voltage phase angle (θ_g) and frequency of the voltage at the Point of Common Coupling (PCC). In essence, this estimation is reached by changing the $\tilde{\theta}_g$ value until the quadrature component of the measured voltage is zero, that can be proven to ensure that $\tilde{\omega}_g = \omega_g$, $\tilde{\theta}_g = \theta_g$, during stationary behaviour. A simple implementation of the PLL is shown in Figure 2.11.

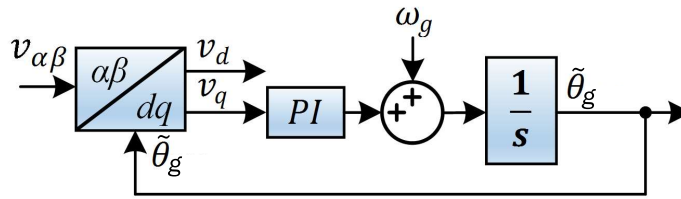


Figure 2.11: PLL control implementation (edited from [51]).

- **The current control loops:** keeps the current dq components at their reference by adjusting the voltage references delivered to the lower level control. For this, a PI controller with decoupling terms is typically used, avoiding high transient coupling between both components [36].
- **The outer control loops:** defines the dq current references. Depending on the system

2.3. Implementation of basic Grid-following and Grid-forming Control

in which the VSC is included, different controls will be needed, such as voltage control, frequency control, and DC bus voltage control; active and reactive power control [52] tend always to be present, as shown in Figure 2.12.

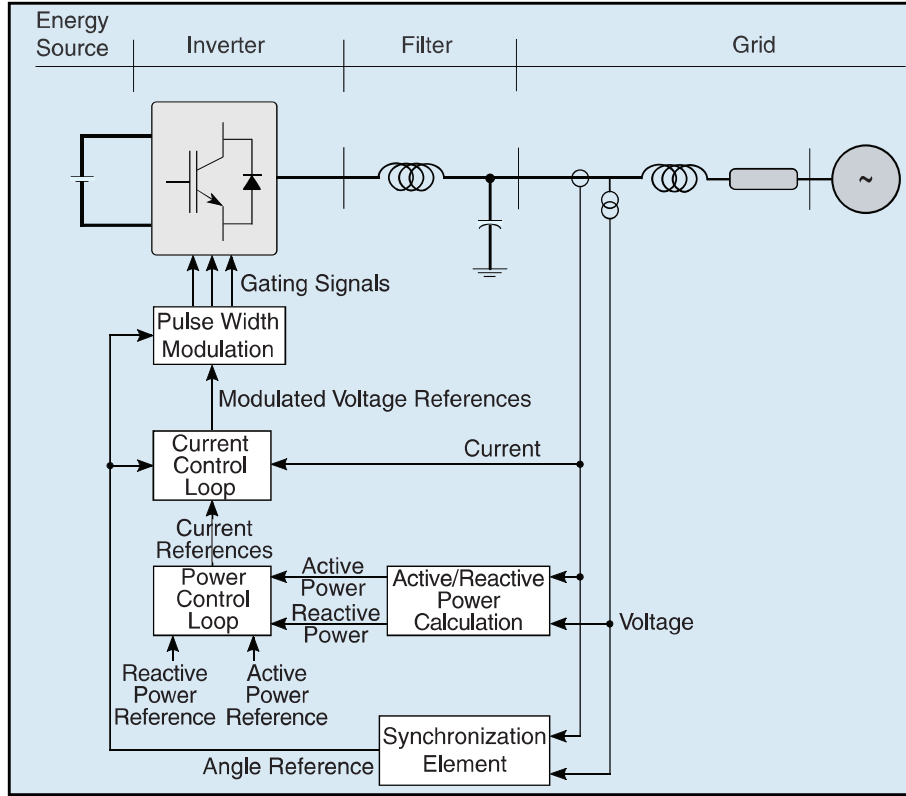


Figure 2.12: Basic Structure of Grid-following control [21].

2.3.2 Grid-Forming

As discussed earlier, various grid-forming control methodologies have been proposed. However, for simplicity, this section will focus exclusively on PLL-free implementations. Figure 2.14 illustrates the two fundamental components present in these implementations: the primary control loop and the inner control loops.

- **The primary control loop**, also known as outer control loop is responsible for the active and reactive power control of the converter, as well as the synchronisation of the converter to the grid, which is mostly performed by the active power control loop, since the voltage magnitude cannot drift too much from its nominal value.

Figure 2.13 depicts 2 possible control implementations for the primary control loop, a virtual synchronous machine and a droop control with a low pass filter. Two implementations that can be proven to be mathematically equal [34].

2.3. Implementation of basic Grid-following and Grid-forming Control

If the primary control is of the frequency-based droop type, the frequency of the modulated voltage wave is adjusted based on the droop value and the difference between the reference power and the measured value. A low-pass filter is typically employed to eliminate high-frequency harmonics [34]. In the case of a simplified swing-based virtual synchronous generator, the frequency of the modulated voltage wave is adjusted according to the parameters of the swing equation and the difference between the reference power and its measured value.

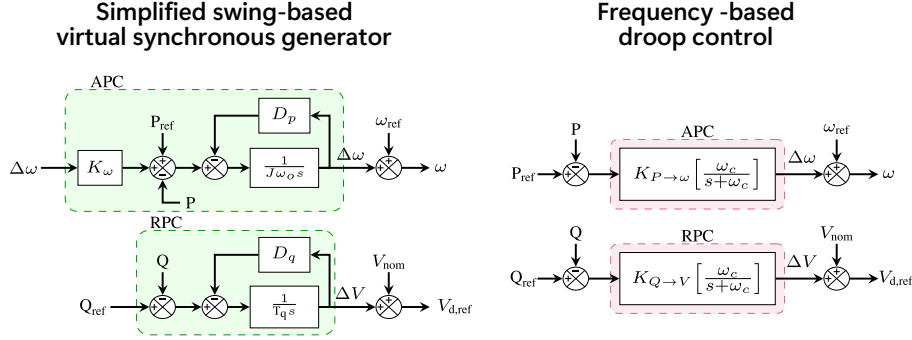


Figure 2.13: Comparison between two primary control loop implementations for GFM controlled converters [34].

- **The internal control loops** are tasked with producing the converter-modulated voltage references from the primary control loop.

In certain implementations, voltage references derived from the primary loop are directed into an inner voltage control loop, which then generates converter current references. Following this, an inner current control loop determines the converter's modulated voltage references. This methodology is termed cascade control [21]. Within this framework, the implemented current limiting scheme typically consists of a straightforward saturation loop, commonly referred to as the Current Saturation Algorithm (CSA) [53].

Although the cascade voltage-current control structure is well-documented in existing literature, recent studies have explored the possibility of eliminating the traditional current and voltage control loops. Instead, voltage references produced by the primary control loop are directly fed into the converter's pulse width modulation (PWM) generator, bypassing the current and voltage control loops. To safeguard the switches against overcurrent, a virtual impedance is employed in the voltage reference signal path [41], working as the current limiting scheme.

2.3. Implementation of basic Grid-following and Grid-forming Control

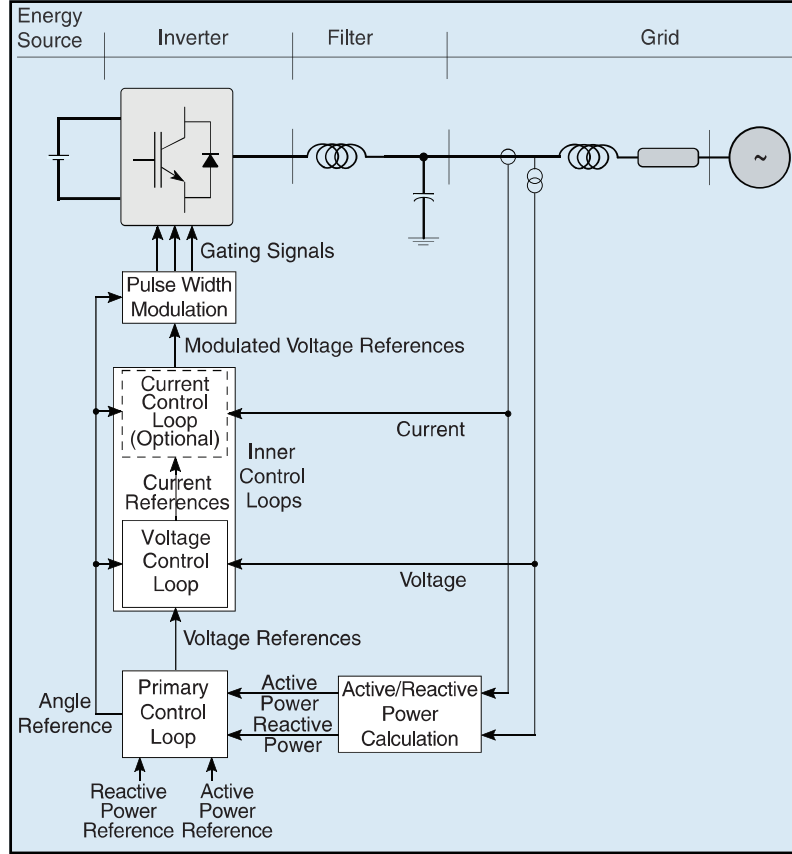


Figure 2.14: Basic structure of Grid-Forming control [21].

The implementation differences addressed during this section can be further understood by analysing Figure 2.15, where a GFM and a GFL implementation are presented side by side.

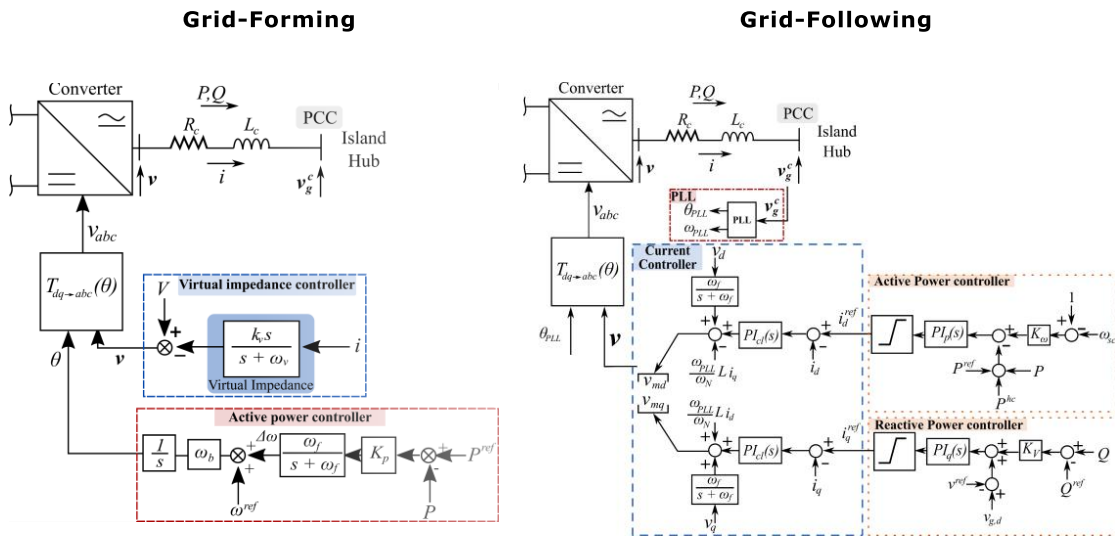


Figure 2.15: Illustration of Grid-forming and grid-following control implementations [50].

2.3. Implementation of basic Grid-following and Grid-forming Control

2.3.3 Real World Applications of GFM Converters in Transmission Systems

Over the last few years, there has been a growing number of support facilities included in power systems that aim at improving the stability of the grid by adopting a control of the GFM type for its converters. These efforts have been mainly conducted within grids with a large penetration of converter-based generation or in systems striving for it.

For a GFM converter to provide its characteristic fast security/stability support, a primary source that offers a readily available energy buffer must exist [16]. In most commercially operational cases, this energy source is a Battery Energy Storage System [21]. The following examples illustrate these systems across various scales, geographies, and contexts:

1. **Large-scale BESS in large power systems** : the 200 MW / 400 MWh Blackhillock BESS in Scotland [54], and the 150MW /194MWh Hornsdale Power Reserve in Australia [55].
2. **Small to Medium-scale BESS in large power systems**: the 15 MWh Bordesholm BESS in Germany [56] and the 25 MW/38 MWh Outer Cape BESS in Provincetown (USA) [57].
3. **BESS in islanded power systems**: the 185 MW / 565 MWh Kapolei Energy Storage in Hawaii [58], the 250 MW/250 MWh GFM BESS in Torrens Islands [59] and the 30 MW / 32.8 MWh BESS fleet in the island of Madeira [60].

A comprehensive list of Battery Energy Storage Systems integrated with converters possessing GFM capabilities can also be found in [61].

HVDC systems equipped with VSC can have one or both terminals controlled in accordance with the GFM paradigm. In this context, several notable implementations are distinguished by their scale: 1) the Kriegers Flak HVDC [62], a 410 MW back-to-back HVDC converter station that interconnects the power grids of Denmark, Germany and three offshore wind farms; 2) the Maritime Link [63], a 500 MW HVDC connection between Newfoundland/Labrador and Nova Scotia that leverages a full VSC bipolar configuration and 3) the Mackinac HVDC [64], a 200 MW scale back-to-back HVDC system using multi-level VSC technology that connects the upper and lower peninsulas of Michigan.

In addition to these various implementations, Transmission System Operators (TSOs) have been actively engaged in defining the specific requirements that characterise Grid-Forming (GFM) capability in power converters. Notably, National Grid in [65] has proposed a non-mandatory technical specification related to Grid Forming Capability to be incorporated into the Grid Code. Furthermore, AEMO in [66] has developed a definition and specification of the core technical capabilities that power electronic devices should possess to be classified as grid-forming inverters. Additionally, MISO in [67] has proposed a requirements framework for

2.4. Location and Sizing of GFM Controlled Converters.

GFM Inverter-Based Resources (IBR) for stand-alone energy storage systems. Similar efforts to define requirements have been undertaken by other associations, such as ENTSO-E [68] and NERC [69].

2.4 Location and Sizing of GFM Controlled Converters.

While Grid-Forming (GFM) converters are widely regarded in the industry as a promising solution for enhancing system stability, their widespread deployment is currently constrained by cost limitations associated with energy storage systems, the converters' overcurrent capacity, and the mechanical wear on primary energy sources (e.g., wind turbines) [21, 70].

Consequently, it is critical to maximise the stability benefits achieved through the integration of GFM converters. This requires careful consideration of multiple factors, such as the optimal location and sizing of the devices [16, 18, 21]. The objective is to enhance overall system stability while ensuring its introduction does not adversely affect grid operations [41, 71].

2.4.1 Studies of the GFM location Impact on the System Security/Stability

Several studies have begun to address this issue, as is the case of [72], where the author examines the ability of a 100% power electronics interfaced system, with variable shares of GFM and GFL, to remain secure in the face of 3-phase faults. Using an equivalent version of the Irish system, the authors show that the minimum share of GFM controllers needed to maintain security is heterogeneous throughout the system, evidencing the spatial nature of converter-driven stability and its relation with the deployed capacity. A similar analysis is performed in [73], where the impact of the location of both GFL and GFM converters on the frequency stability is analysed through a simulation-based approach for the computation of the frequency Nadir and RoCoF. Using a modified version of the 39-bus test system, the authors highlight the importance of the GFM location with respect to the system frequency stability, drawing particular attention to the system topology and regional inertia as critical explanatory variables for such behaviour.

2.4.2 Existing Methods for the Placement of GFM Converters.

In [74], the authors propose a methodology to tune the virtual inertia and damping of multiple grid-spread GFM/GFL, using a H_2 norm optimisation algorithm to improve the system's transient and frequency stability. Sparse allocation of these devices could then be achieved using an l_1 penalty in the optimisation procedure. Alternatively, in [75], the authors propose a methodology for placing grid-forming converters to minimise small signal stability problems raised by the large integration of PLL-based converters in converter-dominated grids. Such methodology involves increasing the smallest eigenvalue of the power network's weighted

2.4. Location and Sizing of GFM Controlled Converters.

and Kron-reduced Laplacian matrix. This work is extended in [76], where the authors present a general method to define the necessary GFM capacity for determining a specific small-signal stability boundary by defining a generalised short-circuit ratio target (gSCR) value. Finally, in [77] an optimisation framework under software-defined grids is proposed to determine the optimal allocation of GFMs and GFLs at each time step of system scheduling. There, frequency stability and small signal stability constraints are simultaneously considered inside a Stochastic Unit Commitment.

Different shortcomings were identified in the just discussed works that address the topic of GFM optimal placement:

1. The problem is frequently addressed under the assumption that dynamic security or stability limits should be maximised [78, 75, 74] or that stiff dynamic security limits should be ensured [76, 77]. This ignores that, under a planning perspective, the simultaneous sizing and placing is a multi-criteria problem, since the system operator wishes to reduce costs while maximising security, like in other power system planning tasks (e.g., preventive/corrective maintenance [79] and transmission expansion planning [80]).
2. Existing studies often discuss fully power-electronic-powered grids, as seen in [75] and [76], which do not adequately represent systems with significant hydro or nuclear shares. These traditional energy sources are expected to remain in operation due to their low emission rates, even as the transition to renewable energy progresses.
3. Often, the system linearisation is used as a foundational tool to evaluate stability, either by performing mathematical manipulation of the resulting matrices (e.g, eigenvalue analysis [75, 76], H_2 norm computation [74]) or by directly using it to obtain the system response to step disturbances [74]. While this approach is valid for small-signal stability analysis, it may not fully capture the system's response to large disturbances, such as short-circuits in transmission lines, which are critical for studying transient stability and dynamic security [24]. In this context, several system non-linearities cannot be fully captured through the system linearisation: 1) the power transfer characteristic of multi-machine systems, a highly non-linear relation that includes the sin of the rotor angle displacements between different machines, and that is deeply correlated with the loss of transient stability [81]; 2) fault-ride through and current limiting controls of converters (GFL and GFM), which strongly affects the current response of converters during the fault, and hence the improvement they can bring to the system transient stability [82, 53]. In the case of GFM converters, in particular, the stability of the converter itself is also affected [45, 53]; 3) saturation loops of other grid spread controls (e.g. AVR, PSSs and missing), which are also known to affect the system's transient stability.

2.5. Dynamic Security Assessment, Base and Future

Therefore, using system linearisation to quantify transient stability-related dynamic security for scoring the fitness of a solution (i.e., the location and size of a collection of GFMs) may lead to erroneous evaluations. This can easily distort the determination of the truly optimal solution, particularly in a large non-linear problem such as the placement and sizing of new GFM converters.

4. There is a common focus on improving a single stability class, disregarding the effects of the GFM introduction on the other stability problems.

2.5 Dynamic Security Assessment, Base and Future

Dynamic Security Assessment can be defined as a group of methodologies for evaluating the stability and quality of the transient processes between the pre-contingency and post-contingency states [25]. In essence, DSA aims to ensure that the system will be stable after the contingency occurrence and that the transients caused by such a contingency will be well-damped, of small amplitude, and with little impact on the quality of service. This type of analysis should be performed for all plausible contingencies [83].

The computations needed to accurately assess the security of a single defined system condition are technically rigorous and require considerable effort. As a result, security assessment has been historically conducted in an offline operation-planning environment in which the steady-state and dynamic performance of the near-term forecasted system conditions are exhaustively determined using tools such as power flow and time-domain simulations. This required performing the security analysis well in advance of the time at which they were expected to occur [25].

In response to the challenges of predicting future operating conditions in recent decades, significant efforts have been made to develop an online approach to security assessment [84, 22]. This approach involves evaluating the system stability in real-time during current operating conditions [85], ensuring that assessments are conducted swiftly enough to trigger automatic control actions or to provide operators with the necessary time to respond [25].

Real word implementations of an online DSA exist/(ed) in the control centres of Brazil (ONS) [86], Australia (NEMMCO), Tokyo (TEPCO) [25], China (State Grid) [87] and Canada (B.C. Hydro) [88].

2.5.1 Traditional Online DSA

Online DSA takes measurements of the system condition, performs security analysis in near real-time, and passes information to the operator or directly onto control systems. To achieve

2.5. Dynamic Security Assessment, Base and Future

this, an online DSA must comprise various sub-modules; the most common online DSA includes modules such as:

- **Measurement:** collects the data required to perform the dynamic security assessment. This data, which can come from other SCADA functions and dedicated PMU units, is used to update the state of the system model continuously and to perform the computations of the security level.
- **Modelling:** corresponds to the different models of the power system, which are used to simulate the system condition or its response to the most relevant disturbances. The type of model required (size, detail, and extent of component models) is very much dependent on which security or stability issues are relevant for the power system in question.
- **Computation:** this module includes a group of assessment techniques that determine the security level of the current system state or after a state change (Security classification) and that propose remedial measures in case of an unacceptable security level.
- **Control:** remedial control actions may be undertaken once security level calculations are completed. These actions can either be initiated by the operator based on the DSA system's recommendations or, though infrequently, automatically executed by the DSA system itself. In this way, the DSA system can become a vital component of specialised protection systems.

The role of these packages in a traditional DSA architecture, amongst other functions such as the reporting and visualisation module, is depicted in the schematic of Figure 2.16.

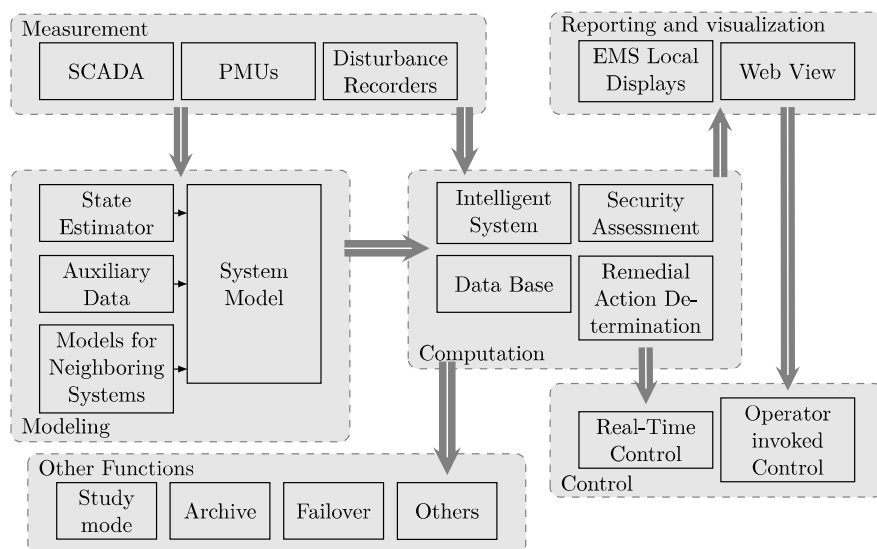


Figure 2.16: Traditional DSA architecture [89].

2.5. Dynamic Security Assessment, Base and Future

While not all online DSA packages are the same, typically, two major functions exist in the computation module: Security Classification and Remedial Action Definition.

Security Classification (SC) is the task of classifying a system operating point within its defined states, this can be as defined by Dy Liacco [90], in one of 5 states (see fig 2.17) or it can be a more narrow classification between secure or insecure [91]. When the SC function identifies a specific contingency or system condition that could potentially result in an insecure situation, it is essential to determine appropriate remedial measures. These measures may be classified as either preventative or corrective control actions, based on their objective: to pre-emptively avoid any violation of the system's security or to restore the system to a secure state after it has entered an insecure situation. Examples of remedial actions are: load shedding, capacitor switching, generator rescheduling, transformer tapping, switching operations, commitment/de-commitment of generators or synchronous condensers [25].

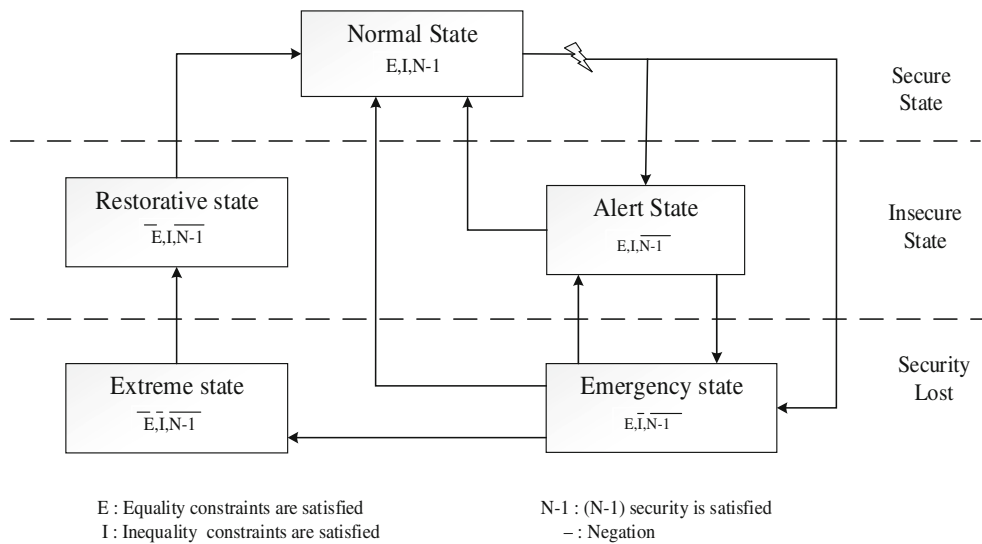


Figure 2.17: Power System Security States [92].

Traditionally, to perform these tasks, operators have relied on comprehensive assessment methods such as time-domain simulations or eigenvalue analysis within a well-established dynamic model. However, both of these methods can be prohibitively expensive in terms of computational resources. As a result, alternative approximate methods, which offer a more limited scope for dynamic security assessment, have also been adopted. These include Single Machine Equivalent Methods [93], energy-based functions for transient stability [94], sensitivity methods for voltage security [95], and Prony Analysis for small signal stability [96]. While approximate methods provide speed advantages, full simulation methods offer the most accurate assessment of security, resolving concerns about the validity of the assumptions made in approximate methods under changing system conditions [25].

2.5.2 DSA in Converter Dominated Power Systems

As previously mentioned, the large-scale integration of RES is leading the power system towards operating conditions characterised by low inertia, high temporal variability of generation, and an increasing number of DER [1]. In control rooms, this change will drastically increase the supervision and control needs of human operators [14], hindering their task of ensuring a secure and reliable operation.

In particular, the DSA task has become more complex as the system is more prone to instability and has more interacting elements of the DER type, whose behaviour depends on the primary source (e.g., wind, solar) and control methodology (grid-following and grid-forming variants). The number of scenarios that must be evaluated online also increases due to the variability and uncertainty of RES. This increased complexity and the widespread presence of power electronics lead to large and complex state models that turn online DSA into a problem too large to be solved using model-based techniques [23]. Despite advances in high-performance computing, resorting to time-domain simulation in model-based approaches still makes the process computationally very demanding for an online task [97].

Data-driven approaches have long been regarded as promising solutions [98] due to their ability to: 1) quickly diagnose system conditions across multiple operational scenarios with reasonable accuracy, and 2) carry out predictions or classifications without requiring an in-depth understanding of the underlying phenomena, which can be challenging to articulate, especially when those phenomena are complex [10]. Consequently, many operators and utilities now consider the integration of technologies such as artificial intelligence (AI) into dynamic security assessment to be a high priority [10].

The advantages of these techniques have often been overshadowed by the "black-box" nature of many AI methods, which can lead to algorithmic aversion among human operators. This scepticism is particularly pronounced among power system operators, who are acutely aware of the significant societal consequences of maloperation or blackouts. Consequently, they find it challenging to trust models they do not fully comprehend. This underscores the importance of developing inherently interpretable AI DSA models that are not only easy for humans to understand but also seamlessly align with their domain expertise.

In the context of isolated power systems, these tools hold significant potential, as human operators often seek understandable and secure methods for system operation that are easy to validate and do not require extensive domain knowledge (since the human resources are frequently already low). Additionally, the urgent need to assess the security of inherently weak systems — due to their lack of interconnections — highlights the importance of developing interpretable DSA tools as both a crucial issue and an opportunity in island systems.

2.5.3 Data-driven Techniques Applied to the DSA

Pattern recognition techniques emerged as key methodologies in the early stages of data-driven applications within the DSA. These techniques, which originate from fields such as statistics and signal processing, identify or recognise a pattern — be it a function or a surface — that divides the attribute space into distinct zones, thereby facilitating classification. Noteworthy examples of these techniques include the k-nearest neighbours algorithm [99], Bayesian regression [100], and linear regression [101]. These methods are often combined with various feature extraction or selection techniques, such as wavelet multi-resolution analysis [99] and Fisher transform [100], among others [102].

Among the first endeavours of AI in the power systems industry were also the expert systems (ES) [103], an inference engine (programming logic) that uses a combination of expert-defined rules and factual knowledge to make deductions about the system state and decisions. Despite ES's strong presence at the early stages of the DSA [104], it became evident that this approach could pose challenges due to its inability to ensure near-optimal performance, lack of leverage on available data, and the demanding nature of deriving a large number of rules through arduous reasoning. Knowledge-based systems were combined with data-driven methods to address the inherent challenges of conventional ES. At first, such combinations used techniques such as decision trees (DT) [105] or fuzzy inference systems (FIS) to derive the ES's rules. Later, this experience culminated in the creation of a hybrid ES that included data-driven techniques or some of its characteristics inside the ES [106].

Despite the aforementioned efforts, approaches mainly led by Artificial Neural Network (ANN) and DT grew popular. ANNs were first used within the DSA context in [107] and, since then, the classical multi-layer perceptrons have evolved into more complex structures, such as convolutional neural networks [108], graph neural networks [109], and other deep learning based architectures [110]. The classifier/regressor training paradigm has also undergone different changes, from supervised to semi-supervised learning that augments the training set with the addition of other unlabelled samples [111]. The security categorisation enabled by ANNs has often been integrated into preventive control modules that promote the generator rescheduling/dispatch, either by iteratively comparing the dispatch output with the regressor security quantification [112] or by including ANN-extracted sensitivity factors in the optimisation method [113]. While ANNs exhibit high generalisation capabilities, their interpretability poses inherent challenges for human operators during the learning and operational phases [114], which can result in algorithm aversion.

Unlike an ANN, a DT is inherently interpretable since the space partition performed to achieve a classification or regression task can be easily transformed into “if-then” rules. Among the widely adopted DT algorithms in DSA, ID3 [115] and CART [116] stand out. Two other algo-

2.5. Dynamic Security Assessment, Base and Future

Algorithms worth mentioning are the random forest [117], which addresses the overfitting problem of conventional DT algorithms, and the optimal classification tree [118], in which the problem of obtaining local rather than global optimal DTs is addressed by forming the entire DT in a single step. Regardless of the algorithm, DTs node splitting criteria are based on linear inequalities of the data-set attributes (e.g., “ $X_1 < k_1$ ”, “ $X_1 < k_1 \& X_2 < k_2$ ”, “ $X_1 + X_2 < k_{12}$ ”), which means that the attribute search space can only be linearly partitioned. In that sense, more complex “real-world” attribute relations that non-linear inequations may represent (e.g., $X_1/X_2 < k_{12}$ or $\sin(X_1/X_2) < k_{12}$) will not be modelled in the DT, only linearly approximated, which is a limitation. These DT’s rules have been used to find preventive actions either via their inclusion as constraints of the re-dispatch optimisation [119] or by providing indicators on the most effective control variables [115, 116]. Similar to ANNs, these rules have also served as a way to iteratively verify the security of a re-scheduled solution [120]. Still, in complex problems, the number of decision rules can grow fairly quickly [121], challenging the human ability to understand the overall model functioning (e.g., key features, governing laws), which is a characteristic known as global interpretability [122]. Thus, strategies like tree pruning [121], multi-objective DT model selection [123] or penalty functions related to the tree complexity [124] are commonly adopted to limit the tree depth, which can lead to a complex trade-off between accuracy and interpretability [118]. Moreover, an approach that uses gene expression programming was proposed in [125] to classify the system’s transient stability, and that outperformed ANNs.

Other relevant data-driven approaches applied to DSA are support vector machines and fuzzy inference systems. For a comprehensive review, the interested reader is referred to [110].

Due to the extended model size and complexity, many of the reviewed AI-based approaches hinder humans from fully understanding the model’s capabilities and limitations and developing an accurate mental model of AI. As a result, risk-averse human operators may have restricted confidence in these approaches. Recent advances in explainable AI (XAI), such as SHapley Additive exPlanations (SHAP) [126], aim at providing additional information about the model’s processes and decisions, usually denoted as explanations. These “explanations” generally correspond to feature or layer-wise importance factors for a set of specific model outputs. On a different path, and to provide a dimension of interpretability, methods that derive interpretable proxy models, such as trees or rule-based models from “black-box” models, have also been proposed [127].

XAI techniques still have different “challenges” [114], especially in the case of high-stakes decision problems such as the DSA, namely: a) the “explanations” may not consistently align with the computations of the original model, which may result in the operator’s misunderstanding of the model behaviour; b) the XAI algorithm is an additional model to be debugged

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in the development phase, which is not error-free. Therefore, adhering to an inherently interpretable model is preferable, as discussed in [114]. Such models, characterised by their symbolic and compact nature, enable a straightforward grasp of their internal dynamics, ensuring interpretability and the ability to offer articulate explanations.

In regards to other works that still seek to improve the confidence of the operator in the AI/ML methods used for the DSA, but that do not align with this work's point of view of providing an inherently interpretable model, it is worth mentioning: 1) Approaches that use ANNs for the security classification, while delivering a certificate on how the neural network will behave for all possible inputs and not just statistically [128]. This allows for providing information on the maximum prediction error for a set of inputs, information that increases the operator's confidence in the method — when the error is low. 2) Approaches that include power system domain knowledge (e.g. governing physical equations) in the training procedure of the ANN, denoted by the name of Physics Informed Neural Networks (PINN) [129]. This approach not only decreases the number of required training data set samples [130] but also boosts the security of the ANN prediction, as the intrinsic physical laws of the power system were utilised during training.

The development of DSA data-driven tools with an inherently interpretable nature is, therefore, an open research gap within the online DSA context. Particularly, in the European case, this research has a new degree of importance since AI tools have to align with the pillars of human-centred and trustworthiness to comply with the AI Act legislation [12].

2.6 Final Considerations - Literature Gaps

The literature review revealed significant gaps concerning the optimal placement of GFM converters and the use of AI techniques for dynamic security assessment. Given the breadth of these research gaps, it is not feasible to address all of them in detail within this thesis. Therefore, this work will focus on a selected set of research topics deemed most relevant by the authors, namely:

- **The role of the GFM converter location in the degree of achievable improvement of the system stability.** Particularly, the understanding of the impact of the GFM location in different stability classes, as well as the understanding of the underlying physical phenomena that explain the optimality of the preference for specific locations.
- **The optimal placement and sizing of Grid-Forming converters.** Namely, concerning two particular topics: solving the problem as a multi-criteria problem, considering both cost and security, and solving the problem by considering multiple stability classes.
- **Inherently interpretable Dynamic Security Assessment tools that establish true physical relations and can be co-created between AI and a human operator.** Particularly, data-driven methods that create easily interpretable AI models for security classification and preventive control definition, aligning with the pillars of human-centredness and trustworthiness defined in the AI Act legislation.

Exploring the Role of GFM Converters Location in the Enhancement of the System Stability

As previously discussed (Section 2.4), most studies addressing the grid-forming (GFM) spatial distribution problem focus on enhancing a single stability class, often disregarding its impact on the remaining stability classes. Additionally, the type of disturbance for which the system stability is evaluated (e.g. power impulses, load steps, generation losses, or short circuits) is frequently overlooked, despite its distinct effect on system voltage and frequency and their unique interactions with existing control loops.

That said, this chapter serves as an exploratory study for the aforementioned matters, with the goal of better understanding the impact of the location on the system stability and providing hints on the adequate formulation for the problem of optimally placing GFM converters for stability/security purposes. For that purpose, in Section 3.2, a Multi-Class Stability Analysis is conducted to examine the placement of a single GFM converter. This analysis leverages various stability variables to assess the feasibility of different GFM locations across multiple stability classes while accounting for two different disturbance types (short circuits and generation losses).

Additionally, in Section 3.1, the two test systems used throughout this work to evaluate the effectiveness of the different proposed methodologies are introduced, including a general overview of each system and a discussion of the modelling approach adopted.

3.1 Test Systems

Two distinct test systems are employed throughout this thesis to ensure clarity through detailed methodological explanations and to assess the practical application of the proposed methods. These test systems, which are detailed in the following subsections, correspond to a future version of the Madeira Island Power System (3.1.2) and a modified version of the well-known IEEE 39-Bus Test System (3.1.1).

3.1.1 Modified IEEE 39 Bus Test System

The IEEE 39 Bus Test System, also known as the New England Test System, consists of a 345 kV transmission network with 39 buses, 34 lines and 10 generators. Among these ten generators, one represents the New York system, which is interconnected with the New England system [131].

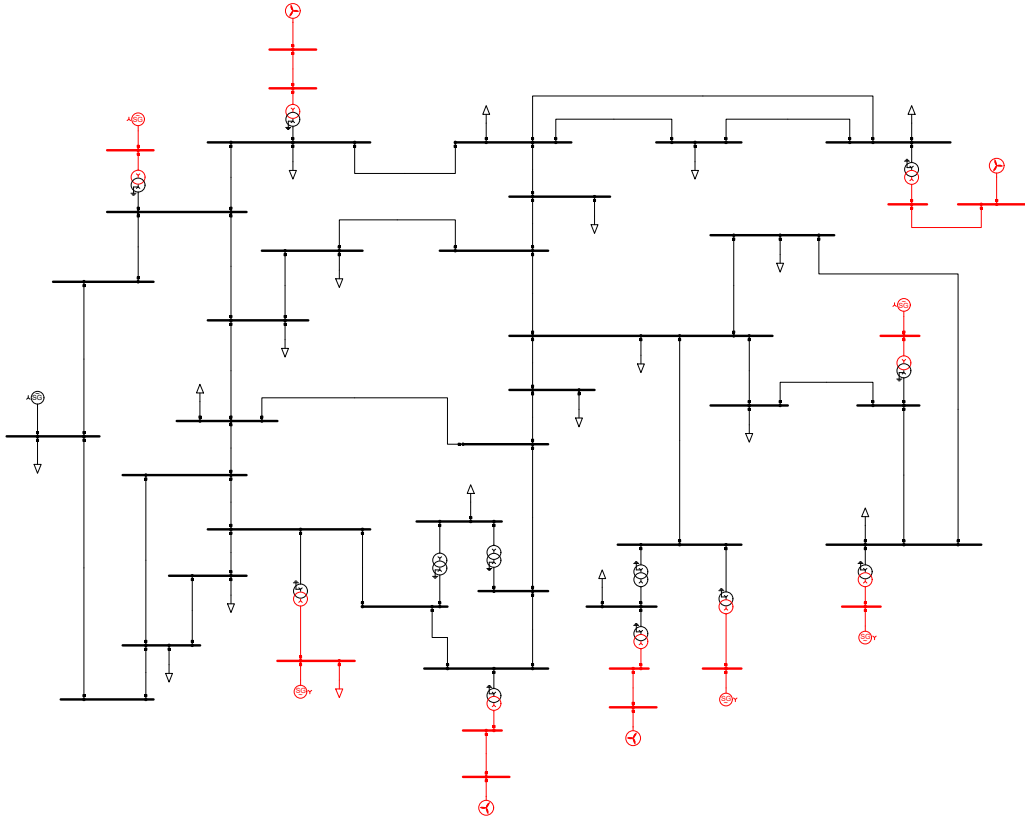


Figure 3.1: Single line diagram of Modified IEEE 39-bus test system.

In this modified version of the established testbed, four of the original synchronous-based power stations (G3, G5, G8, and G9) have been replaced with equivalent representations of large-scale RES Plants featuring GFL converters (R3, R5, R8, and R9). The models adopted for these plants were parametrised so that the plant conforms with the grid-code require-

3.1. Test Systems

ments in terms of fault response defined in [38]. Moreover, the inertia and short circuit ratio (SCR) [132] of the New York system's equivalent generator (G1) have been reduced to half their original value. The single-line diagram of this modified version of the system is depicted in Figure 3.1.

Modelling

The system elements that existed in the traditional IEEE 39 test bed were represented as described in [131], both in terms of its steady-state and dynamic model. Regarding the dynamic modelling, this translates into the use of adequate state-of-the-art models of the different generator elements (Synch. Machine, Governor, AVR, PSS) and with the respective parametrisation in conformity with [131].

As for the newly introduced large-scale RES Plants, one considers the steady-state representation of Figure 3.2, where an equivalent converter, an equivalent pad-mounted transformer, an equivalent collector system, and a substation transformer represent the plant.

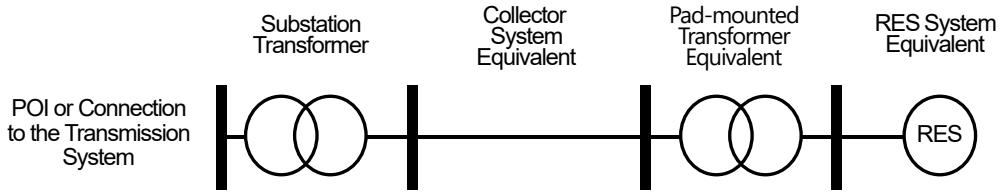


Figure 3.2: *Equivalent steady-state representation of the centralised type RES generation.*

In regard to the plants' transitory behaviour, a dynamic model that leverages second-generation generic WECC RES models was developed. The interconnection between these models and their interface with the grid is depicted in Figure 3.3.

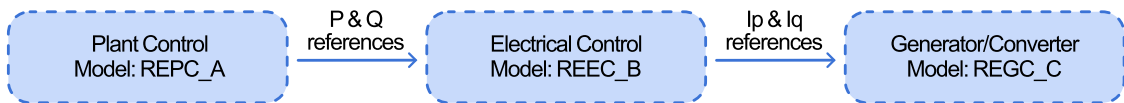


Figure 3.3: *Schematic representation of the models used to represent the RES Plants' dynamics.*

The block diagram of each model depicted in Figure 3.3 is shown below in Figures 3.4 to 3.6, along with a brief description of its modelling role. For larger detail, see also [133] and [134].

- **REPC_A:** models the plant-level automatic controller, which includes the generation of active and reactive power references, considering different types of controls (set-point following, frequency control, voltage control).

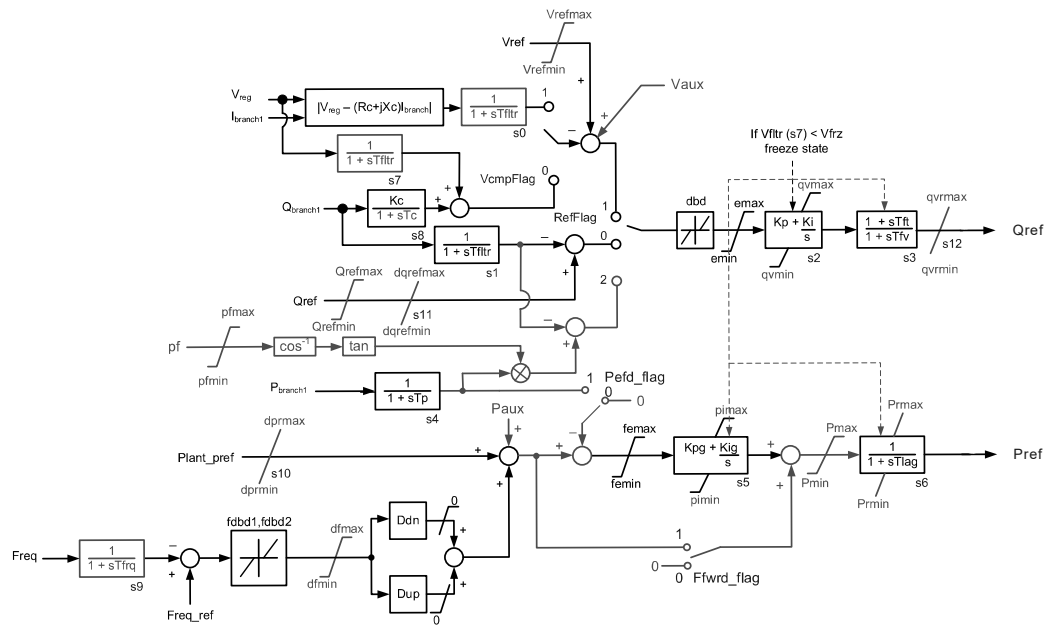


Figure 3.4: Block diagram of REPC_A Model (adapted from [133]).

- **REEC_B**: models the automatic controls at the converter level, which act on the active and reactive power reference and provide real and reactive current commands to the converter interface model. It includes the current limiting control and other important in-fault controls, such as the reactive current contribution during voltage dips.

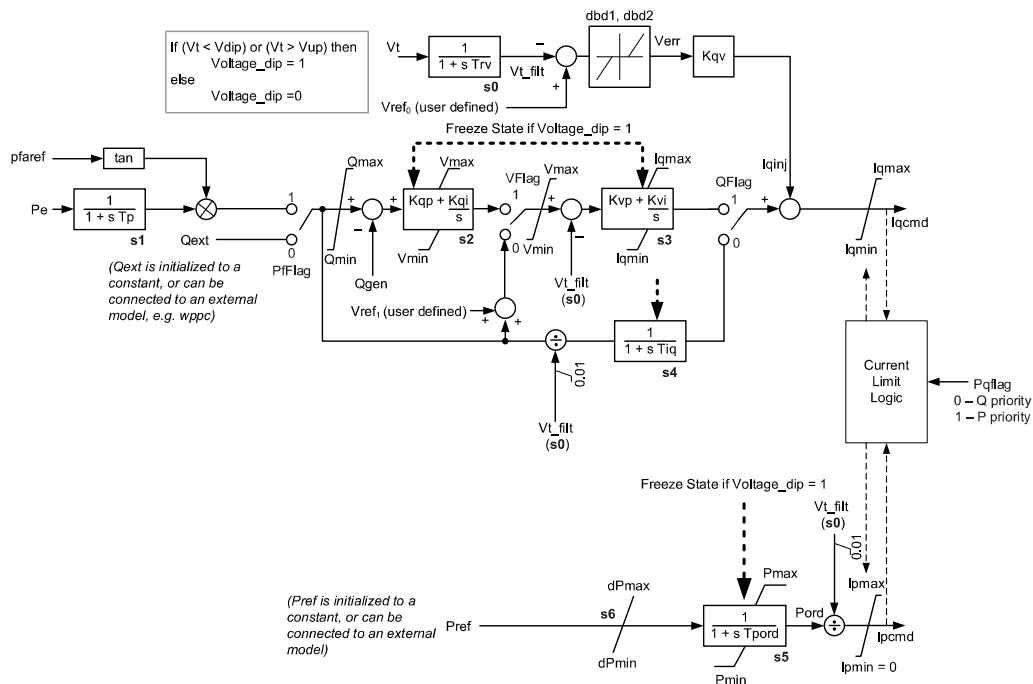


Figure 3.5: Block diagram of REEC B Model (adapted from [133]).

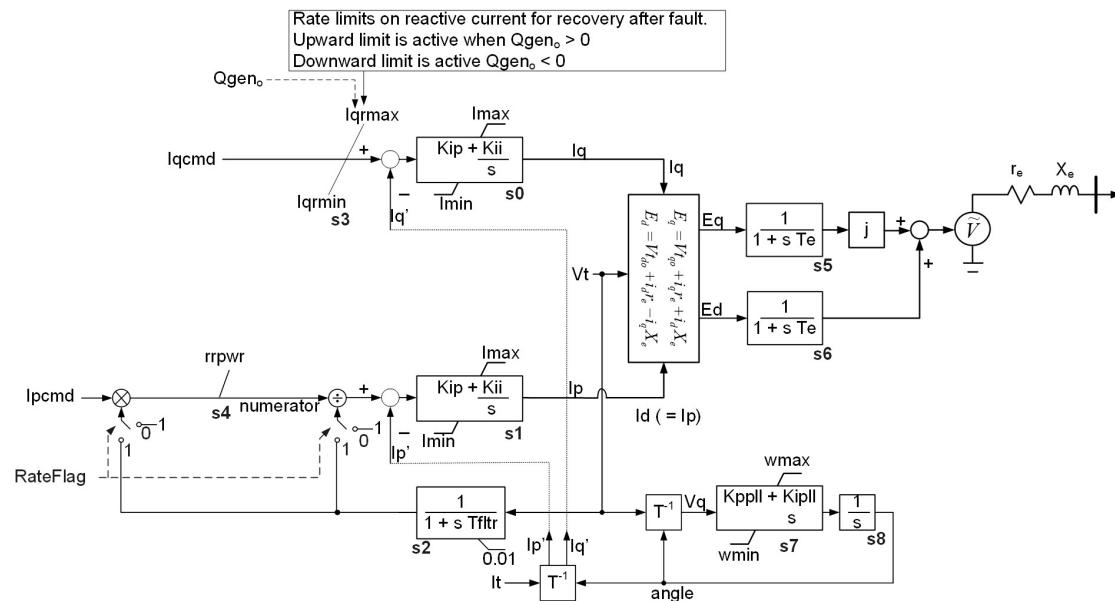


Figure 3.6: Block diagram of REGC_C Model (adapted from [134]).

For the studies conducted in this work, it is paramount to have a converter model that allows for a good representation of the behaviour of IBRs of the GFL type when connected to locations of low short circuit ratio (SCR). Otherwise, not only can the credibility of the results be jeopardised, but the convergence of the grid dynamic model will also be hindered [136]. Hence, the use of a model like *REGC_C* or similar, that represents elements and controls with faster dynamics like the PLL or the inner current control loops and that converts the current commands into voltage reference commands behind an impedance is paramount [133].

In summary, by integrating the previous models, one can analyse the impact of the rising share of IBRs on classical instability issues, as well as on instability phenomena driven by the converter itself. This includes the examination of slow-interaction converter-driven stability, which can often be captured through RMS simulation. This ability to analyse different instability phenomena is crucial in the context of the thesis.

This version of the IEEE 39 Test System does not initially include any elements with a GFM converter. However, throughout this work, multiple studies will be conducted considering

3.1. Test Systems

its integration alongside a BESS unit. The modelling approach adopted for this converter is detailed in Section 3.1.3.

The block diagram of the aforementioned dynamic models and their respective parameterisation can be found in the appendix section, specifically in Appendix A.1.

3.1.2 Madeira Power System

The Power System of Madeira Island comprises a network operated at 30/60 kV, a diverse generation portfolio (hydro, thermal, wind, solar and waste to energy) and a load that varies between 60 and 100 MW, between valley hours and peak periods. To ease the operation in a system where the share of RES is already high, the TSO now relies on different reversible hydro stations that can function as synchronous condensers and two 24 MVA battery-based storage facilities, whose converters can be controlled according to different control philosophies (grid-forming and grid-following). In the coming years, the share of wind and solar is expected to keep growing, leading to challenging operating scenarios due to system stability concerns arising in zero thermal generation scenarios. Thus, the power system may soon be enhanced by installing another 15 MVA synchronous condenser. The next figure describes the single-line diagram of the Madeira power system.

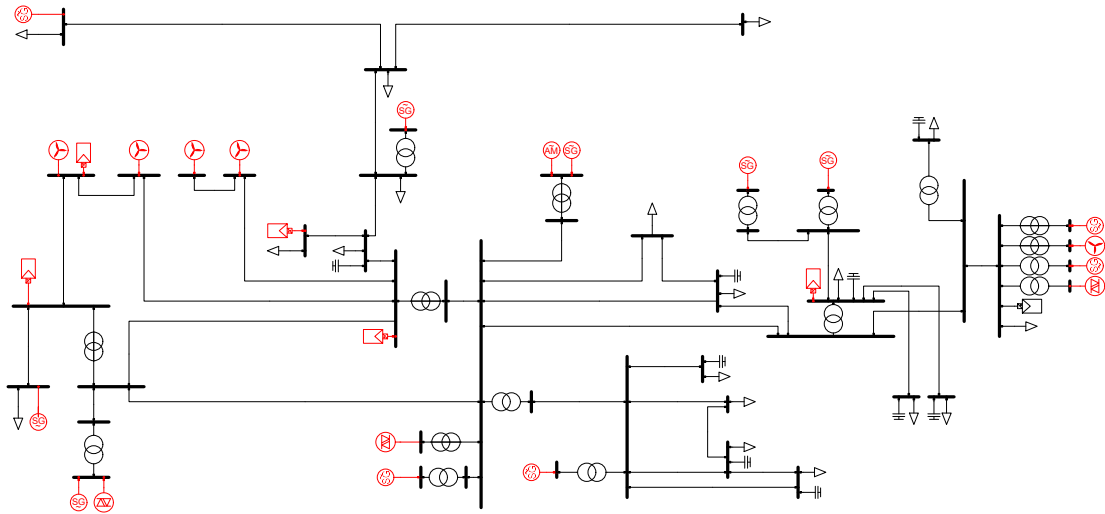


Figure 3.7: *Simplified single-line diagram of the Madeira Island Power System*

Modelling

The positive sequence model of the Madeira power system was built in cooperation with Empresa de Eletricidade da Madeira (EEM) within the framework of several cooperative projects between INESC TEC and EEM. In that sense, some of the information regarding the modelling of the grid can not be disclosed. Still, the following more generic details are worth highlighting:

3.1. Test Systems

- **Synchronous generation units:** the synchronous machines are modelled using a 6th order transient model, while the excitation and the governor systems are represented using state-of-the-art models widely described in the literature (e.g. IEEX1, TGOV1, HYGOV, etc).
- **Wind and PV Plants:** if vendor-specific models exist, then these are used to represent the unit. Otherwise, WECC generic models are calibrated to fit TSO-provided descriptions of the unit's behaviour during a fault and the island grid-code requirements. Examples of these descriptions correspond to the existence of fault-ride through, the behaviour of the reactive and active current, response to frequency deviations, etc.
- **BESS Units:** when the unit is operating in GFM mode, the GFM model described in Section 3.1.3 is used; when the unit is in GFL mode, a representation using WECC models that resembles a TSO described behaviour is used.
- **Pumps:** for the pump units directly connected to the system, the asynchronous machine model available in the Digsilent PowerFactory library is used. For the pumps connected to the grid using a full-converter solution, an approximate representation is achieved using the WECC models.

3.1.3 Grid-Forming Converter Model

As discussed in Section 2.2.3, there are multiple GFM control methodologies with different performances in providing a range of new system needs (inertial effect, frequency support, voltage stiffness and Ssc). That being said, it's highly likely that the choice of GFM control to use in this work's analysis will, to some degree, impact the results. Still, due to the impossibility of performing this work's studies for a variety of GFM controls due to size limitations, a GFM model of the VSM type was adopted. This choice is in agreement with the industry trends in terms of GFM control implementations (often VSMs or droop control) [21, 18] and aligns with the needs required for this work. The main control loops of such a model are described next:

- **Voltage phase angle control:** a Virtual Synchronous Machine (VSM) with variable inertia (H), which was parametrised with $H_0=4$ and $D=100$. The H value is proportionally controlled as a function of the voltage set-point value (V_{set}), in order to improve the GFM transient stability during short-circuit conditions [36].

The base value of the virtual inertia (H_0) was selected to create an inertial response that resembles that of a synchronous machine during power variations. Thus, a standard synchronous inertia value across various technologies was utilised [137]. As for the damping constant, a value of 100 p.u. was adopted. This value calibrates D to ensure that, under low SCR conditions ($SCR \approx 3$), the damping ratio (ζ) of the second-order

3.1. Test Systems

system—comprising the VSM and a simple grid equivalent—is around 0.707. This value represents a typical compromise between response time and overshoot. The complete mathematical derivation of the second-order characteristic equation for the simplified control system, which enables achieving this damping value, is presented in Appendix B.

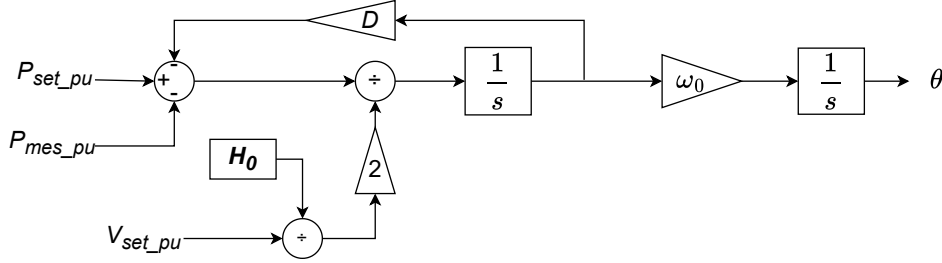


Figure 3.8: Virtual Synchronous Machine (VSM) model

- **Current limitation control:** a virtual impedance that is enabled once the converter current passes 1.01 p.u. and is then linearly increased according to the current magnitude value. The proportional gains that control the values of the virtual impedance (R_v and X_v) were adjusted to ensure that the current of the converter is limited to 1.3 p.u. [41, 53], for 3-phase symmetrical short-circuits in the converter surroundings. The adopted control parameters are listed in the appendix Section A.2.

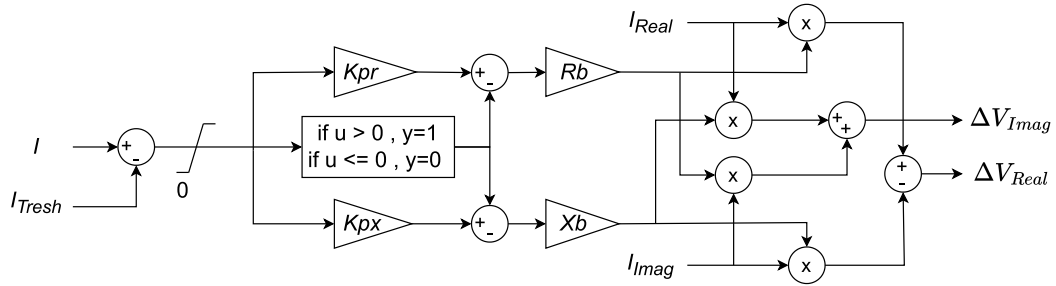


Figure 3.9: Virtual Impedance model.

- **Voltage magnitude control:** a proportional controller that was parametrised with a small gain value of 0.5 p.u.
- The converter grid interface is modelled using an ideal voltage source behind an impedance, which receives the voltage references from the remaining control loops.

The root of this GFM model is available in the Power Factory template library, which was then modified to ensure the characteristics mentioned above. No limitations were considered for the battery, which provides a readily available energy buffer to respond to disturbances, in terms of its energy and power gradient.

3.2 Impact of the GFM Location on the System Stability Regarding Different Classes

This section presents a Multi-Class Stability Analysis of the placement of a single GFM converter in the modified version of the IEEE39 test system presented earlier. For that purpose, a simplified contingency analysis is first performed, where system stability is evaluated for different GFM locations, and its results are then thoroughly analysed. The key steps of this analysis procedure, which quantifies stability based on the computation of four distinct stability variables, are summarised in the following pseudo-code algorithm.

Algorithm 1: Simplified Contingency Analysis

- 1: **for** all system buses ($\forall l \in \Omega_b$) **do**
 - 2: Place GFM converter in bus j
 - 3: **for** all disturbances ($\forall d \in \Omega_d^o$) **do**
 - 4: Dynamic simulation of disturbance d
 - 5: Calculation of stability variables
-

The GFM model utilised in this analysis corresponds to the one introduced in Section 3.1.3 and is assumed to have a nominal capacity of 250 MVA.

As indicated above, for all grid nodes, Ω_b , the system response to a representative group of disturbances, Ω_d , is studied using an index-based stability assessment. Since this work focuses on large events that frequently impact system stability rather than minor system variations, which are primarily relevant from a small-signal stability perspective, the disturbance collection includes:

- **Generation Losses:** the unplanned loss of a generator; performed for all the generation units within the control area;
- **Line Faults:** a solid 3-phase symmetrical short-circuit that takes place in the middle of a line for 150 ms and is then cleared via the line's opening. Performed for all system lines.

As for the variables used to quantify the impact of the GFM location on the system's stability, a set of variables that accurately reflect the degree of stability across different classes was chosen, namely:

- **Max Δf_{SM} :** The maximum frequency deviation from its nominal value (50 Hz), found among the frequencies of all the system's synchronous machines (Ω_{sm}).

$$Max \Delta f_{SM} = \max_{\forall i \in \Omega_{sm}} \overline{\Delta f_{SM_i}} \quad (3.1)$$

3.2. Impact of the GFM Location on the System Stability Regarding Different Classes

$\overline{\overline{\Delta f}}_{SM_i}$ corresponds to the value of $\overline{\overline{\Delta f}}$ when the considered frequency quantity is the frequency of the synchronous machine i .

$\overline{\overline{\Delta f}}$ represents the maximum deviation of the frequency curve $f(t)$ from its nominal value (50 Hz) observed during the time interval T . Figure 3.10 depicts the $\overline{\overline{\Delta f}}$ computation for an illustrative frequency response curve, and Equation 3.2 provides the variable mathematical formulation.

$$\overline{\overline{\Delta f}} = \max_{t \in [0, T]} f(t) - 50 = \max_{t \in [0, T]} \Delta f(t) \quad (3.2)$$

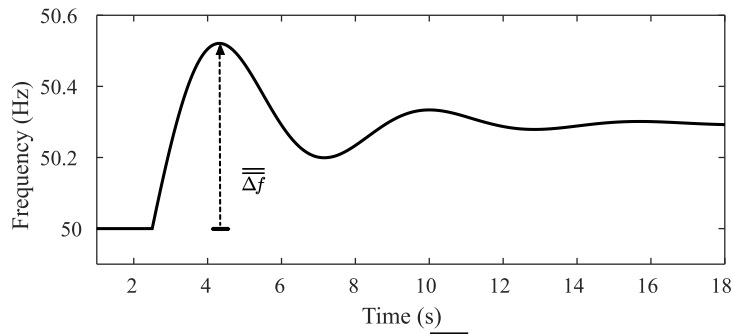


Figure 3.10: Illustration of $\overline{\overline{\Delta f}}$ computation.

- **Max $|Rocof_{SM}|$:** The maximum absolute value of the *Rocof* found among the frequencies of all the system's synchronous machines.

$$\text{Max } |Rocof_{SM}| = \max_{\forall i \in \Omega_{sm}} \overline{\overline{|Rocof_{SM_i}|}} \quad (3.3)$$

$\overline{\overline{|Rocof_{SM_i}|}}$ corresponds to the value of $\overline{\overline{|Rocof|}}$ when the considered frequency quantity is the frequency of the synchronous machine i .

The *Rocof*, also known as the *Rate of change of Frequency*, corresponds to the time derivative of the frequency curve $f(t)$. In its turn, $\overline{\overline{|Rocof|}}$ corresponds to the maximum absolute value of the *Rocof* observed during the time interval T . Figure 3.11 depicts the $\overline{\overline{|Rocof|}}$ computation for an illustrative frequency response curve, and Equation 3.4 provides the variable mathematical formulation.

$$\overline{\overline{|Rocof|}} = \max_{t \in [0, T]} \left| \frac{\partial f(t)}{\partial t} \right| \quad (3.4)$$

3.2. Impact of the GFM Location on the System Stability Regarding Different Classes

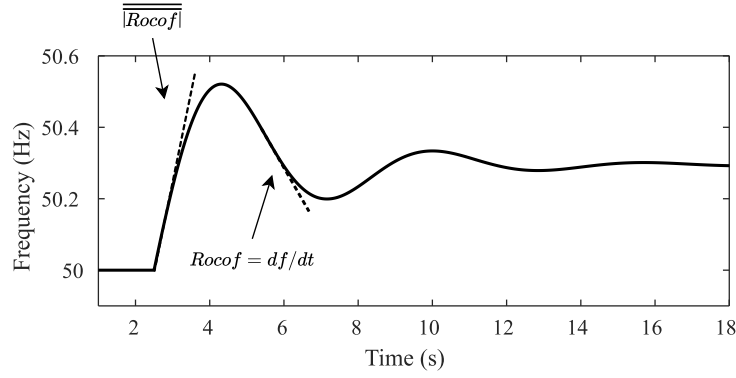


Figure 3.11: Illustration of $\overline{|Rocof|}$ computation.

The *Rocof* index is here adopted, given its ability to: 1) reflect the in-fault unbalance between electromagnetic and mechanical torque experienced by synchronous machines; 2) contribute to the analysis of the system's transient stability via the value of the in-fault rotor angle acceleration.

- **Max CVD:** The maximum Cumulative Voltage Deviation found among the voltages of all buses with Load or Generation (Ω_b^{LG}).

$$Max\ CVD = \max_{\forall z \in \Omega_b^{LG}} CVD_z \quad (3.5)$$

CVD_z corresponds to the *CVD* value for the voltage at bus z .

The *CVD* measures short-term voltage fluctuations by evaluating the voltage deviations that exceed a certain threshold, providing in this way a quantification of the severity of short-term voltage deviations. A more detailed explanation of such a variable is available in [32]; however, a graphical illustration of the variable computation is depicted in Figure 3.12, and its mathematical formulation is detailed in Equation 3.6.

$$CVD = \sum_{t=t_f}^{t=t_f+T} \begin{cases} V(t) - V_U(t), & \text{if } V(t) > V_U(t) \\ V_D(t) - V(t), & \text{if } V(t) < V_D(t) \\ 0, & \text{else} \end{cases} \quad (3.6)$$

where t_f is the fault inception moment and T is the evaluation time.

$V_U(t)$ and $V_D(t)$ are given as follows:

3.2. Impact of the GFM Location on the System Stability Regarding Different Classes

$$V_U(t) = (1 + a) \cdot V_0 - \frac{t}{b} \quad | \quad V_D(t) = (1 - a)V_0 + \frac{t}{b}$$

where a and b correspond to the slope of the curves $V_U(t)$ and $V_D(t)$ respectively; V_0 corresponds to the pre-disturbance value of the voltage $V(t)$; a and b are computed so that points of Figure 3.12 are as follows: $A = 1.1 \cdot V_0$, $C = 0.9 \cdot V_0$, $B = 1.05 \cdot V_0$, $D = 0.95 \cdot V_0$;

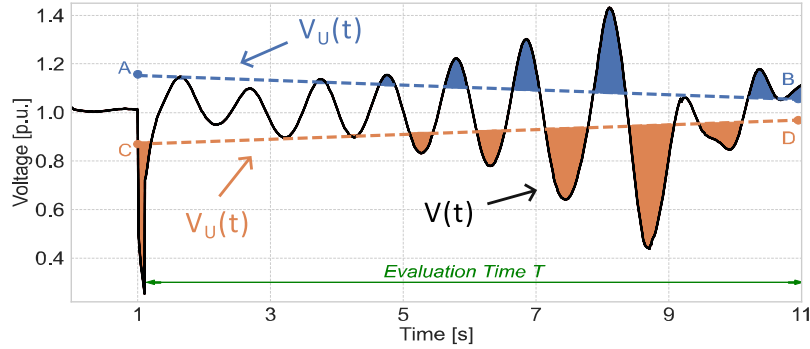


Figure 3.12: Illustrative Example of CVD computation (modified from [32]).

- **Max CQPD_{PLL}**: The maximum Cumulative Quadratic Phase Deviation found among the phases of the PLLs of all the System's GFL converters (Ω_{GFL}).

$$Max CQPD_{PLL} = \max_{\forall j \in \Omega_{GFL}} CQPD_{PLL_j} \quad (3.7)$$

$CQPD_{PLL_j}$ corresponds to the $CQPD_{PLL}$ value for the phase of the PLL of the GFL converter j .

The $CQPD_{PLL}$ is proposed here to assess the PLL's ability to track the voltage phase angle during and after a disturbance, thereby monitoring the system converter-driven stability. The $CQPD_{PLL}$ for PLL j , may be calculated as:

$$CQPD_{PLL_j} = \int_0^T (\Theta_{PLL_j}(t) - \Theta_{B-PLL_j}(t))^2 dt \quad (3.8)$$

$\Theta_{PLL_j}(t)$ - is the time evolution of the phase angle estimation of PLL j (internal PLL variable); $\Theta_{B-PLL_j}(t)$ - is the time evolution of the voltage phase angle in the terminal bus of PLL j ; T - time window of interest.

3.2. Impact of the GFM Location on the System Stability Regarding Different Classes

3.2.1 Generic Results Analysis

The results of the aforementioned contingency analysis were compiled into eight different boxplots, one per stability index for each type of disturbance. Figure 3.13 illustrates how the resulting stability variable data can be transformed into a boxplot, using as an example the $Max \Delta f_{SM}$ variable for the case of the short-circuit events. For the sake of interpretability, only 9 out of the 34 events are included in the box plots. For now, events that led to the loss of synchronism in any system components have been excluded due to very large values of the stability variables that hinder the graphic visualisation.

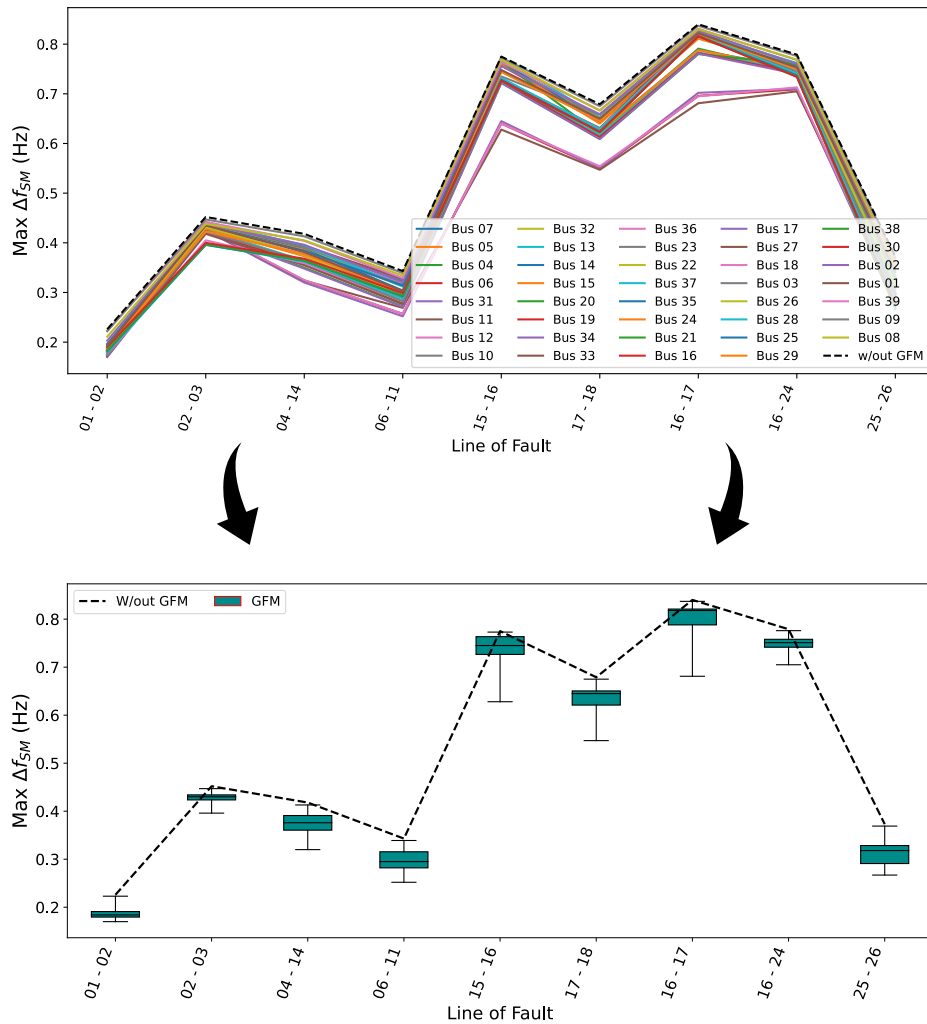


Figure 3.13: Construction of the $Max \Delta f_{SM}$ Boxplot using the data from the contingency analysis.

A preliminary analysis of the graphic above shows that adding a new GFM converter of 150 MVA always has a non-adverse effect on the $Max \Delta f_{SM}$ value, which means that regardless of the chosen location, the $Max \Delta f_{SM}$ is either reduced or maintained. Furthermore, it is clear that irrespective of the event, the degree of achievable stability improvement has a visible degree of uncertainty, which stems from the considered GFM location. This finding underscores

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the critical importance of considering the location as a key factor in planning decisions related to deploying new GFM capacity when the goal is the improvement of the system stability. Finally, it is also evident that the achievable degree of frequency stability improvement differs depending on the considered fault.

Figure 3.14 depicts the same type of box plot but now focused on the other three stability variables. Many of the previously highlighted findings remain applicable when examining these additional stability variables. However, it is now clear that the value of the stability variable may be larger when the GFM converter is introduced than in the base case. This suggests that adding new GFM capacity does not necessarily yield a positive impact on system stability and may, in some instances, lead to a deterioration. The outcome, whether an improvement or a decline, will be contingent upon both the location and the stability variable.

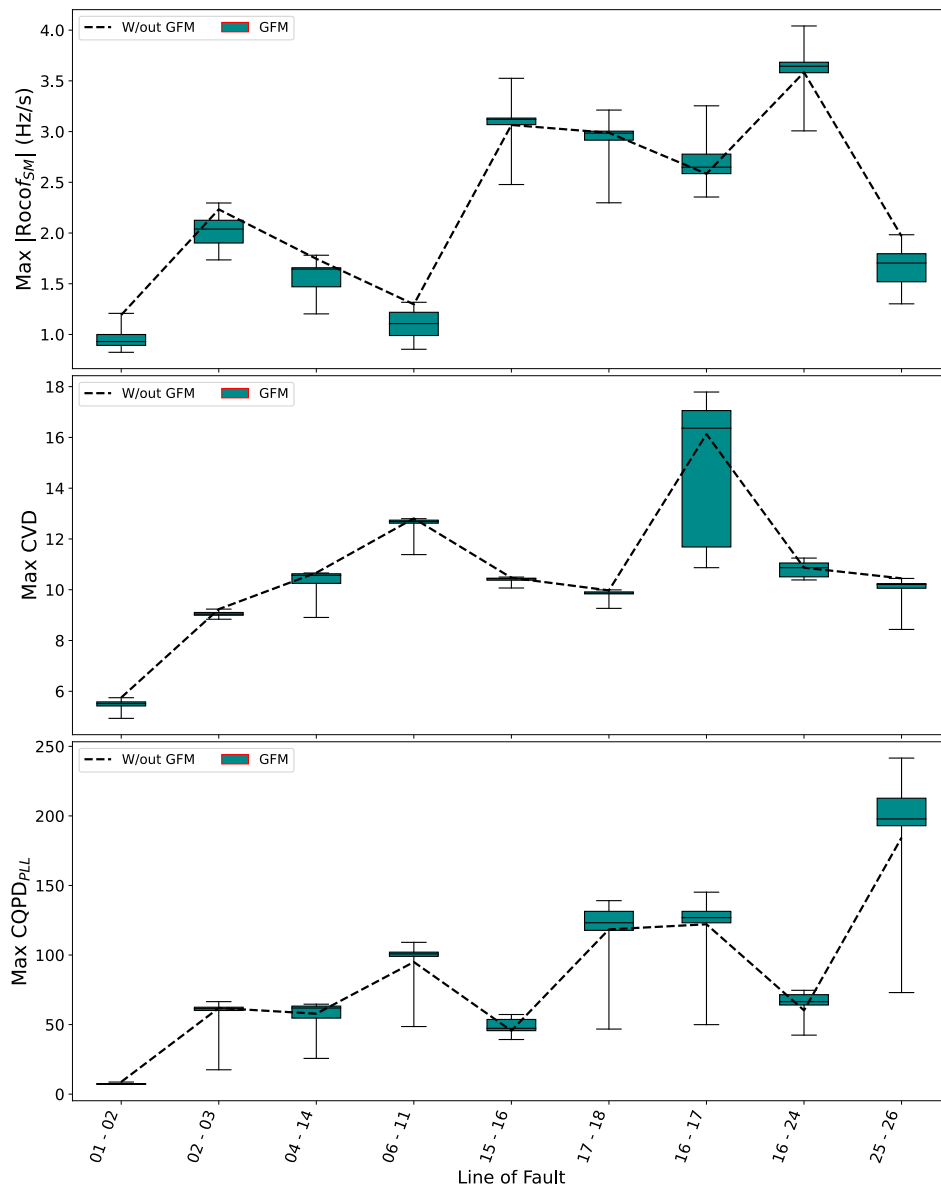


Figure 3.14: Boxplot of remaining stability variables (type of event: short-circuit).

3.2. Impact of the GFM Location on the System Stability Regarding Different Classes

Other relevant observations from the graphics above include the following: (1) The black trend line, representing the stability variable's value in the base case, exhibits a distinct profile that varies depending on the specific stability variable; and (2) the extent of improvement achieved by deploying additional GFM capacity differs across the considered events, contingent on the particular stability variable under analysis. These observations can be more clearly discerned in the stability variable radar plots of Figures 3.15 and 3.16.

In Figure 3.15, each polygon depicts the stability variables value when a different fault happens in the system without GFMs. The four presented polygons correspond to the faults that more strongly affect each of the four stability variables (excluding events resulting in stability loss). It is evident that the faults most detrimental to each stability variable differ.

In Figure 3.16, each polygon depicts the maximum value of the stability variables across all disturbances when the GFM is placed in a specific location. The presented polygons correspond to the placement of the GFM, which results in the largest improvement of each stability variable compared to the case without GFMs. As noted, the locations that facilitate the most significant improvement for each stability variable vary.

Both these graphics underscore the importance of accounting for the effect of different fault events when searching for the location that best benefits the system's stability, since not only does the severity of the disturbance vary, depending on the considered stability class (or variable), but also the contribution that the new GFM capacity can provide.

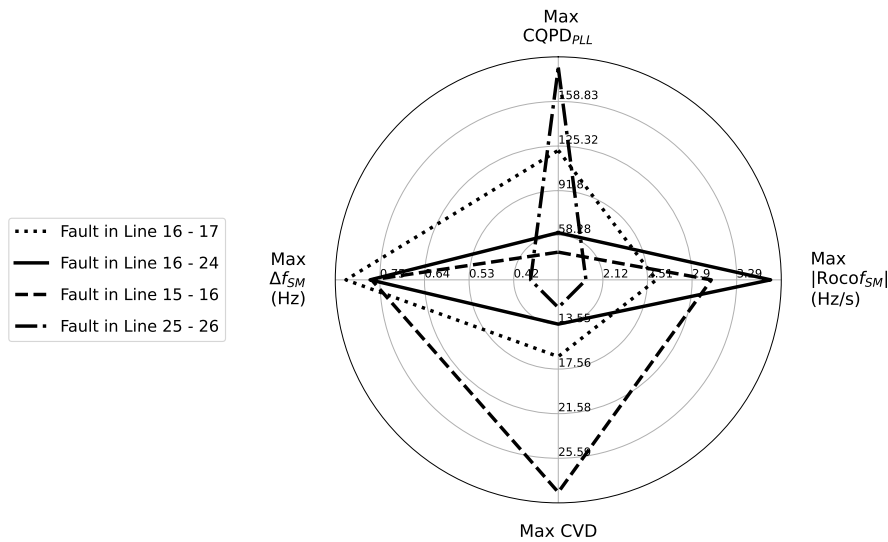


Figure 3.15: Radar plot of the most severe disturbances for each stability index in the system without GFM (excluding events that result in stability loss).

3.2. Impact of the GFM Location on the System Stability Regarding Different Classes

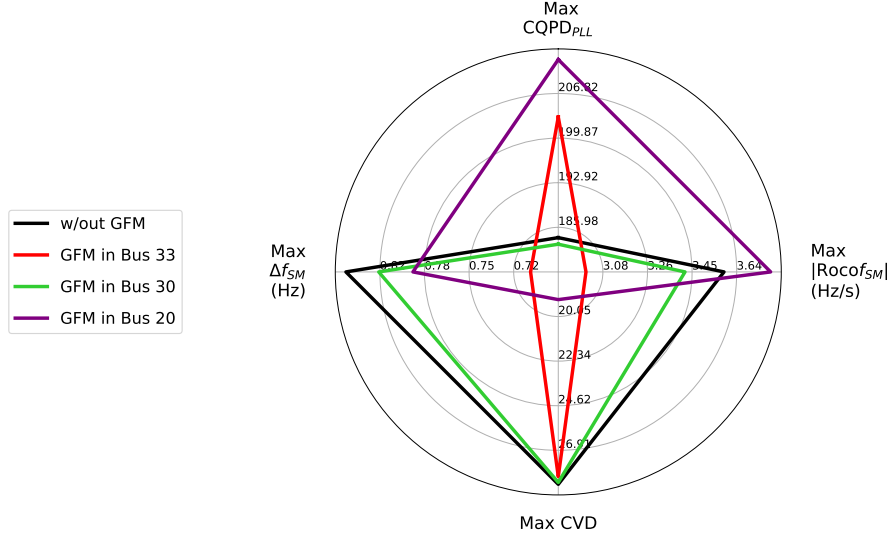


Figure 3.16: Stability Variable Radar Plot, for the GFM locations, that result in the largest improvement for each stability variable (excluding events that result in stability loss).

This boxplot-based analysis, which was performed considering the short-circuit events, can be repeated for the case of generation outages. Accordingly, Figure 3.17 and 3.18 illustrate the box plots of the four stability variables, considering disturbances arising from generation outages instead of short circuits.

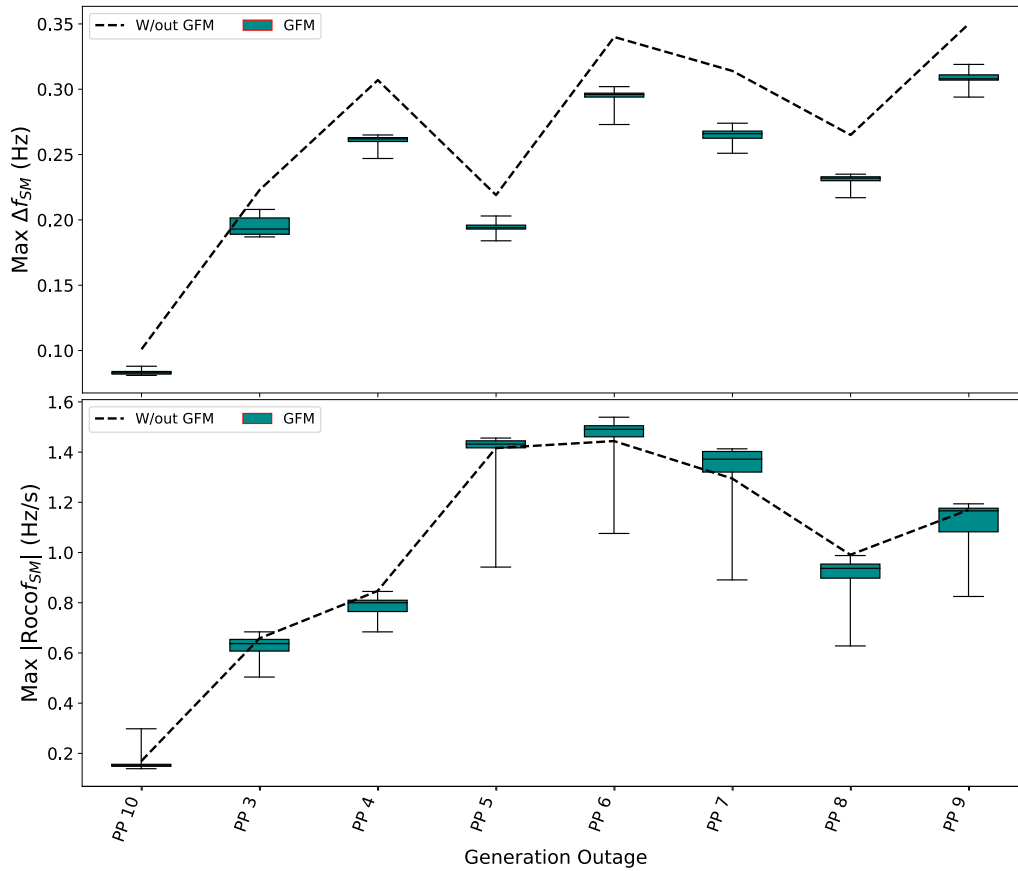


Figure 3.17: Boxplot of Max |Rocof_{SM}| and Max Δf_{SM} (type of event: loss of generations).

3.2. Impact of the GFM Location on the System Stability Regarding Different Classes

By comparing the box plots that concern the generation outages with the ones that correspond to the short-circuits, the following conclusions can be drawn:

- The improvement observed in the $Max \Delta f$ variable is consistent regardless of the location, exhibiting minimal associated uncertainty. This suggests that for the case of the generation outages, the frequency stability improvement resulting from the introduction of GFM capacity is only marginally influenced by the specific placement of the converter.
- Regardless of the considered stability variable, the boxplot whiskers have a smaller amplitude compared to the case of the short circuits. This shows that the impact of the location on the achievable degree of improvement is less pronounced compared to the case of the short circuits.

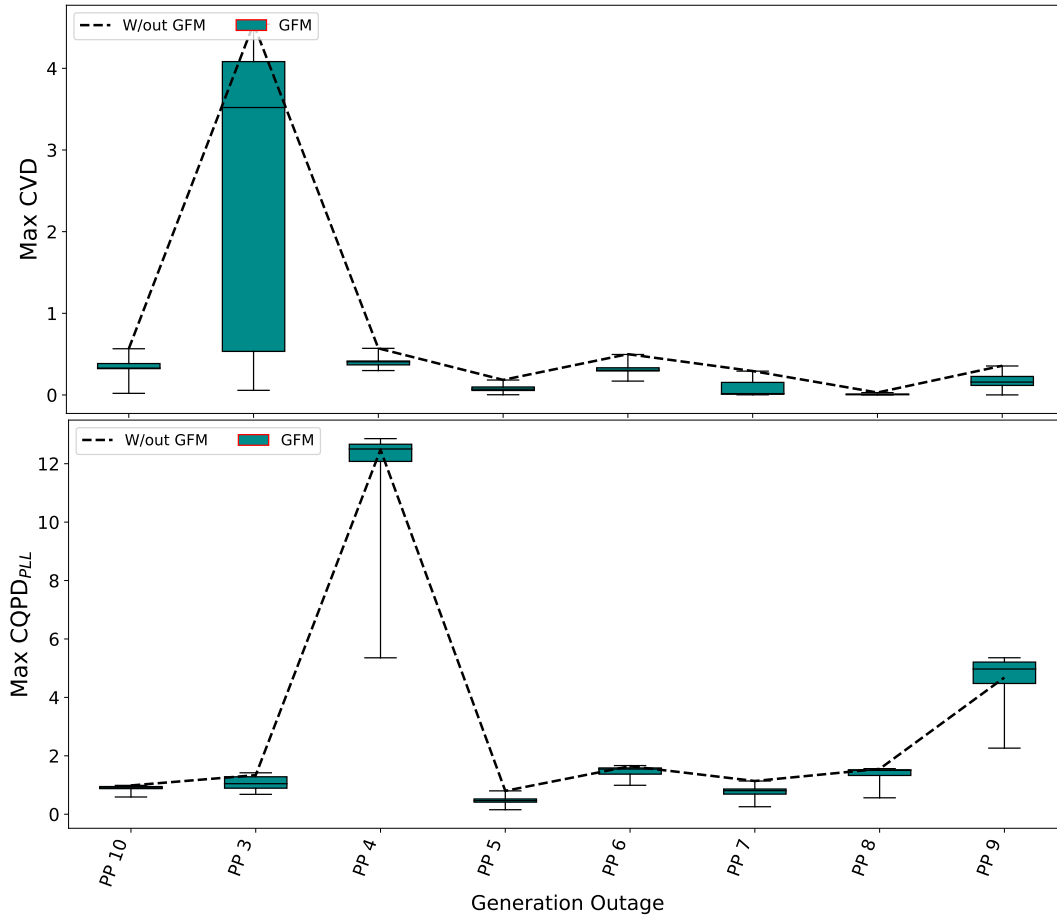


Figure 3.18: Boxplot of $Max CVD$ and $Max CQPD_{PLL}$ (type of event: loss of generations).

The data-driven analysis above highlights several important conclusions regarding the critical role of GFM location in influencing system stability. However, a comprehensive understanding of the reasons behind some of these findings remains elusive. To address this, the following subsection focuses on a detailed examination of some of the most severe events, aiming to

3.2. Impact of the GFM Location on the System Stability Regarding Different Classes

uncover the underlying physical mechanisms driving these outcomes. The selection of the most severe events for this analysis is justified by their pivotal importance in the definition of the system stability margin and, consequently, in any planning decisions related to stability enhancement.

3.2.2 Events without Loss of Stability

Figure 3.19 illustrates the time evolution of various system variables following the loss of unit G6, with the GFM converter placed at two distinct locations (Bus 35 and Bus 36). The illustrated variables are: (1) the frequency of all the system's synchronous machines (left), (2) the frequency of the PLLs of all system converters (right).

As shown there, while both GFM locations improve the system's stability, they affect the existing stability classes differently. That is, while the GFM placement in Bus 36 allows for a more considerable reduction of the $Max \Delta f$, which is a good frequency stability indicator, the placement in Bus 35 results in a more damped oscillatory behaviour of the converters' PLL frequency which, in its turn, conveys the converter-driven stability. This same pattern is also clear in Figure 3.20, where the same frequency plots are presented for the case of the short-circuit in line 17-18 fault, considering two other GFM locations: Bus 33 and Bus 38.

As evidenced in the disturbances depicted below, there is a trade-off between the stability gains achieved for the two different classes (Frequency and Converter-Driven Stability). Despite not always happening, in this case, the laws that establish the degree of improvement in each stability class have conflicting natures.

On one side, the best GFM locations to improve frequency stability are the ones that minimise the accelerating torque during the relevant time frame of the frequency stability phenomena in the machines that are more affected by the fault (electrically close to the disturbance or with small inertia constants). To minimise such torque, one must reduce the electrical power variation that the machine experiences, which tends to happen when the GFM is placed in the surroundings of those machines.

On the other hand, for converter-driven stability, particularly of the existing GFL converters, the best GFM locations are the ones that minimise the voltage phase angle rate-of-change at the terminals of the GFL converters that are more affected by the disturbance. Since all converters were parametrised with the same inner current and PLL gains (for the sake of simplicity), a good placement for the GFM tends to be near the converters in low SCR conditions or near the disturbance. Therefore, since the areas with lower Short-circuit Power (S_{sc}) and GFL type-generation presence do not match the Synchronous Machines' locations (generally high S_{sc}), the optimal GFM location for each of these stability categories will also rarely match.

Loss of Synchronous Generator 6

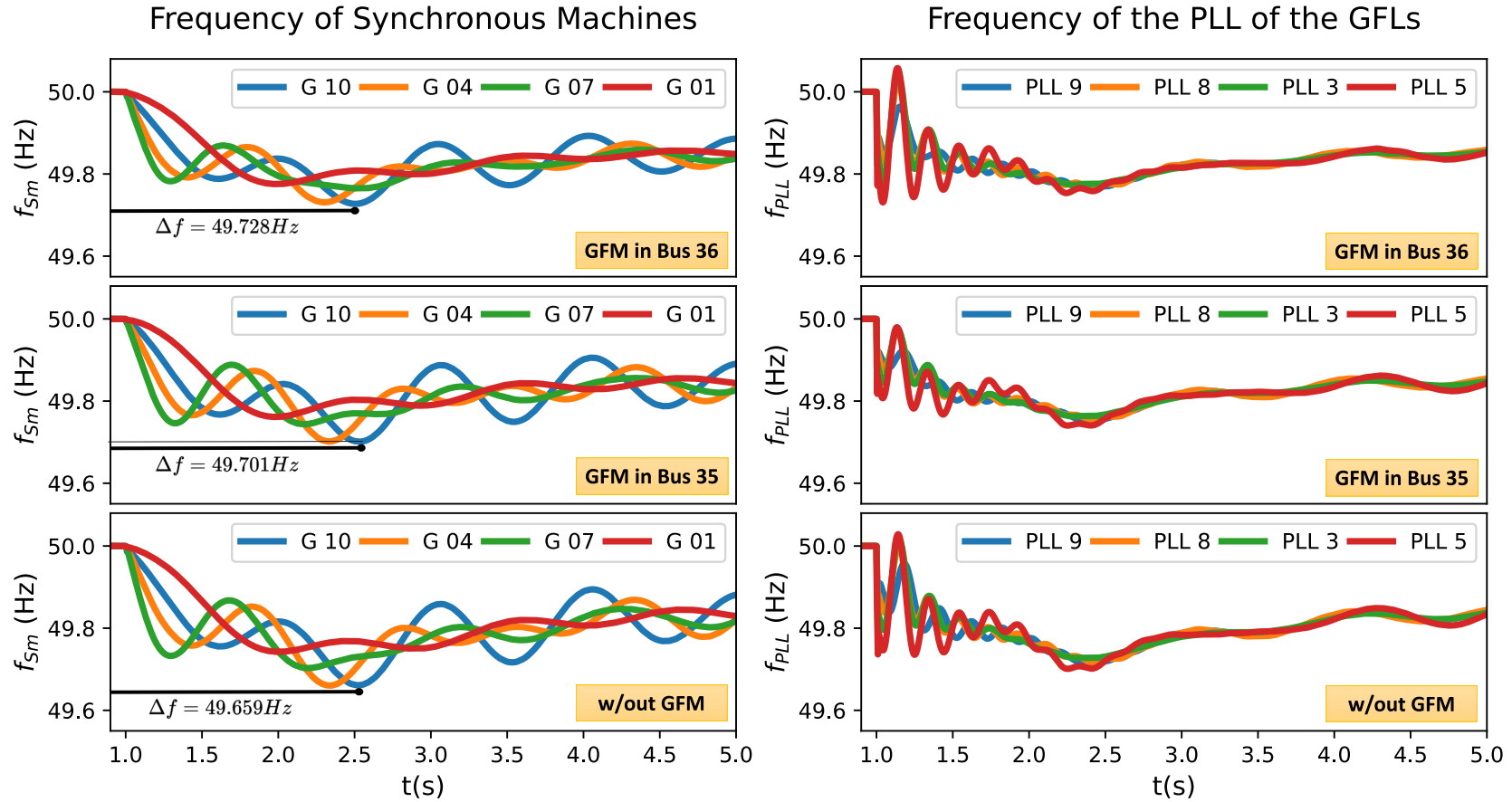


Figure 3.19: Frequency response of the Systems' Generators and PLLs to the loss of G6, for different GFM locations

Short Circuit in Line 17-18

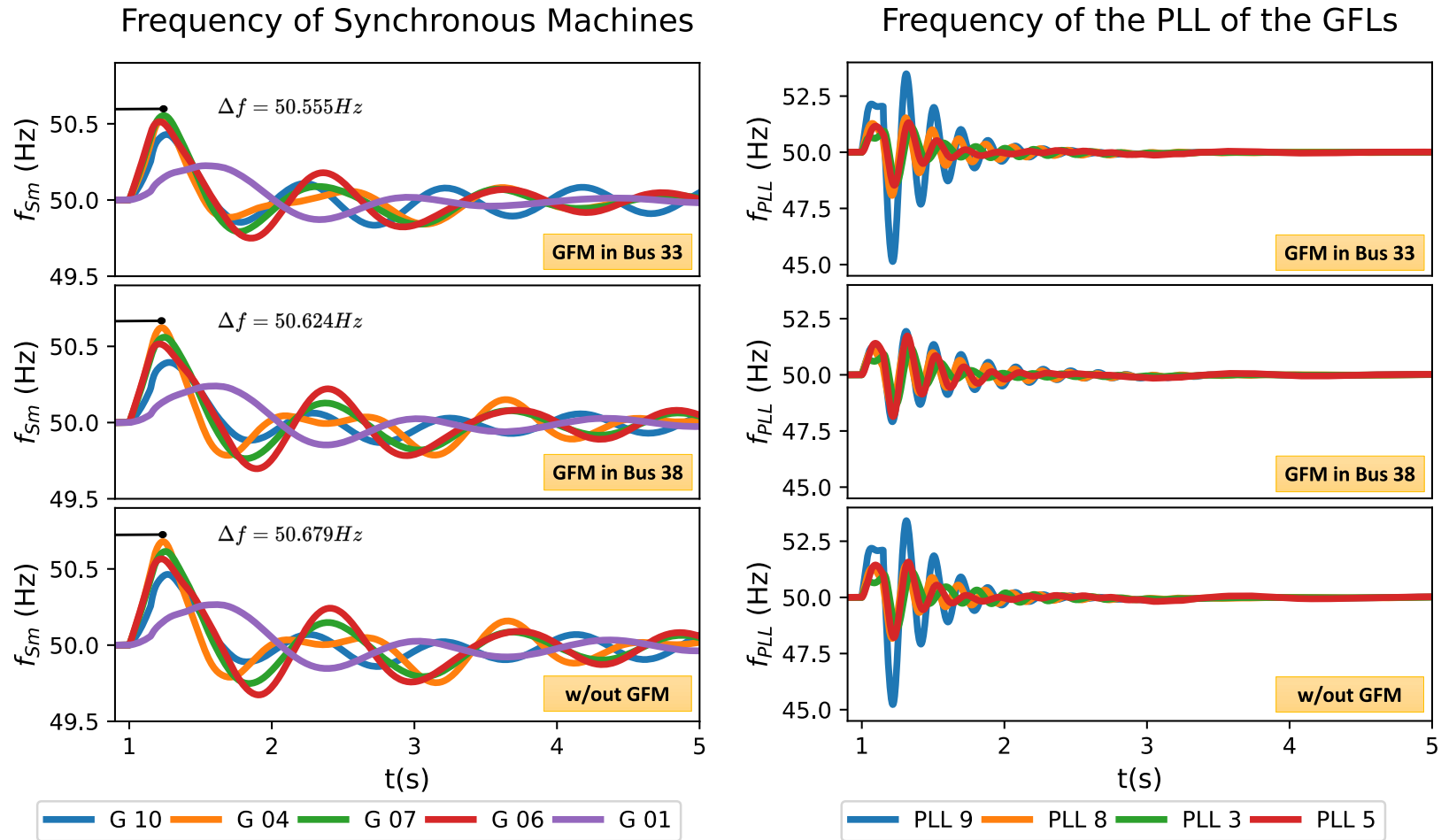


Figure 3.20: Frequency response of the Systems' Generators and PLLs to a short-circuit in line 17-18, for different GFM locations.

3.2. Impact of the GFM Location on the System Stability Regarding Different Classes

To further illustrate this phenomenon, the values achieved by the stability variables in these two events, when different GFM locations are chosen, were compiled into 4-vertex radar charts. In figures 3.21 and 3.22, the polygonal curves corresponding to the GFM locations that result in the minimisation of each stability index for each event are plotted. Such graphics show that the earlier identified trade-off between the stability improvements for frequency ($\text{Max } \Delta f_{SM}$) and converter-driven stability ($\text{Max } CQPD_{PLL}$) may also extend to other classes, such as voltage (Max CVD) and transient stability ($\text{Max } |Rocof_{SM}|$). This hints at the fact that if one performs a single-class optimisation of the GFM location, considering a single disturbance, poor improvements or deterioration of other stability classes may occur.

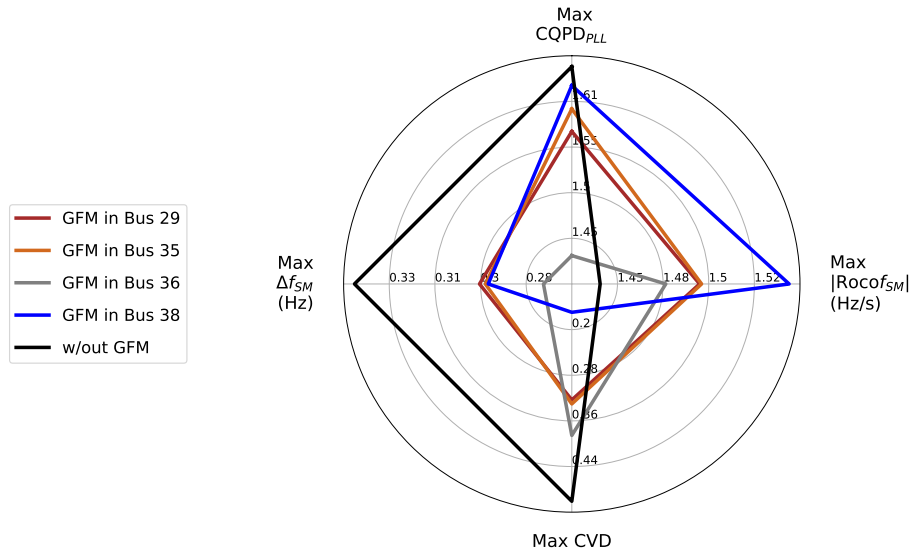


Figure 3.21: Stability indices Radar Plot, for the loss of G6.

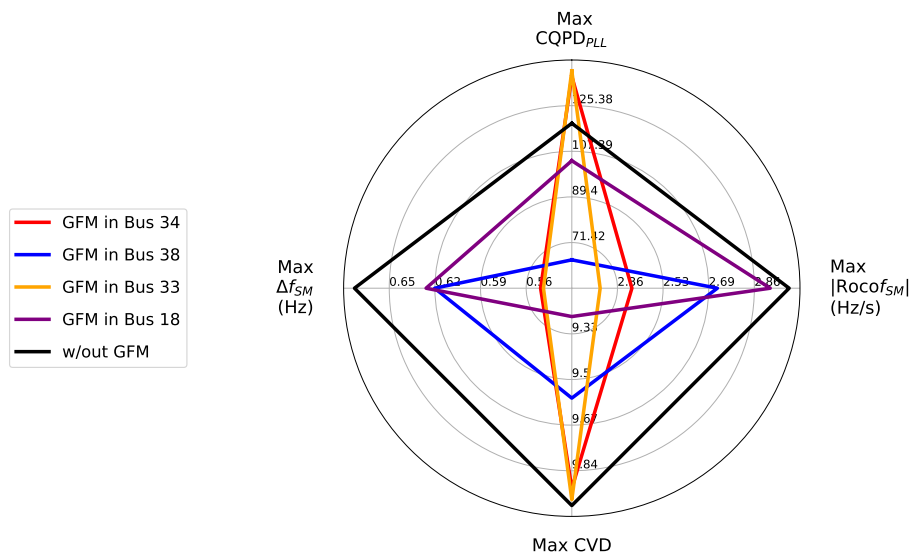


Figure 3.22: Stability indices Radar Plot, for a short-circuit in line 17-18.

3.2. Impact of the GFM Location on the System Stability Regarding Different Classes

The time evolutions of Figures 3.19 and 3.20 also reveal that, in the case of generation outages, the frequency across different points in the system is more uniform compared to short circuits. This phenomenon can be attributed to two main factors: 1) During a fault, the voltage drop across the system is non-uniform, causing the power variation—and consequently the accelerating torque experienced by each synchronous machine—to depend significantly on its proximity to the fault. In contrast, during generation outages, the power mismatch is rapidly distributed throughout the system. 2) The power mismatch resulting from a fault is typically larger than that of a generation outage, which amplifies even minor differences in the distribution of this mismatch across the grid.

This partially justifies why the location of the converter has less effect on the frequency stability when the disturbances at hand are generation outages. The other reason is the fact that the fast voltage support provided by the GFM during fault is circumscribed to a zone of the grid (due to grid topology, converter current limits and converter sizing), which does not happen in the generation outages case, where the benefits tend to be more widespread as the stability improvement tends to result from the GFM active power response;

That said, when the stability analysis extends beyond the scope of small-signal stability, it is more logical to prioritise short-circuit events when determining the optimal placement of new GFM converters. This preference is justified by the severity of such events, which are more likely to influence the system's stability margin, as well as the greater impact that the converter's location has on the degree of stability improvement achievable.

3.2. Impact of the GFM Location on the System Stability Regarding Different Classes

3.2.3 Events with Loss of Stability

The previously observed mismatch between locations that enhance different stability variables (and thus stability classes) may also extend to the ability to prevent system stability loss. That is, placing the GFM in a certain location may prevent the loss of stability for one phenomenon but be ineffective for another, and vice versa. The simplified contingency analysis of Algorithm 1 identified two events leading to instability in at least one stability class: the short circuit in line 21-22 and the short circuit in line 26-27. In both cases, introducing the GFM mitigated the instability; however, only a limited set of GFM placements ensured a stable system response for each event.

Regarding the event on line 21-22, illustrated in Figure 3.23, the original system (w/out GFM) experiences a rotor angle stability problem characterised by the loss of synchronism of generators G6 and G7. This is evident in the power angle characteristic of G7 (shown on the top right), where the rotor angle continually deviates from the Centre of Inertia (CoI), and in the continuous increase of the synchronous machines' frequency (shown on the top centre). This instability arises because, following fault clearance, G6 and G7 remain connected to the system solely through the extended transmission line of 23-24. The weak connection significantly reduces the machines' synchronising torque with the rest of the system, eventually leading to their loss of synchronism.

Placing the GFM at one of the buses closer to G6 and G7 (e.g., 22, 23, 35, or 36) can mitigate the loss of synchronism. This mitigation arises from two key factors: 1) the GFM's inherent reactive current response, which boosts voltage in its vicinity, and 2) its inherent active current response, which mitigates phase angle variations at nearby buses (see the bottom graphics of Figure 3.23). These responses collectively reduce the rotor acceleration of G6 and G7 during the fault and enhance the post-fault decelerating torque, thereby avoiding the loss of synchronism.

If any other location is chosen, the GFM will have a minor effect on the voltage magnitude and phase angle of the terminal bus of G7; hence, its terminal power variation will remain unaffected, as shown in Figure 3.23 for the case of the GFM location in bus 38.

Fault in line 21-22

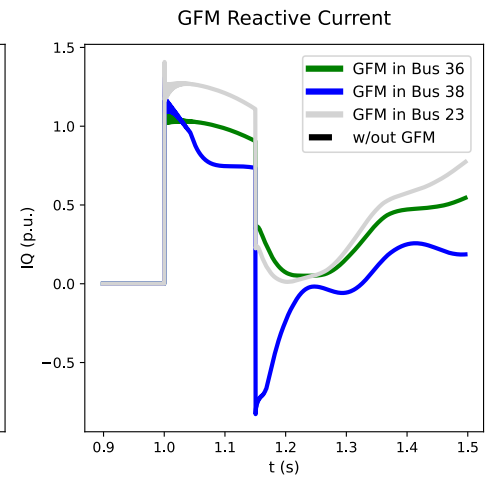
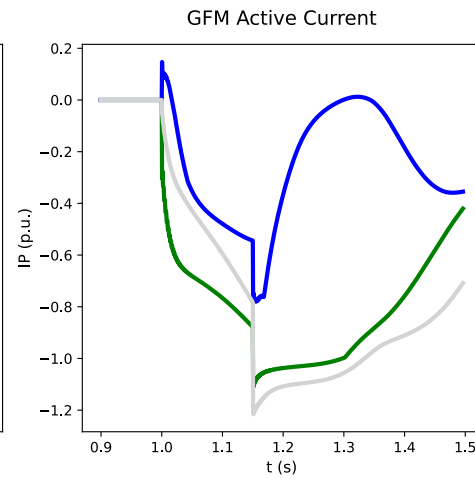
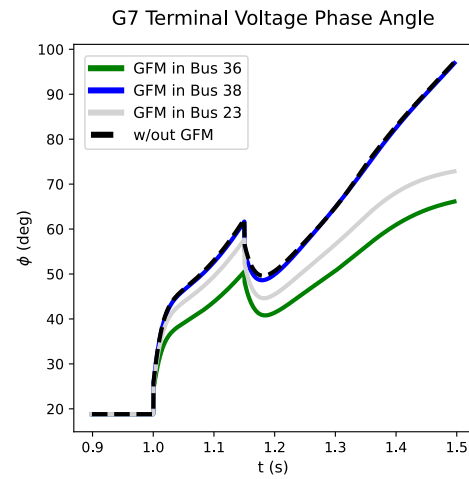
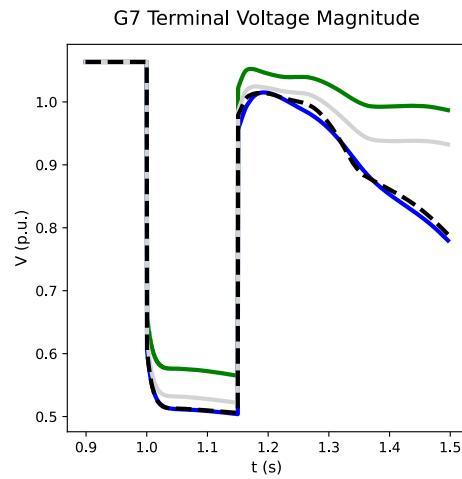
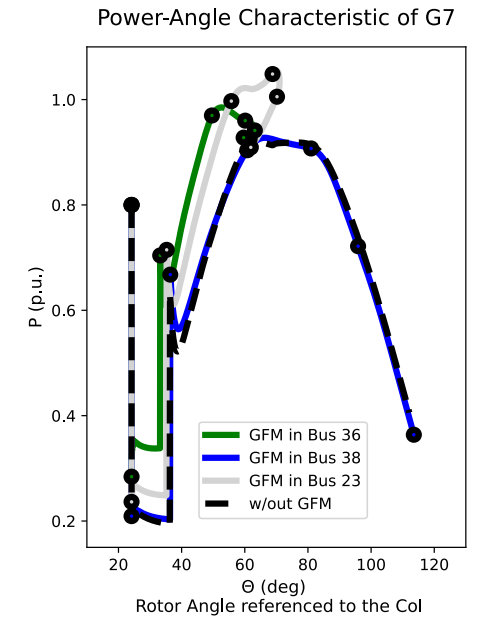
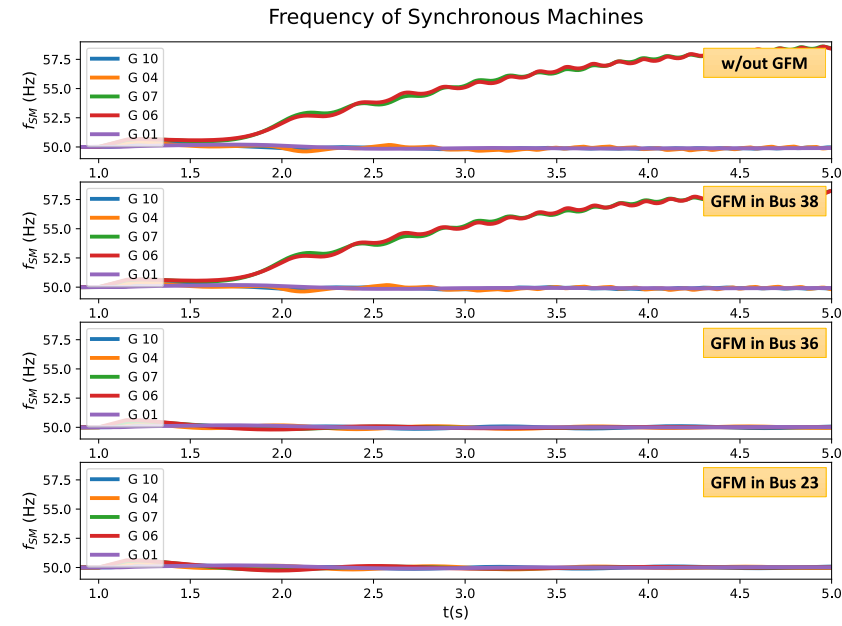
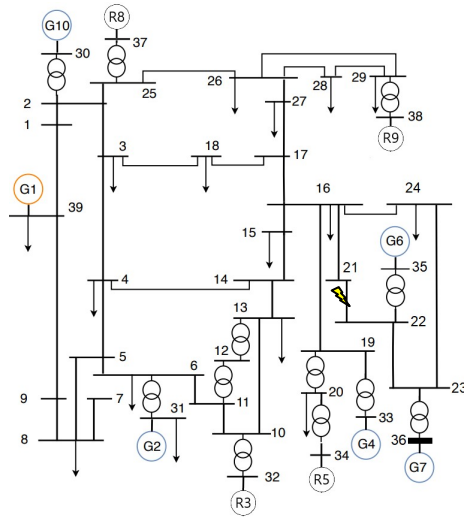
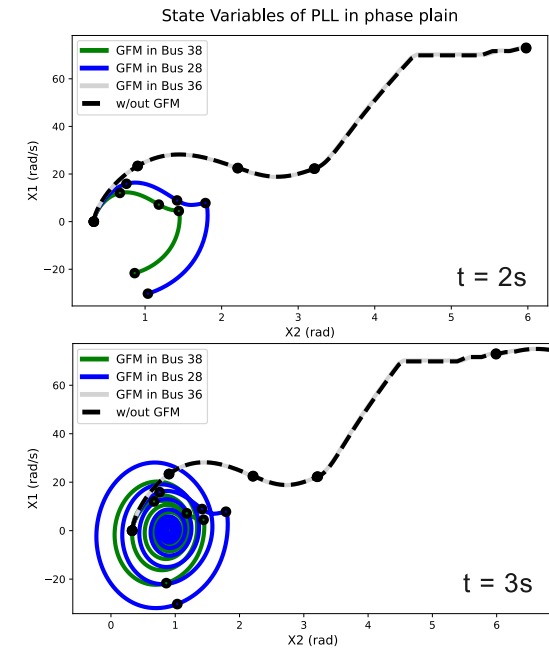
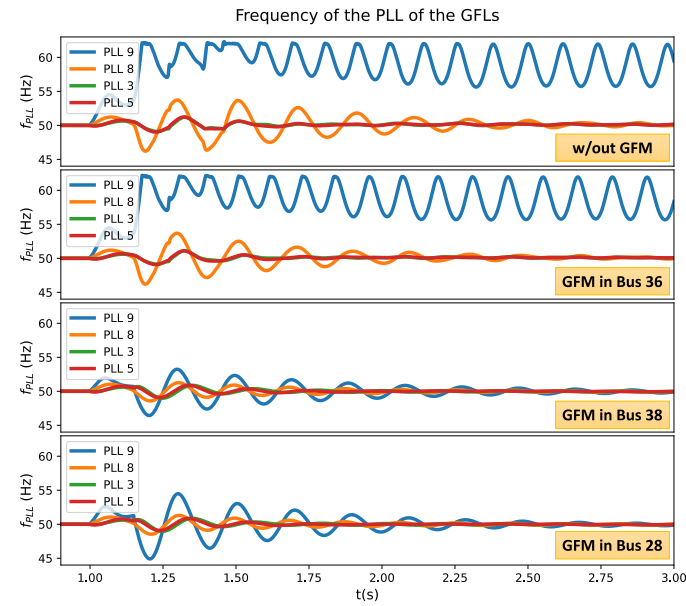
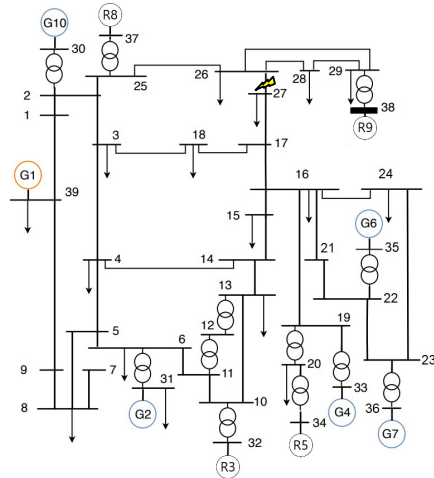
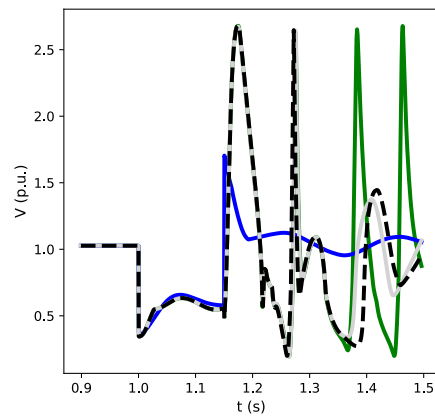


Figure 3.23: Graphic-based analysis of fault in line 21-22.

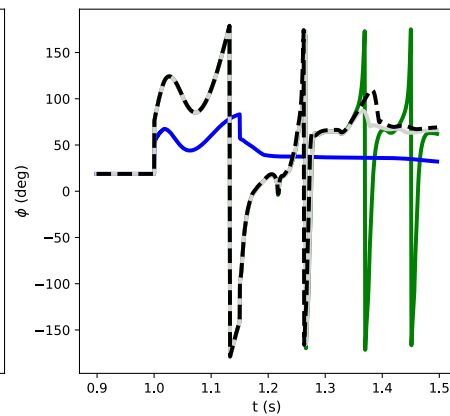
Fault in line 26-27



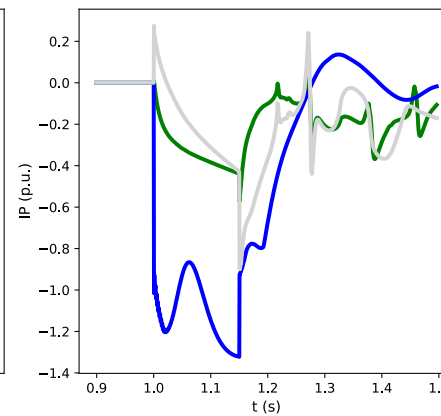
R9 Terminal Voltage Magnitude



R9 Terminal Voltage Phase Angle



GFM Active Current



GFM Reactive Current

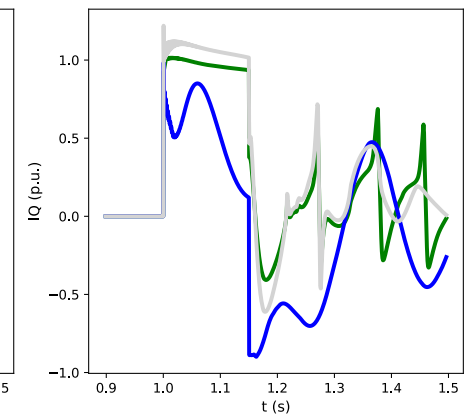


Figure 3.24: Graphic-based analysis of fault in line 26-27.

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Regarding the fault in lines 26-27, the system experiences a converter-driven stability problem characterised by the loss of synchronism of the PLL of converter R9. This loss of synchronism, which is visible in the trajectory plot of the PLL state variables (upper right part of Figure 3.24), materialises in sustained oscillations in voltage magnitude and phase angle after fault clearance (bottom part of Figure 3.24).

Due to the grid's weak nature (low S_{sc}) in the surroundings of the generator R9, the voltage magnitude and phase angle experience large and fast variations when nearby faults are cleared. In the specific case of line 26-27, R9s' PLL is incapable of following the erratic variation of the angle after the fault clearance, providing an erroneous angle value to the inner current control loop [33]. Consequently, the current injected by the converter is at the wrong phase, resulting in a voltage low-frequency oscillatory behaviour, visible also in the PLL frequency plot of Figure 3.24 (top centre).

To mitigate this converter-driven instability issue without recalibrating the PLL or adjusting the inner current control loop gains, reducing the rate of change of R9's bus voltage magnitude and phase angle is necessary. The inherent current response of GFMs (within their current limits) helps to moderate rapid variations in voltage magnitude and phase angle (see lower graphics of Figure 3.24), thereby enhancing local voltage stiffness and damping unwanted oscillations. Consequently, the instability described can be addressed by placing the GFM near the GFL converter previously experiencing instability (R9), specifically at buses 38, 29, or 28. As seen in Figure 3.24, when the GFM is placed in these locations, the PLL state variables return close to their initial values without exhibiting any momentary erratic behaviour, allowing for the correct definition of current control set points and thereby preventing low-frequency oscillations in the voltage.

Analogously to the fault in lines 21-22, if any other location (other than these three) is chosen, this loss of synchronism cannot be contained; this is the case of the placement of the GFM in Bus 36, as seen in Figure 3.24.

Summing up, the group of locations capable of mitigating instability for each event does not align. Therefore, it can be concluded that a single VSM-type GFM, with the characteristics outlined in Section 3.1.3, cannot guarantee a stable system response for all analysed faults, regardless of its placement.

This limitation arises because short circuits are inherently complex events that impact the grid in a non-uniform manner, particularly with respect to variations in voltage magnitude and phase angle. The root cause of instability in each event is tied to the grid's specific characteristics and control mechanisms in a particular zone (e.g., low short-circuit capacity, converter current controls, PLLs, AVR control, among others). Given that the reach of the GFM sup-

3.3. Final Remarks

port is constrained by factors such as current limits, converter sizing, and grid topology, it is unsurprising that when instability-prone elements are geographically distant, a single GFM placement cannot ensure stability for all affected zones. This is especially true when the instability involves different classes, such as transient stability and converter-driven stability. This fact was not changed by a reasonable increase in GFM size or control parameters adjustment, which shows that a compromise solution is not possible in this case.

3.3 Final Remarks

In this chapter, a multi-class stability assessment of the GFM location was performed by leveraging different stability variables. For that purpose, a simplified contingency analysis that accounts for the GFM location and disturbance nature was conducted. The results of such analysis were first assessed using a data-based analysis that resorted to box plots and radar plots to ease the drawing of conclusions. Secondly, a detailed analysis of some specific disturbances was performed, always considering the GFM location and its effect on stability as the focal point. The results of such analysis show that:

- The impact of introducing a new GFM converter in the system on the stability variables is highly dependent on the location. Depending on the location of the converter and on the stability variable at hand, the converter introduction may bring an improvement or a deterioration of stability (see Section 3.2.1).
- The impact of the location on the achievable degree of improvement for the different stability variables is less pronounced in the case of generation outages compared to the case of short circuits (see Section 3.2.1).
- Frequently, the locations of the GFM that enhance certain stability classes lead to minor improvements or even deterioration in others. This highlights a trade-off in the degree of stability improvement achievable across different classes when the converter location is the variable being adjusted (see Section 3.2.2).
- When severe stability problems, of local nature, co-exist in the system, a single GFM converter is not enough to ensure stability (see Section 3.2.3).

These conclusions underscore the importance of:

- Adopting a methodology to optimally place and size GFM converters, in order to maximise the stability benefits for the system.
- When the scope of stability analysis extends beyond the small signal stability scope, short-circuit events should be considered as the main disturbance when evaluating the

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contribution of different locations for the system stability.

- Formulating the optimal placement problem as a multi-class optimisation problem in order to achieve an overall enhancement of system stability, rather than prioritising a single class.

In the following chapter (Chapter 4), different placement methodologies that incorporate these findings are proposed.

Optimal Location and Sizing of GFM Converters, for Dynamic Security Purposes.

In the literature reviewed in chapter 2, the problem has been frequently addressed under the assumption that dynamic security should just be maximised or that stiff dynamic security limits should be ensured. This ignores the fact that simultaneous sizing and placing is indeed a multi-criteria problem that is constrained/influenced by the TSO's preference for cost and security. Secondly, there is no particular regard for the design of the converter's overcurrent capacity, an essential characteristic in the case of GFM converters, that significantly affects the power system dynamic behaviour for large disturbances [21] and the converter solution's cost [16]. At last, there is also a prevalence of methods that rely on system linearisation, which can misrepresent the system behaviour in the case of large disturbances where the converter's current limitation controls are enabled [15].

This chapter presents a new robust methodology to place and size a fleet of GFM converters in a power system where synchronous-based generation co-exists with a growing share of converter-based generation. The problem is first formulated in Section 4.1 as a multi-criteria issue, and a preferred solution is obtained using a decision support system. Subsequently, in Section 4.2, the proposed methodology for solving the formulated placement problem is outlined. The chapter concludes by introducing an alternative formulation for the system security index that considers multiple stability classes; this formulation is then integrated into a search methodology to optimally place the converters.

4.1. Formulation of the GFM Placement Problem: Considering the TSO Non-linear Valorisation of Security Throughout the Dynamic Security Domain.

4.1 Formulation of the GFM Placement Problem: Considering the TSO Non-linear Valorisation of Security Throughout the Dynamic Security Domain.

From a pure system stability point of view, the placement problem corresponds to the search for the location and size of the N GFM-controlled converters that maximise the system stability. Such an approach is of value when the goal is to bring stability into an unstable system or to achieve a deeper understanding of the dynamic behaviour of a GFM-populated system. However, for practical applications, the solution cost must also be considered, as operators have a tendency to seek a balanced solution between the system security and the planning costs.

This multi-criteria paradigm, which is illustrated in Figure 4.1, is also characterised by a set of non-linearities, which appear as a consequence of the way TSOs value the solution cost differently throughout the system security domain, mapped here through the system security index (ε). Note that the security index value varies inversely to the system security, as in many power system stability variables (e.g. Frequency Nadir, Rcof, etc.). Hence, the solution with the maximum security has a value of ε_{Min} and the solution with the minimum security has a value of ε_{Max} .

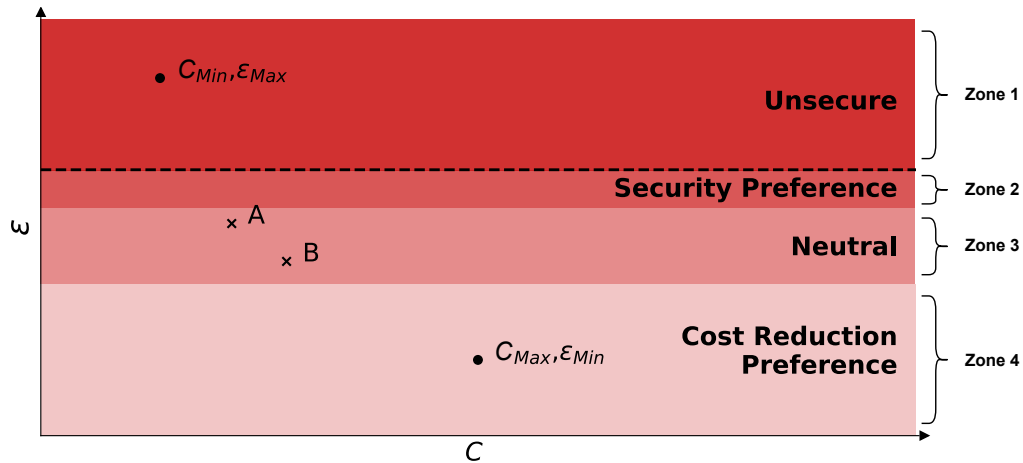


Figure 4.1: Illustration of the multi-criteria nature of the placement problem, with the zones of different security valorisation by the TSO highlighted.

The typical valorisation of security by TSOs can be explained by considering four different behavioural traits:

- A disregard for the increase in solution cost when the system is insecure ($\varepsilon \geq \varepsilon_{lim}$) due to the fundamental role of the TSO in safeguarding the system security (Zone 1 in Figure 4.1).

4.1. Formulation of the GFM Placement Problem: Considering the TSO Non-linear Valorisation of Security Throughout the Dynamic Security Domain.

- A preference for improving security when the solution ensures marginal security. This results from the uncertainty in analysing large disturbances in interconnected systems and the risk-averse nature of TSOs that demand buffer zones near the security boundary (Zone 2 in Figure 4.1).
- A preference for cost reduction, when the solution ensures a system state that is very far from the security boundary ($\varepsilon \ll \varepsilon_{lim}$) (Zone 4 in Figure 4.1).
- A willingness to evaluate different solutions, sometimes manifesting indifference between them, when none of the prior conditions apply (Zone 3 in Figure 4.1).

Regardless of the zone in the plane of Figure 4.1, if two solutions have equal cost, the TSO always prefers the one with better security. The same applies to solutions with equal security.

4.1.1 Problem Formulation

To completely address the multi-criteria paradigm that arises when factoring in the capacity cost in the placement problem, a decision-making formulation that expresses the complex preference structures exhibited by the TSO must be adopted. Therefore, an approach focused on maximising a multi-criteria value function that adequately models the TSO's cost-security preferences within the secure zone of the search space ($\varepsilon \geq \varepsilon_{lim}$) was followed.

Let X be the problem state variable array, which includes the bus location (l_k), the nominal capacity (s_k) and the overcurrent capacity (i_k) of each GFM-controlled converter k that is to be placed:

$$X = [L_X, S_X, I_X] = [l_1, l_2, \dots, l_{N_g}, s_1, s_2, \dots, s_{N_g}, i_1, i_2, \dots, i_{N_g}] \quad (4.1)$$

$$l_k \in \Omega_b^o, s_k \in [0, s_{max}], i_k \in [0, i_{max}]$$

where N_g is the maximum number of GFM converters that can be placed; Ω_b^o is the set of possible bus locations for the converters; s_{max} and i_{max} are the considered maximum values of the nominal and overcurrent capacity of the converters, respectively;

In a similar manner, let $\varepsilon(X)$ be the system security index for a solution X and $C(X)$ be the cost for a solution X ; variables that will be referred to as ε_X and C_X , for ease in notation.

Then, the value function maximisation problem that gives the solution to the placement problem can be formulated as follows:

$$\begin{aligned} & \max_X V(X) \\ & s.t. \ \varepsilon_X \geq \varepsilon_{lim} \end{aligned} \quad (4.2)$$

4.1. Formulation of the GFM Placement Problem: Considering the TSO Non-linear Valorisation of Security Throughout the Dynamic Security Domain.

Assuming that the conditions for additivity apply in the secure zone of the search space [138], then the additive value function described in Equation 4.3, $V(X)$, can be used as a means to evaluate the value of a solution X .

$$V(X) = V(\varepsilon_X, C_X) = K_w \cdot w(\varepsilon_X) + K_p \cdot p(C_X) \quad (4.3)$$

where K_w and K_p are the two parameters of the constructed value function, also known as weights, which express the relative importance of each criterion for the decision agent.

$V(X)$ combines two individual value functions, $p(C_X)$ and $w(\varepsilon_X)$, which express the way TSOs respectively value cost and security in the secure search space zone. The form of these individual value functions, which is plotted in Figure 4.2, is detailed in Equations 4.4 and 4.5. The function weights, K_w and K_p , can be obtained by inquiring the TSO through an indifference judgment, obtaining in this way two indifferent solutions (e.g. A and B in Figure 4.1) that are then used to determine the weights ($K_w + K_p = 1$) [139].

$$p(C_X) = \overline{C_X}, \quad \overline{C_X} = \frac{C_{max} - C_X}{C_{max} - C_{min}} \quad (4.4)$$

$$w(\varepsilon_X) = \frac{e^{b \cdot \overline{\varepsilon_X}} - 1}{e^b - 1}, \quad \overline{\varepsilon_X} = \frac{\varepsilon_{max} - \varepsilon_X}{\varepsilon_{max} - \varepsilon_{min}} \quad (4.5)$$

where $\overline{C_X}$ and $\overline{\varepsilon_X}$ are the respective normalised values of the cost and the system security index for a solution X , and b is a tunable parameter of the individual value function.

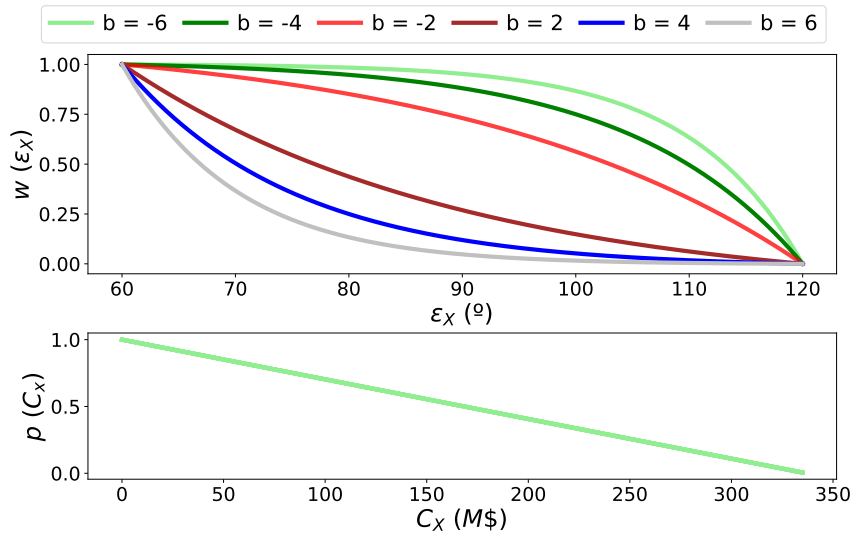


Figure 4.2: Illustration of the individual value functions form ($w(\varepsilon_X)$ and $p(C_X)$).

4.1. Formulation of the GFM Placement Problem: Considering the TSO Non-linear Valorisation of Security Throughout the Dynamic Security Domain.

When b is negative, the exponential form of $w(\varepsilon_X)$ enables the representation of a decision maker (DA) that is very favourable to the decrease of $\overline{\varepsilon_X}$ when its level is high, but not so enthusiastic when its level is already acceptable or low. This preference structure, which can also be reversed if b is positive, perfectly portrays the previously described desire of the TSO to enhance security across the security domain. Hence, a negative value of b that best replicated the foreseen valorisation of security by the TSO was adopted ($b=-4$). This value can be estimated by inquiring the TSO about the ranking of a group of possible solutions and then using a method known as direct ranking [140].

The optimisation problem formulated in Equation 4.2 will be solved using an unconstrained solution-seeking algorithm based on Bayesian Optimisation. Consequently, it is necessary to convert the problem into an unconstrained optimisation problem, which is achieved here by employing a penalising function $P(X)$. This function assigns a negligible value to insecure solutions ($\varepsilon_X < \varepsilon_{lim}$) through a sizeable penalising constant k_{pen} (refer to Equation 4.6), rendering them unappealing.

$$P(X) = P(\varepsilon_X) = \overline{\varepsilon_X} - k_{pen} \quad (4.6)$$

To accommodate the change between $P(X)$ and $V(X)$, the adaptation function $A(X)$ is used. Ultimately, the solution to the placement problem will be achieved by finding X that maximises $A(X)$, as seen in Equation 4.7.

$$\max_X A(X), A(X) = \begin{cases} P(X), & \text{if } \varepsilon_X \geq \varepsilon_{lim} \\ V(X), & \text{if } \varepsilon_X < \varepsilon_{lim} \end{cases} \quad (4.7)$$

4.1.2 Solution Cost

For a GFM converter to be able to provide its characteristic fast security/stability support, a primary source that offers a readily available energy buffer must exist [16]. In most commercially operational cases, this energy source is a Battery Storage system [21], which is the option considered in this work. Still, wind turbines and PV systems can also offer similar support, subject to the availability of the endogenous resource, if adequate adaptations to the GFM control, DC link and primary source control are implemented [21, 46].

To consider the cost associated with the battery-converter complex, this work uses a cost model that accounts for the price of the battery storage module, standard power converters, the transformer, the communication system, the installation, et al. [141]. Additionally, for the supplementary costs that result from enhancing a normal converter with GFM capability, particularly the current overload capacity, a second-price parcel is introduced. Overall, the cost of a solution X is given by:

4.1. Formulation of the GFM Placement Problem: Considering the TSO Non-linear Valorisation of Security Throughout the Dynamic Security Domain.

$$C_X = \sum_{k=1}^{N_g} a \cdot s_k + f \cdot \frac{s_k \cdot (i_k - 1)}{\sqrt{3} \cdot v_{Nom}} \quad (4.8)$$

where v_{Nom} is the converters' nominal voltage; a is the cost in $M\$/MW$ of the BESS, with a power converter designed with 0 overcurrent capacity ($i_k = 1$); f is the cost in $M\$/A$ of the converters' overcurrent capacity;

Both a and f depend on the vendor supplying the solution; however, this study adopts a generic estimation of these values derived from an analysis of multiple real-world systems [141]. Specifically, for a lithium-ion BESS, a is assumed to be $0.715 M\$/MW$ [141], while f is set at $0.02 M\$/A$. It is worth mentioning that there is an inherent difficulty in estimating the cost of the converter's overcurrent capability. Consequently, the presented value ($0.02 M\$/A$) results from a first estimate that corresponds to 50 % of the generic power converter cost provided in [141]. To address the uncertainty associated with this assumption, a sensitivity analysis of f in the results of the formulated placement problem is conducted in Section 6.2.4.

In this model, the battery energy capacity is assumed to be just twice the value of its nominal power capacity. This is justified by the main goals of the batteries being the support of the grid transient problems and not other, more energy-intensive tasks, like arbitrage or reserve provision. Also, only investment costs are included in this formulation. Still, an estimation of the operation cost can also be included by adding a term that is a function of the system life cycle.

4.1.3 Security Index

The system security index (ε_X) is a composite indicator that expresses how the system security behaves when a solution X is chosen. This indicator links the values of a generic system security variable (μ) for all combinations of scenarios and disturbances that are relevant to the optimisation. Equation 4.9 describes the conjugation approach followed in this work, where ε_X is defined as the maximum value of μ found among all combinations of scenarios and disturbances.

$$\varepsilon_X = \max_{m \in \Omega_m^o, d \in \Omega_d^o} \mu(X|m, d) \quad (4.9)$$

where $\mu(X|m, d)$ is the value of the system security variable in scenario m given the disturbance d , for a solution X ; Ω_m^o is the set of all optimization-relevant scenarios and Ω_d^o is the set of optimization-relevant disturbances;

The above procedure avoids the masking effect of sum-based formulations and allows direct detection of solutions that lead to insecurity in any of the scenarios/disturbances considered.

4.1. Formulation of the GFM Placement Problem: Considering the TSO Non-linear Valorisation of Security Throughout the Dynamic Security Domain.

Note that if appropriate information on the probability of each disturbance is available (for instance, through historical data), then a stochastic definition for the security index can also be adopted. This would mean that ε_X would be the probability of μ being above a generic threshold, instead of being the maximum value of μ found among all disturbances and scenarios

Depending on the Stability class(es) that the TSO wishes to improve (e.g. Frequency Stability, Voltage Stability, Converter-Driven et.al), different variables can be chosen to quantify the security of the system given a disturbance d in a scenario m (e.g. Nadir, Rocof, TVDI, H2 norm, et.al) [142]. In this section, the focus is on improving the system's dynamic security with respect to transient stability. Hence, the maximum rotor angle deviation with regard to the centre of inertia, found among all the system's synchronous machines, $\overline{\overline{\Delta\delta_{coi}}}$, was chosen as the system security variable (see Equations 4.10 and 4.11).

$$\overline{\overline{\Delta\delta_{coi}}}(X|m, d) = \max_{g \in \Omega_{sm}, t \in T, \forall m \in \Omega_m^o, \forall d \in \Omega_d^o} \Delta\delta_{coi}(X|g, t, m, d) \quad (4.10)$$

where $\Delta\delta_{coi}(X|g, t, m, d)$ is the rotor angle deviation of machine g in regards to the centre of inertia, for instance t , given a disturbance d at scenario m , when a solution X is adopted; Ω_{sm} is the set of all system synchronous machines; T is the time interval in which the system's dynamic response is evaluated.

That said, within the context of the system's dynamic security with respect to transient stability, the security index can be given as follows:

$$\varepsilon_X = \max_{m \in \Omega_m^o, d \in \Omega_d^o} \overline{\overline{\Delta\delta_{coi}}}(X|m, d) = \max_{m \in \Omega_m^o, d \in \Omega_d^o, g \in \Omega_{sm}, t \in T} \Delta\delta_{coi}(X|g, t, m, d) \quad (4.11)$$

To obtain $\overline{\overline{\Delta\delta_{coi}}}(X|m, d, g, t)$, a parallelised time-domain simulation is performed on a complete positive sequence model of the power system. The decision to use time domain simulation is justified by the need to accurately represent the behaviour of the existing system and the degree to which the additional GFM-controlled converters can improve system security. In both cases, the system has highly non-linear behaviour during large disturbances (e.g. the intrinsic power transfer characteristic of multi-machine systems [81], the current limiting action, saturation effects in synchronous machines) that makes other approaches, such as system linearisation, unfit. A similar path has been followed in other stability-related optimisation problems scattered in the literature [143, 144, 145]. Since the converter's overcurrent capacity is one of the problem state variables, it is paramount to precisely portray the effect of the converter's current limiting control loops on the system's dynamic behaviour, which be-

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comes hard without time-domain simulation. Different transient stability-based assessment criteria (e.g. energy function methods, equivalent equal criteria et al.) could also be adopted, as long as adequate changes are performed to include the converter's effect and fully capture the aforementioned dynamics.

Despite being parallelised, RMS simulations can still be computationally intensive, particularly when applied to real-scale systems. While this does not necessarily hinder the practical adoption of the methodology, as time constraints are usually more relaxed in planning problems, reducing the required computational effort can make the method suitable for large interconnected power systems and make it more feasible for developing sensitivity studies. That said, this work includes three fundamental features: 1) a selection procedure that identifies the most critical events to the system's dynamic security by quickly screening through multiple disturbances/scenarios; 2) an algorithm that performs a reduction of the search space and an intelligent initialisation of the optimisation engine using a Kullback-Leibler (KL) divergence Sensibility Analysis; 3) an optimisation engine suitable for problems where it is expensive to evaluate each solution;

4.2 Solver Methodology

As briefly outlined before, the proposed methodology for addressing the formulated placement problem consists of three fundamental steps:

- A selection of the most critical and representative scenarios/disturbances for the system's dynamic security. For that purpose, a rule-based filtering and clustering is conducted in an initial collection of disturbances and scenarios. This analysis evaluates an estimation of the synchronous machines' state variables at the fault clearance instance, derived from a low-order Taylor expansion of each machine's swing equation dynamics. Here, a short-circuit module that accounts for the effect of the existing GFL converters is used to compute the accelerating power of each synchronous machine during the fault.
- A search space reduction technique that eliminates the locations that don't exhibit practical impact on system dynamic security from the set of possible locations. This is achieved through a sensitivity analysis of the effect of adding GFM capacity at each location on the system's dynamic security. The Kullback-Leibler divergence is used to differentiate the impact of various placements for the filtered disturbances and scenarios. Full dynamic simulations are employed to compute the machine's rotor angle evolutions, rather than the state variable estimate mentioned earlier.
- A Bayesian optimisation-powered algorithm that intelligently searches the search space for the solution of the decision support problem and that is fitted for expensive to eval-

4.2. Solver Methodology

uate problems. This algorithm leverages the exploration capacity of Bayesian Optimisation and uses full dynamic simulation when evaluating the value (or fitness) of each solution.

To provide a comprehensive understanding of the methodology, a graphical abstract is presented in Figure 4.3, offering a clear and concise overview of the entire process. A comprehensive description of the design choices made in each stage is then provided in the subsequent subsections.

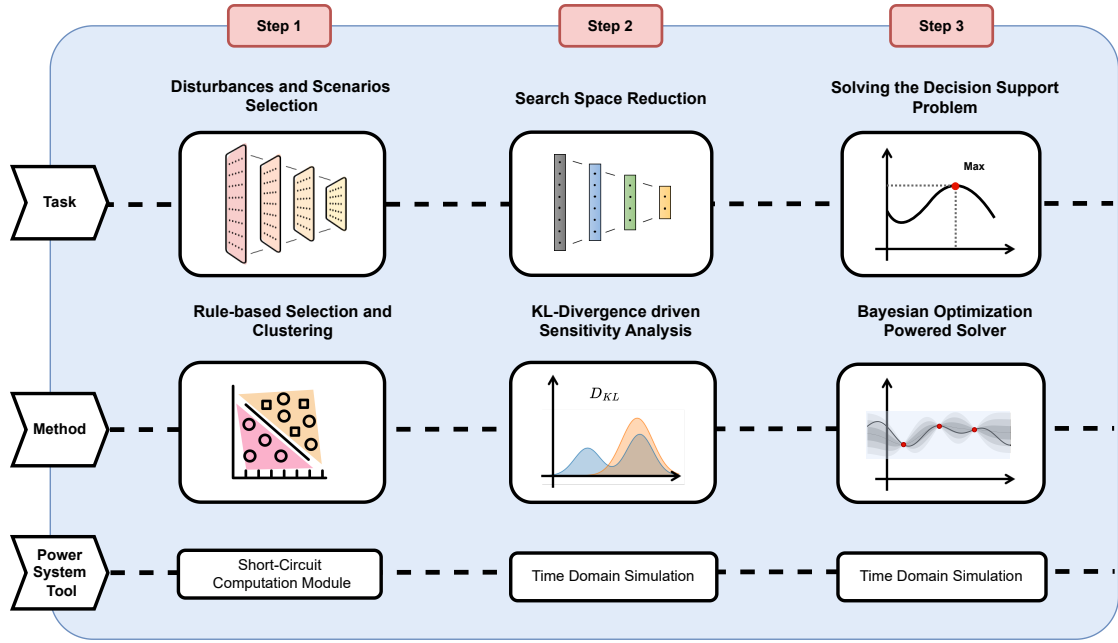


Figure 4.3: Illustration of Methodology Steps.

4.2.1 Selection of Disturbances and Scenarios

The solution of the optimisation problem formulated in Equation 4.7 is heavily influenced by the set of disturbances (Ω_d^o) and scenarios (Ω_m^o) that are considered when quantifying the system security for a solution X (see Equation 4.9). Since it is virtually impossible to consider all foreseen system scenarios and all possible N-1 system disturbances due to computational and time limitations, a shortlist of representative scenarios and disturbances must first be carefully selected. This short-list should comprise a limited number of severe disturbances or scenarios that effectively represent other, less critical elements within the set. This ensures that system security can be assessed efficiently with minimal computational effort.

The goal of this selection procedure, f_s , is mathematically defined in Equation 4.12, where Ω_d and Ω_m are the sets of disturbances and scenarios that are initially considered.

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$$f_s : \Omega_d \times \Omega_m \rightarrow \Omega_d^o \times \Omega_m^o \quad (4.12)$$

As mentioned before, this approach foresees dynamic security from the point of view of the system's transient stability. Hence, the scope of the disturbance analysis is limited to that of severe disturbances [24], specifically short circuits on transmission lines. This screening method also assumes that a pre-selection of the system operation scenarios has already been performed. This pre-selection, which is a high-order methodology, selects operation scenarios that are simultaneously prone to instability (e.g., with low synchronous inertia, low short-circuit power, etc) and that have diversification in terms of grid topology and generation dispatch. While this method was effectively used, its discussion falls outside of the main scope of this work. Hence, the interested reader is referred to [146] for similar methodologies.

The selection approach adopted here performs a rule-based evaluation of an estimate of the variable $\overline{\overline{\Delta\delta_{coi}^{T_{sc}}}}$ (see Equation 4.13), for all initially considered disturbances and scenarios. Equation 4.13 provides a mathematical definition of such a variable, given a disturbance d and scenario m .

$$\overline{\overline{\Delta\delta_{coi}^{T_{sc}}}}(X_0|m, d) = \max_{g \in \Omega_{sm}, t \in T_{sc}, \forall m \in \Omega_m^o, \forall d \in \Omega_d^o} \Delta\delta_{coi}(X_0|g, t, m, d) \quad (4.13)$$

where $\overline{\overline{\Delta\delta_{coi}^{T_{sc}}}}(X_0|m, d)$ corresponds to the value of $\overline{\overline{\Delta\delta_{coi}}}(X|m, d)$ for the elementary solution where no additional GFM capacity is added (X_0), and the considered time interval is T_{sc} ; T_{sc} is the time interval between the fault inception and the fault clearance instances;

To achieve an estimate of $\overline{\overline{\Delta\delta_{coi}^{T_{sc}}}}(X_0)$ ($\overline{\overline{\hat{\Delta\delta_{coi}^{T_{sc}}}}}(X_0)$), this screening method takes advantage of a short-circuit calculation module to estimate the synchronous machines' in-fault electrical power variation. Then it computes the time evolution of the machine state variables using the expressions of Equations 4.14 to 4.16. In such equations, a third and second-order Taylor expansion is considered for the rotor angle and speed, respectively.

$$\hat{\delta}(t+1) = \hat{\delta}(t) + \hat{\delta}'(t) \cdot \Delta t + \hat{\delta}''(t) \cdot \frac{\Delta t^2}{2} \quad (4.14)$$

$$\hat{\delta}'(t) = \overline{\overline{\Delta\omega}}(t) \cdot \omega_0 \oplus \overline{\overline{\Delta\hat{\omega}}}(t) = \overline{\overline{\Delta\hat{\omega}}}(t-1) + \overline{\overline{\Delta\hat{\omega}'}}(t) \cdot \Delta t \quad (4.15)$$

$$\overline{\overline{\Delta\hat{\omega}'}}(t) \approx \frac{P_a}{2H} \quad (4.16)$$

4.2. Solver Methodology

where δ and ω are the rotor angle and speed of a generic synchronous machine; $\hat{\delta}$ and $\hat{\omega}$ are estimates of δ and ω ; Δt is a small numerical integration step and H is the inertia of the synchronous machine whose state variables are being estimated.

To minimise the computational burden, the proposed approach assumes that the synchronous machines' accelerating power at the fault inception moment (P_a) remains constant throughout the fault. For the purpose of this analysis (obtaining an initial estimate of the machine state variables so that the less severe disturbances can be discarded), this simplification is reasonable enough. Its widespread use in transient stability studies that employ Lyapunov-like methods [147] further supports this approach.

The validity of this approach within the context of this work (bulk power systems where synchronous-based generation co-exists with a growing share of converter-based generation) is also reinforced by the low absolute error of estimation (AE) as illustrated in the histogram of Figure 4.4. Such a histogram condenses the results of a small experiment, where the estimated value of $\overline{\overline{\Delta\delta_{coi}^{T_{sc}}(X_0)}}$ is computed for 520 different events (150 ms self-clearing faults). These estimates, when compared with their ground truth value, give rise to the AE histogram of Figure 4.4. For a definition on the AE given a disturbance d and scenario m see Equation 4.17.

$$\begin{aligned} AE(\overline{\overline{\Delta\delta_{coi}^{T_{sc}}(X_0|m,d)}}, \overline{\overline{\Delta\hat{\delta}_{coi}^{T_{sc}}(X_0|m,d)}}) = \\ = \overline{\overline{\Delta\delta_{coi}^{T_{sc}}(X_0|m,d)}} - \overline{\overline{\Delta\hat{\delta}_{coi}^{T_{sc}}(X_0|m,d)}}, \forall m \in \Omega_m, \forall d \in \Omega_d \end{aligned} \quad (4.17)$$

$\overline{\overline{\Delta\hat{\delta}_{coi}^{T_{sc}}(X_0|m,d)}}$ corresponds to the estimative value of $\overline{\overline{\Delta\delta_{coi}^{T_{sc}}(X_0|m,d)}}$ using the proposed method. The ground truth value is computed using a full dynamic simulation model of the grid.

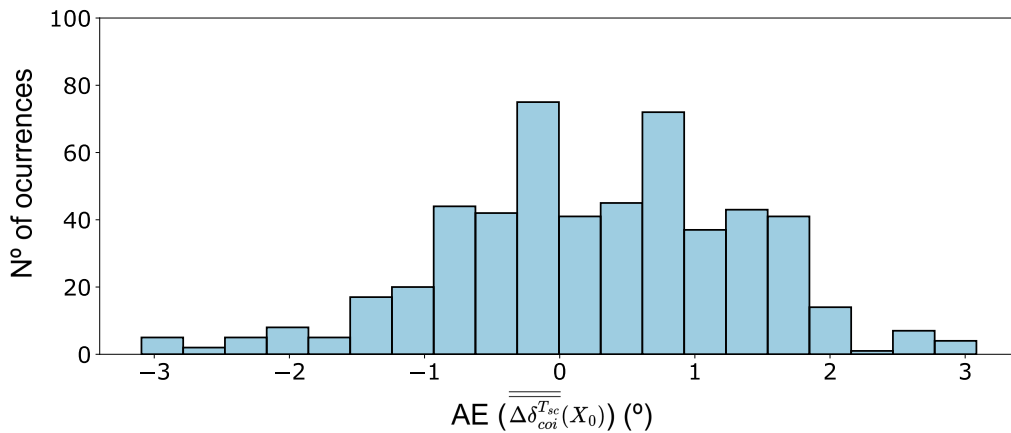


Figure 4.4: Absolute error of estimation histogram for the variable $\overline{\overline{\Delta\delta_{coi}^{T_{sc}}(X_0)}}$. The total number of estimated values is 520 (8 scenarios x 65 disturbances).

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Note that in recognition of this small uncertainty in the rotor angle projection, a conservative approach must be followed when using these values to diagnose the severity of each event.

This way of projecting the synchronous machines' rotor angle value not only enables an important reduction in terms of computational weight but also dramatically reduces the amount of information needed to run the model, especially when compared to techniques based on full dynamic simulation or eigenvalue analysis where there is often a lack of access to data due to proprietary nature of inverter controls [21].

The success of the angle estimation stems mainly from an accurate computation of the ΔP_{SC} value. Hence, a short-circuit module capable of capturing the main current contributions during the fault is fundamental. The module proposed here considers that, despite the typical current contributions of synchronous machines according to their sub-transitory reactance, a contribution from the converters in line with the standard grid code requirements [38] should also be considered.

This contribution, which should be enabled once the IBR terminal voltage passes an operator-defined voltage threshold (V_{Sup}), corresponds to a fast reactive current injection that is proportional to the terminal voltage deviation ($k \cdot \Delta V$). Such behaviour is included in a conventional superposition short-circuit computation model by introducing an additional iterative loop that adjusts a converter sub-transitory virtual impedance (Z_v) according to the expected control response. A detailed description of this method is given in Algorithm 2.

In the algorithm 2 V is the IBRs' terminal voltage; P and Q are the IBRs' active and reactive power; I_p and I_q are the IBRs' active and reactive currents; I_{lim} is the maximum current of the converter; α and β are algorithm hyperparameters designed to limit large variations of V_c and $\bar{I}_{set}$ between iterations, enabling convergence to an accurate value within a reasonable number of iterations; and N_{it} the number of iterations.

As seen below, the proposed iterative method adjusts a virtual impedance representing the converter's transient response. However, other converter representations may be used (e.g., as a current injector or a compound model) as long as step n° 7 of the algorithm is adjusted in conformity. This also implies that other converter controls, such as the GFM control, could be integrated into the loop if, for example, the system in which the fleet of GFM converters is to be placed and sized already incorporates some GFM converters.

Algorithm 2: Short-Circuit Computation Technique

Require: $\alpha, \beta, k, V_{Sup}, I_{lim}$

- 1: Run Load Flow
For all IBRs register pre-fault values: V_0, P_0, Q_0
 - 2: Run SC Model w/out IBR Contribution
For all IBRs register in-fault values: V_{sc}, I_p, I_q
 - 3: Identify IBRs that will provide I_q support (D_{Sup})
If $V_{sc} < 0.9 \rightarrow$ IBRs are considered to provide I_q support
 - 4: **while** $i \leq N_{it}$ **do**
 - 5: **for** All IBRs **do**
 - 6: Compute Converters Control Response (I_{set})
 #Adjust measured voltage, V_c
 $V_c = V_c + (V_{sc} - V_c) \cdot \alpha$
 #Define current control set-points, I_{ctr}
 $I_{pctr} = P_0/V_c$
 if (IBR $\in D_{Sup}$), **then:** $I_{qctr} = Q_0/V_0 + k \cdot (V_0 - V_c)$
 else: $I_{qctr} = Q_0/V_c$
 #Limit current set-points
 $I_{qctr} = [I_{qctr}]_0^{I_{lim}} \parallel I_{pctr} = [I_{pctr}]_0^{\sqrt{I_{lim}^2 - I_{qctr}^2}}$
 #Update converter current response
 $\bar{I}_{ctr} = I_{pctr} + I_{qctr} \cdot j$
 $\bar{I}_{set} = \bar{I}_{set} + (\bar{I}_{ctr} - \bar{I}_{set}) \cdot \beta$
 - 7: Adjust IBR virtual impedance according to I_{set}
 $\bar{Z}_v = (\bar{V}_0 - \bar{V}_{sc})/(\bar{I}_{set} - \bar{I}_0)$
 - 8: Run SC Model w/ IBR Contribution (get new V_{sc} value)
-

Value-based filtering

Using the aforementioned estimation method, $\overline{\Delta \delta_{col}^{T_{sc}}(X_0)}$ is computed for all initially defined disturbances and scenarios. These values are then inspected using the conditions of Equations 4.18 and 4.19, so the scenarios and disturbances that do not threaten the system security can be discarded. An illustrative example of the effect that this simple value-based filtering can have on the space of optimisation-relevant scenarios and disturbances is depicted in Figure 4.5, namely in the transition from the top heat map to the one on the left.

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$$\begin{aligned} & \text{if } \overline{\overline{\Delta \hat{\delta}_{coi}^{T_{sc}}}}(X_0|m, d) < 30^\circ, \forall d \in \Omega_d, \text{ then } \Omega_m^o = \Omega_m \setminus \{m\} \\ & \text{if } \overline{\overline{\Delta \hat{\delta}_{coi}^{T_{sc}}}}(X_0|m, c) < 15^\circ \wedge \overline{\overline{\Delta \hat{\delta}_{coi}^{T_{sc}}}}(X_0|m, d) < 45^\circ, \forall d \in \Omega_d^o, \text{ then } \Omega_m^o = \Omega_m^o \setminus \{m\} \end{aligned} \quad (4.18)$$

$$\begin{aligned} & \text{if } \overline{\overline{\Delta \hat{\delta}_{coi}^{T_{sc}}}}(X_0|m, d) < 30^\circ, \forall s \in \Omega_m^o, \text{ then } \Omega_d^o = \Omega_d \setminus \{d\} \\ & \text{if } \overline{\overline{\Delta \hat{\delta}_{coi}^{T_{sc}}}}(X_0|m, c) < 15^\circ \wedge \overline{\overline{\Delta \hat{\delta}_{coi}^{T_{sc}}}}(X_0|m, d) < 45^\circ, \forall m \in \Omega_m^o, \text{ then } \Omega_d^o = \Omega_d^o \setminus \{d\} \end{aligned} \quad (4.19)$$

where $\overline{\overline{\Delta \hat{\delta}_{coi}^{T_{sc}}}}(X_0|m, d)$ corresponds to the maximum excursion of the rotor angle deviation in regards to the centre of inertia, found among all the system's synchronous machines, during the time interval T_{sc} .

The threshold values used in the above equation are defined by leveraging existing knowledge about the system behaviour. A cautious approach must be taken in defining these values, considering the error pattern observed in the estimation (e.g. Figure 4.4) and anticipating the system's potential non-linear behaviour after fault clearance. This approach ensures the eliminated disturbances are unlikely to pose a security concern for the system. The threshold values depicted in the above equations align with the appropriate values utilised in one of the test cases within this study.

Representativeness-based clustering

Apart from removing the less severe disturbances and scenarios, a second step that discards scenarios and disturbances when well represented by other set elements of larger severity is also performed. The premise for representativeness adopted here relies on two aspects:

- Electrical Proximity: faults that are electrically close to each other.
- Affecting with the largest severity the same generator: faults where the generator that has a larger angle excursion ($\overline{\overline{\Delta \hat{\delta}_{coi}^{T_{sc}}}}(X_0|m, d)$) is the same.

Equations 4.20 and 4.21 depict the rule-based selection conditions that incorporate the two aforementioned factors; An illustrative example of the effect that the application of the above conditions can have on the space of optimisation-relevant scenarios and disturbances is depicted in the two bottom heat-maps of Figure 4.5.

$$\text{if } \exists k \in \Omega_m^o : \overline{\overline{\Delta \hat{\delta}_{coi}^{T_{sc}}}}(X_0|m, d) < \overline{\overline{\Delta \hat{\delta}_{coi}^{T_{sc}}}}(X_0|k, d) \wedge G_{md} = G_{kd}, \forall d \in \Omega_d^o, \text{ then } \Omega_m^o = \Omega_m^o \setminus \{m\} \quad (4.20)$$

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$$\begin{aligned}
 &\text{if } \exists z \in \Omega_d^o: \overline{\overline{\Delta \delta_{coi}^{T_{sc}}(X_0|m, d)}} < \overline{\overline{\Delta \delta_{coi}^{T_{sc}}(X_0|m, z)}} \wedge G_{md} == G_{sz} \wedge D_{z-d} < D_{max}, \forall m \in \Omega_m^o, \\
 &\quad \text{then } \Omega_d^o = \Omega_d^o \setminus \{d\}
 \end{aligned} \tag{4.21}$$

where D_{z-d} is the electrical distance between the locations of disturbance d and z , considering the electrical distance definition specified in [148]; D_{max} is the maximum electrical distance that a disturbance can be from each other so that they are considered neighbours; G_{md} is the synchronous machine with the largest $\Delta \delta_{coi}$ value in scenario m for disturbance d ;

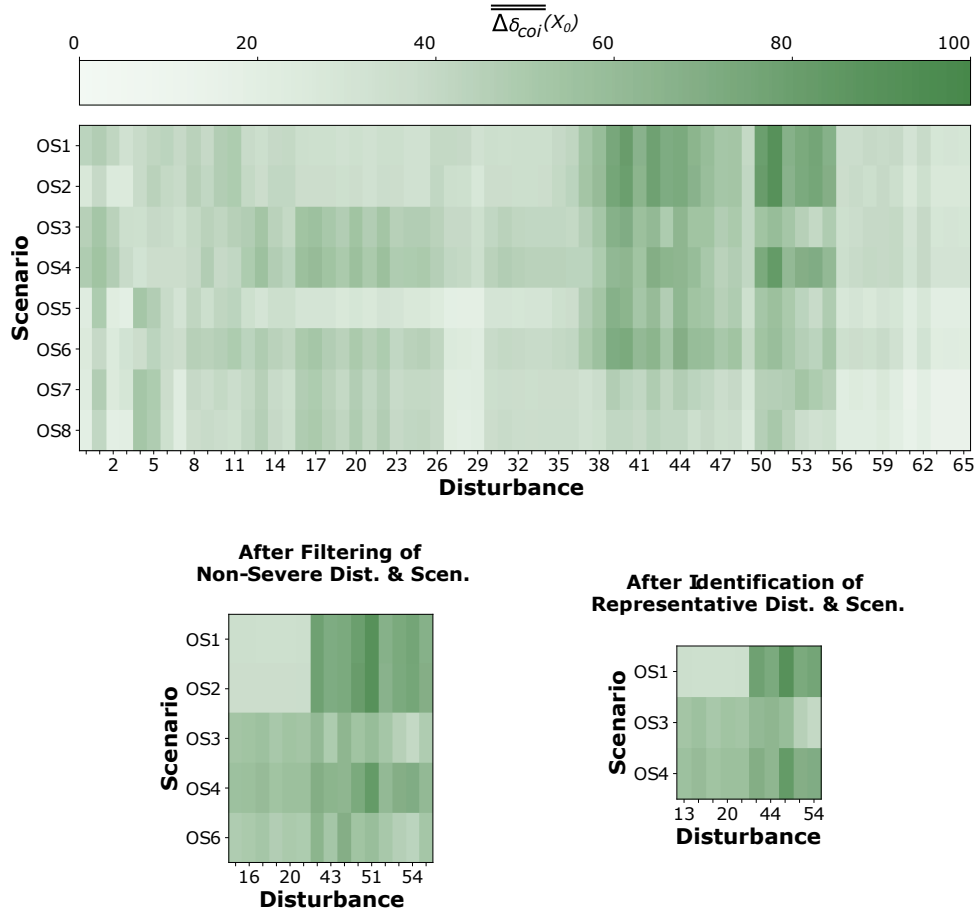


Figure 4.5: Effect of the selection techniques on the map of relevant scenarios and disturbances using, as an example, a collection of scenarios from the modified version of IEEE39.

Note that the proposed filtering techniques were used since they don't demand any pre-tuning or training. Still, this filtering step is not a fundamental contribution of this work, and other filtering techniques that achieve similar reductions in the Disturbance/Scenario space could also be used. For instance, if the user still wants to maintain an interpretable way to select the right

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scenarios and disturbances while leveraging the proposed angle estimation, the methodology of Chapter 5 can be adapted to generate a sequence of simple rules.

4.2.2 Search Space Reduction

The combinatorial nature of the placement problem results in an explosive growth of the solution search space with the number of possible locations. Hence, restricting the set of possible locations (Ω_b^o) to those where an additional GFM capacity can effectively impact dynamic security is fundamental for a successful yet computationally affordable solution search.

This work narrows the solution space by evaluating, for all possible locations Ω_b , the effect that adding a marginal GFM capacity ΔS has on the distribution $\mathcal{D}$. Based on the findings from this preliminary evaluation, locations that yield an insignificant distortion of $\mathcal{D}$ are then eliminated. For a comprehensive explanation of the steps involved in this procedure, refer to Algorithm 3.

A graphical illustration of the distribution $\mathcal{D}$ with GFM capacity added at two distinct locations is presented in Figure 4.6 to provide further insight into how the placement of new GFM capacity may impact and distort this distribution.

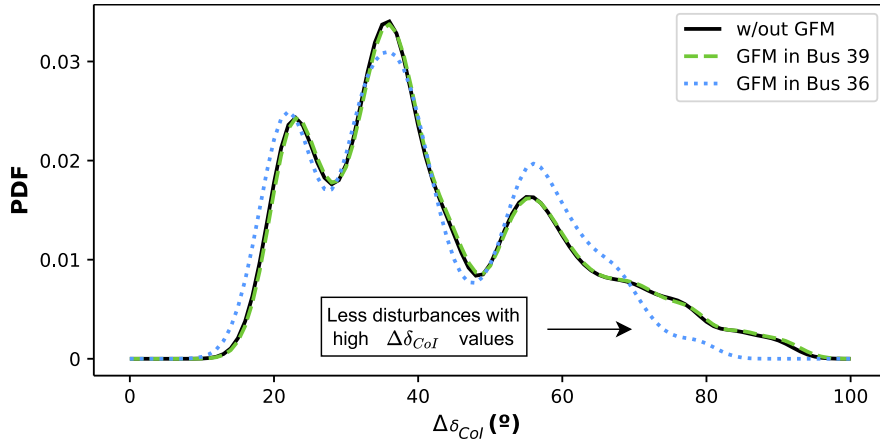


Figure 4.6: Impact of adding a GFM-controlled battery of 100 MVA on the distribution $\mathcal{D}$ for 2 different locations.

$\mathcal{D}_X$ corresponds to the distribution of the $\Delta\delta_{coi}$ values of all system synchronous machines for all disturbances (Ω_d^o) and scenarios (Ω_m^o), when the solution X is adopted. This distribution can be mathematically defined as follows:

$$\{\{\max_{t \in T} \Delta\delta_{coi}(X|g, m, d, t)\} : \forall g \in \Omega_{sm}, \forall m \in \Omega_m^o, \forall d \in \Omega_d^o\} \sim \mathcal{D}_X \quad (4.22)$$

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Algorithm 3: Search Space Reduction Algorithm

```

1: // ----- Location Sensitivity Analysis ----- /
2: for each  $l \in \Omega_b$  do
3:   Place GFM capacity  $\Delta S$  in bus  $l$ 
4:   for each  $m \in \Omega_m^o$  do
5:     for each  $d \in \Omega_d^o$  do
6:       RMS simulation of disturbance  $d$  in scenario  $m$ ;
7:       Add resulting  $\Delta \delta_{coi}$  values to distribution  $\mathcal{D}_{X_l}$ 
8:       Compute  $D_{KL}(\mathcal{D}_{X_0} || \mathcal{D}_{X_l})$  and save value within  $D_{KL}$  dataset
9: // ----- Discard Locations w/out effective security impact ----- /
10: Use k-mean clustering on  $D_{KL}$  dataset to identify set of less effective locations  $\Omega_b^e$ 
11: Discard  $\Omega_{be}$  from  $\Omega_b$  and get set of locations that are used in the optimisation,  $\Omega_b^o$ 

```

where $\mathcal{D}_{X_0}$ is the system $\mathcal{D}_X$ distribution when no additional GFM capacity is introduced; $\mathcal{D}_{X_l}$ is the system $\mathcal{D}_X$ distribution when the marginal GFM capacity ΔS is introduced in bus l ;

The choice to measure the impact of the additional capacity ΔS on system security from the $\mathcal{D}$ distortion, rather than evaluating the effect on ε_X , is down to the ability to quantify the effect on the system security for all cases and not just the most severe. In this way, greater value is given to the solutions that provide the greatest improvements in security, whether they are more modest for different faults or significant for specific faults. This enables maintaining locations that may not be the best at reducing ε_X alone but can play an important role when combined with others.

To quantify the distortion in the $\mathcal{D}$ distribution resulting from the additional GFM capacity at bus l , the difference between the $\mathcal{D}$ distribution without the additional GFM capacity ($\mathcal{D}_{X_0}$) and the $\mathcal{D}$ distribution after introducing the marginal GFM capacity, ΔS , at bus l ($\mathcal{D}_{X_l}$), is calculated. The Kullback-Leibler divergence, D_{KL} , is utilised for this purpose, serving as a rigorous metric to quantify differences between the two probability distributions [149]. An illustrative example of the search space reduction that can be achieved when using the above methodology for this work's test case is shown in Figure 4.7.

After narrowing down the search space, a simplification procedure based on the concept of the electrical neighbourhood was also implemented. The premise behind this simplification is that adding GFM capacities in nearby locations results in similar improvements to the system's security. Therefore, during this process, each bus is compared with its two nearest neighbours and only the location with the highest $D_{KL}(\mathcal{D}_{X_0} || \mathcal{D}_{X_l})$ is retained. The resulting location set (Ω_b^{init}), which will be used exclusively for initial purposes, as detailed in Section 4.2.3, is also depicted in Figure 4.7. Note that this phase does not correspond to a further reduction of the search space. Therefore, the solution-seeking algorithm will still be able to choose between

4.2. Solver Methodology

the set of locations depicted in the 3rd array of Figure 4.7 (Ω_b^o) and is not restricted to the locations of the Ω_b^{init} set.

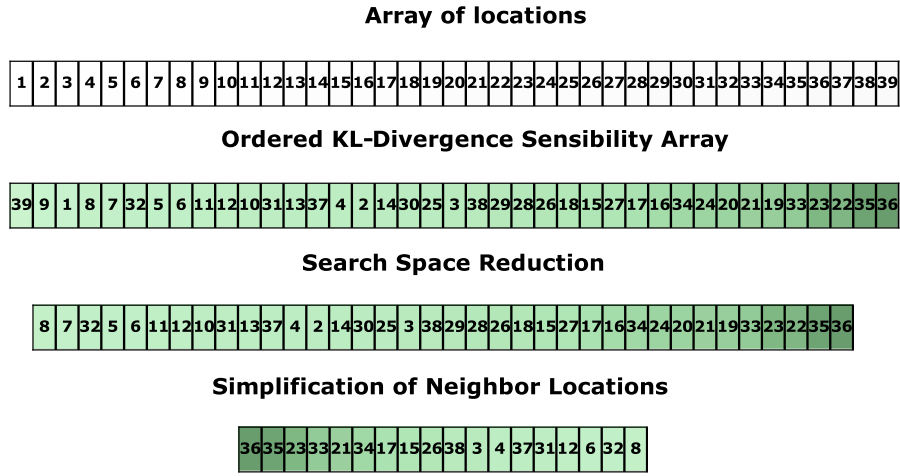


Figure 4.7: Example of achievable search space reduction and simplification of neighbour locations. (Obtained using the modified version of IEEE39.)

4.2.3 Bayesian Optimisation Powered Solution Seeking Algorithms

In Bayesian Optimisation [150], a statistical surrogate model of the objective function (e.g. Gaussian Process: $\tilde{A}(X)$) is iteratively built by sampling points from the real function $A(X)$, according to the sampling "suggestions" provided by an acquisition function. This sampling scheme, which tends to suggest points in areas yet to be explored or close to the optimum of $A(X)$, enables a fast and efficient search space exploration, making the method particularly suitable for expensive evaluation problems. Hence, this work resorts to Bayesian Optimisation to perform the fundamental search space exploration needed to find the solution of the optimisation problem formulated in equation 4.7.

As seen in the illustrative example of Figure 4.8, Bayesian Optimisation comprises two key components: a Bayesian statistical model (Gaussian Process) for modelling the objective function (graphic at the top) and an acquisition function that guides the selection of the next sampling point (graphic at the bottom) [150]. At each algorithm step, the Gaussian Process is fitted to the available samples (points previously explored), and the posterior distribution, combined with an exploration strategy, is used to determine the next point to be explored (highlighted in Fig 4.8). As the number of observations grows, the posterior distribution improves, and the algorithm becomes more confident about which regions of the search space are worth exploring [151].

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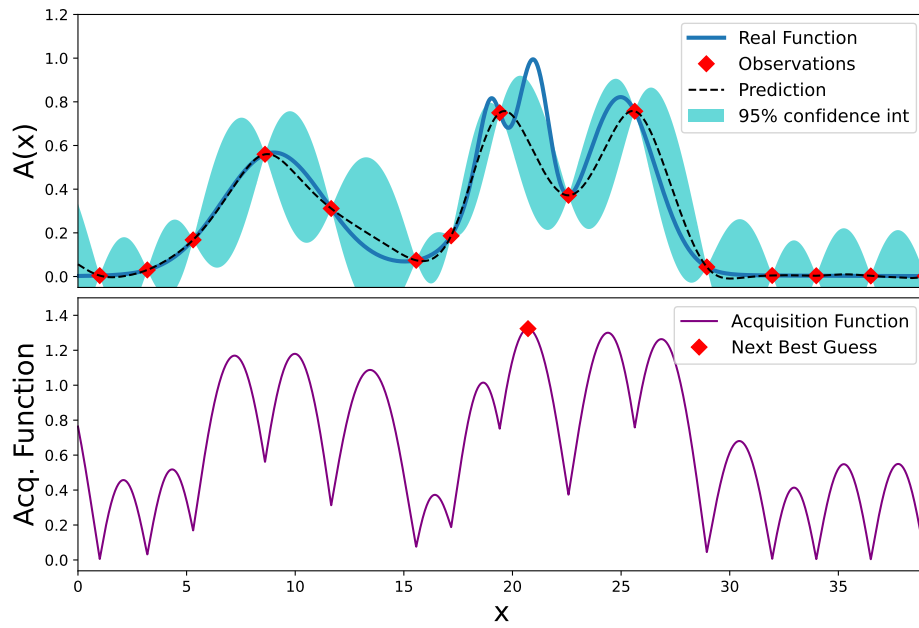


Figure 4.8: Illustrative example of the sampling process of Bayesian optimisation, assuming $A(X)$ is a one-dimensional function (inspired by [151]).

The main steps of the Bayesian Optimisation procedure, when applied to this work's problem, are depicted next in the flowchart of Figure 4.9.

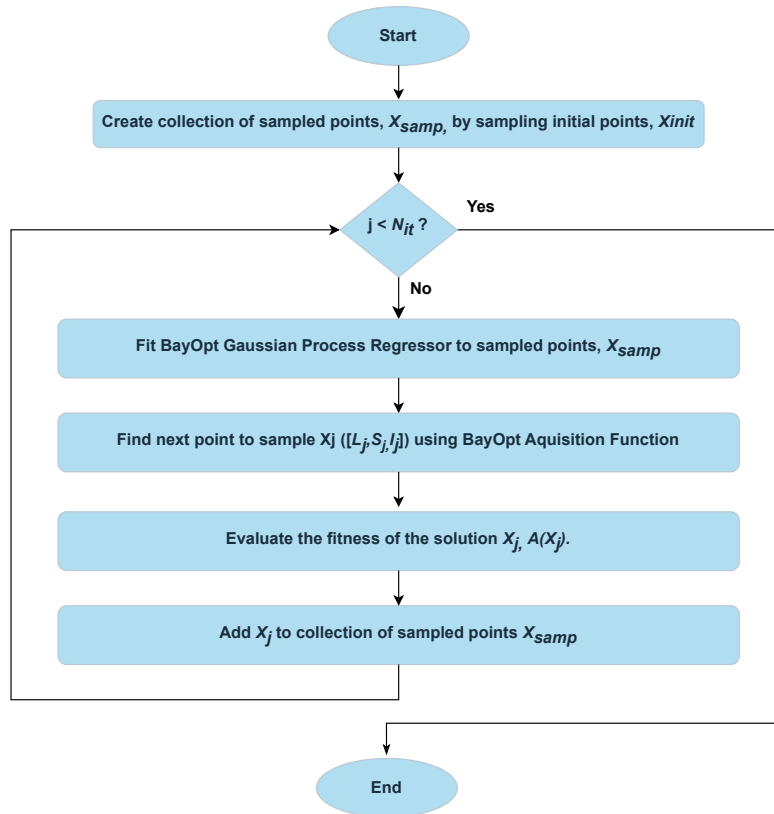


Figure 4.9: Flowchart of Bayesian Optimisation procedure in the context of this work's problem.

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For a swift and successful method convergence, it is paramount to choose the adequate parameters of the Gaussian Process Regressor (Kernel and α) and the right acquisition function. That said, this approach uses a Radial Basis Function (RBF) kernel [152] and an α value of 10^{-7} for the GPR Regressor and the expected improvement acquisition function [153] with a decaying trade-off, to balance exploration and exploitation throughout the method run. This choice results from a sensitivity analysis of different combinations of acquisition functions (Expected Improvement, Probability of Improvement and Upper Confidence Bound) and GPR kernels (RBF, Mattern and Rational Quadratic) in a validation problem of smaller dimensions.

Bi-level Solution Seeking algorithm

In Section 6.1, the methodology that is being detailed will be adopted to optimally place and size a small fleet of converters; however, at first, only the converter's nominal capacity will be considered. Within this context, which is a state-of-the-art procedure outside of this work (e.g. [77]), the solution-searching algorithm described in the flowchart of Figure 4.9 is further modified into the bi-level procedure of Algorithm 4.

To that end, Bayesian Optimisation is used to optimally move along the space of possible converter locations, while the Limited-memory Broyden–Fletcher–Goldfarb–Shanno (L-BFGS) algorithm is adopted to define the optimal capacity of the converters. This 2-step partition restricts the dimension of the problem that the Bayesian Optimisation has to address to N_g (the locations of the converters to place) instead of $2N_g$ (the locations and the size of the converters to place), enabling a faster and more efficient exploration of the location search space that improves convergence. The decision to use L-BFGS as the optimisation engine for capacity optimisation is based on its proven ability to converge towards the optimum while utilising limited computational resources, particularly for problems with larger dimensions [154].

In this bi-level process (see Algorithm 4), a surrogate function of the fitness function, $A_s(X)$, is adopted by the L-BFGS in the capacity optimisation. At the same time, in the Bayesian Optimisation, the real value of $A(X)$ is accessed through RMS simulations in the complete system model (see Section 4.1.3). Using the surrogate function $A_s(X)$ in the capacity optimisation allows a swift determination of a near-optimal value of the capacities of the converters (S_i) for each combination of locations (L_i), something that would be computationally unfeasible if the real value function, $A(X)$, was used.

The surrogate function, $A_s(X)$, has the same form as $A(X)$ (see Equation 4.23), but it resorts to a simple sigmoid-based regression model ($\hat{\varepsilon}_X$) to compute an approximated value of ε_X .

$$A_s(X) = \begin{cases} P_s(X) = P(\hat{\varepsilon}_X), & \text{if } \hat{\varepsilon}_X \geq \varepsilon_{lim} \\ V_s(X) = V(\hat{\varepsilon}_X, C_X), & \text{if } \hat{\varepsilon}_X < \varepsilon_{lim} \end{cases} \quad (4.23)$$

4.2. Solver Methodology

$\hat{\varepsilon}_X$, which is described in Equation 4.24, is initially defined through the location-based sensitivity analysis of Algorithm 3. Then, after the initial sampling phase of BO, which enables the construction of the first Gaussian Process Regressor (GPR), $\hat{\varepsilon}_X$ is recalibrated, now considering the effect of the combination of different locations on the security index.

$$\hat{\varepsilon}_X = \max[\varepsilon_{d0} + Xt \cdot A + B \cdot \text{atan}\left(\frac{St_X}{St_{max}} \cdot E\right)] \quad (4.24)$$

where St_X is the sum of capacities of all GFM converters in solution X ; St_{max} is the maximum capacity that can be added to the system ($St_{max} = N_g \cdot s_{max}$); N_d^o is the number of disturbances in set Ω_d^o and N_b^o is the number of locations in the set Ω_b^o , respectively, considered in the optimisation; $A_{[N_b^o \times N_d^o]}$, $B_{[1 \times 1]}$ and $E_{[1 \times N_d^o]}$ are the matrices adjusted to fit the function to the data; Xt is a line array with the dimension of the number of possible locations (N_b^o), whose value per line corresponds to the GFM capacity in that location for the solution X ; ε_{d0} is a line array containing the stability variable values prior to the disturbance occurring in each scenario.

Algorithm 4: Solution Seeking Algorithm

- 1: // ----- Sampling of BO initial points ----- //
 - 2: **for** each combination of locations $L_j \in \Omega_{comb}^{init}$ **do**
 - 3: Use L-BFGS to establish the capacity of converters (S_j) that maximises $A_S(X)$ for combination of locations L_j .
 - 4: Evaluate $A(X_j)$ using RMS simulation ($X_j = [L_j, S_j]$).
 - 5: Add $X_j, A(X_j)$ to the list of BO initial points (X_{init}, A_{init}).
 - 6: Readjust $A_S(X)$
 - 7: // ----- Main BO procedure ----- //
 - 8: Fit BO Gaussian Process Regressor to X_{init}, A_{init} .
 - 9: **for** i in N_{it} **do**
 - 10: Sample next combination of locations L_i using BO acquisition function.
 - 11: Use L-BFGS to establish the capacity of converters (S_i) that maximises $A_S(X)$ for combination of locations L_i .
 - 12: Evaluate $A(X_i)$ using RMS simulation ($X_i = [L_i, S_i]$).
 - 13: Re-fit the BO Gaussian Process Regressor, considering the new X_i point.
-

Ω_{comb}^{init} is a set of points, where each point L_j is a combination of N_g converter locations.

The first version of the BO Gaussian Process (GP) is achieved by fitting an initially sampled population of solutions X_{init} and its respective adaptation function values A_{init} into a GP through a regression technique (see line 8 of Algorithm 4). This population of solutions greatly influences the development of the BO procedure; hence, making an adequate choice of such points

4.2. Solver Methodology

is paramount for a successful and swift convergence towards the optimum. As seen in the algorithm, these points are defined using a 2-step approach: 1) the combination of locations (L_j) used for each point (X_j) is sampled from the set of combinations of locations Ω_{comb}^{init} . 2) the optimal capacity of the converters S_j , when placed in the combinations of locations L_j is defined by maximizing $A_S(X)$ with resort to the L-BFGS algorithm.

The set of combinations of locations, Ω_{comb}^{init} , is composed of all possible combinations of N_g locations from the set Ω_b^{init} (e.g. if $\Omega_b^{init} = \{1, 2, 3\}$, $N_g = 2$, then $\Omega_{comb}^{init} = \{[1, 2], [1, 3], [2, 3]\}$). As discussed in 4.2.2, the elements of Ω_b^{init} correspond to non-adjacent locations, where adding a marginal GFM capacity significantly improves security. Hence, employing them to delineate the set of initial points enables a satisfactory exploration of the promising search space zones and, consequently, a good initial GP regression.

4.2.4 Solution Polishing using Meta-heuristic Solvers

As depicted in the flowchart of Figure 4.10, the final step of the solving methodology involves refining the best-found solutions. This refinement leverages metaheuristic solvers to fine-tune the converter capacities at the specific locations corresponding to the best solutions. In this case, the use of metaheuristics, particularly population-based versions (EPSO & DE), is largely justified by its fast convergence [155, 156] and the non-differentiability of the value function $A(X)$, which demands the use of sampling-based methods.

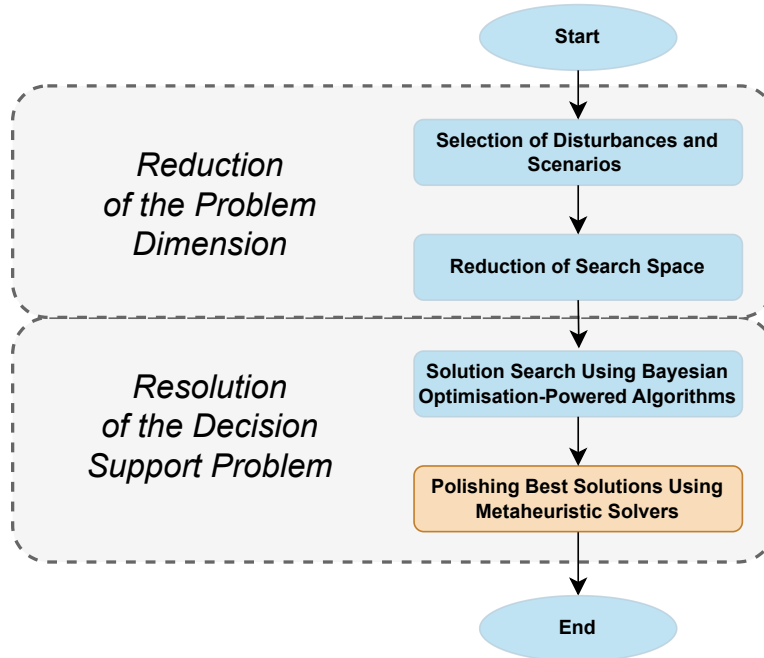


Figure 4.10: Flowchart of the methodology used to solve the formulated placement problem.

4.3. Multi-Class Placement

The integration of this complementary phase within the context of the proposed method is depicted in the flowchart of Figure 4.10. As seen there, the phase dedicated to solving the decision support problem consists of two key steps: a major block (highlighted in blue) featuring Bayesian Optimisation Powered Algorithms and a complementary step (marked in orange) where Meta-heuristic solvers are employed to refine the best solutions.

4.3 Multi-Class Placement

While the methodology discussed in the previous sections directly addresses some of the previously identified research gaps (e.g. the simultaneous sizing and placement of the GFMs considering the TSO cost preferences), it only manages to improve the system security regarding one stability class, namely the system's transient stability. By purely focusing on one stability class, one tends to achieve solutions that may result in poor improvements or even in the deterioration of other stability classes [142] (see Chapter 3). Hence, this section presents an alternative formulation for the system security index that considers multiple stability classes ($F_M(X)$).

Considering $F_M(X)$ as the security index in the multi-criteria formulation of Equation 4.7 would enable reaching an optimal placement and sizing that respects the TSO cost security preferences when foreseeing security from the point of view of different stability classes. That said, it is important to emphasise that this section does not delve into a multi-criteria approach (cost-security) for placement and sizing; instead, it concentrates solely on the placement of converters for the purpose of improving the overall system stability.

By concentrating solely on the converter's location, a cost-detached formulation that is directly related to stability can be used. This will later ease the comprehension of different stability-related sensibility analyses that demonstrate the need for a multi-class formulation and the effectiveness of the proposed methodology in addressing it. This is only feasible since the location has a minimal impact on the solution's cost, while the capacities of the converter and primary source have a significant influence.

That said, for the purpose of this section, the placement problem can be re-stated as:

"In which Buses should the N_c GFM-controlled converters be placed so that the improvement in the system's stability is maximal?"

To properly address this problem, one must establish a methodology capable of solving non-linear integer optimisation problems of large dimensions (Section 4.3.2) while also being able to quantify the impact of the GFMs on the system stability when different stability classes are considered (Section 4.3.1).

4.3. Multi-Class Placement

4.3.1 Quantifying the Impact of the GFM Introduction on the System's stability

To evaluate the improvement to the system stability that results from the placement of the GFM units in a combination of locations X , this research introduces a fitness function that incorporates up to four different composite stability indicators. These composite stability indicators leverage state-of-the-art stability variables (e.g. Nadir, CVD, et al.), whose values are inversely proportional to stability. Hence, to find the combination of N_c buses that maximises the system stability, one must find the value of the problem state array X that minimises the value of the fitness function, $F_M(X)$, as detailed in Equation 4.25.

$$\min_X : F_M(X)$$

$$F_M(X) = \sum_{j=1}^4 K_{\mu_j} \cdot M_{\mu_j}(X) \quad (4.25)$$

Where:

- X is the problem state variable array that contains the location of the N_c GFMs that are to be placed ($X = [l_1, l_1 \dots l_{N_c}]$).
- $M_{\mu_j}(X)$ is the value of the system composite stability indicator, associated with the stability variable μ_j when evaluating a particular solution X .
- K_{μ_j} is a numerical weight that translates the importance of the stability class expressed by the stability variable μ_j to the system security.

With this approach, the TSO/DA can prioritise the improvement in the stability classes with a higher prevalence of instability in its system and get a marginal improvement in the others by adequately choosing the values of the weights.

Definition of the Weights

Despite the decision agent's freedom to choose the weights, this work suggests that their adjustments should adhere to the rule outlined in Equation 4.26. In this rule, the importance of each stability class is defined by the normalised distance between the largest value achieved by the stability variable in the system without any additional GFM capacity (μ_j^0) and its limit (μ_{jlim}).

$$K_{\mu_j} = \frac{\mu_j^0 - \mu_{jlim}}{\mu_{jlim}}, K_{\mu_j} \in [0, \infty[\quad (4.26)$$

4.3. Multi-Class Placement

$$\mu_j^0 = \max_{m \in \Omega_m^0, d \in \Omega_d^0} \mu_j(X_0|m, d) \quad (4.27)$$

where X_0 is the elementary solution where no GFM converter is introduced in the system; $\mu_j(X|m, d)$ is the value of the stability variable μ_j in scenario m given disturbance d , for the case of the solution X_0 .

To define the limit value of each stability indicator, one may use the system grid code requirements or priorly gained knowledge about the system behaviour. As an explanatory example, let one consider the maximum frequency deviation found in the system, $Max \Delta f$, as one of the system variables, then, its corresponding weight could be defined as shown in equation 4.28. Where the value of the stability variable limit (0.8 Hz) was chosen according to the specified value of the maximum frequency deviation defined for the CE area in the guideline for establishing electricity transmission system operation [157].

$$K_{\Delta f} = \frac{Max \Delta f^0 - 0.8}{0.8} \quad (4.28)$$

$$Max \Delta f^0 = \max_{m \in \Omega_m^0, d \in \Omega_d^0} Max \Delta f(X_0|m, d) \quad (4.29)$$

Composite Stability Indicators

In what concerns the definition of each composite stability indicator, M_{μ_j} , a methodology similar to that described in Section 4.1.3 was employed. However, instead of using the absolute value of the stability variable, the maximum normalised value identified across all relevant combinations of scenarios and disturbances is adopted. Therefore, the value of the stability indicator M_{μ_j} , for a solution X can be obtained as described in Equation 4.31.

$$M_{\mu_j}(X) = \max_{m \in \Omega_m^0, d \in \Omega_d^0} \bar{\mu}_j(X|m, d) \quad (4.30)$$

Where the value of the stability variable μ_j for a solution X , in a scenario m and disturbance d , $\mu_j(X|m, d)$, is normalised in relation to μ_j^0 , as shown in Equation 4.31.

$$\bar{\mu}_j(X) = \frac{\mu_j(X|m, d)}{\mu_j^0} \quad (4.31)$$

As in Section 4.1, the value of $\mu_j(X|m, d)$ is obtained by performing a parallelised time domain in a positive-sequence model of the power system. A phase of disturbance and scenario selec-

4.3. Multi-Class Placement

tion analogous to the one described in Section 4.2.1 should also be performed beforehand to reduce the computational effort needed to evaluate a solution X .

Instead of the maximum-based formulation of Equations 4.30, an alternative formulation based on the sum of the normalised stability variables can also be used. In this case, each composite stability indicator would be defined as described in Equation 4.32.

$$S_{\mu_j}(X) = \sum_{m=0}^{N_m} \sum_{d=0}^{N_d} \bar{\mu}_j(X|m, d) \quad (4.32)$$

Both options ($S_{\mu_j}(X)$ and $M_{\mu_j}(X)$) are valid as formulations for the composite stability indicators. Adopting the first option in the optimisation problem of Equation 4.25 tends to yield a balanced solution, promoting reasonable improvements in the stability variable across various disturbances. In contrast, the second option promotes a maximum improvement of the system stability margin by reducing the stability variable for the more severe disturbances. While the results of adopting these different formulations will be compared in Chapter 6, it is important to highlight that both of them could be adopted as long as the DA/TSO is aware of their limitations, while interpreting the results (e.g. mask effect of sum-based formulations). Indeed, it is up to the Transmission System Operator/Decision Agent (TSO/DA) to make this choice according to its goals and available resources.

Stability Variables

The multi-class nature of the formulation detailed in Equation 4.25 is greatly influenced by the selected stability variables. Hence, it is crucial to choose stability variables that accurately reflect the degree of stability across different classes; otherwise, improvements may be biased toward a single class, regardless of the indices employed. With that in mind, this study adopts the following four stability variables, which were previously introduced and detailed in Section 3.2 :

- **Max Δf_{SM}** : The maximum frequency deviation from its nominal value (50 Hz), found among the frequencies of all the system's synchronous machines (Ω_{sm}).

Given its importance to the system protection schemes, the *Max Δf* was also computed for the case of the electrical frequency (f_{ele}), which is measured in all the system buses with Load/Generation using a PLL (Phase Locked Loop).

- **Max *Rocof*_{SM}**: The maximum value of the *Rocof* found among the frequencies of all the system's synchronous machines. In this case, a 50 ms sliding window was adopted to slightly filter the *Rocof* Value.

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- **Max CVD**: The maximum Cumulative Voltage Deviation found among the voltages of all buses with Load or Generation (Ω_b^{LG}).
- **Max CQPD_{PLL}**: The maximum Cumulative Quadratic Phase Deviation found among the phases of the PLLs of all the System's GFL converters (Ω_{GFL}).

Building upon these four stability variables, the problem formulation introduced in Equation 4.25 is refined into its final form for this work. The form that adopts a composite stability variable using a max-based formulation ($F_M(X)$) is presented in Equation 4.33, while the one that adopts a sum-based formulation ($F_S(X)$) is depicted in Equation 4.34.

$$\min_X F_M(X)$$

$$F_M(X) = K_{\Delta f_{SM}} \cdot M_{\Delta f_{SM}}(X) + K_{Rocof_{SM}} \cdot M_{Rocof_{SM}}(X) + K_{CVD} \cdot M_{CVD}(X) + K_{CQPD} \cdot M_{CQPD}(X) \quad (4.33)$$

$$\min_X F_S(X)$$

$$F_S(X) = K_{\Delta f_{SM}} \cdot S_{\Delta f_{SM}}(X) + K_{Rocof_{SM}} \cdot S_{Rocof_{SM}}(X) + K_{CVD} \cdot S_{CVD}(X) + K_{CQPD} \cdot S_{CQPD}(X) \quad (4.34)$$

For ease in notation, in the formulations above and the remaining parts of this work, the complete names of the stability variables were replaced by a short version, where the word *Max* no longer appears. For instance, instead of writing $K_{Max\Delta f_{SM}}$ the compact notation $K_{\Delta f_{SM}}$ is adopted.

4.3.2 Optimisation Engines

Meta-heuristics are known for finding optimal/near-optimal solutions to non-linear optimisation problems of large dimensions and doing so with a reduced computational effort compared to conventional optimisation approaches [156]. They have been successfully used to address problems of a diverse nature in the field of power systems [158, 159, 160], with stability-related optimisation problems being no exception [161, 162, 144, 143].

That being said, two different meta-heuristic algorithms were considered potential candidates for the optimisation engine that is used to find the solution of the problem formulated in Equation 4.25: Simulated Annealing (SA) and Evolutionary Particle Swarm Optimisation (EPSO). Besides being one of the most used techniques among meta-heuristics, Simulated Annealing also has the particularity of having an associated extensive study regarding its proof of convergence/convergence in probability to the optimum [163, 164]. This theoretical grounding

4.3. Multi-Class Placement

justifies our choice of the SA as one of the potential candidates. As for the EPSO, the fast convergence to the optimum and its success in different power system use cases [160, 165] were the main motivations for its choice.

Using convergence tracking and solution dispersion analysis, these techniques are compared in the results section and a single technique is then adopted. While a detailed explanation of these techniques may be found in [166, 167], the main steps of each algorithm are also presented in the following two pseudo-code samples.

Algorithm 5: EPSO

- 1: Choose Initial Swarm X
 - 2: **while** Stopping criteria not met **do**
 - 3: **for** Each Particle X_i **do**
 - 4: Generate Clone C_i
 - 5: Mutate Weights W_i of EPSO movement equation
 - 6: Move X_i and C_i using the EPSO movement equation
 - 7: Compute fitness of Particle X_i and its clone $C_i \rightarrow F_M(X_i), F_M(C_i)$
 - 8: **if** $F_M(X_i) > F_M(C_i)$ **then**
 - 9: $X_i = C_i$
 - 10: Update Global and Particle Best
-

Algorithm 6: Simulated Annealing

- 1: Chose Initial Solution, X_i
 - 2: **while** $T_C > T_F$ **do**
 - 3: Select Random Neighbor N
 - 4: Compute fitness of solution X_i and its neighbor $N \rightarrow F_M(X_i), F_M(N)$
 - 5: **if** $F_M(X_i) > F_M(N)$ **or** $R(0, 1) < e^{\frac{F_M(X_i) - F_M(N)}{T_C \cdot K_b}}$ **then**
 - 6: $X_i = N$
 - 7: Update current Temperature, T_C
-

where K_b is the virtual Boltzmann constant

In what concerns the Simulated Annealing neighbourhood definition, an approach based on the impedance-based electrical distance was adopted, as defined in [148]. This significantly reduces the computational effort needed for the algorithm's convergence compared to the case where a simple Gaussian kernel is used.

4.4 Final Remarks

This chapter introduced a robust methodology for the GFM placement problem that simultaneously considers the capacity cost and the security gains while accounting for the TSO's non-linear cost-security preferences. Additionally, it also elaborated on the placement of GFM converters for stability improvement when considering multiple stability classes. In Chapter 6, the effectiveness of these methodologies will be assessed through their application to a modified version of the IEEE 39 Test System.

Evolving Symbolic Models for Dynamic Security Classification

The increasing complexity of studying system stability, and thus its security, is evident from previous chapters. On the one side, the growing presence of converter-based generation introduces different stability phenomena, such as the loss of synchronism of the converter PLL (Section 3.2.2) and other converter-driven stability problems (Section 2.1.1). On the other side, it also offers new stabilisation solutions like GFM control, which provide higher control flexibility but at the cost of behaving in more non-linear ways than traditional methods (e.g., synchronous condensers). Therefore, developing tools that can effectively diagnose the system's dynamic security under these conditions is crucial for the system's safe operation.

Given the inherent variability associated with RES, dynamic security assessment of the system must now be conducted for multiple scenarios, rather than just one, while still meeting the time requirements needed for real-time grid operation. This evolving requirement for DSA has made AI-based approaches particularly appealing, as they can rapidly evaluate system security across multiple operation points (OP).

As discussed in Section 2.5, most AI-based approaches to the DSA, due to their extended model size and complexity, hinder humans from fully understanding the model's capabilities and limitations and developing an accurate mental model of AI. As a result, risk-averse human operators may have restricted confidence in these approaches. Even with the advances in the field of explainable AI (XAI), these techniques still face different “challenges” [114], namely: a) the “explanations” may not consistently align with the computations of the original model, which may result in the operator's misunderstanding of the model behaviour; b) the XAI algorithm is an additional model to be debugged in the development phase, which

is not error-free. Hence, adhering to an inherently interpretable model is preferable, as discussed in [114]. Such models, characterised by their symbolic and compact nature, enable a straightforward grasp of their internal dynamics, ensuring interpretability and the ability to offer articulate explanations.

Therefore, this chapter presents a novel methodology, the Evolving Symbolic Model (ESM), for generating highly interpretable data-driven models for dynamic security assessment (DSA), namely in system security classification (SC) and the definition of preventive control (PC) actions. Figure 5.1 provides a general overview of an online DSA proposed in this chapter that leverages symbolic models created using the ESM methodology for SC and PC. The characteristic interpretability of these models, which enables effortless analysis by the operator in order to validate the model or to grasp new physical relations about the system, is also evidenced in the figure.

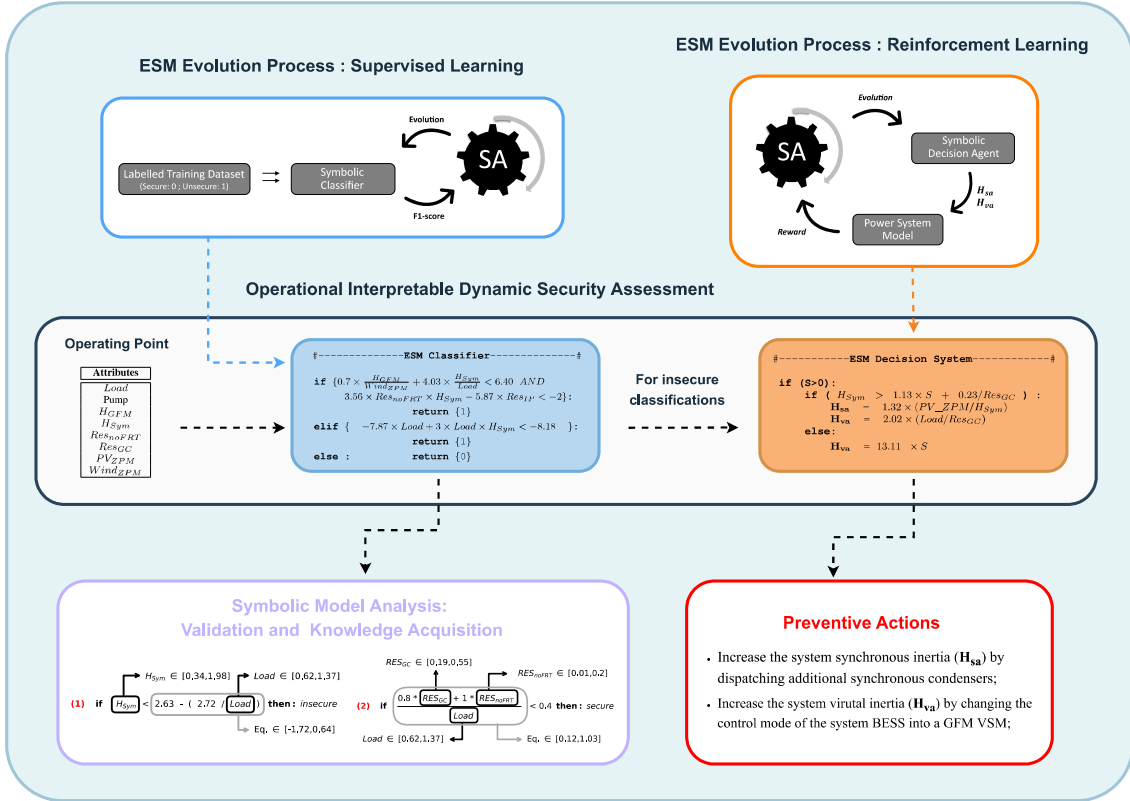


Figure 5.1: Overview of an online DSA that leverages symbolic models created using the ESM methodology.

The chapter is organised into five main sections: Section 5.1 introduces the ESM concept with respect to knowledge representation and model design, while Section 5.2 outlines the evolutionary process for data-driven learning within both supervised and reinforcement learning (RL) frameworks. Sections 5.3 and 5.4 address the specific application of ESMs to the DSA in isolated power systems, focusing on online security classification and preventive control,

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respectively. Finally, Section 5.4.2 provides concluding remarks.

5.1 Fundamental Principles

5.1.1 Knowledge Representation

A symbolic model (SM) is an explicit representation of knowledge that combines language items (“symbols”, e.g., $a, 1, +, -$) and formal languages (“words”, e.g., variable var_1) to construct symbolic primitives and inference rules and create a framework that facilitates the human interpretation of information within the context of the model. The basic building blocks used in the SM model, the symbols, can be language items of a general-purpose programming language (GPL) or domain-specific language (DSL). This work adopts symbols or keywords (reserved words that have a particular meaning to the compiler, e.g., *if*, *else*, *return*) from a GPL. Still, it is important to mention that in cases where non-traditional operators are needed to represent knowledge (e.g., in the decision system), a DSL should be created as it enables the use of customised building blocks. Equation 5.1 shows a generic example of an SM, Θ_0 , designed using symbols and words from the set $S_0 = \{x, y, z, 1, 2, 3, +, \times, =, <, >, \text{and}, \text{if}, \text{else}\}$.

$$\Theta_0 : \left\{ \begin{array}{l} \text{if}(x < 2 \text{ and } y > 1) : z = x \times 3 \\ \text{else} : z = x + 2 \end{array} \right\} \quad (5.1)$$

When the elements of an SM can be mutated using an evolutionary or a stochastic technique so that another SM is created (or evolved) by learning from data (Section 5.2.4), it is referred to as an Evolving Symbolic Model (ESM). This evolution (or mutation) of the model Θ_0 to model Θ_1 is illustrated by Equation 5.2.

$$\begin{aligned} \Theta_0 : & \left\{ \begin{array}{l} \text{if}(x < 2 \text{ and } y > 1) : z = x \times 3 \\ \text{else} : z = x + 2 \end{array} \right\} \\ \Theta_1 : & \left\{ \begin{array}{l} \text{if}(x < 2 \text{ or } y > 1) : z = x \div 3 \\ \text{else} : z = x + 5.1 \end{array} \right\} \end{aligned} \quad (5.2)$$

The spectrum of SM that an ESM can potentially transform into is constrained by the symbols defined within its domain S_E . This domain encompasses all elements found in the *primitive model* Θ_0 (Section 5.1.2) and those that can be employed in creating new models (Section 5.2). A generic example is:

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$$\begin{aligned}
S_E &\cup \{V_E, N_E, A_E, C_E, L_E, W_E\} \\
V_E &= \{a, b, c, d, x, y, z\}, N_E = \{\mathbb{R}\} \\
A_E &= \{+, -, \times, \div, =\}, C_E = \{<, >\} \\
L_E &= \{and, or\}, W_E = \{if, elif, else\}
\end{aligned} \tag{5.3}$$

In theory, an ESM has the potential to embody all possible symbol combinations within its domain S_E . However, in practice, the universe of models is constrained by the *primitive model*, the model template, the evolutionary or stochastic technique used to guide the evolution, and the specific mutations under consideration, as described in Section 5.2.

5.1.2 Primitive Model Design

A fundamental element of the knowledge presentation in ESM is the *primitive model*, encompassing the definition of the model's template (or sketch) and its initialisation. Defining the template includes specifying the architecture and all other parts of the model that are not eligible for mutation, thereby setting clear boundaries for evolution. This precaution prevents unchecked expansion or reduction of the model, ensuring that it remains capable of performing the designated task. Figure 5.2 depicts an illustrative example of a basic template, with mutable statements in plain lettering and immutable model parts highlighted in bold.

```

    if { Conditional Statements } :
        { Sequence of Action }
    elif { Conditional Statements }:
        { Sequence of Action }
    else: { Sequence of Action }

```

Figure 5.2: Example of a simplistic template for ESM

In this case, the mutable components of the SM, such as conditions or actions, can be fully specified by a human operator, randomly generated by the machine, or collaboratively defined if the operator inputs part of the model and the other part is randomly generated. Incorporating the human expert into the initialisation loop leverages the valuable prior knowledge typically held by experts through their interactions with the environment (e.g., the power system) or their grasp of physical reasoning. This prior knowledge enhances the *primitive model* of the SM, providing a more effective starting point for the learning process and often resulting in improved convergence. Although this may seem like a potential source of bias in model development, it should not introduce more biases than similar operations in other AI methods (such as the choice of the ANN model architecture or the DT depth). This is because, in ESMs, the model structure develops into forms that deliver better performance as the learning process progresses.

5.2 Evolution Process

This section describes the process of evolving the SM from data, considering both supervised learning and RL settings. Throughout the section, Figure 5.3 will be used to illustrate the evolution process that creates a DSA classifier, drawing from the case study of Section 7.2. This example considers a *primitive model*, which is either randomly generated or cooperatively defined by a human as discussed in Section 5.1.2, resulting in distinct initial solutions and evolution patterns. The figure shows three snapshots of the ESM classifier, representing its initial, intermediate, and final states.

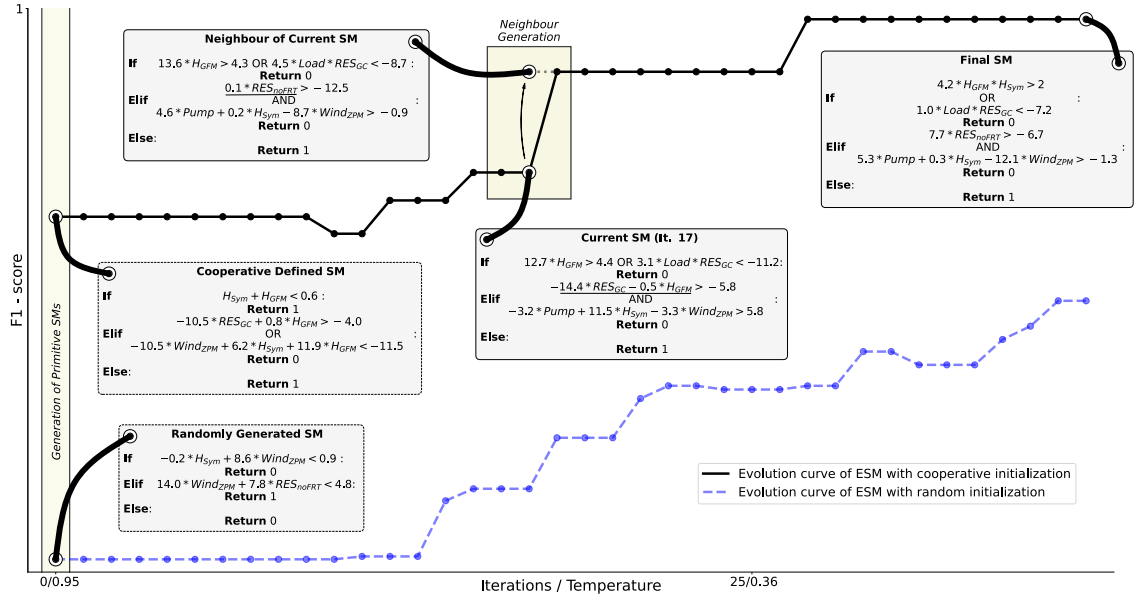


Figure 5.3: Illustrative example of SM evolution process. “0” corresponds to secure operation, and “1” to insecure.

5.2.1 Guided Evolution

A *parent-child* architecture was used to guide the evolution of the SM, where SA is the *parent* that manages the evolution of the SM model’s structure by controlling the mutations, and differential evolution (DE) is the *child* algorithm responsible for the tuning of the program’s numerical constants.

The SA enables effortless evolution control via its temperature equation and neighbourhood definition, removing the need for defining a map between symbols and numeric values (e.g., required in particle swarm optimisation), which is a non-trivial task for large symbolic models. Its single-solution nature also allows the operator to easily inspect and/or update the ESM at any point in the evolution without the need to make any assumptions, as with other population methods (e.g., inspect or analyse only the best individual from a population). The DE is a simple, effective, and fast method for tuning the program’s constants, which displayed

5.2. Evolution Process

superiority in accuracy and computational effort compared to the other methodologies. Table 5.1 summarises the results of a study where the constants of 50 randomly generated ESM classifiers were adjusted using different numerical optimisers. The results reinforce the choice of the DE as a fast and reliable method for tuning the ESMs' constants.

Table 5.1: Average Tuning time and Average Classification Score ($\min = 0$, $\max = 1$), achieved by each optimisation engine in the calibration of 50 randomly generated ESM classifiers in a validation Set.

	Basin hopping	BFGS	L-BFGS	Simulated Annealing	Differential Evolution
Average Tuning Time (s)	43.39	38.45	29.85	91.45	36.99
Average Classification Score	0.29	0.26	0.30	0.59	0.60

The pseudo-code for the proposed evolution process is presented in Algorithm 7, where SM_i is the current symbolic model, $\mathcal{F}_i$ is SM_i 's fitness to perform the task of interest, $\mathcal{F}_n$ is SM_n 's fitness to perform the task of interest, I_T is the number of iterations per temperature, T is the temperature of the SA cooling scheme, K_b is the virtual Boltzmann constant, T_0 and T_f are the initial and final temperatures of the SA cooling scheme.

Algorithm 7: Evolution process of the ESM

Require: K_b, T_0, T_f

- 1: Generate a symbolic model, SM_i (5.1.2).
 - 2: Tune numerical constants of SM_i (DE).
 - 3: **while** $T > T_f$ **do**
 - 4: Generate neighbor symbolic model, SM_n (5.2.2).
 - 5: Tune numerical constants of SM_n (DE).
 - 6: **if** $\mathcal{F}_i > \mathcal{F}_n$ **or** $\mathcal{R}(0, 1) < e^{\frac{\mathcal{F}_i - \mathcal{F}_n}{T \cdot K_b}}$ **then**
 - 7: $SM_i = SM_n$
 - 8: Adjust T according to cooling scheme
 - 9: Perform simplification on SM_i (5.2.3).
-

The foundational characteristics of the SA [164] algorithm remain visible in this symbolic model version. During a designated cooling scheme (e.g., linear, exponential), a solution will pass through different neighbourhood states and change according to the Metropolis acceptance criterion until its energy reaches a minimum. However, given that the solution is no longer an array of dimension N but a sequence of expressions forming an SM, this version has distinct features, particularly regarding neighbourhood definition (Section 5.2.2). Moreover, it introduces an additional phase known as *simplification*, during which the model is inspected and possibly automatically simplified to enhance interpretability (Section 5.2.3).

5.2. Evolution Process

The main hyperparameters of this symbolic SA remain the Boltzmann constant (K_b), the initial temperature (T_i) and the final temperature (T_f). These parameters, along with the temperature cooling schedule, allow controlling the degree of exploration and exploitation throughout the evolution of the ESM. For an improved convergence, the method should start by promoting the acceptance of slightly worse solutions, prioritising explorations, and then steadily promoting a change between exploration and exploitation so that, in the end, only solutions with better fitness are adopted [168].

The condition governing the acceptance of solutions with worse fitness than the current one is shown in Equation 5.4. This condition involves comparing a randomly generated uniform number between 0 and 1 with an exponential function that determines the probability of accepting the worst solution. The function depends on the current temperature (T), the difference in scores between the two solutions ($\mathcal{F}_i - \mathcal{F}_n$), and the Boltzmann constant (K_b).

$$\mathcal{R}(0, 1) < e^{\frac{\mathcal{F}_i - \mathcal{F}_n}{T \cdot K_b}} \quad (5.4)$$

Figure 5.4 evidences how the Boltzmann constant influences the probability of accepting the worst solutions throughout a temperature schedule that extends from 0.95 to 0.05. In each graph, the probability of accepting a neighbour that has a worse fitness function value is plotted for multiple fitness function differences ($\mathcal{F}_i - \mathcal{F}_n$).

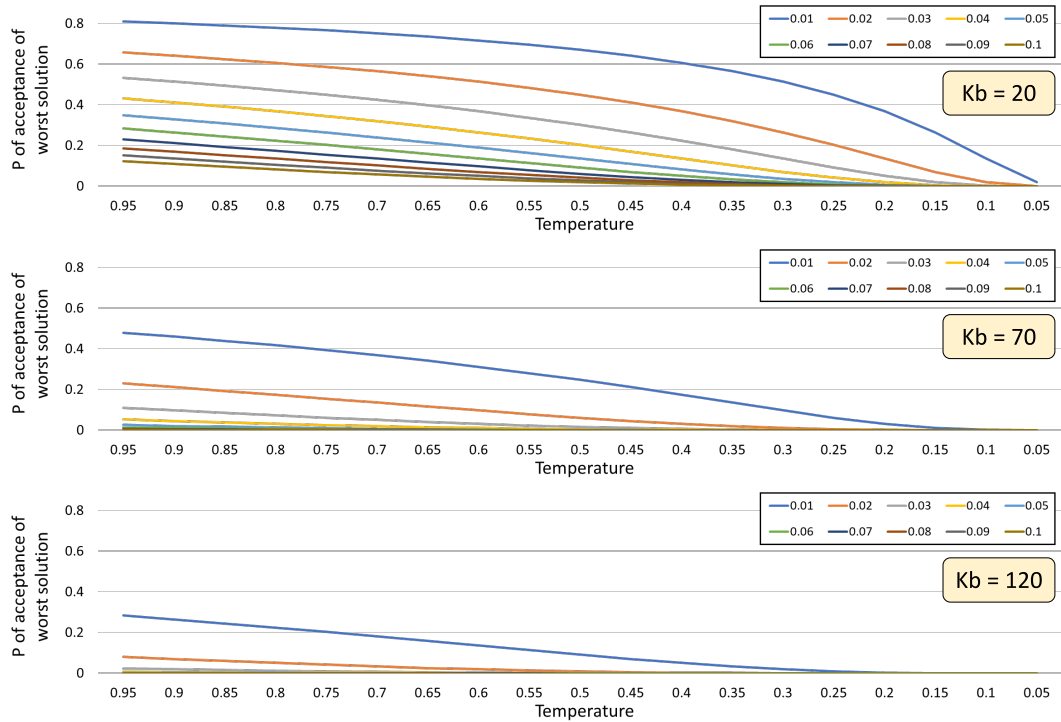


Figure 5.4: Effect of K_b in the probability of accepting worst solutions, for a linear T schedule.

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As demonstrated above, small K_b values (approximately 20) produce a high probability of accepting worst solutions throughout the entire temperature schedule. While this encourages exploration, it prevents the method from converging to an optimal solution. Conversely, larger K_b values (approximately 120) reduce the likelihood of accepting worst solutions in the later stages of the temperature schedule, fostering sufficient exploitation but limiting exploration in the earlier stages. A value of approximately 70 strikes a balance, enabling the acceptance of worst solutions early on while ensuring the method effectively converges by avoiding significant deviations from promising solutions in later stages.

Note that this is valid for fitness function differences between the current solution and its neighbours around 0.01-0.1, which fits problems where the fitness function is normalised. For other problems, the same analysis must be performed considering the forecasted fitness function differences, and the adequate K_b value must be chosen.

5.2.2 Neighbour SM Generator

In the SA, a solution may transition into neighbouring states, also recognised as candidate states, depending on that state's fitness and the value of a sampled probability (Metropolis acceptance criterion). A particle neighbourhood can be easily defined in numerical optimisation by coupling a distance limit with a random number generator $\mathfrak{R}(\cdot)$, e.g., $N(X) = X + 0.1 \cdot \mathfrak{R}(\cdot)$. Yet, when the solution is no longer an array but a symbolic model, this technique crumbles unless some coordinate scheme is introduced. Therefore, a mutation-based stochastic neighbour generator is proposed here.

In this scheme, the neighbouring SM is obtained by performing a sequence of mutations sampled from a user-defined mutation pool on a copy of the current SM. To sample the mutations, the value of a uniformly generated random number, $U(0, 1)$, is compared with the probability of adopting each mutation Pa , being a mutation m_j drawn if the condition of Equation 5.5 applies. The mutations used throughout this work and their respective probability of adoption are listed in Table 5.2. They were chosen given their ease of implementation within the environment of most GPL and their ability to generate new neighbours and not just simply random solutions.

$$\begin{aligned} \forall j, \text{ if } (U(0, 1) < Pa_j) : SM_n = m_j(SM_i) \\ \{j \in \mathbf{Z}^+ : j \leq N_{Mut}\} \end{aligned} \tag{5.5}$$

As seen in Table 5.2, the mutations with a larger transformation power (e.g., *Addition/Removal of Condition* or *Logical Operator Change*) have a smaller probability of adoption, compared to the ones that perform minor changes on the model syntax (e.g., *Parcel Removal* or *Parcel Mutation*). This enables a frequent generation of neighbours sufficiently close to the current

5.2. Evolution Process

solution, hence ensuring convergence while allowing the sporadic generation of more diverse neighbours in the name of a larger search space exploration. These probabilities can be determined through trial-and-error experiments on a validation set to improve the convergence of the SA algorithm, or by following a hyperparameter optimisation approach. Figure 5.3 illustrates an SM transformation using some of these mutations, where the difference between the current and the neighbour model is underlined.

Table 5.2: *Mutation pool used in the neighbour generation*

Mutation	P_a
<i>Addition/Removal of Condition</i> e.g., $if(x + y > 1) \rightarrow if(x + y > 4 \text{ AND } z < 3)$	1/15
<i>Logical Operator Change</i> e.g., $if(x + y > 4 \text{ AND } z < 3) \rightarrow if(x + y > 4 \text{ OR } z < 3)$	1/10
<i>Comparison Operator Change</i> e.g., $if(x + y > 4) \rightarrow if(x + y < 4)$	1/5
<i>Addition or Removal of Parcels</i> e.g., $if(x + y > 4) \rightarrow if(x + y - z > 4)$	1/3
<i>Parcel Mutation</i> e.g., $if(x > 4) \rightarrow if(z > 4) \mid if(x \times z > 4) \rightarrow if(x \div z > 4)$	1

The decision to resort to a pool of diverse and structured mutations instead of using a single and more generic mutation (e.g., symbol-for-symbol replacement) is justified by the increase in the controllability of the model transformations. On the one hand, this eases the implementation process within the environment of most GPL, as it avoids syntax errors that would result from the misplacement of the language operators (e.g., replacing a logical operator with a number). On the other hand, it allows better management of the diversity between the existing and the candidate model, thus ensuring that these are sufficiently close to be considered neighbours, which is essential for method convergence.

Regarding the ESM *Parcel Mutation* process, it is worth mentioning that particular success was found when using a mutual information (MI)-based variable neighbourhood. Such a neighbourhood is defined at the beginning of the evolution by computing the MI between all domain variables and the classification labels.

Note that as long as the reasoning regarding the generation of sufficiently close neighbours is kept and a similar scheme is considered for the probability of adoption, the user is free to choose different mutations. This means that if the user introduces very transformative mutations from a logical point of view, lower probabilities should be attached to them and

5.2. Evolution Process

vice versa.

Assuming that the established model template and the ESM symbolic domain are respected, the human expert can even directly perform mutations during the learning process, e.g., determining which model parts should be mutated. To enhance the operator's understanding of the transformative power of each mutation and ease the generation of close neighbours, the effect of each type of mutation on the output of different expressions can be assessed by means of the Kullback-Leibler (KL) divergence [149]. Since KL-divergence measures the difference between two distributions, mutations resulting in a large average KL-divergence should be considered highly transformative, and those with smaller values should be less.

5.2.3 SM Simplification

The SM may evolve into a program featuring redundant statements with increased size and diminished overall interpretability. To solve this problem, a periodic model inspection, denoted as *simplification*, is introduced here. The effects that the different SM statements have on the model output are evaluated, removing the ones with no effect and carrying out a classical mathematical inspection of each expression. The considered model template influences this phase greatly. Hence, its transference to other problems must be performed with adequate modifications. The approach followed to simplify the SMs is described in Algorithm 8.

Algorithm 8: *Simplification* process of the ESM

- 1: **Output based simplification:**
 - 2: **for** All Statements (St_i) **do**
 - 3: Evaluate the effect of St_i on the SM output.
 - 4: **if** St_i does not affect the SM output **then**
 - 5: Remove part or the totality of statement St_i .
 - 6: **Mathematical Inspection:**
 - 7: **for** All Statements (St_i) **do**
 - 8: Remove model parcels with multiplications by 0.
e.g., $\text{if}(3 \times x + 0 \times y > 1): \rightarrow \text{if}(3 \times x > 1):$
 - 9: Sum all zero-degree polynomials in each expression.
e.g., $\text{if}(x + y - 3 > 1): \rightarrow \text{if}(x + y > 4):$
-

As illustrated in Figure 5.3, the model maintains complete interpretability throughout its evolution. This ensures that the operator can readily comprehend the dynamics and decisions of the model, even during the learning phases. Due to the *simplification*, the constant tuning process becomes faster as simpler models tend to have fewer constants, translating into a problem of smaller dimensions for the DE (*child*) to solve.

5.2.4 Supervised and Reinforcement Learning

As illustrated in Figure 5.5, the SA algorithm is used to guide the evolution of both i) the ESM-based classifier under a supervised learning setting by minimising a loss function and ii) an ESM-based decision agent following an RL-based setting via trial-and-error interactions between the (simulation) environment and the decision agent aiming to maximise an environment-returned reward function.

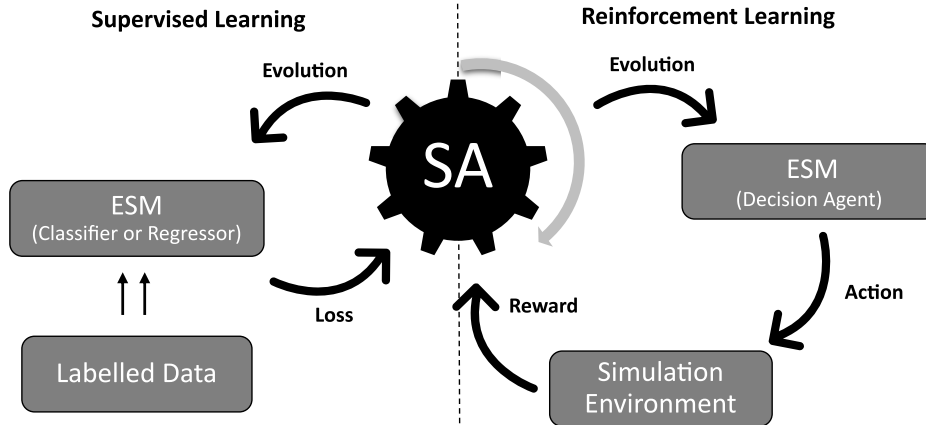


Figure 5.5: ESM evolution in different learning settings

In these two settings, adjustments to the ESM characteristics, such as templates and symbolic domains, may become necessary to align with the distinctive tasks executed by the model (refer to Sections 7.2 and 7.3 for a more comprehensive discussion). Regarding the SA component, no substantial changes are required, as the only modification pertains to the fitness function used to evaluate an ESM solution – either a loss or reward function. Recalibration of the SA's hyperparameters, particularly the virtual Boltzmann constant (K_b), is required only when large differences in magnitude exist between the loss and reward functions.

Note that the RL approach adopted in this work does not construct value estimates of particular state-action pairs; instead, it reasons solely about the value of entire policies [169, 170], and it does so via the use of cumulative reward functions.

5.3 ESMs Applied to Online Security Classification

Security Classification (SC), one of the DSA's typical functions, is the task of classifying a system operating point as secure (0) or insecure (1). In the case of isolated power systems, operators frequently look for understandable and secure ways of operating the system that are easy to validate and do not demand an extension of the existing domain knowledge. Hence, fully interpretable models like the ones generated by ESMs have a large degree of acceptance.

5.3. ESMs Applied to Online Security Classification

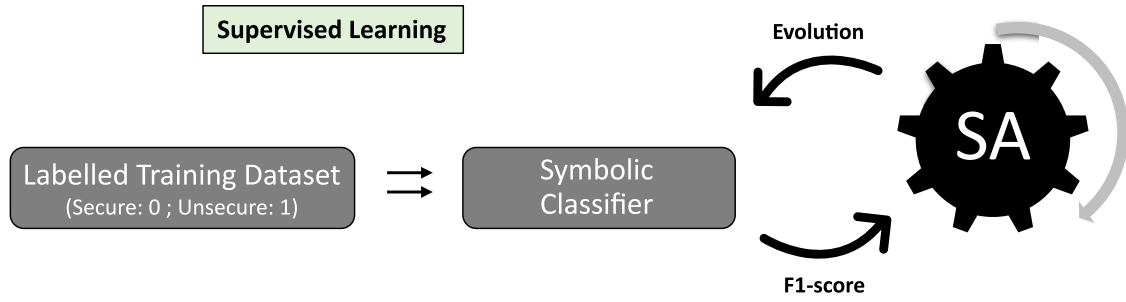


Figure 5.6: Illustration of the training procedure for generating a Symbolic Dynamic Security Classifier.

To generate a symbolic classifier using the ESM methodology, Algorithm 7 should be used under a supervised learning approach, as illustrated in Figure 5.6. Within this context, the fitness function adopted by the SA has to be a classification metric that represents the ability of the ESM to correctly classify a collection of operation points. The chosen metric in this work corresponds to the ESM classification F1-Score in the training dataset. The computation formula for the F1-score, a variable that varies between 0 (completely wrong classification) and 1 (perfect classification), is described in 5.6:

$$F1 - score = 2 \cdot \frac{P \times R}{P + R} \quad (5.6)$$

where P the Precision and R the Recall can be calculated as follows:

$$P = \frac{TI}{TI + FI} \quad (5.7)$$

$$R = \frac{TI}{TI + FS} \quad (5.8)$$

where: TI is the number of samples correctly predicted as “insecure” (True Positives); FI is the number of samples wrongly predicted as “insecure” (False Positives); FS is the number of samples wrongly predicted as “secure” (False Negatives);

As seen above, the F1-score is defined as the harmonic mean of Recall and Precision, making it a valuable metric that provides two key advantages over accuracy: 1) its ability to handle imbalanced datasets, and 2) its capacity to yield a high value only when both precision and recall are elevated. When either precision or recall is low, the F1 score declines significantly. This characteristic ensures that for a model to achieve a favourable F1 score, it must maintain a low incidence of both false positives and false negatives [171].

5.4. ESMs Applied to Preventive Control

These characteristics underscore the rationale for selecting the F1-score, particularly because: 1) datasets related to security classification often exhibit imbalance, with the majority of power system operating states being secure, and 2) the implications of false negatives and false positives in classifications are critical for security assessments, as such errors could result in system blackouts or unnecessary resource expenditures aimed at maintaining security.

5.3.1 Generation of Functional Knowledge & Symbol Domain

As depicted above, the ESM is evolved to maximise the classification F1 score in the training dataset. Hence, a previously generated dataset of operating scenarios (OS) must exist. The generation of such a dataset can be performed by sampling different combinations of load, share of synchronous generation and RES generation. This OS generation should seek to find scenarios close to the system's security boundary while preserving sufficient coverage of the system's feasible region.

The system variables selected to characterise each operation point within this dataset will be included in the symbol domain that the ESM can utilise to generate the symbolic classifier, specifically within the variable set V_E (see Equation 5.3). Therefore, these variables should exhibit high discrimination capability in regard to the system's stability problems being addressed; otherwise, it would be infeasible to create classification conditions that possess an intrinsic physical significance. It is important to note that this does not imply a necessity to initially restrict the set of variables V_E , as the employed methodology can identify and preserve the most relevant variables throughout the ESM evolution, as illustrated in Figure 5.3.

5.4 ESMs Applied to Preventive Control

When the operation point is classified as insecure, the human operator requires a preventive control action that can mitigate system instability in the case of any disturbance. In isolated power systems, this action frequently entails deploying additional synchronous and/or virtual inertia (H_{sa} and H_{va}) rather than a more classical approach, such as the generation re-dispatch. This choice is often justified by the high share of low synchronous machine scenarios that make: 1) small *OP* changes inefficient from a security point of view, and 2) significant *OP* changes costly due to the RES curtailment expenses.

To address this task, a symbolic decision agent that suggests the right amount of additional inertia (virtual or synchronous) that the operator should re-dispatch can be generated, leveraging once again the power of ESMs. For that purpose, Algorithm 7 needs to be applied to evolve a symbolic decision agent within a RL setting, focusing on maximising a reward function (described in Section 5.4.1) rather than the F1-score used previously for classifier generation. A simple illustration of this training process is depicted next in Figure 5.7.

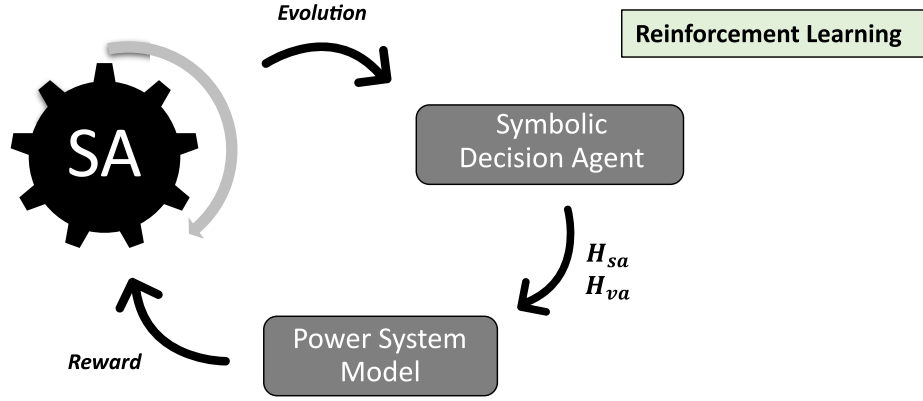


Figure 5.7: Illustration of the training procedure for generating a Symbolic Decision System for preventive control.

5.4.1 Reward function

Synchronous inertia can be dispatched via synchronous condensers (i.e., dedicated or generation units qualified for it), while the virtual inertia is typically dispatched by changing the control mode of the different grid assets that can provide it (GFL converter equipped with a virtual inertia loop, GFM converters, among others). Regardless of the type of inertia, there is generally a cost associated with additionally dispatching the inertia:

- **Synchronous inertia:** In the case of dedicated synchronous condensers, there is a cost associated with the electricity needed to drive the motor; as for the hydro units, there is an additional cost and a preparation time related to the opening of the drainage valves located at the bottom of the turbine chamber to empty it from the water before it can be used as a synchronous condenser.
- **Virtual inertia:** When virtual inertia is supplied by a wind turbine or solar PV converter, there may be costs associated with running the generator below its optimal power extraction point (known as deloading) [46, 172]. In contrast, if a BESS provides the inertia, the only cost incurred is related to the energy required to respond to a disturbance, which is negligible.

That said, the cumulative reward function R , described in Equation 5.9, is proposed for the RL procedure.

$$R = \sum_{i=0}^{N_T} R_i = \sum_{i=0}^{N_T} (1 - 0.25 * (S_i + 1)^2 - C_{a_i} \times K_H) \quad (5.9)$$

5.4. ESMs Applied to Preventive Control

$$C_{a_i} = \frac{\sigma_v * H_{va_i} + \sigma_s * H_{sa_i}}{C_{max}} \quad (5.10)$$

where R_i is the environment reward for an OP i ; S_i is the environment security indicator for OP i ; C_{a_i} is the normalised cost of additional inertia for OP i ; K_H is the trade-off between the cost of additional inertia and the enhanced system security, σ_v and σ_s are the costs, in euro per p.u., of an extra unit of virtual and synchronous inertia, respectively.

This reward function was chosen given its ability to represent two fundamental features of the problem, namely (1) the non-linear relation between the need to improve further the system's security and the current security state (S_i), and (2) the costs of dispatching additional inertia (C_{a_i}). The feature (1) is captured by the behaviour of the reward function derivative ($\frac{\partial R}{\partial S}$), whose form results in the provision of more significant rewards for improvements in unsecured zones ($S_i \gg 0$) where the agent action is much needed and poor rewards for improvements in zones already very secure ($S_i \ll 0$). The characteristic (2) is captured by using a trade-off function ($C_{a_i} \times K_H$) that reflects how much additional synchronous inertia the operator is willing to dispatch to achieve a sufficient improvement in the system security. The trade-off value can be obtained by inquiring the decision-maker through an indifference judgment, as explained in [138].

To ease the understanding of the aforementioned characteristics of the reward function, Figure 5.8 presents an illustrative example of the 3d plot of $R(S, C_a)$ and the 2d plots of the two parcels that form R .

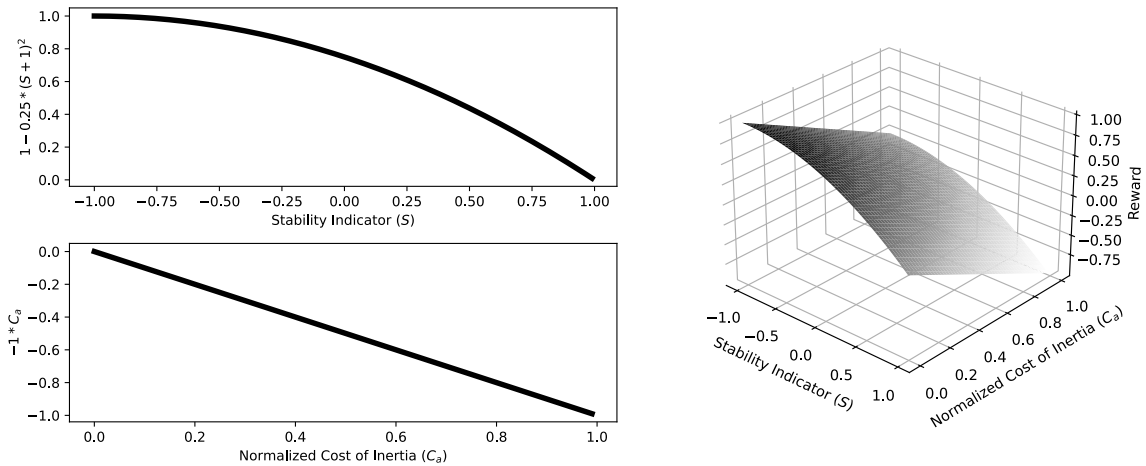


Figure 5.8: Illustrative example of the reward function form.

5.4.2 Final Remarks

In this chapter, a detailed description of the ESM method and its application to DSA in isolated power systems was provided. To validate this method, Chapter 7 will demonstrate its application in generating interpretable DSA models for a real-world isolated power system, specifically for the case of the Madeira system. The performance of this method will then be compared to other state-of-the-art methods for DSA.

Grid-Forming Robust Placement and Sizing Results

This chapter presents the results of the proposed methodology for the optimal placement and sizing of Grid-Forming (GFM) converters. It focuses on the influence of different optimisation criteria on final placement and sizing decisions, considering the trade-off between system security improvements and cost considerations. The study case for this assessment corresponds to the IEEE 39 Test System introduced in Section 3.1.1. In order to provide a structured analysis, this chapter is organised into three main sections:

- First, in Section 6.1, the proposed decision support tool is used to optimally place and size the converters, disregarding at first the sizing of the overcurrent capacity. Additionally, a sensitivity analysis is conducted to evaluate the impact of the GFM converter's overcurrent capacity on the solution to the formulated placement problem.
- Secondly, in Section 6.2, the proposed decision support tool is used to optimally place the converters and simultaneously size the converters' nominal and overcurrent capacity. Furthermore, two distinct sensitivity analyses are performed: one investigates the costs associated with the converter overcurrent capacity, while the other evaluates the effect of TSO cost-security capacity on the problem solution.
- At last, in Section 6.3, the alternative formulation introduced in Section 4.3 is applied to optimally place the converters, aiming to enhance the stability of multiple stability classes. First, the problem is simplified into a single-class formulation and solved while considering the different stability variables. This approach enables understanding the underlying physical phenomena that drive the optimality of the solutions and under-

6.1. Optimal Placement and Nominal Capacity Sizing of GFM converters in the Modified IEEE 39 Power System.

scores the necessity of adopting a multi-class framework. Subsequently, the multi-class approach is implemented, and its results are thoroughly analysed.

6.1 Optimal Placement and Nominal Capacity Sizing of GFM converters in the Modified IEEE 39 Power System.

In this section, the focus is on placing and sizing the nominal capacity of the GFM converters so that the satisfaction of the DA, given its cost-security preferences, is maximised. As explained earlier (see Section 4.1), this can be generically achieved by maximising the value function of Equation 4.2. However, since the overcurrent capacity is, for now, not a concern, the cost function introduced earlier (Equation 4.8) can be simplified into Equation 6.5 by assuming that all converters have the same overcurrent capacity. This simplification process is described next from Equation 6.1 to Equation 6.5.

Consider the formulation of the cost function previously introduced in Equation 4.8:

$$C_X = \sum_{k=1}^{N_g} a \cdot s_k + f \cdot \frac{s_k \cdot (i_k - 1)}{\sqrt{3} \cdot v_{Nom}} \quad (6.1)$$

Assuming that all converters have a uniform value of overcurrent capacity of I_{Max} , the cost function C_X then becomes:

$$C_X = \sum_{k=1}^{N_g} a \cdot s_k + f \cdot \frac{s_k \cdot (I_{Max} - 1)}{\sqrt{3} \cdot v_{Nom}} \quad (6.2)$$

$$C_X = \left(a + \frac{f \cdot (I_{Max} - 1)}{\sqrt{3} \cdot v_{Nom}} \right) \cdot \sum_{k=1}^{N_g} s_k \quad (6.3)$$

$$C_X = \left(a + \frac{f \cdot (I_{Max} - 1)}{\sqrt{3} \cdot v_{Nom}} \right) \cdot St_X \quad (6.4)$$

Since, in this work, all the buses that can host new GFM capacity are assumed to have the same nominal voltage level. Then, for a generic solution X , the cost function can be expressed as a linear function of the total GFM nominal capacity, St_X , as shown in the equation below.

$$C_X = k_S \cdot St_X, \quad k_S = a + \frac{f \cdot (I_{Max} - 1)}{\sqrt{3} \cdot v_{Nom}} \quad (6.5)$$

6.1. Optimal Placement and Nominal Capacity Sizing of GFM converters in the Modified IEEE 39 Power System.

This means that the normalised cost value becomes a linear function of the normalised total nominal capacity, as shown in Equation 6.6.

$$\overline{C_X} = \frac{C_{max} - C_X}{C_{max} - C_{min}} = \frac{k_S \cdot St_{max} - k_S \cdot St_X}{k_S \cdot St_{max} - k_S \cdot St_{min}} = k_S \cdot \overline{St_X} \quad (6.6)$$

Hence, for the sake of simplicity, in this section, the capacity will be considered as a proxy of the cost, which results in the following transformation of the decision support problem:

$$\begin{aligned} & \max_X V(X) \\ & V(X) = V(\varepsilon_X, C_X) = K_w \cdot w(\varepsilon_X) + K_p \cdot p(C_X) \\ & s.t. \varepsilon_X \geq \varepsilon_{lim} \\ & X = [L_X, S_X, I_X] = [l_1, l_2 \dots l_{N_g}, s_1, s_2 \dots s_{N_g}, i_1, i_2 \dots i_{N_g}] \\ & \quad \downarrow \quad \downarrow \quad \downarrow \\ & \max_X V(X) \\ & V(X) = V(\varepsilon_X, St_X) = K_w \cdot w(\varepsilon_X) + K_p \cdot p(St_X) \\ & s.t. \varepsilon_X \geq \varepsilon_{lim} \\ & X = [L_X, S_X] = [l_1, l_2 \dots l_{N_g}, s_1, s_2 \dots s_{N_g}] \end{aligned} \quad (6.7)$$

Assuming the above function is an adequate value function for this section, the proposed methodology was employed to place and size a small fleet of GFM-equipped batteries in the aforementioned test system. The maximum number of GFM converters to be placed in the grid was limited to five, with each bus restricted to hosting a single converter and a maximum capacity of 150 MVA per converter. This represents a maximum addition of 750 MVA of GFM capacity to the system, which is deemed appropriate considering: 1) the typical network size managed by most system operators; and 2) the primary objective of GFM-equipped batteries considered in this work, which is to enhance system security. The indifferent solutions derived from the decision-maker (DM) inquiry (in this case, a power system expert), which are used to estimate the weights of the value function (K_w and K_p), are shown in Table 6.1, together with the resulting weights.

Table 6.1: Solutions to which the TSO is indifferent (A & B) and respective value function weights.

$A (St_A, \varepsilon_A)$	$B (St_B; \varepsilon_B)$	K_w	K_p
(171 ; 72.4)	(272 ; 67.4)	0.762	0.238

6.1. Optimal Placement and Nominal Capacity Sizing of GFM converters in the Modified IEEE 39 Power System.

To evidence the methodology's success in finding the solution to the DS problem and ease the problem's comprehension, the problem's Pareto boundary was also computed. For that purpose, the converter configuration ensuring a specific ε (ε_{spec}) was determined for seven distinct levels of ε . The mathematical formulation of the constrained minimisation problem solved to compute each point on the Pareto boundary is provided in Equation 6.8.

$$\min_X T(X) \quad (6.8)$$

$$T(X) = \overline{St_X} + k_{pen} \cdot [\varepsilon_X - \varepsilon_{spec}]_0^{+\infty}$$

6.1.1 Reduction of the problem dimension

In this section, the set of disturbances (Ω_d^o) and scenarios (Ω_m^o) that are considered when evaluating a solution X is depicted in the bottom heatmap of Figure 6.1. This set results from applying the selection procedure detailed in Section 4.2.1 to an initial collection of 512 events (64x8). The disturbance set that is initially considered (Ω_d), which has 64 elements, includes two faults per system line, one at each end, and assumes each fault to be a 3-phase symmetrical short circuit that is cleared via the line tripping after a time Δ_t (e.g. 150 ms). As for the initial set of operation scenarios, (Ω_m), which has eight elements, it consists of a collection of 8 diverse operation points.

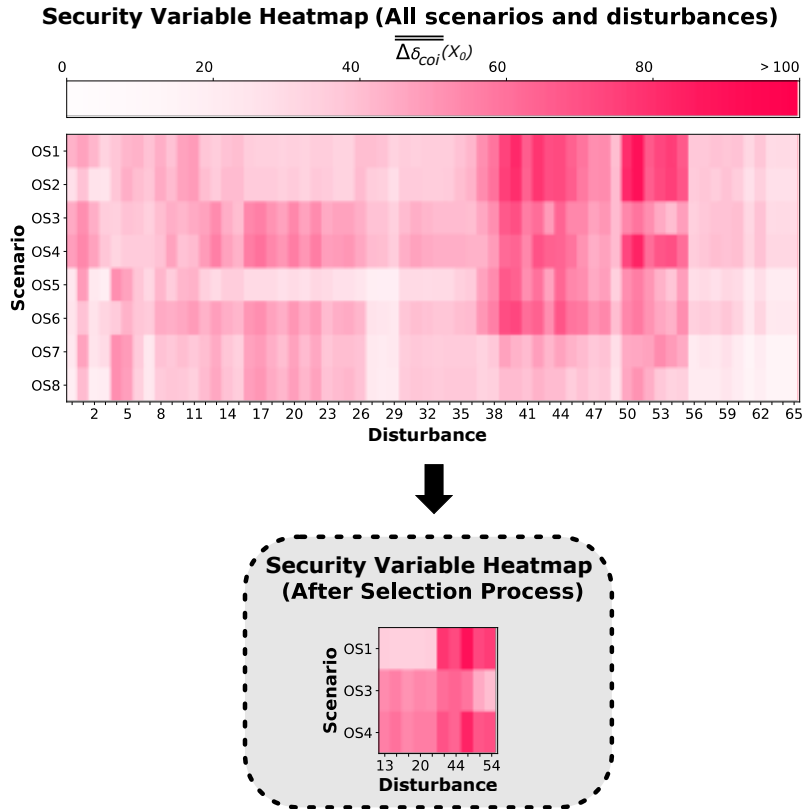


Figure 6.1: Effect of the selection process on the heatmap of relevant scenarios and disturbances.

6.1. Optimal Placement and Nominal Capacity Sizing of GFM converters in the Modified IEEE 39 Power System.

The reduced problem search space, comprising the set of locations available for selection by the optimisation engine (Ω_b^0), is represented in Equation 6.9. This collection corresponds to the set of locations obtained after applying the search space reduction procedure outlined in Section 4.2.2 to the original set comprising all 39 system buses (Ω_b).

$$\Omega_b^0 = \{2, 3, 4, 5, 6, 7, 8, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38\} \quad (6.9)$$

6.1.2 Implementation, Convergence and Computation Analysis

The proposed methodology was implemented on a computer equipped with an Intel(R) Xeon(R) CPU E3-1245 v6 @ 3.70GHz processor and 32 GB of RAM. The solution-seeking algorithms described in Section 4.2.3 were implemented in Python 3.9, and the dynamic system model was built in PowerFactory. The PowerFactory Python API enabled the communication between both modules.

Figure 6.2 illustrates several convergence curves of Algorithm 4 as it is applied to solve the Decision Support Problem outlined in Equation 6.7. Each curve represents a different seed from the random number generator. These varied curves serve to demonstrate that the inherent randomness of both Bayesian optimisation and the meta-heuristic employed for fine-tuning does not impact the solution. As shown, there is minimal variance in the final solution, regardless of the chosen seed. Furthermore, the solution is attained within 782 evaluations of $A(X)$ on average, which is significantly fewer than the total required for a brute-force approach. This is particularly important, as evaluating $A(X)$ implies conducting a full dynamic simulation of multiple disturbances.

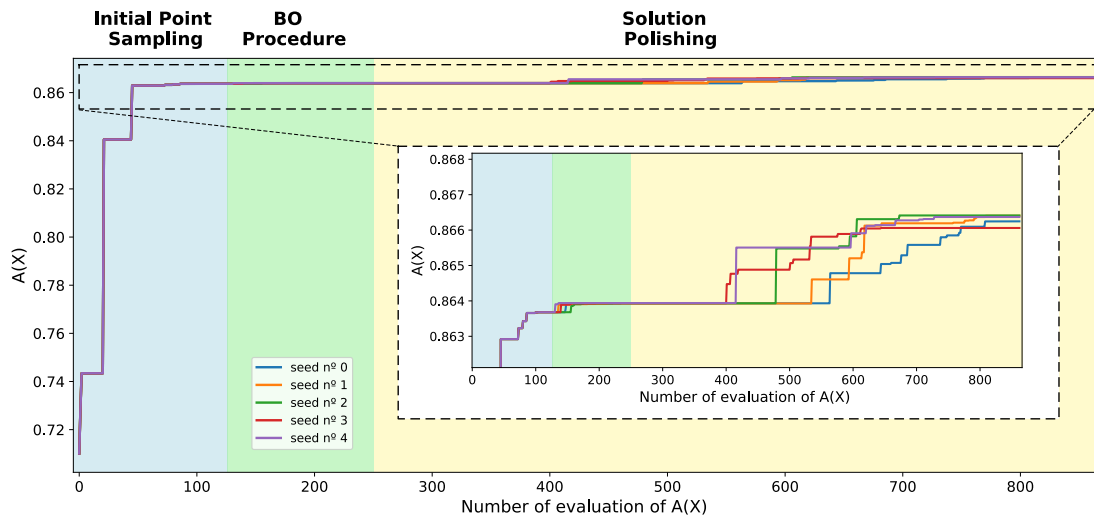


Figure 6.2: Algorithm Convergence Curves.

6.1. Optimal Placement and Nominal Capacity Sizing of GFM converters in the Modified IEEE 39 Power System.

As for the time taken to execute the method, the different runs depicted above correspond to 35226 seconds on average. For larger systems, the computation time would naturally escalate. However, this fact does not shadow the method adoption since the associated time restrictions are generally loose and unprioritised, as the placement problem is of planning and not an operational nature. Additionally, the computational capacities of TSOs would also be better than those presented here.

With regard to the method's ability to converge in larger systems, it is worth saying that the version of the IEEE 39 test system adopted in this work displays complex dynamic behaviour due to the differently controlled elements that coexist in the grid, including large-scale synchronous power plants, large-scale RES power plants and large-scale BESS. As a consequence of the modelling options taken in this work (e.g. conformity with the typical grid code requirements of the RES power plants, type of grid-forming converter model, et al.), the system's response to disturbances often exhibits various kinds of instability. These include traditional rotor angle stability issues, frequency stability problems that stem from the converter's behaviour, and instability rooted in the converters [142]. These instability patterns are not exclusive to this system; in fact, they are becoming increasingly prevalent in large interconnected power systems, as discussed in [15] and [17].

That being said, the successful performance of the proposed algorithm in placing and sizing large-scale GFM converters in this system instils confidence in the potential applicability of the method for larger power systems. This assumption is supported by the ability of Bayesian Optimisation to successfully solve optimisation problems with up to two/three dozen dimensions [150, 173]. This suggests the possibility of deploying up to thirty megawatt-scale BESS units with GFM converters in a converter-dominated power system, with the primary objective of enhancing system dynamic security. This figure appears to be well-suited for most real power systems, especially considering that the optimal solution in this study allocated only three converters to simultaneously ensure security and manage cost (see following sections).

6.1.3 Solution of Decision Support Problem

Figure 6.3 depicts the achieved results in regards to the two-dimensional attribute space; more specifically, it presents the achieved preferred solution (solution of the DS problem), along with the problem's Pareto boundary and several indifference curves (regions of the attribute space where the value function remains constant and the DM is indifferent to any solutions along this curve). The converter locations and their capacities for each solution depicted in Figure 6.3 are also detailed in Table 6.2.

6.1. Optimal Placement and Nominal Capacity Sizing of GFM converters in the Modified IEEE 39 Power System.

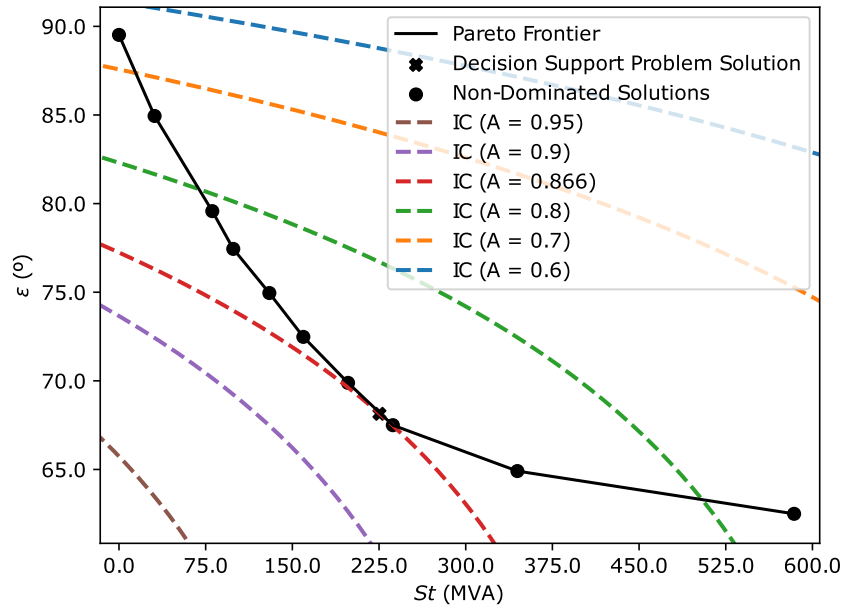


Figure 6.3: Results illustration on the attribute plane.

Table 6.2: Points of Pareto Boundary and Solution of the DS Problem.

l_1	l_2	l_3	l_4	l_5	s_1 (MVA)	s_2 (MVA)	s_3 (MVA)	s_4 (MVA)	s_5 (MVA)	ε (°)
35	-	-	-	-	31	-	-	-	-	84.94
36	35	-	-	-	76	84	-	-	-	72.48
36	35	-	-	-	119	107	-	-	-	68.14
36	35	-	-	-	127	110	-	-	-	67.5
36	35	25	-	-	89	121	135	-	-	64.91
36	20	35	21	22	141	104	117	119	102	62.5

As seen in Figure 6.3, the preferred solution to the Decision Support (DS) problem corresponds to the point of the Pareto Boundary that is crossed by an Indifference curve of a larger value, in this case, the red curve ($A = 0.867$). This evidences the ability of the developed solution-seeking algorithm to maximise the value function, thereby solving a heavily non-linear combinatorial problem. In what concerns the solution itself, which is highlighted in bold in Table 6.2, it corresponds to the placement of 2 battery-equipped GFM converters, one in bus 36 with a capacity of 119 MVA and one in bus 35 with a capacity of 107 MVA. For visual reference, Figure 6.5 shows the single-line diagram of the grid, with GFM converters placed at Bus 35 and 36.

6.1. Optimal Placement and Nominal Capacity Sizing of GFM converters in the Modified IEEE 39 Power System.

6.1.4 Discussion on the Achieved GFM Placements and Sizing

Bus 36 and Bus 35 are the terminal buses of the two system synchronous generators that experience the largest synchronising torque reduction during the fault (G6 & G7). The GFM placement in such buses reduces the active power variation that the synchronous generators experience since the converters' fast reactive and active current response reduces the bus voltage magnitude drop and the phase angle excursion. This leads to the reduction of the synchronous machine's accelerating power and, consequently, the rotor angle excursion during a fault.

This behaviour is clear in Figure 6.4, where the time evolution of the system's synchronous machine's active power and rotor angle in the face of two different disturbances is depicted, considering the condition with the optimally placed GFMs and without them. Hence, one can conclude that the algorithm's solution is also feasible from a physical perspective. For a more detailed analysis of the effect of the GFM converter on the transient stability of the system's synchronous generators, refer to Section 3.2.3 and 3.2.2.

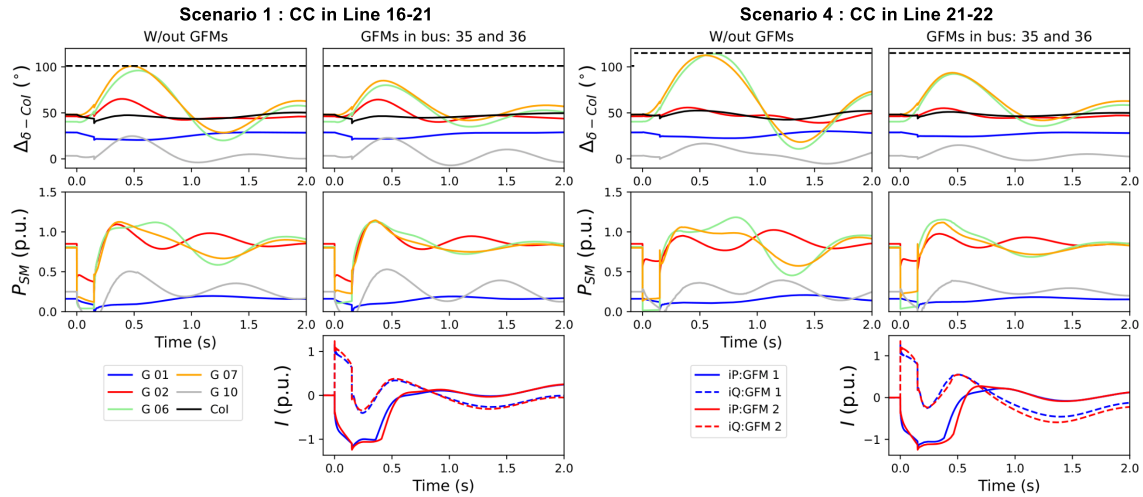


Figure 6.4: Time Evolution of different system variables for two events with and without the effect of the optimally placed GFMs (CoI - Centre of Inertia).

The locations that correspond to the non-dominated solutions also exhibit a similar behaviour in terms of proximity to the synchronous generators more prone to loss of synchronism. As expected, for larger security levels (lower ϵ), more GFM capacity is needed to ensure that level of security, which also materialises in terms of the number of converters (see Figure 6.3 and Table 6.2). While this was expected, it is worth mentioning that this relation is non-linear, meaning that to achieve similar improvements in terms of security ($\Delta\epsilon$) in zones of lower security index, the needed capacity is substantially larger. This important conclusion should be taken into account by TSOs when considering the use of GFM converters as a means to enhance dynamic security.

6.1. Optimal Placement and Nominal Capacity Sizing of GFM converters in the Modified IEEE 39 Power System.

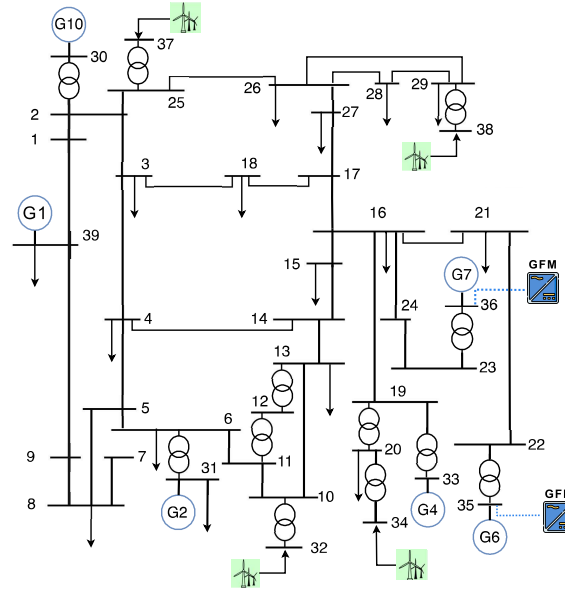


Figure 6.5: Visual illustration of optimal GFM placement.

The effect of the solution of the DS problem on all initially considered system disturbances is also highlighted in the heatmaps of Figure 6.6. The achieved optimal locations and sizing not only led to an overall enhancement of system security for the disturbances and scenarios that were deemed critical by the selection procedure, but also did not compromise system security for the remaining disturbances and scenarios.

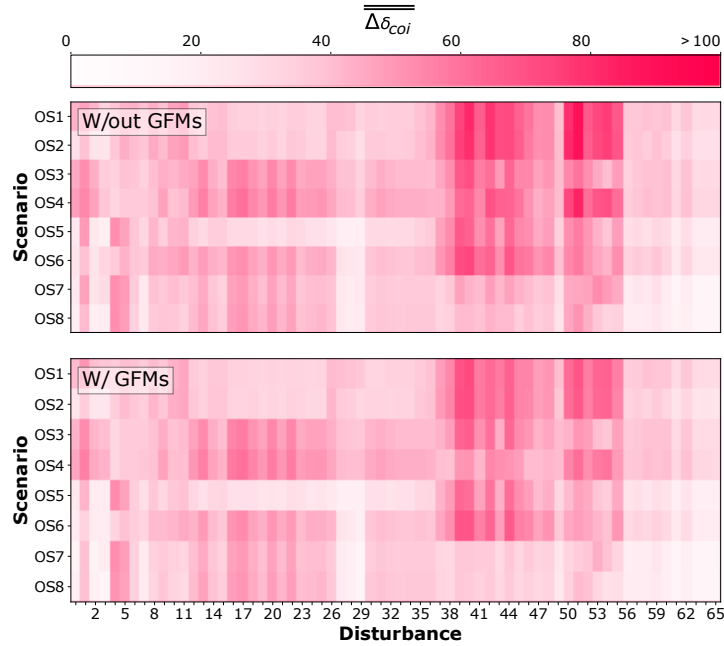


Figure 6.6: Effect of the preferred solution in the map of initially considered Disturbances and Scenarios.

6.1. Optimal Placement and Nominal Capacity Sizing of GFM converters in the Modified IEEE 39 Power System.

6.1.5 Impact of the GFM Converters Current Limitation Loop

The GFM converter's current limitation control has been shown to be a particularly relevant piece of control regarding the system's behaviour during short circuits [21]. Given the non-linearity of some of the existing control schemes (e.g. virtual impedance), the correlation between different amounts of overcurrent capacity and the resulting security gain is not always straightforward. That being said, it is worth inspecting the relationship that the overcurrent capacity (I_{Max}) may have on both the achieved locations (L) and the overall sized GFM capacity (St), through a sensitivity-based analysis. For that purpose, the previously defined decision support problem was solved for different values of I_{Max} , the fixed value of the overcurrent capacity for all GFM converters that are to be placed. The resulting values of the most relevant problem variables, $A(X)$, ε , S , St , and L , were then registered. The results of this sensitivity analysis are depicted in Figure 6.7 and Table 6.3.

Table 6.3: Optimal locations and sized capacity for tested I_{Max} values.

I_{Max}	1.15	1.3	1.45	1.6	1.75	1.9	2.05	2.2	2.35	2.5
l_1	36	36	36	36	36	36	36	36	36	36
l_2	35	35	35	35	35	35	35	35	35	35
s_1	124	123	120	118	117	117	120	121	122	121
s_2	118	116	111	106	103	100	101	100	100	100

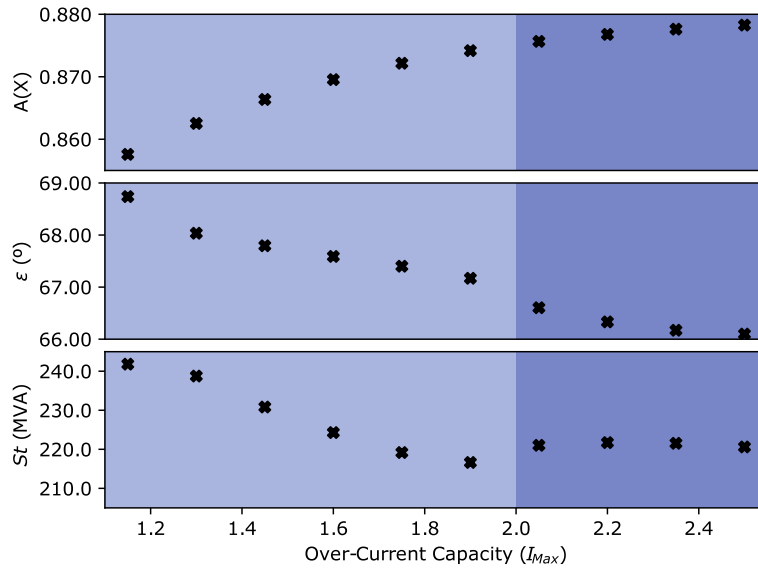


Figure 6.7: Variation of $A(X)$, ε , St as a function of I_{Max} .

As can be seen, the progressive increase of I_{Max} results, initially (blue zone), in a sustained increase of $A(X)$, which translates into a reduction of the sized capacity and an improvement of the security (ε reduction). This means that an initial increase in the current overcurrent

6.2. Simultaneous Sizing of the Converters Nominal and Overcurrent Capacity.

capacity results in an increase in TSO satisfaction that is noticeable in both criteria of analysis. However, above a certain value of I_{Max} (in this case 2.0), the increase in overcurrent capacity no longer guarantees significant improvements in $A(X)$ (dark blue zone). A behaviour that is reflected in both criteria plateauing. As for the optimal locations, the previously determined pair (36 and 35) remains the solution, regardless of the I_{Max} value.

As previously discussed, if correctly placed, the GFM converters' current response can reduce the synchronous machines' accelerating power during a fault. This response is primarily determined by the VSM and voltage control loops, but is constrained by the available converter overcurrent capacity. Therefore, an initial increase in I_{Max} noticeably enhances system security, as the current response defined by the outer loops becomes less constrained by the current limiting control.

Likewise, when I_{Max} reaches or exceeds the current response defined by the outer loops, the current limiting control ceases to constrain the response. As a result, further increases in I_{Max} yield only marginal security improvements. These slight gains stem from the current limiting method employed, referred to as Virtual Impedance, which elevates its value directly from 1.0 p.u. rather than exclusively from I_{Max} onwards.

In practical terms, this means that to satisfy the TSO security-cost concerns, one should not always strive for more overcurrent capacity but rather understand the point at which additional increases in such variables become less relevant to the system dynamics. Ideally, the point where the costs of the converter's nominal and overcurrent capacity satisfy the TSO cost-security concerns should be found. This requires a formulation where the cost attribute is no longer considered using the capacity as its proxy, but instead with an informed perspective on the costs of the converter's nominal and overcurrent capacity. This analysis is presented in the following section.

6.2 Simultaneous Sizing of the Converters Nominal and Overcurrent Capacity.

As just mentioned, the overcurrent capacity of the GFM converters has a significant impact on the solution of the problem formulated in Equation 6.7, particularly in the degree of satisfaction that the TSO achieves (value function) and on the solution cost (sized capacity). That said, in this section, the formulation first introduced in Section 4.1, which aims at maximising the DA satisfaction by appropriately placing and sizing the converter's nominal and overcurrent capacity, is adopted. For the sake of comprehension, the previously introduced problem formulation is presented again in Equation 6.10.

6.2. Simultaneous Sizing of the Converters Nominal and Overcurrent Capacity.

$$\begin{aligned}
& \max_X : V(X) \\
& V(X) = V(\varepsilon_X, C_X) = K_w \cdot w(\varepsilon_X) + K_p \cdot p(C_X) \\
& \text{s.t. } \varepsilon_X \geq \varepsilon_{lim} \\
& X = [L_X, S_X, I_X] = [l_1, l_2 \dots l_{N_g}, s_1, s_2 \dots s_{N_g}, i_1, i_2 \dots i_{N_g}]
\end{aligned} \tag{6.10}$$

As in the previous subsection, the proposed methodology was employed to place and size a small fleet of GFM-equipped batteries in the Modified IEEE39 test system, now considering the value function described above as the function to maximise. The indifferent solutions derived from the DM inquiry (e.g., the TSO), which are used to estimate the weights of the value function (K_w and K_p), are shown in Table 6.4, together with the resulting weights. Note that these values differ from those presented in the previous section since the cost attribute now depends on the selected nominal and overcurrent capacity. An analysis of the effect of different choices of indifferent solutions on the problem optimum is presented later in Section 6.2.3.

Table 6.4: Solutions to which the TSO is indifferent (A & B) and respective value function weights.

A (C_A, ε_A)	B (C_B, ε_B)	K_w	K_p
(100;95)	(175;85)	0.704	0.296

Once again, the problem's Pareto boundary was computed to demonstrate the methodology's effectiveness in solving the DS problem and to enhance understanding of the problem. In this case, the points of the Pareto boundary were identified by minimising the function of Equation 6.11, for 8 different values of ε_{spec} .

$$\begin{aligned}
& \min_X T(X) \\
& T(X) = \overline{C_X} + k_{pen} \cdot [\varepsilon_X - \varepsilon_{spec}]_0^{+\infty}
\end{aligned} \tag{6.11}$$

6.2.1 Reduction of the Problem Dimension.

In this section, the initial set of operation scenarios (Ω_m) is expanded to a collection of 50 elements to more effectively demonstrate the effectiveness of the selection methodology. This collection comprises operating points that are both prone to instability (e.g., characterised by low inertia, low short-circuit power, etc.) and diverse in terms of grid topology, generation dispatch, and load profiles. As for the initial disturbance set (Ω_d), it remains the same as the one detailed in Section 6.1.1.

The effect of the selection process on this space of optimisation-relevant scenarios and disturbances ($\Omega_m^o \times \Omega_d^o$) is illustrated in the heatmaps of Figure 6.8, with the bottom heatmap

6.2. Simultaneous Sizing of the Converters Nominal and Overcurrent Capacity.

illustrating the collection of events used by the search engine to evaluate a solution X . Each heatmap illustrates the system security index under the baseline condition, where no additional GFM capacity is implemented. As observed, the number of events required to evaluate a given solution X is significantly reduced, decreasing from an initial $3,200$ events (60×50) to just 49 (7×7). This reduction substantially decreases the computational effort required for the analysis while preserving the most critical events. This is evident in the darker shades of the second heatmap, which highlight events with higher values of $\overline{\Delta\delta_{coi}}(X_0)$.

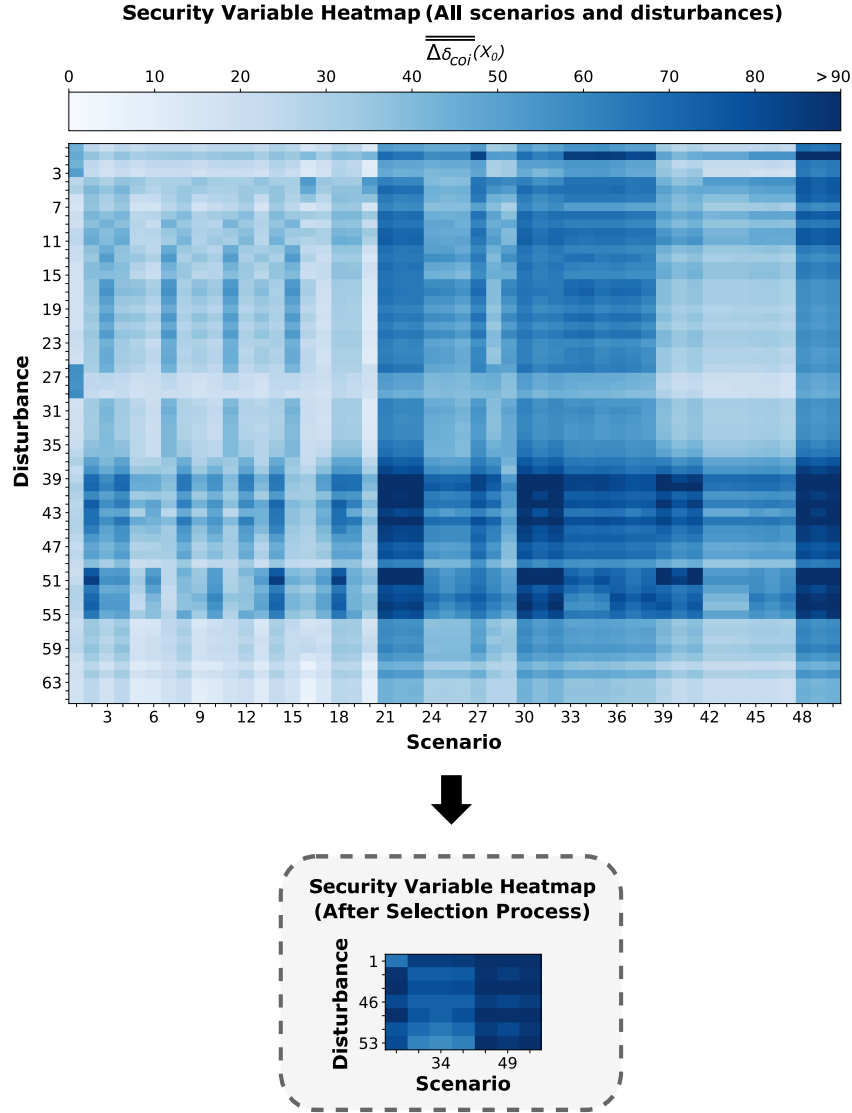


Figure 6.8: Effect of the selection process on the heatmap of relevant scenarios and disturbances.

The reduced problem search space, which corresponds to the locations where an additional GFM capacity can effectively be added, is depicted in the set of locations of Equation 6.12:

$$\Omega_b^o = \{19, 20, 21, 22, 23, 24, 33, 34, 35, 36\} \quad (6.12)$$

6.2. Simultaneous Sizing of the Converters Nominal and Overcurrent Capacity.

Compared to the reduced search space employed in the previous section, this one exhibits a significantly smaller dimension. This reduction is attributed to the distinct set of scenarios and disturbances considered, where the introduction of additional GFM capacity at the specified locations yields a noticeably greater impact than earlier.

6.2.2 Numerical Results: Solution of Decision Support Problem

Figure 6.9 depicts the results regarding the two-dimensional attribute space; more specifically, it presents the achieved preferred solution (solution of the DS problem), along with the problem's Pareto boundary and several indifference curves (regions of the attribute space where the value function remains constant and the DM is indifferent to any solutions along this curve). The converter locations and their capacities for each solution are also detailed in Table 6.5.

Table 6.5: *Points of Pareto Boundary and Solution of the DS Problem.*

l_1	l_2	l_3	s_1 (MVA)	s_2 (MVA)	s_3 (MVA)	i_1 (p.u.)	i_2 (p.u.)	i_3 (p.u.)	ε (°)
35	-	-	36.6	-	-	2	-	-	115
35	-	-	53.8	-	-	2	-	-	110
35	36	-	67.5	8.9	-	2	2	-	105
35	36	-	91	13.8	-	2	2	-	100
35	36	-	82.7	63	-	2	2	-	95
35	36	-	101	79	-	2	2	-	91.3
35	36	-	104.1	89.4	-	2	2	-	90
36	35	-	135.5	124.8	-	1.93	2	-	85
36	35	23	150	135.1	90.9	2	2	2	80

As shown in Table 6.2, the converters' overcurrent capacity is consistently sized to its maximum value (2 p.u.), regardless of the security level. In contrast, the nominal capacity is sized appropriately to achieve the desired objective, whether it corresponds to a point on the Pareto frontier or a solution to the decision-support problem. This differentiation between nominal and overcurrent capacity arises directly from the substantial cost disparity in the cost model of Equation 4.8 ($a \gg f$).

The higher cost associated with nominal capacity (a) is justified by its direct impact on all solution cost components, including the battery modules, transformers, installation, and communication systems infrastructure, etc. Conversely, an increase in overcurrent capacity, which represents a temporary current overload, primarily affects the cost of the converters and protection systems. Hence, its contribution to the overall solution cost is comparatively smaller.

6.2. Simultaneous Sizing of the Converters Nominal and Overcurrent Capacity.

Note that factoring the increase in the solution cost due to the increase in the converter overcurrent capacity can be a challenging task due to difficulty in obtaining related cost data; hence, as mentioned earlier, Section 6.2.4 presents a sensitivity analysis of f to further investigate the previously drawn conclusions.

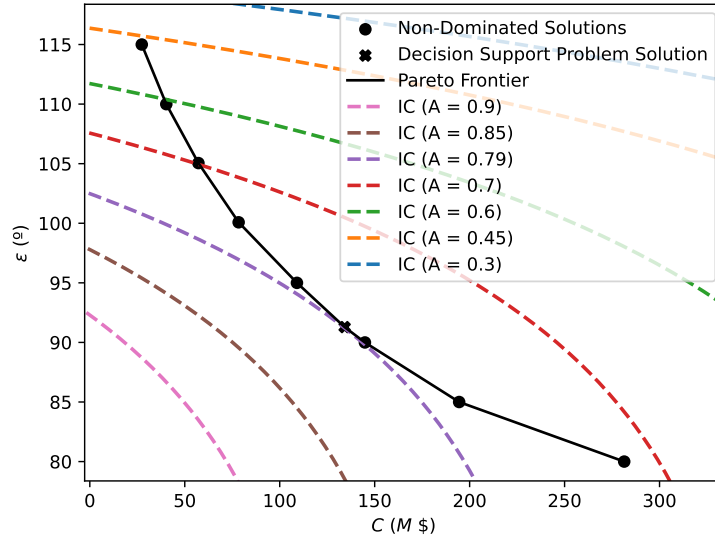


Figure 6.9: Solution of the decision support problem in the 2-criteria plane.

An analysis of the results depicted in Figure 6.9, enables confirming some of the conclusions previously drawn in Section 6.1.4 and 6.1.3, namely:

- The proposed solution-seeking algorithm effectively maximises the value function, as evidenced by the achieved solution to the DS problem (indicated by the crossed point). This solution corresponds to the point on the Pareto Boundary intersected by an indifference curve with a higher value ($IC(A = 0.79)$), thereby validating the algorithm's efficacy.
- The relation between security and the solution cost is non-linear, meaning that to achieve similar improvements in terms of security ($\Delta\epsilon$) in zones of lower security index, the needed investment is substantially larger.
- The GFM converters are still placed in terminal buses of the two system synchronous generators that experience the largest synchronising torque reduction during the most severe faults (B 35 & B 36). Compared to the previous section, the difference lies in the sized nominal capacity since the converter's overcurrent capacity is now a state variable, and both the value function weights and the set of considered scenarios differ.
- The achieved optimal locations and sizing resulted in an overall enhancement of system security for the selected disturbances and scenarios without compromising security for disturbances and scenarios that were deemed non-critical (Refer to Figure 6.10 for an

6.2. Simultaneous Sizing of the Converters Nominal and Overcurrent Capacity.

illustration of the effect of the optimal solution on all considered system disturbances).

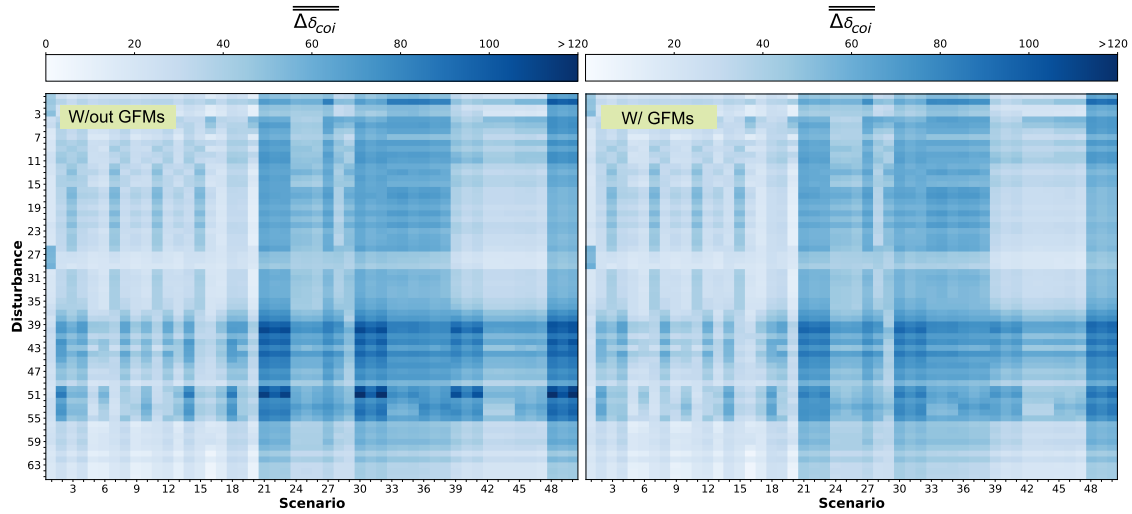


Figure 6.10: Effect of the preferred solution in the map of Disturbances and Scenarios.

The stability improvement resulting from adopting the DS problem solution is once again demonstrated through the dynamic simulations of two specific disturbances. Figure 6.11 illustrates the power-angle characteristic and the terminal voltage of two synchronous machines for two different disturbances, comparing conditions with and without the optimally placed and sized GFMs. The current response of the GFM converters is also depicted. As can be seen, for the first disturbance (curves on the left), the strategic placement of the GFMs avoided the loss of synchronism of G6; which is evident by the arrest of the generator rotor angle that no longer continuously separates from the CoI; As for the disturbance on the right, it contributed to a significant decrease of the angle deviation of G7.

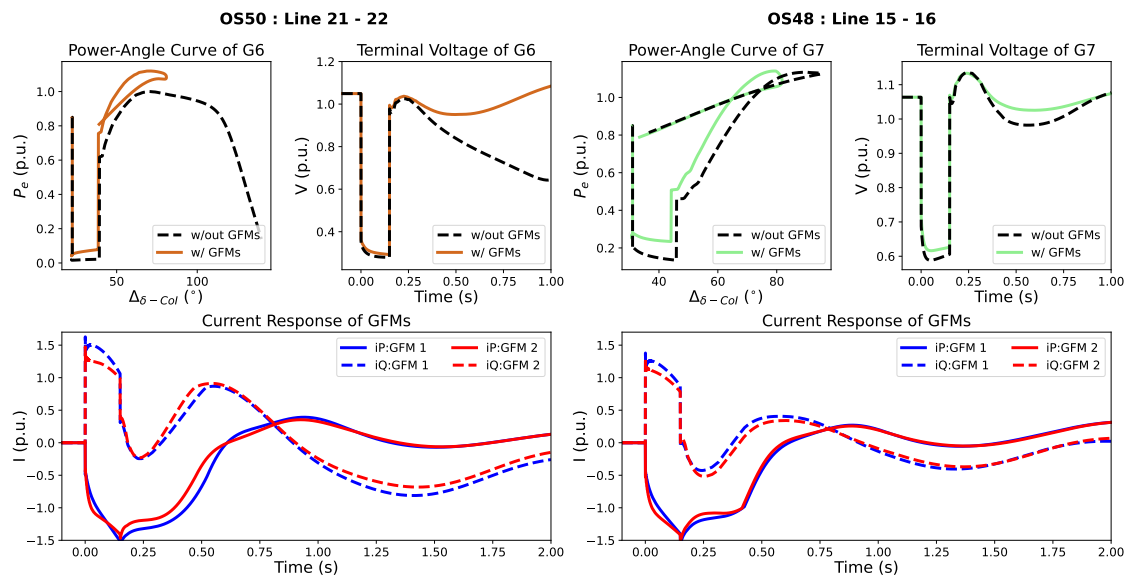


Figure 6.11: Evolution of different system variables for two different events, with and without the effect of the optimally placed GFMs.

6.2. Simultaneous Sizing of the Converters Nominal and Overcurrent Capacity.

6.2.3 Impact of the TSO Cost-Preferences on the Achieved Solution Problem

As previously detailed, the solution to the decision support problem corresponds to the placement and sizing of the N GFM converters that maximise the DM satisfaction for the cost-security preferences expressed in the value function $V(x)$. Besides the structure of the value function itself (an additive value function), the DM preference characteristic is embedded into $V(X)$ by fitting three parameters: b , K_w and K_p .

As shown in Figure 4.2, the parameter b enables adjusting the decision agent's valorisation of security throughout the security domain. TSOs are often very favourable to the decrease of ε_X when its level is high, but not so enthusiastic when it is already acceptable/low. Hence, b should only vary marginally for different TSOs. In contrast, K_w and K_p , which model the relative weight of each attribute, are highly TSO-specific as these have different budgets.

Given the impact of K_w and K_p on the structure of the additive value function and, consequently, its maximum, it is essential to analyse how variations in these parameters – representing different TSO cost-security preferences – influence the resulting preferred solution. To this end, a sensitivity analysis was conducted for various values of the value function weights.

In this study, K_w and K_p are derived from inquiring about the DM through an indifference judgment, which involves identifying two solutions deemed indifferent by the DM/TSO. Accordingly, different pairs of indifferent solutions, each corresponding to distinct weight values, were analysed, and the resulting value of the achieved preferred solution was registered. The results of this small analysis are presented in Table 6.7 and Figure 6.12.

The analysed pairs of indifferent solutions were identified by inquiring different power system experts through an indifference judgment. These experts are meant to represent the different decision-makers that exist in transmission system operators. These points and their corresponding value function weights are depicted in Table 6.6.

Table 6.6: Pairs of weigh values that were analyzed, and corresponding indifferent solutions.

DM	$A (C_A, \varepsilon_A)$	$B (C_B, \varepsilon_B)$	K_w	K_p	$L\text{-Tradeoff}$
DM 1	(25,110)	(50,100)	0.23	0.77	-0.4
DM 2	(50,100)	(90,90)	0.48	0.52	-0.25
DM 3	(100,95)	(175,85)	0.7	0.3	-0.13
DM 4	(100,93)	(250,83)	0.84	0.16	-0.07

where $L\text{-Tradeoff}$ corresponds to the linear tradeoff calculated using the two indifference solutions. These values are computed with the sole purpose of easing the explanation of results,

6.2. Simultaneous Sizing of the Converters Nominal and Overcurrent Capacity.

as they provide an estimation of how much each TSO expects to reduce the security index for each paid cost unit.

As seen in Figure 6.12, adopting different weights (K_w and K_p) transforms the direction of the value function indifference curves. This means that the preferred solution, which is the point of the Pareto frontier that crosses the indifference curve of a larger value, will change for the different weight values. Particularly, for larger values of K_w (and consequently smaller of K_p), the preferred solution results in larger security levels (lower ε) at a larger cost. This was expected as larger values of K_w (and consequently smaller values of K_p) traduce lower absolute values of L -Tradeoff, meaning that the Decision Maker expects smaller improvements of ε for each invested cost unity. In other words, they are willing to pay more to achieve the same levels of security improvement. Hence, the solution that best fits their preferences will manifest higher security (lower ε) at a larger cost.

Table 6.7: Effect of different DM/TSO cost-security preferences on the solution of the DS problem.

DM	l_1	l_2	l_3	s_1 (MVA)	s_2 (MVA)	s_3 (MVA)	i_1 (p.u.)	i_2 (p.u.)	i_3 (p.u.)	$V(X)$
1	35	-	-	59	-	-	2	-	-	0.794
2	36	35	-	16.6	92.8	-	2	2	-	0.759
3	36	35	-	78.7	100.7	-	2	2	-	0.789
4	36	35	-	137.5	125.2	-	2	2	-	0.843

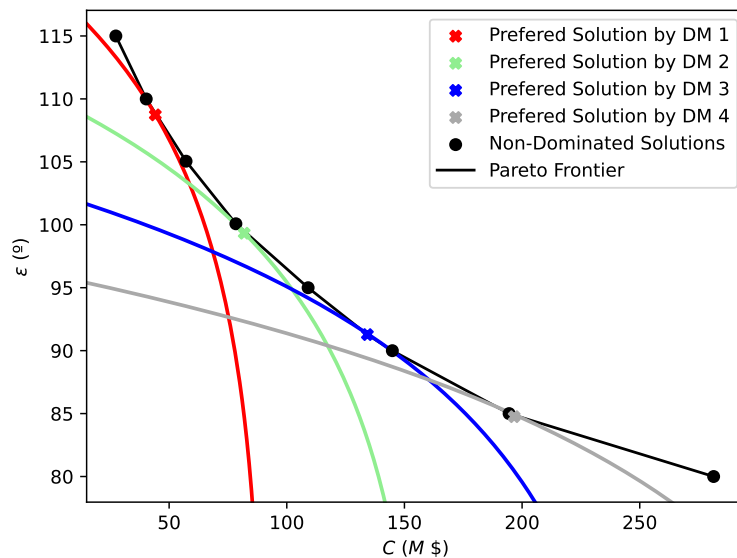


Figure 6.12: Effect of different DM/TSO cost-security preferences on the solution of the DS problem (attribute space illustration).

A brief analysis of Table 6.7 enables identifying that the split between the nominal and over-

6.2. Simultaneous Sizing of the Converters Nominal and Overcurrent Capacity.

current capacity of the sized converters remains constant regardless of the TSO cost-security preference. This means that the overcurrent capacity is still fully sized while the nominal capacity is adjusted to maximise the value function. This behaviour is expected, as the cost of the overcurrent capacity (f) is still the same and, as mentioned before, is much smaller than a .

It is also important to note that the value of $V(X)$ for the preferred solution varies across the different TSO preferences analysed. This indicates that some TSOs achieve higher degrees of satisfaction than others. Such variation is expected, as certain decision-makers express cost-security preferences that are more challenging to fulfil, considering how the system's dynamic security relates to the increase in GFM capacity. Still, it is worth noting that for the cost-security preferences expressed by each TSO, the method consistently identifies the solution that maximises the satisfaction of the decision agent.

6.2.4 Sensitivity Analysis of the Overcurrent Price on the Solution of the Formulated Problem.

The cost of incrementing the overcurrent capacity of a converter is often hard to quantify due to the lack of data on the subject, hindering the task of defining an optimal capacity that respects the decision agent's cost-security preferences. That being said, it is worth inspecting the impact that the cost attributed to an extra unit of overcurrent capacity (f in Equation 4.8) may have on the preferred locations and sizing of the converters for the specified TSO preferences. Hence, a sensitivity analysis of f on the main variables of the formulated decision support problem was conducted. For that purpose, the problem formulated in Equation 6.10 was solved for different values of f and the relevant problem variables ε_X , C_X , L_X , S_X and I_X , were registered. The results of this sensitivity analysis are depicted in Figure 6.13 and Table 6.8.

Table 6.8: Achieved preferred solution for each studied f value.

f	l_1	l_2	l_3	s_1 (MVA)	s_2 (MVA)	s_3 (MVA)	i_1 (p.u.)	i_2 (p.u.)	i_3 (p.u.)
0.02	7	9	-	101	79	-	2	2	-
0.05	7	9	-	100	75	-	2	2	-
0.075	7	9	-	99	72	-	2	2	-
0.1	7	9	-	98	68	-	2	2	-
0.125	7	9	-	99	69	-	1.96	1.83	-
0.15	7	9	-	101	70	-	1.82	1.63	-
0.175	7	9	-	104	72	-	1.7	1.48	-

6.2. Simultaneous Sizing of the Converters Nominal and Overcurrent Capacity.

As illustrated in Figure 6.13, the sustained increase of f resulted in a natural reduction of the value function (V_X) for the preferred solution, which indicates reduced alignment with the TSO's security preferences. This was already expected since the increase in the overcurrent capacity cost would at least result in a cost increase (C_X), even if the decision variables remained unaffected (L_X , S_X and I_X). However, it is clear that the cost increase is also followed by a security reduction (larger ε), which means that to contain the cost increase to a value that respects the TSO preferences, the security boundary is marginally reduced. This evidences how the defined formulation can model the extent to which the TSO is willing to accept a marginal cost increase depending on its cost-security preferences, which is essential for guiding the TSO in its investments to improve system dynamic security.

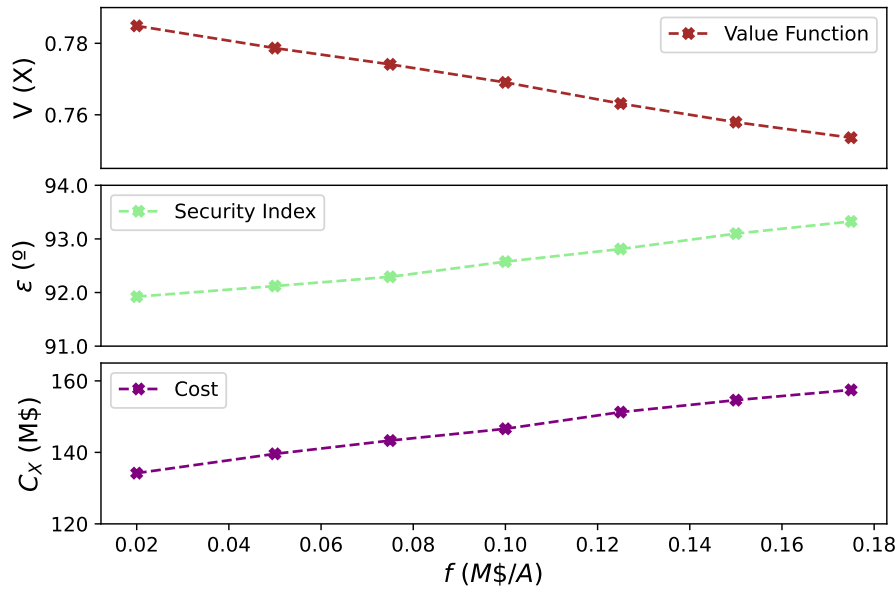


Figure 6.13: Variation of the DS problem value function and its attributes as a function of the overcurrent cost (f).

Interestingly, although the problem attributes and the value function exhibit a monotonous behaviour for the studied variation of f , the cost components associated with each capacity type do not, revealing an intriguing insight. As shown in Figure 6.14, until an overcurrent capacity cost of 0.1, the cost of the sized overcurrent capacity ($I_{Total} * f$) is the main driver for the solution cost increase (C_X), being the cost of the sized nominal capacity ($S_{Total} * a$) even slightly reduced. This behaviour is attributed to the relatively low value of f compared to a , which, given the TSO's cost preferences, continues to incentivise the sizing of the full overcurrent capacity of the converters (2 p.u.). This is also evident in the radar plot of Figure 6.15, which displays the nominal and overcurrent capacities of the two converters sized for each studied f value.

For a mathematical definition of S_{Total} and I_{Total} , see equation 6.13.

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$$S_{Total} = \sum_{j=1}^{N_g} s_j \oplus I_{Total} = \sum_{j=1}^{N_g} \frac{s_j \cdot (i_j - 1)}{\sqrt{3} \cdot v_{Nom}} \quad (6.13)$$

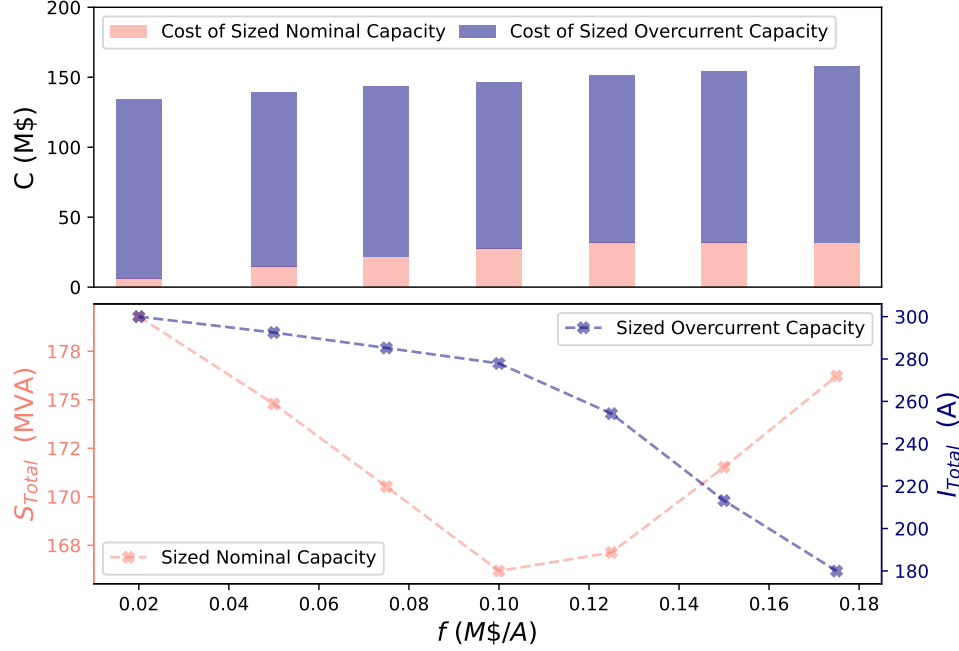


Figure 6.14: Variation of the solution cost parcels as a function of the overcurrent capacity cost (f).

Beyond 0.1, however, the cost increase is no longer driven by the parcel related to the sized overcurrent capacity but rather by the rise in the sized nominal capacity, being the cost of the solution overcurrent capacity approximately constant (see Fig 6.14). This means that: 1) the increase in f is being compensated by the reduction of I_{Total} ; 2) the increase in solution cost results from the rise in nominal capacity, which is necessary to mitigate the security reduction caused by a smaller I_{Total} , thereby ensuring alignment with the TSO's security preferences. Note that the specific threshold of 0.1, as identified here, depends on the DM/TSO cost-security preferences and is not a generic conclusion. Still, the developed decision support tool allows an easy identification of its value for other DM/TSOs.

Once again, this new split between the nominal and the overcurrent capacity of the sized converters is visible in Figure 6.15, showcasing that the overcurrent capacity is no longer sized to its maximum but is instead strategically optimised, similar to the nominal capacity. This also highlights the methodology's ability to balance the converters' nominal and overcurrent capacities to maximise the TSO's satisfaction with respect to its cost-security preferences.

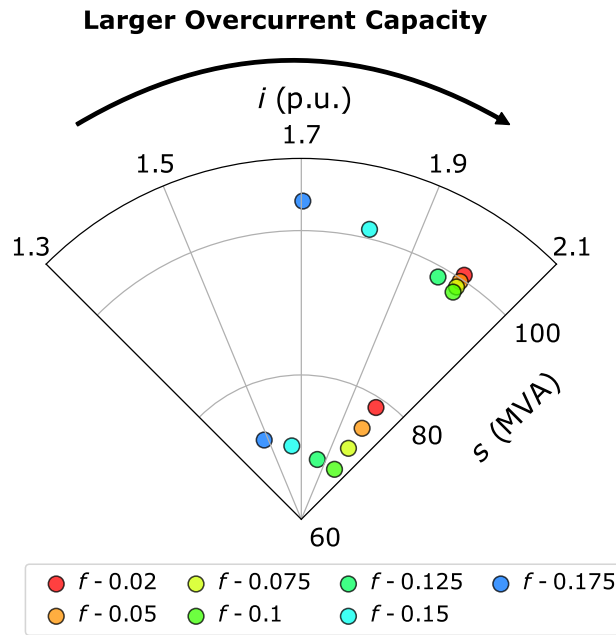


Figure 6.15: Effect of the overcurrent capacity cost (f) on the nominal and overcurrent capacity of the placed converters for the preferred solution.

Based on [141], the cost of the power equipment (converter and its accessories) in a generic BESS system (Lithium-ion) can be considered to be around $0.06 \text{ M\$/MW}$. Hence, assuming that the overcurrent capacity cost would take values closer to $0.1 \text{ M\$/A}$, would not only mean that it would cost more than the converter nominal capacity (if converted to A), but it would also need to represent other significant modifications done to the BESS system components, which seems unfeasible. Therefore, one may conclude that for the considered TSO-security preferences (defined through the points of Table 6.1), the preferred solution will always consist of a strategic optimisation of the nominal capacity and maximum sizing of the overcurrent capacity. Essentially, this shows that in these conditions, the overcurrent capacity cost of the converters has a minor value, considering the benefits it can bring to the system security.

6.3 Multi-Class Placement

This section presents the results of applying the multi-class placement methodology, discussed in Section 4.3, to the Modified IEEE39 Test System. Such methodology proposes an alternative formulation for the GFM placement problem that solely focuses on maximising stability improvement when considering multiple stability classes.

As mentioned earlier (see Section 4.3), this formulation does not delve into a multi-criteria approach (cost-security) for placement and sizing; instead, it concentrates solely on the place-

6.3. Multi-Class Placement

ment of converters. This focus helps to achieve two key objectives: 1) to demonstrate the need for a multi-class formulation of the security index in the placement problem, and 2) to validate that the proposed methodology can identify an optimal configuration for the GFM converters, maximising system stability gains across multiple stability classes.

The methodology is demonstrated by placing and sizing two GFM converters, each with a predefined capacity of 150 MVA. For reference, the multi-class formulations introduced in Section 4.3, whose minimisation enables determining the optimal solution, are revisited in Equations 6.14 and 6.15. These correspond to the multi-class formulations that diverge in terms of the adopted composite stability indicators, as explained in Section 4.3.1.

$$\min_X F_M(X)$$

$$F_M(X) = K_{\Delta f_{SM}} \cdot M_{\Delta f_{SM}}(X) + K_{Rocof_{SM}} \cdot M_{Rocof_{SM}}(X) + K_{CVD} \cdot M_{CVD}(X) + K_{CQPD} \cdot M_{CQPD}(X) \quad (6.14)$$

$$\min_X F_S(X)$$

$$F_S(X) = K_{\Delta f_{SM}} \cdot S_{\Delta f_{SM}}(X) + K_{Rocof_{SM}} \cdot S_{Rocof_{SM}}(X) + K_{CVD} \cdot S_{CVD}(X) + K_{CQPD} \cdot S_{CQPD}(X) \quad (6.15)$$

Note that in this section, X corresponds to a two-dimensional state vector with the locations of the two converters to be placed (e.g. $[l_1, l_2]$).

6.3.1 Disturbances

When evaluating a solution X , through the computation of the different stability variables aggregated in the fitness function, a group of 10 representative line faults, highlighted with a cross in Figure 6.16, is considered. The faults, assumed to be 3-phase symmetrical short circuits, take place in the middle of the line for 150 ms and are then cleared via the line tripping. These events were chosen given their severity to the different stability classes and their ability to represent the effect of other nearby faults, which was identified via a simplified contingency analysis that considered both generation outages and short circuits [142].

The disregard of the generation outages is here justified in a two-folded way: 1) its impact on the stability indexes is of minor intensity when compared to the short-circuit cases [142]; 2) the fast voltage support provided by the GFM during fault is circumscribed to a zone of the grid (due to grid topology, converter current limits and converter sizing), which does not happen in the generation outages case, where the benefits tend to be more widespread as the stability improvement tends to result from the GFM active power response; Nevertheless,

6.3. Multi-Class Placement

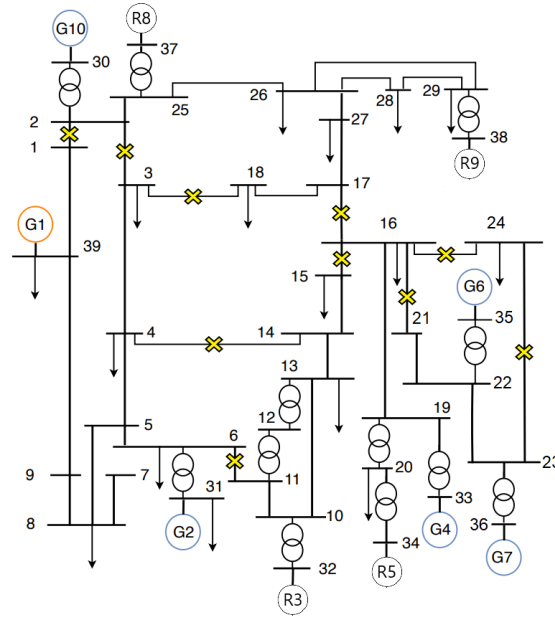


Figure 6.16: Schematic of Modified 39 bus test system (based on [174])

different generation outages are easily included in the proposed methodology, as is any other disturbance.

A single operation scenario is considered in this case since it eases the inspection of the results and the conclusion drawing. The generation dispatch that characterises such a scenario is depicted in table 6.9.

Table 6.9: Generation Dispatch and Inertia Constant (G_2 and G_7 are offline).

Name	G_1	G_4	G_6	G_{10}	R_3	R_5	R_8	R_9
$P(MW)$	1000	632	650	810	650	508	540	830
H_{sb} (s)	250	28.6	34.8	42	-	-	-	-

6.3.2 Choice of Optimisation Engine

The methodology proposed in Section 4.3 leverages the power of meta-heuristics to quickly converge to the solution of the formulated optimisation problem. Two candidates for this methodology were previously introduced, EPSO and SA. To choose which meta-heuristic is most suitable, their performance was compared when solving a simplified placement problem that considers a single stability indicator, in this case, the $Max \Delta f_{SM}$. For that purpose, the two introduced multi-class formulations were simplified into single variable formulations, with the single variable being the $Max \Delta f$. The resulting optimisation problems are presented below:

6.3. Multi-Class Placement

$$\min_X S_{\Delta f_{SM}}(X)$$

$$S_{\Delta f_{SM}}(X) = \sum_{d=1}^{N_d} \frac{\text{Max } \Delta f_{SM}(X|d)}{\text{Max } \Delta f_{SM}^0} \quad (6.16)$$

$$\min_X M_{\Delta f_{SM}}(X)$$

$$M_{\Delta f_{SM}}(X) = \max_{\forall d \in \Omega_d^0} \frac{\text{Max } \Delta f_{SM}(X|d)}{\text{Max } \Delta f_{SM}^0} \quad (6.17)$$

In order to achieve a fair comparison of both engines of optimisation and eliminate their intrinsic randomness, each algorithm was run 20 times. The line plots that follow the optimum fitness during each run and the average progression of all runs are presented in Figure 6.17.

The convergence tracking curves show that both algorithms were able to converge towards the optimum before the maximum number of iterations (741), despite showing different convergence times. In fact, the average fitness curves evidence a faster convergence of the EPSO, which may indicate that, in this specific case, the guided search that characterises the EPSO has outperformed the advantages of the neighbourhood definition of the SA. Something that may be a consequence of the small grid size.

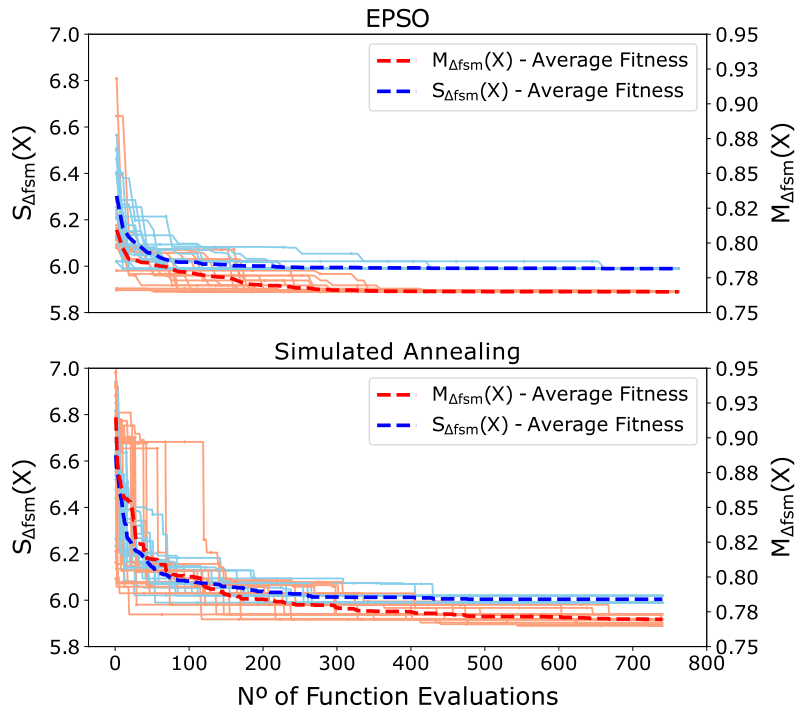


Figure 6.17: Algorithms convergence tracking in the 20 performed tests. The blue curves represent the formulation based on the sum of the normalised indices, and the red curves represent the formulation based on the maximum of the normalised indices.

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The EPSO adoption allowed finding the optimum before the 250 fitness function evaluation mark for most of the 20 runs. This shows that the use of such an algorithm enables 491 evaluations less than the enumeration-based approach, where all combinations of the 2 locations are tested (741). This is particularly relevant given the computational intensity of the evaluation phase, which involves the dynamic simulation of several disturbances. Therefore, from this point onward, the EPSO algorithm will be used as the primary optimisation engine to determine the optimal location for the GFM's regardless of the fitness functions.

Before moving on to the minimisation of the multi-class formulation, the single-class optimisation approach will be applied to the remaining stability classes addressed in this study.

This will help gain a deeper understanding of the factors that justify the optimal locations identified for each class.

6.3.3 Minimisation of the Maximum Frequency Deviation

The minimisation of the system Nadir or of the $Max \Delta f$ is a classical way to assess the degree of frequency stability improvement that results from adopting any mitigation measure. Hence, building on the optimisation performed in the prior section, EPSO was used to minimise the two other fitness functions that consider the $Max \Delta f$ index ($S_{\Delta f_{ele}}(X)$ and $M_{\Delta f_{ele}}(X)$). This allows for addressing all the different combinations of fitness function formulations and frequency quantities. The achieved optimal combinations are listed in Table 6.10:

Table 6.10: *Optimal Combination of Locations achieved when different fitness functions were minimised.*

Minimised Funtion:	$S_{\Delta f_{SM}}$	$M_{\Delta f_{SM}}$	$S_{\Delta f_{ele}}$	$M_{\Delta f_{ele}}$
Optimal Combination:	30 & 33	33 & 38	34 & 38	34 & 38

The $Max \Delta f$ achieved in each of the considered events when the GFM's are placed in the optimal location pairs listed above are depicted next in Figure 6.18 (solid lines). For comparison purposes, a pair of locations that poorly improve the system's frequency stability, which is labelled as a misplacement (dashed lines), is also portrayed. In the first graphic, the adopted frequency quantity is the synchronous machine speed deviation, while in the second, it is the deviation of the electrical frequency (PLL measured).

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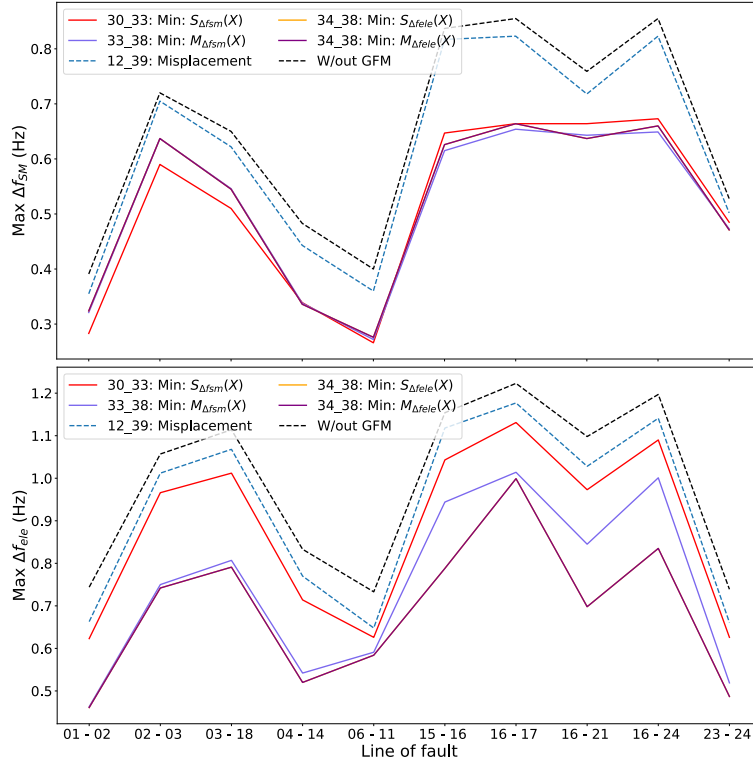


Figure 6.18: Line plots of the system $Max \Delta f$, for all relevant disturbances, considering the GFM locations mentioned above.

A comparison of the different curves of Figure 6.18 reveals differences of up to 0.2 Hz for the case of the f_{SM} and up to 0.4 Hz for the case of the f_{ele} in terms of the $Max \Delta f$ reductions. This significant difference highlights the impact of the GFM location on the degree of attainable stability improvement while clarifying the benefit of a capable placement methodology.

The aforementioned results also show that the optimal combination of GFM locations not only varies with the fitness function formulation but also with the frequency quantity adopted for the $Max \Delta f$.

As discussed in [175], the frequency deviation that each synchronous machine experiences is directly correlated to its inertia constant and the electrical power variation at its terminals. This relates to the fact that in order to minimise the system's $Max \Delta f_{SM}$, the electrical power variation of the machines that are more affected by the fault (electrically close to the disturbance or with small inertia constants) must be reduced. Therefore, the GFMs must be placed in the buses that minimise those power variations during the relevant time frame of the frequency stability phenomena. This pattern is very clear in the first two lines of Figure 6.19, where the synchronous generators' frequency and power response to a fault in line 15-16 are plotted for the cases where the GFMs are placed in the locations depicted above.

6.3. Multi-Class Placement

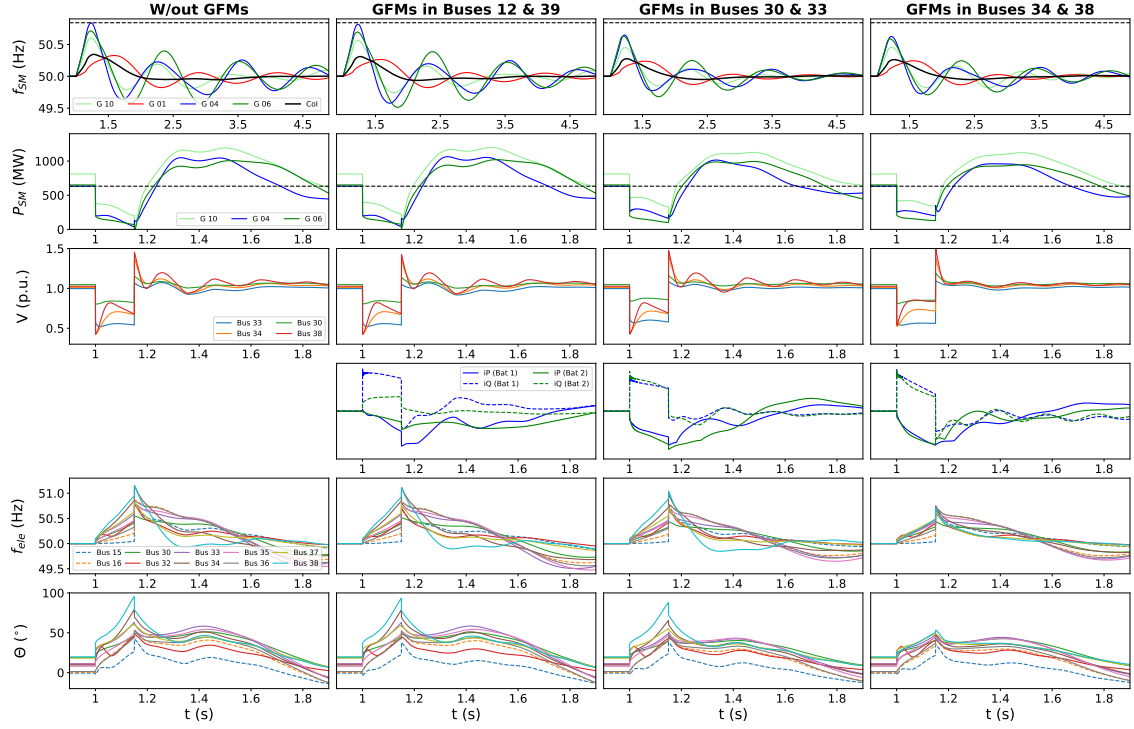


Figure 6.19: Time Evolution of different system variables to a fault in line 15-16, for different GFM locations. (CoI - Centre of Inertia of Synch.Gens.)

The degree of attainable power reduction at the machine terminals will then depend on the converter's current response and the reorganisation of the power flow during and after the fault. While the power flow reorganisation is highly non-linear, the converter current response depends directly on its terminal voltage dip and phase jump. Therefore, the converter must be placed in zones where the fault is felt in order to provide a considerable contribution to the system's stability. This explains why the pair of locations 12 & 39 (misplacement) results in an insignificant improvement of the systems' $Max \Delta f_{SM}$, as these buses tend to be electrically far from most severe faults, and therefore provide a very modest current contribution (visible in the 4th line of Figure 6.19).

The two other placement options depicted in Figure 6.19 include at least one location that is simultaneously close to the fault and to the synchronous machine that is more exposed to the fault (electrically close to the disturbance or with small inertia constants). Thus, a significant active current contribution that mitigates the terminal active power variation of G 04 is enabled. In this case, the GFM converters support the grid by injecting reactive current and absorbing active current due to the large in-fault VSM inertia that leads to a slower increase in the VSM internal rotor angle when compared with the remaining grid angles (including the synchronous generator's angles).

The small difference between the $Max \Delta f_{SM}$ achieved in these two placement options is ex-

6.3. Multi-Class Placement

plained by the voltage support provided to the terminals of the GFL in Bus 34, which results in an indirect reduction of G 04's power variation in the relevant time domain. Still, it is worth mentioning that these smaller differences tend to be associated with different phenomena depending on the fault location, such as load power drop, phase jump arrest in the surroundings of GFLs and the power flow reorganisation due to the voltage source locations.

Despite the same underlying phenomena that affect f_{SM} also affecting f_{ele} , this variable is typically much more sensitive to the phase-angle jumps that occur due to the fault or line trip. Therefore, it tends to manifest a larger value in the buses with weak voltage stiffness, such as the GFL generators in locations of low SCR.

This is very visible in the last two lines of Figure 6.19, where the PLL-measured frequency and the voltage phase angle of some of the system's buses are depicted for the different combinations of GFM locations already discussed. Under its current limits, the GFM can limit the phase angle jump and the magnitude dip in its nearer terminals while reducing the rate of change of these quantities during and after a fault. This explains why the smallest systems' $Max \Delta f_{ele}$ is achieved when the GFMs are placed in buses 38 and 34, since these are the transmission system buses that are closer to the GFL converters in locations of lower Scc.

6.3.4 Single-class Optimal Placement

The same type of single-class optimisation was performed for the remaining stability variables introduced in Section 4.3 to cover the different stability classes that fall under this work's scope. The resulting locations of the GFMs for each of the single-class optimisations are depicted in table 6.11, being the locations that result from optimisation with the sum-based formulation also illustrated in the single line diagram of Figure 6.20. The behaviour of the different stability variables for each solution is also depicted in the line plots of Figure 6.21.

Table 6.11: Optimal Combination of Locations that were achieved when performing a single-class optimisation for the different stability variables.

Minimised Function:	$S_{\Delta f_{SM}}$	$S_{Rocof_{SM}}$	$S_{CVD}(X)$	$S_{CQPD}(X)$
Optimal Combination:	30 & 33	29 & 34	15 & 27	34 & 38
Minimised Function:	$M_{\Delta f_{SM}}$	$M_{Rocof_{SM}}$	$M_{CVD}(X)$	$M_{CQPD}(X)$
Optimal Combination:	38 & 33	34 & 34	15 & 27	32 & 38

6.3. Multi-Class Placement

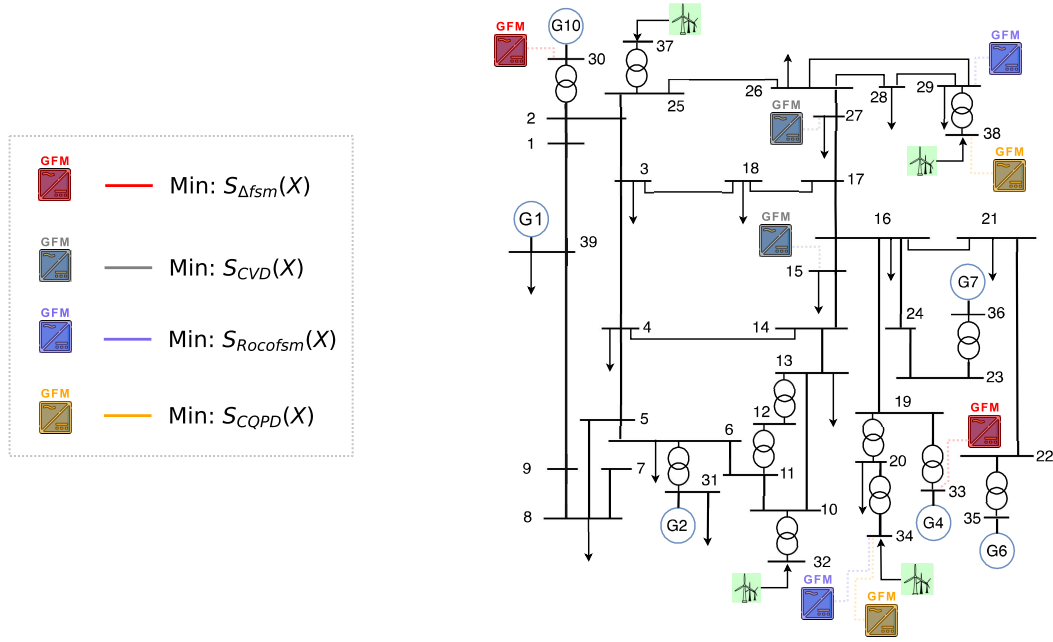


Figure 6.20: Visual illustration of achieved optimal GFM placements for different fitness function optimizations.

Regardless of the combination of fitness function formulation and the stability index that is considered, the results show that the optimal combination of locations always appeared in a subset of buses that have either proximity to generators (converters or synchronous machines) or proximity to the most severe faults in the respective stability class. In addition to the pattern identified in the prior section between the proximity of the GFM to the synchronous machines of lower inertia and the improvements in the system transient/frequency stability, it is also worth mentioning that:

- Regarding converter-driven stability, the best combinations of locations always included the terminal buses of the converters in low short-circuit power conditions (buses 34 & 38) or buses very exposed to the most severe faults (buses 32 & 38).
- For the case of the voltage recovery with oscillatory behaviour after fault elimination, the best combination of locations was found to be independent of the fitness function formulation (buses 15 & 27). Such a combination favours the condition of remoteness with generators and proximity to the most severe faults, in this case, faults that cause the largest phase and magnitude variations in load buses due to the fault inception or clearance.

6.3. Multi-Class Placement

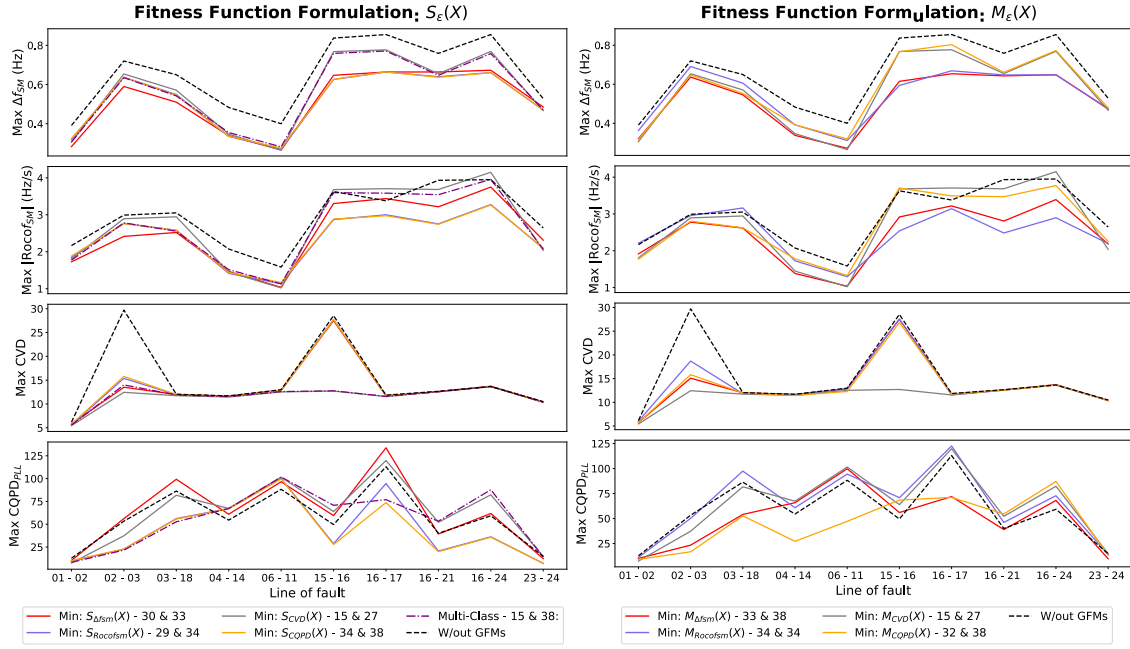


Figure 6.21: Stability indices line plots, considering the different pairs of GFM locations that result from the single index formulation optimisation.

Furthermore, optimising a single stability index tends to result in very poor improvements on some of the remaining ones, highlighting the need for the multi-class formulation proposed in this work and used in the following subsection.

6.3.5 Multi-class Optimal Placement

To evidence the benefit of using a multi-class formulation, the EPSO algorithm was used to minimise the value of F_M (introduced in Equation 6.14 of this chapter). Initially, to simplify the interpretation of the results, the analysis focused solely on two stability variables, $Max \Delta f_{SM}$ and the $Max CVD$. To achieve this setup, the weights $K_{\Delta f_{sm}}$ and K_{CVD} were set to 1, while the other ($K_{Rocof_{sm}}$ and K_{CQPD}), weights were set to 0, resulting in the mathematical representation provided in Equation 6.18.

$$F_M(X) = K_{\Delta f_{SM}} \cdot M_{\Delta f_{SM}}(X) + K_{CVD} \cdot M_{CVD}(X) \quad (6.18)$$

The impact of minimising the above function on the four stability variables for all relevant disturbances is depicted in the line plot of Figure 6.22. There, the maximum value of each stability variable in the case without GFMs (ε_0), which is used to define the weights, is highlighted with a yellow dot. The effect of considering the above multi-index formulation as the fitness function for optimisation instead of the single index functions $M_{\Delta f_{SM}}(X)$ and $M_{CVD}(X)$ is also shown in table 6.12.

6.3. Multi-Class Placement

Table 6.12: Effect of minimising F_M in the value of $M_{\Delta f_{SM}}$ and M_{CVD} .

Minimised Function	X	$M_{\Delta f_{SM}}(X)$	$M_{CVD}(X)$
$M_{\Delta f_{SM}}(X)$	33 & 38	0.76	0.93
$M_{CVD}(X)$	15 & 27	0.91	0.46
$M_F(X)$	33 & 15	0.79	0.55

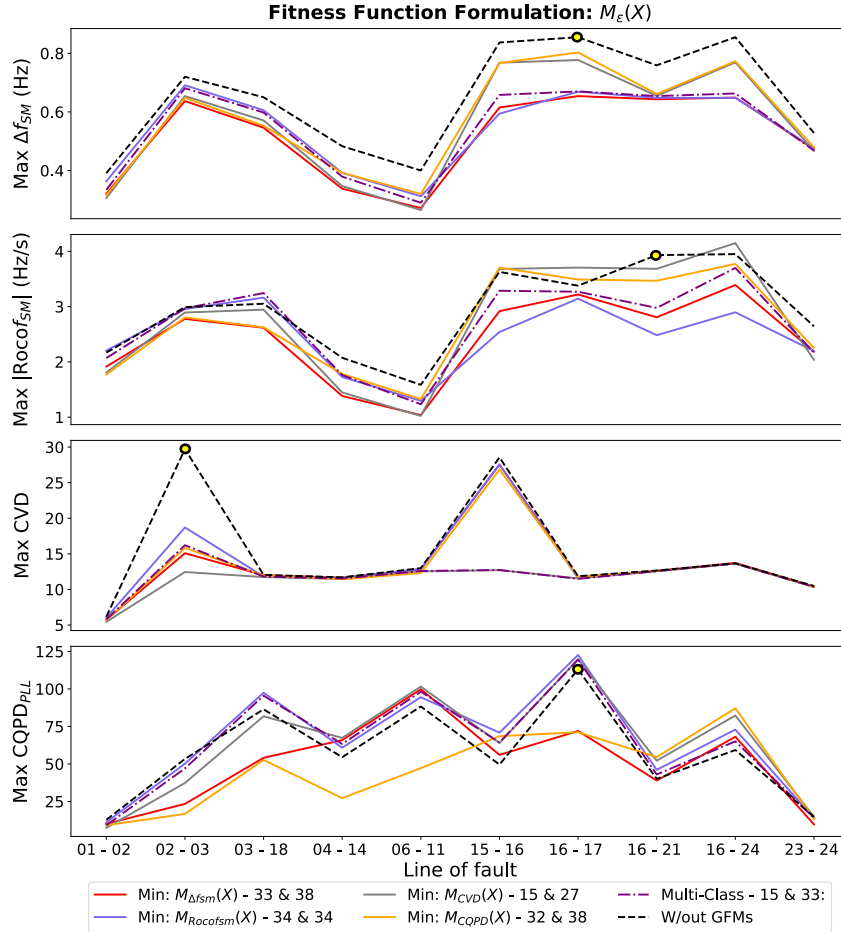


Figure 6.22: Stability indices line plots that include the optimal locations of the single index and multi-index formulation optimisation.

These results show that the achieved solution (15 & 33) enables a significant reduction of the two considered stability variables compared to the case without GFMs. Additionally, they evidence that a compromise solution was achieved, meaning that the chosen locations don't result in the best behaviour of the $Max\ CVD$ or the $Max\ \Delta f_{SM}$ independently, however, they present a solution where both variables improve significantly, instead of just one (see tab 6.12).

While using the above formulation improves the system stability in a more balanced way when compared to the single-class placement, it does not necessarily lead to a placement that max-

6.3. Multi-Class Placement

imises the overall stability of the existing power system. This is because some stability variables are closer to their limits than others, making it more critical to increase the stability margin for those variables. To achieve a solution that truly maximises system stability, it is necessary to account for the existing imbalances across different stability classes.

To this end, the EPSO algorithm was applied one final time to minimise F_M and F_S . In this iteration, all four stability variables were considered, with weights assigned based on the normalised distance of each variable to its respective limit (see Equation 4.26). The limit values considered for each variable were: $Max \Delta f_{SM,lim} = 0.8$, $Max Roco f_{SM,lim} = 3$, $Max CVD_{lim} = 20$ and $Max CQPD_{lim} = 75$; the resulting form of F_M and F_S are shown in Equations 6.19 and 6.20 respectively.

$$F_M(X) = 0.07 \cdot M_{\Delta f_{SM}}(X) + 0.32 \cdot M_{Roco f_{SM}}(X) + 0.49 \cdot M_{CVD}(X) + 0.51 \cdot M_{CQPD}(X) \quad (6.19)$$

$$F_S(X) = 0.07 \cdot S_{\Delta f_{SM}}(X) + 0.32 \cdot S_{Roco f_{SM}}(X) + 0.49 \cdot S_{CVD}(X) + 0.51 \cdot S_{CQPD}(X) \quad (6.20)$$

The results obtained by minimising each of the aforementioned formulations are presented using the already familiar line plots shown in Figure 6.23.

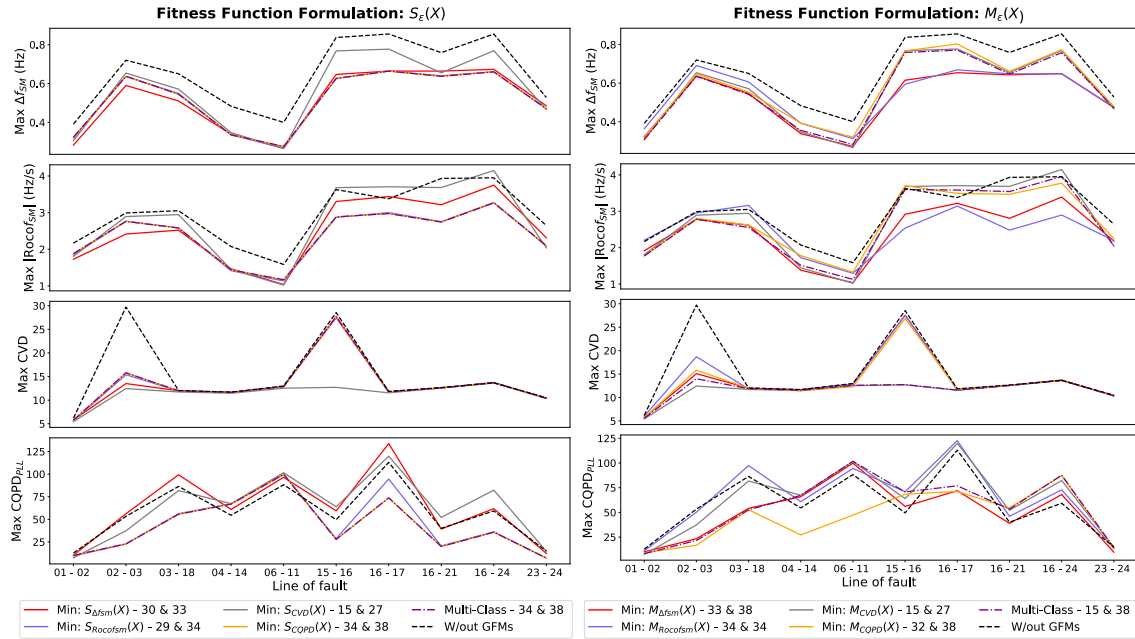


Figure 6.23: Stability indices line plots that include the optimal locations of the single class and multi-class (w/ proposed rule) formulation optimisation.

6.4. Final Remarks

As desired, the pair of locations achieved when minimising the above functions enabled achieving a compromise solution between the different stability classes, while promoting a larger change in the classes whose stability variable was closer to its limit.

It is worth mentioning that the compromise solution may sometimes be the same as the one achieved in the single-class optimisation, which is evidence that one of the stability classes is pronouncedly closer to its limits than the others. This can originate due to an imbalance in the state of stability of each class or due to a distortion caused by the definition of the limit.

6.4 Final Remarks

This chapter tested the application of the methodologies presented in Chapter 4 to place and size GFM converters in the modified version of the IEEE39 Test System presented earlier.

In what concerns the methodology for the GFM placement problem that simultaneously considers the capacity costs and the security gains while accounting for the TSO non-linear cost-security preferences, the main conclusions are as follows:

- The solution-seeking algorithm is capable of finding the solution to both the formulated decision-support problem and the minimum capacity problem (points of Pareto boundary) within an acceptable number of fitness function evaluations. The achieved solution showcased not only mathematical sense, as evidenced by its disposition on the multi-criteria plane regarding the indifference curves of larger value, but also physical reasoning, given the proximity to the synchronous machines more prone to loss of synchronism in the system. The method also showed an ability to simultaneously find the best converter locations and a cost-efficient split between the nominal and the overcurrent capacity (sec 6.2.4).
- The analysis of the problem's Pareto frontier evidenced that the relation between the investment in BESS-equipped GFMs and the resulting security benefit is non-linear, meaning that for more strict security levels (lower ε), more investment is progressively needed to ensure similar improvements of the system security ($\Delta\varepsilon$). The larger deployment or spread of the capacity through different locations for more strict security boundaries is also worth highlighting.
- The success of the techniques used to reduce the problem dimensionality (disturbances screening and search space reduction) is not only justified by the ability to reach meaningful solutions within a limited number of iterations but also by the fact that there was an overall improvement to the security that wasn't limited to the scenarios and disturbances that were selected by the filtering procedure. Most importantly, it did not

6.4. Final Remarks

compromise the system security for any disturbances or scenarios eliminated during this pre-optimisation phase.

- The sensitivity analysis of the GFM overcurrent capacity on the solution of the problem that concerns the placement and the sizing of the converter nominal capacity evidenced that improvements in both security and sized nominal can be achieved via an I_{Max} increase (Section 6.1.5). However, this relation does not extend forever since the converter's current limitation loops become less relevant to the system dynamics.
- The sensitivity analysis of the converters' overcurrent capacity cost on the solution of the problem that concerns the placement and the sizing of the converters' nominal and overcurrent capacity revealed that for feasible values of f , the split between nominal and overcurrent capacity remains unaffected (Section 6.2.4). The maximum overcurrent capacity was consistently adopted, and the nominal capacity was adjusted to meet the desired goal. This suggests that the impact of overcurrent capacity on the overall solution cost is relatively minor, especially when considering the total cost of the BESS system and the significant improvement it can bring to the system's dynamic security regarding its transient stability.

In summary, the proposed decision support tool can aid Transmission System Operators (TSOs) in making informed investment decisions regarding new GFM capacity to enhance system security. By evaluating the strategic placement and sizing of these converters, the tool aligns with the TSO's cost-security preferences and enables comprehensive sensitivity analyses, thereby increasing the TSO's confidence when selecting a solution. An important feature of this placement method is that the system operator not only knows the best locations that satisfy its cost-security preferences but also the specifications of the GFM converters in terms of their nominal and overcurrent capacity. Hence, it simplifies the process of acquiring these capacities through services.

In what concerns the security index formulation that considers multiple stability classes and the methodology to place GFMs with the pure goal of maximising stability, it is worth highlighting that :

- The location of the GFMs significantly impacts the degree of attainable stability improvement independently of the adopted fitness function formulation (composite stability variable formulation, stability variable, etc.).
- The heuristic-based placement methodologies successfully identified optimal solutions within a reasonable number of iterations. Particularly, the EPSO showed a faster convergence and a better ability to optimise different fitness functions without the need for

6.4. Final Remarks

hyperparameter adaptation.

- The single-index optimisation evidenced the existence of different trade-offs between some of the considered stability variables, and therefore classes, regardless of the considered formulation. In fact, for the case of the $Max \Delta f$ index, even the chosen frequency quantity (synchronous machine speed or bus electrical frequency) showed an impact on the optimal combination of locations that is achieved.
- The proposed methodology successfully addressed the existence of such trade-offs by employing a multi-index formulation with linear scalarisation of different composite stability variables. This approach adjusts weights based on the proximity of each index to a DA-defined stability index limit. It effectively achieved a compromise solution among different stability classes while prioritising those closer to their stability limits, thereby maximising the impact of the GFM introduction.

Evolving Symbolic Models Applied to Dynamic Security Assessment in Isolated Power Systems

This chapter validates the application of the ESM methodology for dynamic security assessment, using the Madeira Power System as a test case. To that end, the chapter starts with a small description of the used functional knowledge (Section 7.1) and is then structured into two main sections corresponding to the two modules of the dynamic security assessment addressed here: Online Security Classification (Section 7.2) and Preventive Control (Section 7.3).

In Section 7.2, the accuracy and interpretability of rule-based security classifiers generated using ESMs are evaluated through a comparative analysis with other state-of-the-art methodologies, such as decision trees and pruned decision trees. Additionally, the inherent capability of ESM-generated models to facilitate direct and structured knowledge updates, referred to as reflection, is also discussed. Section 7.3 presents a similar analysis for ESM-generated decision agents in the context of Preventive Control, benchmarking their performance against artificial neural networks trained in a RL fashion with evolutionary strategies.

The predicted future version of the Madeira power system presents a particularly compelling case study due to its potentially unstable nature. This instability stems from its lack of interconnections and is further aggravated by the low inertia and high share of converter-based generation, both resulting from the planned large-scale introduction of RES on the island.

As a result, continuous system security monitoring will be essential, making the online DSA

7.1. Functional Knowledge in the Madeira Power System

function a fundamental aspect of future system operations. Additionally, the presence of diverse DERs—such as RES power plants with varying capabilities (e.g., fault ride-through, participation in frequency control) and BESS operating in different control modes (GFM, GFL)—will lead to highly distinct responses to disturbances, further complicating the online DSA task.

Given this context, the Madeira power system serves as a highly relevant case study for demonstrating the proof-of-concept of ESMs applied to DSA in isolated power systems.

7.1 Functional Knowledge in the Madeira Power System

A dataset with 2095 unique operating scenarios (OS) was first generated to test the proposed methodology in the Madeira Power System, respecting the functional knowledge generation details discussed in Section 5.3.1. For each scenario, the DigsILENT PowerFactory software was used to perform a merit order unit commitment, a power flow, and a dynamic simulation study using a complete RMS model of the island network. After the stationary studies, an operating point (*OP*) is established, which is characterised by the system variables listed in Table 7.1. These variables were engineered based on prior experience and expert knowledge, establishing a recognised correlation with the system’s stability.

Table 7.1: System variables that characterise an *OP*

Variable	Description
$Load$	System Load
$Pump$	Hydro pumping
H_{GFM}	System Virtual Inertia (if BESS is in GFM mode.)
H_{Sym}	System synchronous inertia
Res_{noFRT}	RES without Fault Ride Through (FRT) capability
Res_{GC}	RES that conform with the system grid code
PV_{ZPM}	PV generation with a ZPM type response during fault
$Wind_{ZPM}$	Wind generation with a ZPM type response during fault

The results of the dynamic simulation study, which consists of the simulation of the three most severe short circuits to the system stability, were then integrated with the rules of Equation 7.1. These rules compare the simulation-obtained values of two frequency stability indices with two protection-related threshold values, enabling a security classification for each *OP*. The rationale for using frequency metrics as criteria for security classification in the island of Madeira lies in the fact that security loss following severe events is mainly caused by large frequency swings that trigger the system’s load-shedding protections. The final composition of the gen-

7.2. Online Dynamic Security Classification

erated dataset is 590 (28.2%) insecure OPs and 1505 (71.8%) secure OPs.

$$\begin{aligned}
 & \text{if } (|\overline{\Delta f_{coi}}| \geq 2\text{Hz}) : \text{Insecure} \\
 & \text{elif } (f_{Nad_{coi}} < 49 \text{ Hz} \ \& \ |\overline{Rocof_{coi}}| > 2.5 \text{ Hz/s}) : \text{Insecure} \\
 & \text{else} : \text{Secure}
 \end{aligned} \tag{7.1}$$

where:

$|\overline{\Delta f_{coi}}|$ is the maximum absolute value of the frequency deviation of the centre of inertia after a disturbance; $f_{Nad_{coi}}$ is the minimum value of frequency of the centre of inertia after a disturbance; $|\overline{Rocof_{coi}}|$ is the maximum absolute value of the derivative of the frequency of the centre of inertia after a disturbance; a sliding window of 250 ms is considered for the derivative computation;

7.2 Online Dynamic Security Classification

To address this task in the Madeira power system, the aforementioned ESM methodology was used to generate a rule-based classifier, as explained in Section 5.3. To that end, the *primitive model* of Figure 7.1, which was cooperatively defined with a human expert, was evolved using the instructions of Algorithm 7. The initial version of the classifier includes a well-known stability condition based on the system's inertia to illustrate a cooperative initialisation in the DSA context. This knowledge contribution is highlighted in grey in Figure 7.1, while the model template is highlighted in bold.

```

#- $K_H$  is chosen by the human expert (e.g., 0.5s)-#
if {  $H_{Sym} + H_{GFM} < K_H$  } :
    return { 1 }
elif { Conditional Statements } :
    return { K }
elif { Conditional Statements } :
    return { K }
else:
    return { K }

```

Figure 7.1: *Primitive version of classifier.*

Regarding the domain of symbols available for the construction/mutation of the classifier, the one defined in Equation 5.3 was adopted, with the particularity that the set of variables (V_E) consists of all the variables described in Table 7.1. As for the SA hyperparameters, which were chosen through cross-validation, one adopted a linear-descending temperature schedule from 0.95 (T_i) to 0.05 (T_f) and a Boltzmann constant of 70.

7.2. Online Dynamic Security Classification

7.2.1 Classification Accuracy Analysis

To test the method's ability to create models with good generalisation capacity and remove its intrinsic randomness, the SA was run 20 times independently, and the F1-score in the test dataset was recorded. This same study was also conducted using both standard and pruned versions of scikit-learn Decision Trees (DTs) [176]. In these implementations, the decision tree is constructed using an optimised version of the CART Algorithm [177]. For the tuning, a minimal cost-complexity pruning method is adopted.

For each of the 20 runs, a distinct sequence of pseudo-random numbers was generated for the algorithm to use. Additionally, different partitions of the dataset into training and testing subsets were also created for each run, maintaining a consistent 70/30 (training/testing) proportion. To accomplish these tasks, 20 different seeds were utilised, which correspond to different initial states for the random number generator employed.

All classification results were compiled into the two graphs of Figure 7.2. The boxplot shows the distribution of the test-set F1-score for each classification method when all 20 seeds are considered, while the bar chart presents the same data disaggregated by seed. The average computational time required to train and deliver a classification in each method is also presented in Table 7.2. The depicted times correspond to an implementation in an Apple Mac Mini M2 Pro with 10 CPU cores and 16 GB of RAM. Note that the classification time corresponds to the time taken to classify 2095 dataset instances; otherwise, its value would be immeasurable.

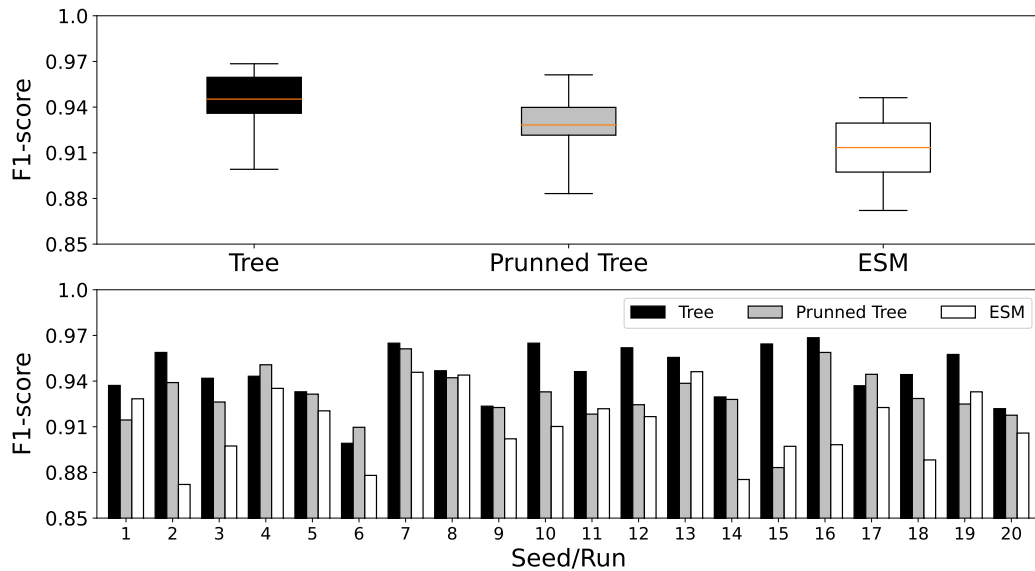


Figure 7.2: Performance Comparison of the classification methods

7.2. Online Dynamic Security Classification

Table 7.2: Average computational time taken for each method in training and classification phases.

Model	ESM	DT	Pruned DT
Average training time (s)	5042	0.01	0.01
Average classification time (ms)	0.55	0.67	0.62

While non-pruned DTs exhibit an accuracy advantage, the results show that ESMs can achieve comparable accuracy levels to pruned DTs. In fact, ESMs can even reach larger accuracy levels for some seeds while ensuring faster OP classification computation times than both benchmarks. Undoubtedly, ESMs require a larger training time due to the need to perform a step of constant tuning (analogous to a smaller-scale ANN weight adjustment) in every iteration, as the model structure is iteratively changing. Nevertheless, this fact does not constrain the method's practical adoption since the resulting SMs are ready to use in an online panorama and provide very fast classification times for thousands of OPs.

For illustration purposes, Figure 7.3 presents one of the 20 generated ESMs and Figure 7.4 presents one of the 20 DTs and one of the 20 pruned DTs. The decision tree is also presented in greater detail in the appendix section. As can be seen, the resulting ESM classifier is significantly less complex than the decision tree, requiring a considerably smaller number of consecutive conditions to reach a classification. This compactness is also evident in the comparison with the pruned decision tree. The efficiency of the conditions derived from the ESM stems from its capacity to identify meaningful relationships between variables, allowing for non-linear divisions of the attribute space, in contrast to the linear partitions created by decision trees. This discussion will be expanded upon in the next subsection, with a particular emphasis on interpretability.

```
#-----ESM Rule-based Classifier-----#

if {  $0.7 \times \frac{H_{GEM}}{Wind_{ZPM}} + 4.03 \times \frac{H_{Sym}}{Load} < 6.40$  AND  $3.56 \times Res_{noFRT} \times H_{Sym} - 5.87 \times Res_{IP} < -2$  }:
    return {1}
elif {  $-7.87 \times Load + 3 \times Load \times H_{Sym} < -8.18$  } :
    return {1}
else :
    return {0}
```

Figure 7.3: Illustration of one of the resulting ESMs.

7.2.2 Interpretability Metrics

In this work, Interpretability refers to understanding a model's decision-making process, with global interpretability focusing on the overall behaviour and local interpretability targeting specific input sets [122].

Global interpretability in a model entails comprehending the principles governing its behaviour across all input ranges, requiring a thorough analysis of the entire model. This is influenced by the model's complexity, leading to increased mental effort during inspection. Consequently, the total number of mental operations TMO required to inspect the complete model can be used for evaluating its global interpretability.

An illustrative example of the TMO computation for the simplistic model Θ_0 (defined in 5.1.1) is depicted in Figure 7.5. Note that the mental operations needed to follow all model decision paths, which are highlighted in grey, include not only arithmetic and logic operators but also every other type of operation that requires mental consideration, as is the case with the selection needed when interpreting “if” and “else”.

$$TMO(\Theta_0) : \left\{ \begin{array}{l} \text{if } (x < 2 \text{ and } y > 1) : z = x \times 3 \\ \text{else} : z = x + 2 \end{array} \right\} = 9$$

Figure 7.5: Illustration of TMO computation for the model Θ_0

When analysing the model's inner dynamics for some of the inputs, the human expert does need to “read” the entire model since a classification may be achieved through the action of a unique part of the model. This model's characteristic is the local interpretability, which can still be measured using the number of mental operations. In this context, the focus is solely on the number of required mental operations (RMO) to trace the model's action path for each input. Figure 7.6 exemplifies the RMO computation in view of given the input (1,0).

$$RMO(\Theta_0(1,0)) : \left\{ \begin{array}{l} \text{if } (x < 2 \text{ and } y > 1) : z = x \times 3 \\ \text{else} : z = x + 2 \end{array} \right\} = 7$$

Figure 7.6: Illustration of RMO computation for the model Θ_0 .

Still, its use as a metric to compare the local interpretability of different models can rapidly become complex since each model will be characterised by multiple values (i.e., one per dataset instance). Thus, the average RMO for all data-set inputs $\overline{RMO}$ is adopted to ease the model comparison process.

7.2.3 Interpretability Analysis

The two proposed interpretability metrics, TMO and $\overline{RMO}$, were used to score the interpretability of the models generated in the prior subsection (DT, pruned DT, and ESM). The results obtained for these metrics are depicted in the radar charts of Figure 7.7, $\overline{RMO}$ on the right and TMO on the left. Despite their high classification accuracy, DTs show very low global interpretability, which is justified by the numerous tree nodes that allow for an intense space partition and, consequently, good accuracy, as they also represent large sequences of mental operations. If pruned, however, DTs can display much better interpretability without a significant loss in classification accuracy, which puts them very close to the ESM. However, the ESM stand out as the model with the ability to achieve the lowest values in terms of TMO , evidencing a small edge in terms of global interpretability.

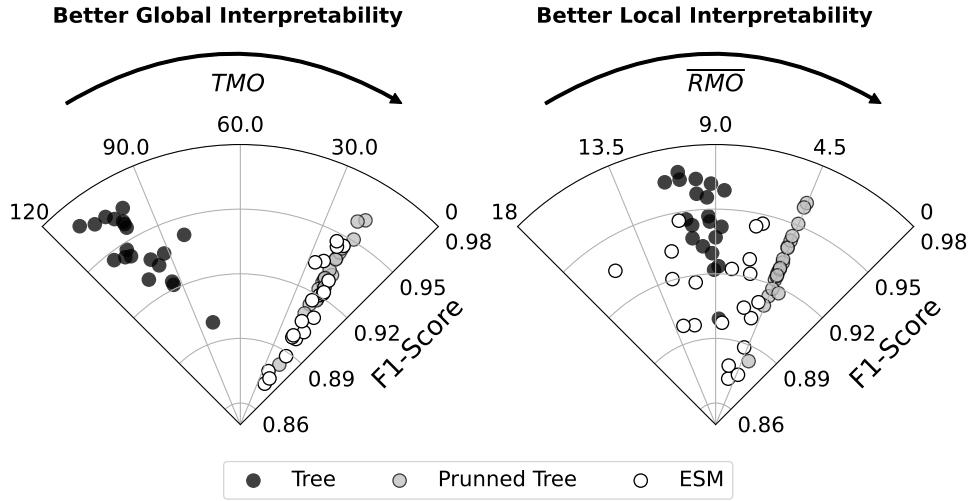


Figure 7.7: Analysis of models' interpretability

In the case of local interpretability, there is a smaller difference between the three methods; even so, it is clear that pruned trees are superior to the other methods. If a classification is achieved in the first nodes/conditions of the models, the number of required mental operations will tend to be higher for the ESM case since conditions are usually expressions (e.g., $3 \times Res_{noFRT} \times H_{Sym} - Res_{IP} < 2$) and not single variable inequations (e.g., $H_{Sym} < 0.9$), as is the case for DTs. This architectural dichotomy explains the visible difference between trees and ESMs regarding the $\overline{RMO}$ values, which is more apparent in the pruned trees case. Still, it is worth mentioning that ESM's mathematical expressions enable non-linear partitions of the attribute space while preserving a compact nature that often evidences true physical relations.

To highlight the inherent knowledge value that the generated expressions can carry, an analysis of two conditions from two of the resulting ESMs is presented hereafter, supported by Figure 7.8. To ease its understanding, the inequations comprising the conditions were hand-

7.2. Online Dynamic Security Classification

manipulated, making the important relations more explicit. The range of values that the involved variables can take is also portrayed.

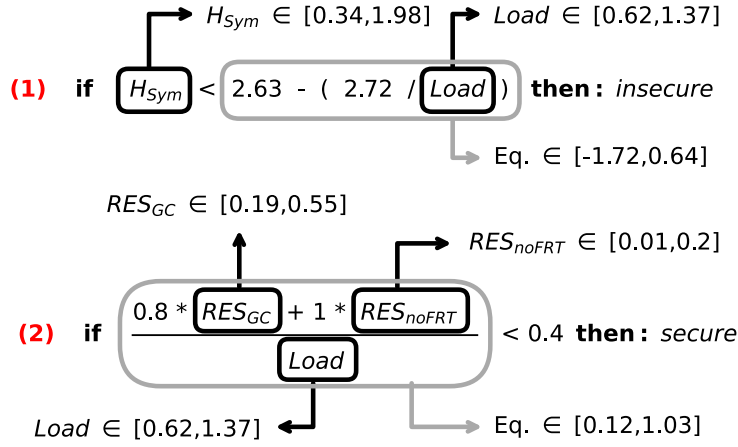


Figure 7.8: Analysis of the ESM conditions interpretability

As seen above, the first condition links the need for synchronous inertia (H_{Sym}) to the system load ($Load$). It demonstrates a greater need for synchronous inertia in higher load scenarios to ensure security. This correlation makes sense as the load levels that meet the condition often coincide with a high presence of photovoltaic and wind generation. These sources have many generators with no FRT capability, or that operate in zero power mode (not injecting active power from fault inception until normal operation of the converter), which results in an increased power mismatch after fault clearance. This provokes a deceleration of the synchronous machines after a fault, causing frequency Nadirs that can trigger system protections (see [78] for more details). By increasing the system's synchronous inertia, it is possible to effectively mitigate the rapid frequency variations that occur in these scenarios [78]. Hence, this condition is theoretically sound and practically valid.

The second condition provides an interesting relation between system load, the RES generation that conforms with the grid code and the RES generation with no FRT capability. Specifically, it establishes a weighted penetration limit for these types of generation based on load. As previously noted, the presence of generation without FRT can exacerbate post-fault frequency dips, potentially leading to insecure system conditions [78]. In contrast, when RES generation complies with grid codes, particularly regarding active current injection, the extent of frequency excursions within the island grid tends to be mitigated [178], although these excursions remain more pronounced than in grids dominated by synchronous generators. Consequently, it is reasonable that less generation without FRT capability is permissible compared to grid code-compliant generation. This is reflected in the larger scalar value associated with Res_{noFRT} compared to Res_{GC} in the given condition.

7.2. Online Dynamic Security Classification

The value of the generated expressions is not only in establishing relations between the right variables in a way that makes sense from a theoretical and practical perspective, but also in the ability to quantify this relation numerically and directly link them with the system security needs.

7.2.4 Reflection Property: Transformation to Regression

The symbolic and interpretable nature of the ESM enables seamless direct model updates by the human expert (operator), a characteristic that can be explored not only for initialisation/mutation purposes during evolution (Sections 5.1.2 and 5.2.2), but also to augment the model so that different tasks can be performed.

This model ability, known as *reflection* in [179], is explored to transform the ESM classifier into a regressor, as this form provides additional information regarding the distance of a state (OS_i) to the system security boundary in the form of a security index (S_i). It should be noted that the method used to create an ESM classifier could also be used to generate the regressors directly. Still, this two-stage approach was undertaken to prove the *reflection* capacity that ESMs have.

To make this manipulation (i.e., from classifier to regressor), the output of the security classes (0-secure,1-insecure) is replaced by the output of a security index (S), whose computation depends on the existing conditional statements. To achieve the security index expressions, the inequations of each conditional statement are manipulated until one of its sides is zero; the non-zero side is then used to determine the security index value when that specific condition is verified. The following example illustrates this manipulation:

```
Small Classifier:
if( $3 \times y < 1$ ): return 1; else: return 0;
Small Regressor:
if( $3 \times y < 1$ ): return  $1 - 3 \times y$ ; else: return  $1 - 3 \times y$ ;
```

Not that, after this manipulation, the regressor will output values larger than zero if the system is insecure and values lower than zero if it is secure. Hence, the regressor output of zero should be understood as the security boundary.

The conditional statements defined in this work can include more than one inequality (e.g. $if(x < 1 \text{ AND } y < 2)$). Hence, in these cases, assessing which inequality should be used to define the stability index expression is necessary. With that purpose, a min/max function is introduced in the regressor output section to select the security index closer to the security boundary (one for each inequality). This transformation is illustrated as follows:

7.2. Online Dynamic Security Classification

```

Small Classifier:
if (3 × y < 9 AND 2 × x > 1): return 1
Small Regressor:
S_1 = 9 - 3 × y ; S_2 = 2 × x - 1;
if (3 × y < 9 AND 2 × x > 1): Return Min(S_1, S_2)

```

The above transformations were applied to one of the 20 ESM classifiers generated in Section 7.2.1. In addition to the modification described earlier, each stability index expression was also normalised to the value of the threshold constant of the respective inequation to ensure a similar range of values for the stability index, regardless of the conditional statement that verifies. The resulting ESM regressor and the original classifier are depicted in Figure 7.9.

```

#-----ESM Classifier-----#
if {0.7 ×  $\frac{H_{GFM}}{Wind_{ZPM}}$  + 4.03 ×  $\frac{H_{Sym}}{Load}$  < 6.40 AND
    3.56 × ResnoFRT × HSym - 5.87 × ResIP < -2}:
    return {1}
elif { -7.87 × Load + 3 × Load × HSym < -8.18 }:
    return {1}
else :
    return {0}
#-----ESM Regressor-----#
#Inequation transformation
S_1 = (6.4 - (0.7 ×  $\frac{H_{GFM}}{Wind_{ZPM}}$  + 4.03 ×  $\frac{H_{Sym}}{Load}$ )) / 6.4
S_2 = -(3.56 × ResnoFRT × HSym - 5.87 × ResIP) - 2 / 2
S_3 = -(-7.87 × Load + 3 × Load × HSym) - 8.18 / 8.18
#Rule-based output
if {0.7 ×  $\frac{H_{GFM}}{Wind_{ZPM}}$  + 4.03 ×  $\frac{H_{Sym}}{Load}$  < 6.40 AND
    3.56 × ResnoFRT × HSym - 5.87 × ResIP < -2}:
    return Min(S_1, S_2)
elif { -7.87 × Load + 3 × Load × HSym < -8.18 }:
    return {S_3}
else :
    return Max(Min(S_1, S_2), S_3)

```

Figure 7.9: Transformation of ESM classifier into a regressor

Alternatively, a stability indicator for the system can be obtained by using dynamic simulation to obtain the stability indices described in Equation 7.1. The distance of these indices from their limits (Equation 7.1) can then be used as an indicator. In this case, the distance of the frequency Nadir from the limit value of 49 Hz ($S_{Nad} = 49 - f_{Nad}$) is a suitable indicator, as this proved to be the determining condition among those in Equation 7.1. Figure 7.10 displays the normalised value of this Nadir-based stability indicator ($\bar{S}_{Nad}$) and the normalised regressor output ($\bar{S}_{Reg}$) for all points in the dataset.

As shown in Figure 7.10, the regressor output pattern is very similar to the nadir-based stability indicator computed with a dynamic simulation model of the Madeira island power system.

7.3. Preventive Control

Hence, it can be concluded that using the manually created regressor to determine the degree of system stability is a good approximation of reality.

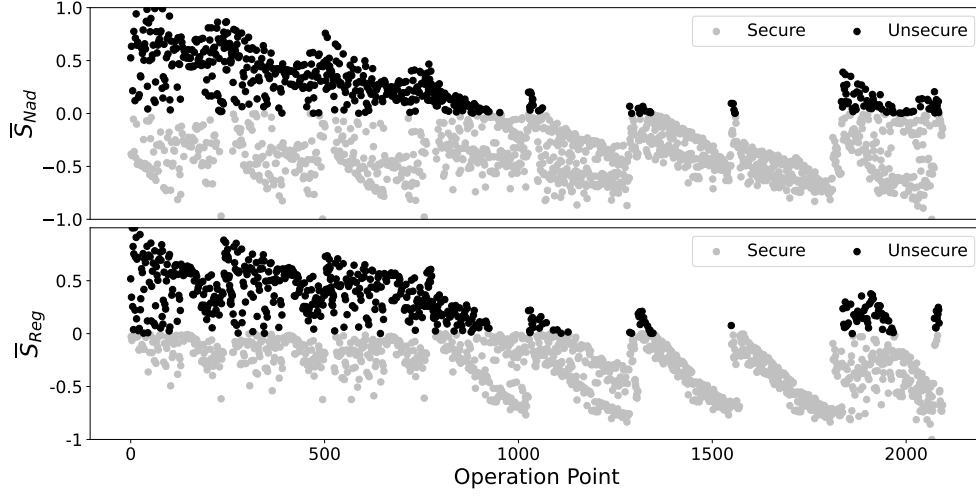


Figure 7.10: Scatter plots of $\bar{S}_{Nad}$ and $\bar{S}_{Reg}$

7.3 Preventive Control

To address this task in the future Madeira power system, the aforementioned ESM methodology was used to generate a rule-based decision agent, following the framework explained in Section 5.4. To that end, the primitive model of Figure 7.11 was evolved under an RL-based setting, where the goal is to maximise the cumulative reward R from Equation 7.5.

7.3.1 Primitive Model

The primitive model used for the decision agent ESM, which is described in Figure 7.11, had minimal operator intervention in its definition, with the main exception being a condition that differentiates the agent's actions based on the online virtual inertia. This allows for prioritising the allocation of extra virtual inertia when capacity is available ($H_{GFM} < 1.92$). In the same figure, the ESM template is highlighted in bold, and the operator's initial contributions are highlighted in grey.

```
if (S>0):
    if {  $H_{GFM} < 1.92$  }:
         $H_{sa} = \{ \text{Action expression} \}$ 
         $H_{va} = \{ \text{Action expression} \}$ 
    else:
         $H_{sa} = \{ \text{Action expression} \}$ 
         $H_{va} = \{ \text{Action expression} \}$ 
```

Figure 7.11: Primitive version of the ESM agent

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The value of the additional synchronous or virtual inertia (H_{sa}/H_{va}) suggested by the agent is always subjected to a saturation block to ensure that this inertia volume exists in the system, i.e., $H_{sa} = \text{clip}(H_{sa}, 0, H_{sa_{max}})$ and $H_{va} = \text{clip}(H_{va}, 0, H_{va_{max}})$. The available inertia volume ($H_{sa_{max}}, H_{va_{max}}$) corresponds to the inertia of all synchronous condensers that are offline in the case of synchronous inertia and to the inertia of the GFM control for all offline BESS in the case of the virtual inertia.

7.3.2 Reward Function

In the future Madeira Power System, the synchronous inertia is dispatched via the different synchronous condensers (i.e., dedicated or hydro units qualified for it), while the virtual inertia is dispatched by changing the control mode from GFL to GFM in the BESS. Since the SO plans to keep the BESS continuously operational for stability support and changing the battery control mode incurs no additional costs, the operational expenses associated with preventive control actions remain unaffected by the additional virtual inertia provided.

Consequently, the reward function presented in Equation 5.9 (Section 5.4) can be simplified by assuming a virtual inertia marginal cost (σ_v) of zero and recognising that the normalised cost of additional inertia becomes a linear function of the volume of additional synchronous inertia. The resulting transformation of the reward function, tailored for the Madeira Power System, is detailed in Equations 7.2 to 7.5.

$$R = \sum_{i=0}^{N_T} R_i = \sum_{i=0}^{N_T} (1 - 0.25 * (S_i + 1)^2 - C_{a_i} \times k_H)$$

$$R = \sum_{i=0}^{N_T} R_i = \sum_{i=0}^{N_T} (1 - 0.25 * (S_i + 1)^2 - \frac{\sigma_v * H_{va_i} + \sigma_s * H_{sa_i}}{C_{max}} \times k_H) \quad (7.2)$$

$$R = \sum_{i=0}^{N_T} R_i = \sum_{i=0}^{N_T} (1 - 0.25 * (S_i + 1)^2 - \frac{0 * H_{va_i} + \sigma_s * H_{sa_i}}{C_{max}} \times k_H) \quad (7.3)$$

$$R = \sum_{i=0}^{N_T} R_i = \sum_{i=0}^{N_T} (1 - 0.25 * (S_i + 1)^2 - \frac{\sigma_s * k_H}{C_{max}} \times H_{sa_i}) \quad (7.4)$$

$$R = \sum_{i=0}^{N_T} R_i = \sum_{i=0}^{N_T} (1 - 0.25(S_i + 1)^2 - K_t \times H_{sa_i}) \quad (7.5)$$

For the trade-off constant, K_t , the value of 0.15, which was obtained by inquiring a human expert through an indifference judgment, was adopted.

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As depicted in Figure 5.7, traditionally, the stability indicator (S) would be attained via time-domain simulation of the reference disturbances. However, this makes the RL procedure extremely heavy in terms of computation. Therefore, to make the procedure feasible, the ESM regressor of Figure 7.9, which showed satisfactory capability in determining the degree of security of the system, is used as a surrogate model of the system behaviour.

7.3.3 Performance Evaluation

Analogously to the classification accuracy study performed in Section 7.2.1, to evaluate the ability of the ESM methodology to generate decision agents for preventive control, the RL setting was executed 20 times. For each run, varying seeds and partitions of the train/test datasets were considered, and three different metrics were computed for the test dataset:

- R_{Test} , the reward function value in the testing dataset;
- H_{add} , the additional volume of synchronous inertia dispatched by the ESM agent, i.e., $H_{add} = \sum_{i=0}^{N_{Test}} Hsa_i$;
- S_{worst} , the highest value of the stability indicator that can still be found when the ESM agent action is considered, i.e., $S_{worst} = \max_{i \in \{Test\ Indices\}} S_i$.

To benchmark the performance of the generated ESM models, this small variance study was also performed considering two other model types, namely:

- A simple symbolic model, depicted in Figure 7.12, designed by a human expert with its constants tuned by the DE method described in Section 5.2.1 – called Human-ES. This model uses different proportional controllers according to the existing amount of virtual inertia (H_{GFM}). Dividing the agent actions based on the online virtual inertia allows for prioritising the allocation of extra virtual inertia when capacity is available ($H_{GFM} < 1.92$).

<pre> if (S>0): if { $H_{GFM} < 1.92$ }: $H_{sa} = S \times K_1$ $H_{va} = S \times K_2$ else: $H_{sa} = S \times K_3$ </pre>	<pre> if (S>0): if { $H_{GFM} < 1.92$ }: $H_{sa} = S \times 0.91$ $H_{va} = S \times 14.98$ else: $H_{sa} = S \times 11.57$ </pre>
---	--

Figure 7.12: Human-ES agent (*Initial vs Tuned with data*)

- An ANN-based agent constructed using the RL framework based on evolutionary strategies from [169] – called RL-ANN. The adopted ANN structure, which was optimised using random search [180] on a validation set, corresponds to a 4-layer network (9x20x20x2)

7.3. Preventive Control

with sigmoid activation functions.

Figure 7.13 presents the values of the three reference metrics across each of the 20 runs, computed for the ESM and the two benchmark methods. This plot shows, once more, the ability of ESMs to successfully adapt to different tasks.

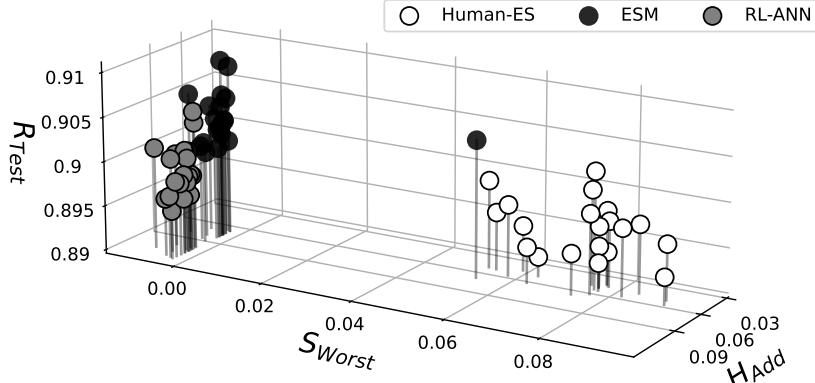


Figure 7.13: Performance of the ESM and the two benchmark methods

As can be seen, the ESM agent consistently maintained security across the entire spectrum of the testing set operating points ($S_{Worst} < 0$), a characteristic not observed in the case of the Human-ES agent. This enhancement in security directly influenced the reward, showing that the agent did not over-dispatch the volume of synchronous inertia to ensure security.

Moreover, and notably, the ESMs retain full interpretability and compact nature, as seen in Figure 7.14, where the resulting ESM is displayed. Conversely, the ANN-based agents showed very limited interpretability, with an average $\overline{RMO}$ and TMO of 1282 compared to the 12.9 and 18.6 values that characterise the ESM collection.

This interpretability feature, not displayed by the ANN, can transform the operator's decision-making process into a simple sequence of conditions and actions, while still outperforming the ANN. In the case of the ESM of Figure 7.14, once a state is classified as unsafe, then the operator only has to evaluate the value of the online synchronous inertia (H_{Sym}) and compare it with the two-term equation that relates the stability score (S) with the online volume of RES generation that conforms with the grid code (RES_{GC}). After the validation of this condition, the additional value of virtual and synchronous inertia (H_{sa}, H_{va}) is directly proposed based on very simple numerical expressions, whose comprehension and even modification due to new experiments or changes in the power system is easily achieved. In real-time, this allows for fast and comprehensible computation of the required inertia volume that the system operator easily validates and later dispatches through synchronous condensers and/or batteries in GFM mode.

7.4. Discussion: Scalability and Replicability to other Systems

```

if (S>0):
    if (  $H_{Sym} > 1.13 \times S + 0.23/Res_{GC}$  ) :
         $H_{sa} = 1.32 \times (PV\_ZPM/H_{Sym})$ 
         $H_{va} = 2.02 \times (Load/Res_{GC})$ 
    else:
         $H_{va} = 13.11 \times S$ 

```

Figure 7.14: Final version of the RL ESM agent

As for the time required to train the different models, depicted in Table 7.3, ESMs still stand out as needing a larger time frame; as discussed in Section 7.2.1, this results from the nuances of their evolution process. Additionally, both symbolic models exhibit faster decision times when compared to the ANN, a normal consequence of the reduced model size.

Table 7.3: Average computational time taken for each method in training and decision phases.

Model	Human-ES	ESM	RL-ANN
Average training time (s)	1.99	1859	1288
Average decision time (ms)	0.68	1.35	1.79

7.4 Discussion: Scalability and Replicability to other Systems

The future power system of Madeira Island will display complex dynamic behaviour as a result of the differently controlled elements that will coexist in the grid (see Section 3.1.2). The system's response to disturbances often exhibits various types of instability, encompassing traditional rotor angle stability issues [181], frequency stability problems that stem from the converter's behaviour [78], and instability rooted in the converters (themselves). These instability patterns are not exclusive to isolated power systems; in fact, they are becoming increasingly prevalent in interconnected power systems, as shown in [15] and [17]. Therefore, the successful performance of the generated ESMs in the Madeira test case instils confidence in the potential applicability of the proposed method to DSA in larger systems with slightly different characteristics. This assumption holds if the distinct characteristics of the new systems are captured in the relevant functional knowledge. In other words, the dataset used to generate the ESM in these systems must include instances of the present differentiating stability phenomena, where advanced synthetic data generation methods are essential to extrapolate beyond historical data and create feasible and rare OP [182].

While the size of the system does not constrain the method's ability to generate ESM models, one must highlight that the resulting symbolic model will tend to become larger for large systems. This is a direct result of complex interactions between more elements and is also expected when using other AI methods (e.g., ANN, DT). Since this influences the model's

7.5. Final Remarks

global interpretability, the technique should be applied regarding control areas rather than the whole interconnected system. This enables a suitable application to other systems, allowing a beneficial use of the ESMs' knowledge interpretation characteristics.

7.5 Final Remarks

This chapter presented the application of the ESM methodology to the dynamic security assessment in converter-dominated isolated power systems, using the Madeira Power System as a test case.

The ESM-generated models developed for the security classification task showed classification accuracy comparable to pruned DT and better global interpretability. They also thoroughly outperformed the unpruned DTs regarding global interpretability, albeit with a marginal reduction in classification accuracy. This evidences an important competitiveness alignment with two state-of-the-art methods that are often associated with interpretability.

The analysis of the ESMs' mathematical expressions, performed in Section 7.2.3, showcased an ability to establish meaningful physical relationships between the appropriate system variables and the system's security requirements. Furthermore, the ESM-generated classifier also demonstrated versatility by transforming seamlessly into a regressor without requiring retraining (Section 7.2.4). Hence, one can conclude that the nature of the ESM mathematical expression offers a unique potential in terms of new knowledge creation and *reflection* capacity.

In preventive actions, ESMs showed high skill in restoring the system security without over-dispatching inertia, outperforming an ANN and a human-designed expert system that responds proportionally to the stability indicator. Notably, the interpretability and compact nature of the ESM-based decision agent aligns well with the regulatory requirements for high-risk sectors in the European Union AI Act [183].

Summing up, the results confirm that the ESM methodology can be used to generate highly interpretable models for the DSA that embody meaningful physical relationships within the system. Furthermore, they instil confidence that this methodology can be used to address multiple other tasks (some of them less complex) within the power system domain, where interpretability is an essential requirement.

Conclusions

The work presented in this thesis delved into the topic of dynamic security in power systems characterised by high levels of converter-based generation. Two main topics were explored: the optimal placement and sizing of grid-forming converters, and the online dynamic security assessment utilising fully interpretable models. An extensive literature review, conducted in Chapter 2, led to the identification of three fundamental research questions related to these topics. In this section, these research questions are revisited, the efforts undertaken to address them are summarised, and the key findings highlighted. Additionally, avenues for future research are discussed.

8.1 Research Answers & Main findings

***RQ1:** How does the location of GFM-controlled converters affect the system stability?*

To answer research question **RQ1**, a multi-class stability assessment of the GFM location was performed in Chapter 3. This analysis consisted of a) a simplified contingency analysis that evaluates the value of multiple system stability variables for different GFM locations and disturbance types, and b) a detailed analysis of the system response to specific disturbances that considers the GFM location and its effect on stability as the focal point. The main findings of such analysis, which concern power systems with high shares of converter-based generation and system disturbances, are as follows:

- The impact of introducing a new GFM converter on the system's stability is highly dependent on its location and the specific stability variable being considered, potentially leading to either an improvement or a deterioration in stability (see Section 3.2.1).

8.1. Research Answers & Main findings

- The effect of the GFM converter's location on the degree of potential stability improvement is less pronounced in the context of generation outages compared to short circuits (see Section 3.2.1). This outcome is attributable to the non-uniform impact of short circuits on voltage levels across the grid, coupled with the fact that the voltage support provided by the GFM is confined to a specific zone due to limitations in the reactive current it can supply.
- Often, the locations of GFM converters that improve certain stability classes lead to only minor enhancements or even deterioration in others. This underscores a trade-off in the extent of stability improvements achievable across various classes when adjusting the converter's location (see Section 3.2.2).
- This trade-off is particularly evident between converter-driven stability (related to weak-grid conditions) and transient/frequency stability. On the one hand, the best GFM locations to improve frequency/transient stability tend to be where the GFM is placed near the machines that are electrically close to the disturbance, with small inertia constants or in low synchronisation coefficient conditions. On the other hand, for converter-driven stability, a good placement for the GFM tends to be near the converters in low SCR conditions or near the disturbance. Consequently, since areas with lower Short-Circuit Power and GFL-type generation are not aligned with the locations of synchronous machines — which usually exhibit higher S_{sc} — the optimal GFM locations for each category of stability will rarely coincide.
- In situations where severe local stability issues coexist within the system, a single GFM converter is insufficient to ensure overall stability (see Section 3.2.3), and parameters. Hence, a methodology to optimally place GFM converters must also include the number of converters and their size.

RQ2: Is it possible to optimally place and size GFM converters for dynamic security purposes within the context of large disturbances while owning the cost of the solution as a fundamental criterion?

To answer the research question **RQ2**, a robust methodology for the GFM placement problem that simultaneously considers the cost of the solution and the security gains while accounting for the TSO cost-security preferences was developed and thoroughly explained in Chapter 4. The methodology frames the placement problem as a multi-criteria decision support problem and uses a solution-seeking algorithm based on Bayesian Optimisation to determine the solution. A key feature of this approach is its simultaneous sizing of both nominal and overcurrent capacities of the converters. The methodology was subsequently applied to a modified version

8.1. Research Answers & Main findings

of the IEEE 39 system to a) evaluate its effectiveness in addressing the placement problem and b) deepen our understanding of the factors that contribute to an optimal solution. Additionally, distinct sensitivity analyses were conducted concerning the converter overcurrent capacity and the TSO's cost-security preferences. The main findings are as follows:

- The proposed solution-seeking algorithm is capable of finding solutions to both the formulated decision-support problem and the minimum cost problem (points on the Pareto boundary) within an acceptable number of fitness function evaluations. This involves simultaneously determining the optimal converter locations and achieving a cost-efficient split between nominal and overcurrent capacity that satisfies the TSO cost-security preferences.
- The relationship between investment in BESS-equipped GFMs and the resulting security benefit is non-linear. For stricter security levels (lower ϵ), progressively higher investments are required to achieve similar improvements in system security. Notably, a larger deployment or spread of capacity across different locations is necessary for more stringent security boundaries.
- When the overcurrent capacity of the converter is treated as a fixed parameter, applicable uniformly across all converters, an increase in this capacity leads to improved security and a reduced nominal capacity in the optimal solution (Section 6.1.5). However, this relationship has its limits, as the constraints imposed by the converter's current limitations become increasingly less significant to the overall system dynamics.
- When the converter overcurrent capacity is considered a decision variable in the placement problem, the maximum overcurrent capacity is consistently sized, and the nominal capacity is adjusted to meet the desired goals. This suggests that the impact of overcurrent capacity on the overall solution cost is relatively minor, especially considering the significant improvements it can bring to the system's dynamic security and the total cost of the BESS system.

In summary, the proposed decision support tool can aid Transmission System Operators (TSOs) in making informed investment decisions regarding new GFM capacity to enhance system security. By evaluating the strategic placement and sizing of these converters, the tool aligns with the TSO's cost-security preferences and enables comprehensive sensitivity analyses, thereby increasing the TSO's confidence when selecting a solution. An important feature of this placement method is that the system operator not only knows the best locations that satisfy its cost-security preferences but also the specifications of the GFM converters in terms of their nominal and overcurrent capacity. Hence, it simplifies the process of acquiring these capacities through services.

8.1. Research Answers & Main findings

To fully respond to **RQ2**, a different formulation for the security index, which aggregates stability variables from different stability classes, was also introduced. This multi-class formulation was maximised using meta-heuristic solvers, namely EPSO and SA, to reach the converters' optimal location. An analysis of the optimal locations for each stability class was also conducted by optimising the different stability variables. The main findings are as follows:

- The meta-heuristic-based placement methodologies successfully identified the optimal solutions within a reasonable number of iterations. Particularly, the EPSO showed a faster convergence and a better ability to optimise different fitness functions without the need for hyperparameter adaptation.
- The single-class optimisation evidenced, once again, the existence of different trade-offs between the solutions that maximise each stability class. This means that these solutions do not match spatially and may result in poor improvements of some of the other classes, regardless of the considered fitness function formulation. In fact, for the case of the $Max \Delta f$ index, even the chosen frequency quantity (synchronous machine speed or bus electrical frequency) showed an impact on the optimal combination of locations that is achieved.
- The proposed multi-class formulation enables successfully addressing the existence of such trade-offs by employing a multi-index formulation with linear scalarisation of different composite stability variables. This approach adjusts weights based on the proximity of each index to a DA-defined stability index limit. It effectively achieved a compromise solution among different stability classes while prioritising those closer to their stability limits, thereby maximising the impact of the GFM introduction.

RQ3 : Can purely interpretable DSA tools be created to support the human operator in assessing the security of the power system in real-time and defining preventive actions?

To address research question RQ3, a novel methodology called the Evolving Symbolic Model (ESM) was developed to generate highly interpretable, data-driven models for dynamic security assessment, namely for security classification and the definition of preventive actions. Chapter 5 presented a thorough explanation of the method, while Chapter 7 displayed its application in generating interpretable DSA models for a real-world isolated power system, specifically for the case of the Madeira island. In this context, the performance of the interpretable data-driven models created using the ESM methodology was compared against various benchmark methods, and the interpretability of models generated through different approaches was thoroughly discussed. The main findings are summarised as follows:

- The ESM-generated models developed for the security classification task showed classi-

8.2. Future Work

fication accuracy comparable to pruned DT and better global interpretability. They also thoroughly outperformed the non-pruned DTs regarding global interpretability, albeit with a marginal reduction in classification accuracy. This evidences an important competitiveness alignment with two state-of-the-art methods that are often associated with interpretability.

- The ESMs' mathematical expressions showcased an ability to establish meaningful physical relationships between the appropriate system variables and the system's security requirements. Furthermore, the ESM-generated classifier also demonstrated versatility by transforming seamlessly into a regressor without requiring retraining (Section 7.2.4). Hence, one can conclude that the nature of the ESM mathematical expression offers a unique potential in terms of new knowledge creation and *reflection* capacity. Moreover, there is also the potential to explore pre-existing domain knowledge from the human operator and use it as a starting solution for the learning process.
- In preventive actions, ESMs showed high skill in restoring the system security without over-dispatching inertia, outperforming a RL-ANN and a human-designed expert system that responds proportionally to the stability indicator. Importantly, the interpretability and compact nature of the ESM-based decision agent aligns well with the regulatory requirements for high-risk sectors in the European Union AI Act [183].

Summing up, the ESM methodology can generate highly interpretable DSA models that embody meaningful physical relationships within the system. This instils confidence that this methodology can be used to address multiple other tasks (some of them less complex) within the power system domain, where interpretability is an essential requirement.

8.2 Future Work

Several interesting research topics related to the presented work, but not limited to, should deserve a proper evaluation in the future.

Regarding the placement and sizing of GFM converters for dynamic security purposes, several potential research avenues can be explored. These include:

- Adopting a stochastic definition for the security index instead of relying solely on the maximum value observed across all disturbances and scenarios. For instance, the security index can be the probability of a simple or compound stability variable being below a certain threshold. A forecasted difficulty related to this is the knowledge of the probability of different system disturbances. This information is often hard to find.

8.2. Future Work

- Integrating the current work with other tools proposed in the literature that address different stability classes, such as small-signal stability. This process could be executed in a two-stage approach. Initially, the lightweight nature of the linearised models utilised in small signal stability would be used to narrow down the number of scenarios and potential locations for GFMs. Then, a modified version of the method presented in this work would be used.
- Expanding the study to encompass other test systems and more detailed converter cost models would further validate the generality of the conclusions drawn.

In regard to the use of the ESM concept within power systems, the following research avenues are of interest:

- Enhancing ESM-human interaction by involving human experts more actively in the learning process, namely in: a) hyper-parameter tuning and b) choosing between multiple available symbolic models.
- Combining the SA method with the optimisation potential of pre-trained large language models.
- Introduce a methodology to intelligently select mutation locations in the model by utilising an information theory-based analysis rather than randomly altering parts of the model.
- Extending the developed DSA method to the case of large interconnected systems, to further validate the generality of the drawn conclusions.
- Applying the ESM framework to other tasks in the power system, such as the automatic generation of power system controllers and protection system rules.
- Utilising the ESM methodology to generate a concise set of easily understandable rules that explain local dynamic behaviour rather than focusing solely on overall system behaviour as in the DSA.

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Models and Parametrisations

This appendix presents the parametrisation and structure of several dynamic models utilised in this work.

A.1 Equivalent Dynamic Models for RES Power Plants

A.1.1 REPC_A

- **Model**

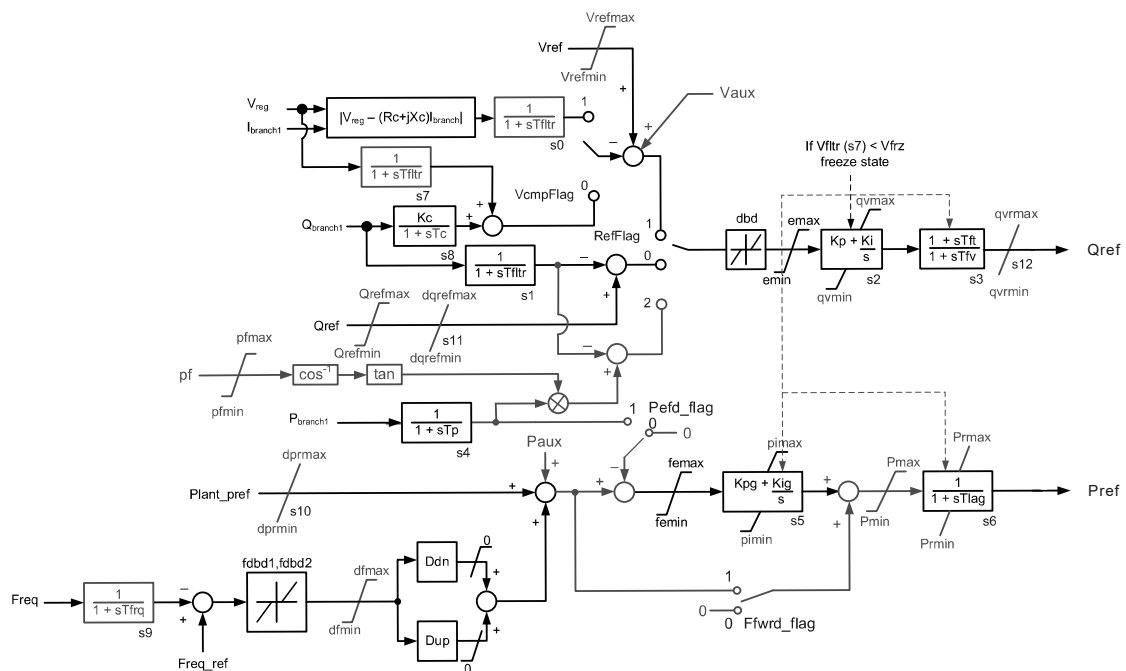


Figure A.1: Block diagram of REPC_A Model (adapted from [133]).

A.1. Equivalent Dynamic Models for RES Power Plants

- Parameters

Table A.1: Adopted Parameters for REPC_A model

Name	Description	Value
Rc	Line drop compensation resistance	0
Xc	Line drop compensation reactance	0
Tfltr	Voltage and reactive power filter time constant	0.02
Tp	Active power filter time constant	0.25
db	Deadband in reactive power or voltage control	0.002
Kp	Volt/VAR regulator proportional gain	1
Ki	Volt/VAR regulator integral gain	10
Vfrz	Voltage for freezing Volt/VAR regulator integrator	0.7
Tft	Plant controller Q output lead time constant	-0.05
Tfv	Plant controller Q output lag time constant	0.05
Kc	Reactive droop gain	0
FrqFlag	Active power control: 0 = disabled, 1 = enabled	1
RefFlag	0 = reactive power control, 1 = voltage control	1
VcmpFlag	0 = reactive droop, 1 = line drop compensation	1
fdbd1	Frequency deadband downside	-0.0006
fdbd2	Frequency deadband upside	0.0006
Ddn	Down regulation droop gain	20
Dup	Up regulation droop gain	0
Kpg	Real power control proportional gain	0.1
Kig	Real power control integral gain	1
Tlag	Plant controller P output lag time constant	0.05
emin	Minimum Volt/VAR error	-0.5
Qmin	Minimum plant reactive power command	-1
femin	Minimum power error in droop regulator	-99
Pmin	Minimum plant active power command	0
emax	Maximum Volt/VAR error	0.5
Qmax	Maximum plant reactive power command	1
femax	Maximum power error in droop regulator	99
Pmax	Maximum plant active power command	1

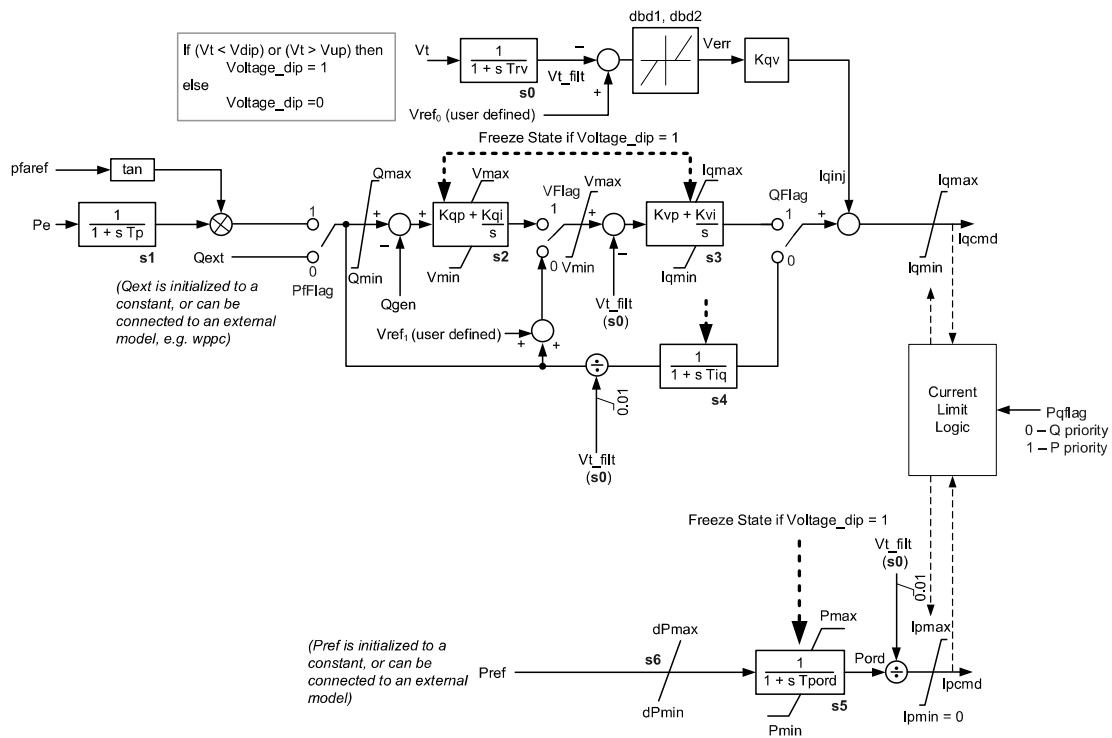
A.1. Equivalent Dynamic Models for RES Power Plants

A.1.2 REEC_B

- Parameters

Table A.2: Adopted Parameters for REEC_B model

Name	Description	Value
PfFlag	Power factor flag: 1 = pf control, 0 = Q control	0
VFlag	Voltage control flag: 1 = Q ctrl., 0 = voltage control	0
Tp	Filter time constant for el. power measurement	0.02
Kqp	Proportional gain	1
Kqi	Integral gain	0.7
QFlag	Q control flag: 1 = voltage/Q, 0 = const. pf or Q ctrl.	0
Kvp	Proportional gain	0
Kvi	Integral gain	40
Trv	Filter time constant for voltage measurements	0.02
db1	Voltage deadband for overvoltage iq injection	0
db2	Voltage deadband for undervoltage iq injection	0
Kqv	Gain for reactive current injection during fault	2
Vdip	Undervoltage condition trigger voltage	0.9
Vup	Overvoltage condition trigger voltage	1.1
Tiq	Time constant on lag delay	0.02
Tpord	Time constant	0.02
PqFlag	Priority flag on current limit: 1 = P, 0 = Q priority	0
Imax	Max. allowable total converter current limit	1.3
Vref0	Reference voltage, enter 0 for terminal voltage	0
Qmin	Reactive power limit minimum	-0.43
Vmin	Voltage control minimum	0.9
Iql1	Minimum limit of reactive current injection	-1.44
Pmin	Minimum power reference	0
dPmin	Ramp rate on power reference	-999
Qmax	Reactive power limit maximum	0.43
Vmax	Voltage control maximum	1.1
Iqh1	Maximum limit of reactive current injection	1.44
Pmax	Maximum power reference	1
dPmax	Ramp rate on power reference	999



Name	Description	Value
Kip	Proportional gain of Inner current control	2
Kii	Integral gain of Inner current control	20
Tfltr	Voltage measurement transducer filter time-constant	0.01
Te	Coverter firing delay emulation time-constant	0.01
Kpll	Proportional gain of PLL	20
Kipll	Integral gain of PLL	300

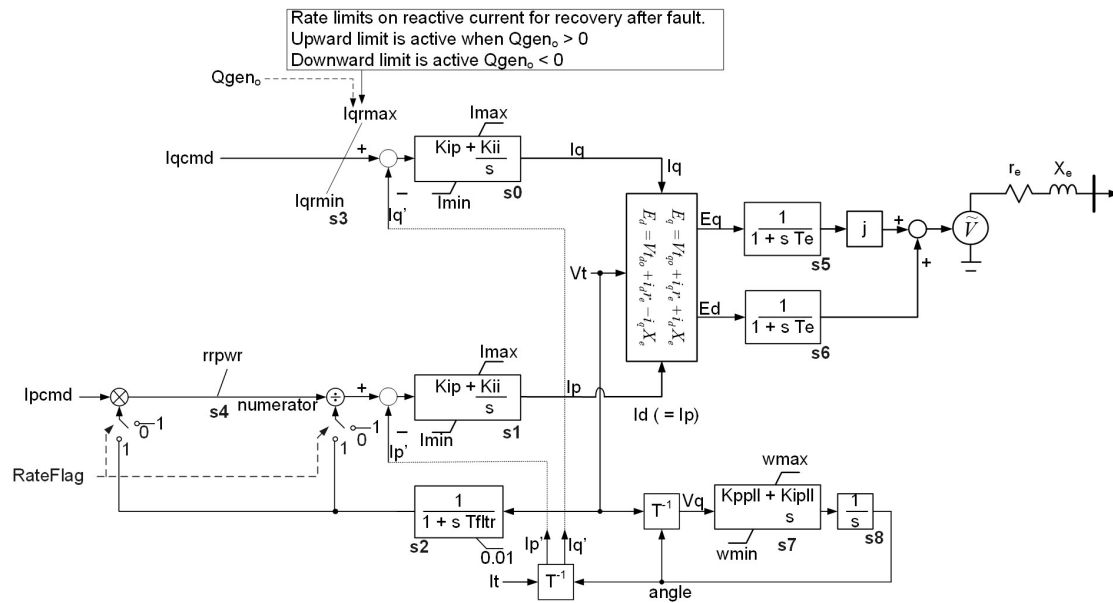


Figure A.3: Block diagram of REGC_C Model (adapted from [134]).

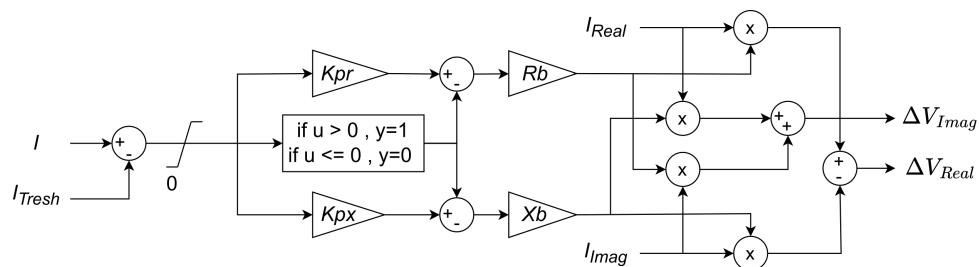


Figure A.4: *Virtual Impedance model.*

Table A.4: Adopted Parameters for Virtual Impedance model

Name	Description	Value
Rb	Basic virtual resistance	0.001
Xb	Basic virtual reactance	0.052
I_{Tresh}	Over-current threshold	1.01
kpr	Proportional factor for additional resistance	36
kpx	Proportional factor for additional reactance	36

Parametrisation of the Virtual Damping Constant of Virtual Synchronous Machine

This appendix presents the mathematical derivation used to define the damping constant of the virtual synchronous machine used in this work's grid-forming control.

Consider the simplified system depicted in Figure B.1, wherein a Grid-Forming (GFM) controlled converter is interfaced with the grid via a coupling transformer, with a per unit impedance of X_c . The grid is modelled as an ideal voltage source $\underline{V}_g$ in series with an impedance X_g , which represents the grid's short-circuit power at the converter terminal.

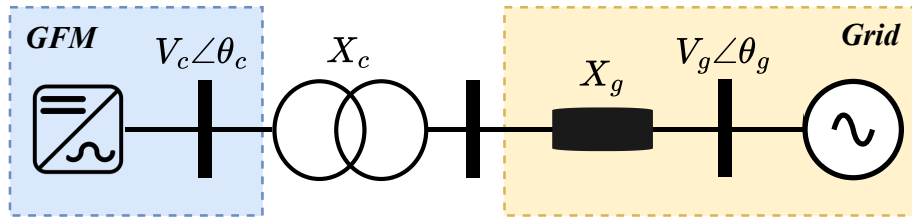


Figure B.1: Approximate representation of the converter closed-loop active power dynamics.

Within this system, the active power flow between the GFM and the grid is governed by the following equation:

$$P_{out} = \frac{V_c \cdot V_g \sin(\theta_c - \theta_g)}{X_g + X_c} \quad (\text{B.1})$$

Chapter B. Parametrisation of the Virtual Damping Constant of Virtual Synchronous Machine

This equation can be simplified under the assumption that the angle differences between the voltage sources are minimal and that the voltage magnitudes are approximately unity. This approximation, which has been extensively utilised in the literature for two source systems [184][175], yields:

$$P_{out} = \frac{(\theta_c - \theta_g)}{X_g + X_c} = \frac{(\theta_c - \theta_g)}{X_T} \quad (B.2)$$

Assuming the GFM active power control loop operates as a Virtual Synchronous Machine (VSM), then, the block diagram illustrated in Figure B.2 can be used as an approximate representation of the converter's closed-loop active power dynamics.

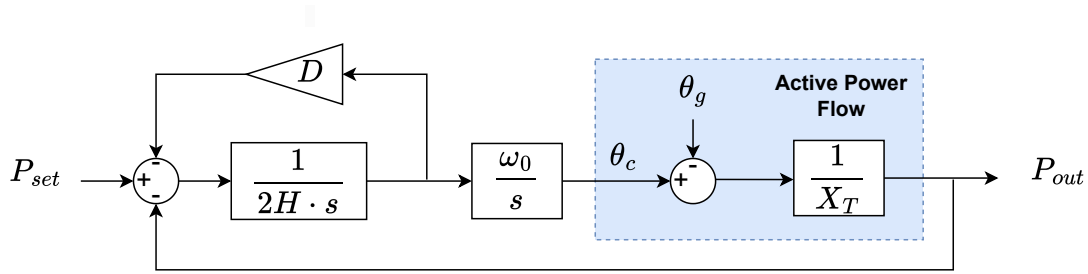


Figure B.2: Approximate representation of the converter closed-loop active power dynamics.

For the aforementioned control block diagram, the transfer function can be derived as:

$$\frac{P_{out}(s)}{P_{set}(s)} = \frac{1}{\frac{2 \cdot H \cdot X_T}{\omega_0} \cdot s^2 + \frac{D \cdot X_T}{\omega_0} \cdot s + 1} \quad (B.3)$$

The second-order characteristic equation of the above transfer function can also be expressed in terms of the system's damping ratio (ζ) and natural frequency (ω_n), as follows:

$$\frac{2 \cdot H \cdot X_T}{\omega_0} \cdot s^2 + \frac{D \cdot X_T}{\omega_0} \cdot s + 1 = \frac{1}{\omega_n^2} \cdot s^2 + \frac{2 \cdot \zeta}{\omega_n} \cdot s + 1 \quad (B.4)$$

Thus, the system's natural frequency and damping ratio are given by:

$$\omega_n = \sqrt{\frac{\omega_0}{2 \cdot H \cdot X_T}} \quad \oplus \quad \zeta = \frac{D \cdot X_T \cdot \omega_n}{\omega_0 \cdot 2} \quad (B.5)$$

The damping constant required to achieve a specific damping ratio is therefore:

$$D = \frac{2 \cdot \zeta \cdot \omega_0}{\omega_n \cdot X_T} \quad (\text{B.6})$$

Given that the Short-Circuit Ratio (SCR) in the per-unit system is the inverse of the grid impedance (X_g), the above expression can be further extended to:

$$D = \frac{2 \cdot \zeta \cdot \omega_0}{\omega_n \cdot (X_c + \frac{1}{SCR})} \quad (\text{B.7})$$

Thus, by selecting a value for the VSM virtual inertia and having the SCR at the converter terminal, it becomes possible to directly calculate the damping constant needed to achieve a specific damping ratio. In this scenario, let H be 4, X_c be 0.15, SCR be 3 (indicative of a weak grid condition), and ζ represent 0.707 (a damping ratio that effectively balances response time and overshoot). Under these parameters, the value of D will be 101.96, as demonstrated below.

$$\begin{aligned} \omega_n &= \sqrt{\frac{2 * \pi * 50}{2 \cdot 4 \cdot (0.15 + \frac{1}{3})}} = 9.013 \\ D &= \frac{2 \cdot 0.707 \cdot (2 * \pi * 50)}{9.013 \cdot (0.15 + \frac{1}{3})} = 101.96 \text{ p.u.} \end{aligned} \quad (\text{B.8})$$

Appendix C

Decision Tree Model

This appendix provides a detailed illustration of one of the decision trees used as a benchmark in Chapter 7.

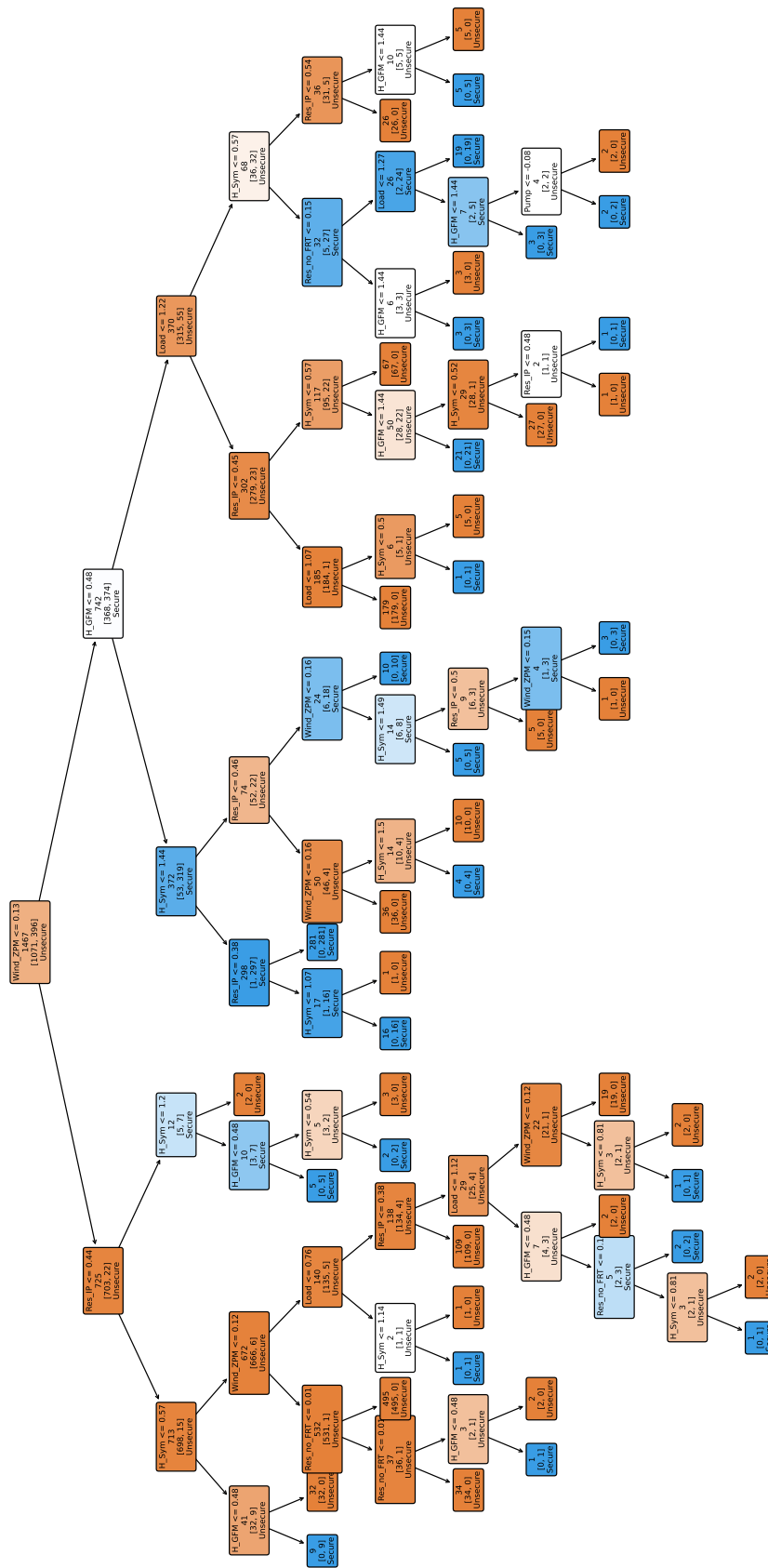


Figure C.1: Detailed Illustration of one of the resulting decision trees.

