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Economic Evaluation of Energy Storage Systems and their Impact on Electricity Markets in a Smart-grid Context

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Abstract

Generation from renewable energy sources has been rising worldwide and is set to grow further, as many countries are implementing and enforcing initiatives to reduce greenhouse gas emission to curb climate change. However, this change in the generation mix is increasingly challenging to handle for the grid operators, as the residual load becomes more volatile and difficult to predict. In order to ensure the continuous balance between supply and demand and minimize the amount of curtailed energy from renewable resources, a range of flexibility options exists. At the consumer end, the flexibility of the load can be increased by demand-side management. Alternatively, by increasing the interconnection capacity, surplus generation can be exchanged with neighboring grid zones. Furthermore, existing generation resources like cogeneration units can be refitted and operated in a more flexible way.

Storage, as another flexibility option, has the advantage of being able to act on both demand and supply sides as well as providing a wide range of system services. Hence, during periods with surplus generation from renewable resources, excess supply can be absorbed by storage systems. Contrary, during times with low contribution from renewable generation, the deficit can be compensated by discharging the storage device. However, while storage is well suited from a technological point of view to fill the gap, it remains unclear how the application of a storage device can be monetized. Furthermore, investors are struggling to evaluate potential projects due to their complexity. As a result, current implementations of new storage installations remain behind expectations. In addition, high uncertainty about future developments causes many investors to delay investment decisions.

In this context, this work identifies and defines several business cases regarding the integration of storage in power systems. Depending on the intended usage of the storage device, benefits might accrue which cannot be internalized by a private agent. Therefore, only commercial applications for energy storage will be considered. In the following, storage dispatch algorithms and an evaluation framework are developed. This allows defining the benefits that a storage device can provide, including barriers and drivers to its deployment. In order to consider uncertainty in the evaluation process, several assessment methodologies are introduced and adapted to the respective context. Furthermore, the impact of storage systems on the electric grid as well as on electricity markets is analyzed.

The results of this research do not only provide a better understanding about potential business cases and related income streams of storage devices to investors, but also provide deep insights into the associated risks of such an investment. Furthermore, the results allow policy makers to identify the relevant parameters for promoting storage in order to facilitate the integration of additional renewable generation capacity. Last, this document gives traditional power producers as well as grid operators a better understanding about the impact of storage installations on generation and demand patterns as well as on the possible impacts on electricity markets.

Resumo

A produção de energia elétrica utilizando recursos renováveis tem vindo a aumentar em todo o mundo e espera-se que continue a crescer dado que muitos países estão a implementar medidas para reduzir a emissão de gases de efeito de estufa de modo a limitar as alterações climáticas. No entanto, esta alteração do mix de produção coloca desafios crescentes à operação dos sistemas elétricos dado que a carga residual se torna cada vez mais volátil e difícil de prever. De modo a assegurar o equilíbrio entre a produção e a carga e a minimizar o corte de produção com origem renovável, encontram-se hoje em dia disponíveis diversas opções. Ao nível dos consumidores, a flexibilidade da carga pode ser aumentada adoptando programas de gestão da procura. Em alternativa, pode ser aumentada a capacidade de interligação de modo a que os excessos de produção possam ser canalizados para sistemas vizinhos ou outras zonas da rede. Por fim, a utilização de diversos recursos já existentes tais como sistemas de cogeração pode ser ajustada de modo a operarem de uma forma mais flexível.

Tal como outras opções relacionadas com a flexibilidade, o armazenamento tem a vantagem de poder atuar quer do lado da produção quer do lado da procura podendo ainda fornecer diversos outros serviços. Assim, em períodos em que exista um excesso de produção de fontes renováveis, a produção em excesso pode ser absorvida pelo sistema de armazenamento. Em contrapartida, em períodos em que a contribuição de fontes renováveis é mais reduzida, o déficit de energia pode ser compensado pela descarga do dispositivo de armazenamento. No entanto, apesar do armazenamento poder constituir uma solução adequada do ponto de vista tecnológico, continua a ser pouco claro como é que se podem avaliar do ponto de vista monetário os investimentos em equipamentos de armazenamento. Para além disso, os investidores continuam a ter dificuldades em avaliar possíveis projectos devido à complexidade associada a essa avaliação. Como resultado, as instalações de armazenamento existentes atualmente continuam a ser em número reduzido face ao que se poderia esperar e a incerteza em relação a desenvolvimentos futuros tem contribuído para o adiamento de muitos investimentos.

Neste contexto, este trabalho identifica e define diversos modelos de negócio relativos à integração de armazenamento em sistemas de energia. Em função da utilização a dar ao sistema de armazenamento, alguns benefícios podem ser dificilmente internalizados por um investidor privado. Assim, neste trabalho foram consideradas apenas aplicações de que possam advir benefícios que seja possível estimar do ponto de vista comercial. Neste âmbito, foram desenvolvidos diversos algoritmos para realizar o despacho dos equipamentos de armazenamento bem como para realizar a sua avaliação. Torna-se assim possível identificar os benefícios associados ao armazenamento, incluindo as barreiras e vectores que poderão influenciar a sua instalação. Por outro lado, foram igualmente desenvolvidas metodologias para integrar incertezas no processo de avaliação e foram analisados diversos impactos das soluções de armazenamento nas redes eléctricas e nos mercados de electricidade.

Os resultados deste trabalho permitem obter uma compreensão mais profunda dos potenciais modelos de negócio e dos fluxos financeiros associados, bem como dos riscos associados a estes investimentos. Por outro lado, os resultados obtidos podem permitir que os decisores políticos identifiquem os aspectos mais relevantes de modo a promover a instalação de equipamentos de armazenamento tendo em vista aumentar a integração de fontes de energia renovável nos sistemas eléctricos. Por último, este documento fornece aos produtores utilizando tecnologias tradicionais bem como aos operadores das redes uma melhor compreensão dos impactos dos equipamentos de armazenamento nos perfis de produção e de carga bem como nos mercados de electricidade.

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List of Acronyms

CAES	Compressed air energy storage
CHP	Combined heat and power
DSO	Distribution system operator
EES	Electrical energy storage
IRR	Internal rate of return
LCOE	Levelized cost of electricity
LCOS	Levelized cost of storage
LP	Linear program
MIP	Mixed integer program
NPV	Net present value
PHS	Pumped hydroelectric storage
PV	Photovoltaic
TSO	Transmission system operator
VaR	Value at risk

List of Symbols

Symbol	Unit	Description

General simulation parameter

t	-	Index
Δt	-	Fraction of an hour between two time steps
T, T^{Hours}, T^{Days}, T^{Years}	-	Number of total time steps as well as number of hours / days / years during T

System components

CHP	-	Combined heat and power plant
GB	-	Gas boiler
Grid	-	Grid connection
HP	-	Heat pump
Load	-	Local demand
PV	-	Photovoltaic system
ST	-	Solar thermal system
Storage	-	Electric storage device
ThStorage	-	Thermal storage device

System parameters

The subscript of a variable indicates the relevant system component.

$E_{Storage}^{Capacity}$	[Wh]	Nominal capacity of the storage device
$L_{System}^{Calendric, Cycle, Operating}$	[a, -, h]	Calendric lifetime (in years), cycle lifetime (in equivalent full cycles) or operating lifetime (in hours)
$P_{System}^{Capacity}$	[W]	Power capacity
$P_{PV}^{max\ feed-in}$	[W]	Maximum permissible feed-in power of a PV installation
$P_{CHP}^{CapacityMin}$	[W]	Minimum power output of a cogeneration unit
$\delta_{Storage}$	[%]	Depth of discharge of the storage device
$\eta_{Storage}$, $\eta_{Storage}^{In}$, $\eta_{Storage}^{Out}$	[%]	Roundtrip / charging / discharging efficiency of the storage device
$\phi_{Storage}$	[%]	Self-discharge per hour of the storage device

Simulation variables

$CoP(t)$	-	Coefficient of performance of a heat pump
$E_{Storage}(t)$	[Wh]	Current charge of the storage device
$H(t)$	[W]	Heat flow
$H_{ThStorage}^{In}(t)$, $H_{ThStorage}^{Out}(t)$	[W]	Heat absorbed / supplied by the thermal storage device
$P(t)$	[W]	Power flow
$P_{Grid}^{Import}(t)$, $P_{Grid}^{Export}(t)$, $P_{Grid}^{Export\ PV}(t)$, $P_{Grid}^{Export\ CHP}(t)$	[W]	Power exchange with the grid
$P_{PV}^{*}(t)$, $H_{ST}^{*}(t)$	[W]	Available generation from intermittent resources
$P_{Storage}^{In}(t)$, $P_{Storage}^{Out}(t)$	[W]	Power absorbed / supplied by the electric storage device
$P_{Regulation}^{Capacity}(t)$	[W]	Tendered capacity for the provision of reserve control
$P_{Grid}^{Capacity}$	[W]	Grid connection capacity
$N(t)$	-	Number of equivalent full charge- and discharge cycles
$SoC(t)$	[%]	State of charge
$y(t)$	-	Binary decision variable for the operation of the storage device
$z(t)$	-	Binary decision variable for the operation of the cogeneration unit

Financial parameters

a	[€]	Sum of attributable fixed annual cost for each time step
$\beta(t)$	[€]	Sum of variable operation cost
C^{Invest}	[€]	Investment cost
C^{Fixed}	[€/a]	Fixed cost
$C^{Variable}$	[€/Wh]	Operating cost
$C_{Grid}^{Capacity}$	[€]	Grid connection cost
$C_{CHP}^{Benefit}$	[€]	Incentive payment for the operation of a cogeneration unit
$CF(t)$, $CF_{Loant}(t)$	[€]	Cash flow, cash flow from financing
irr	[%]	Internal rate of return
$LCOS$	[€/Wh]	Levelized cost of storage
$Loan$	[%]	Amount of loan in percent of the investment amount
NPV	[€]	Net present value (subscripts indicate different system configurations)
r_{Equity}	[%]	Required return hurdle for equity financing
r_{Loan}	[%]	Interest rate for debt financing
T_{Loan}	-	Debt tenor in time steps
$T_{CHP}^{Benefit}$	[a]	Duration of the incentive payments

Electricity prices

$R(t)$	[€/Wh]	Electricity market price
$R_{flat}^{Import}(t)$, $R_{TOU}^{Import}(t)$, $R_{RTP}^{Import}(t)$	[€/Wh]	Flat / time-of-use / real-time pricing tariffs
$R_{PV}^{Export}(t)$, $R_{CHP}^{Export}(t)$	[€/Wh]	Feed-in tariff for photovoltaic systems and cogeneration units
$R^{Regulation}(t)$, $R_i^{Regulation}(t)$, $R_{max}^{Regulation}(t)$	[€/W]	Compensation for the provision of reserve control, compensation for the specific bid *i* in ascending order, marginal bid for the provision of reserve control

Modelling of electricity prices

$X(t)$	[€/Wh]	Trend and seasonality
$J(t)$	[€/Wh]	Price jumps
$S(t)$	[€/Wh]	Stochastic residuals
α_i	-	Coefficients of a linear trend for the modelling of $X(t)$
λ_{jump_up}, λ_{jump_down}	-	Parameters of the exponential distribution
α_{jump_up}, α_{jump_down}	-	Up- / down-shift of the exponential distribution
δ_{jump_up}, δ_{jump_down}	-	Probability of occurrence of a price jump
$\varepsilon(t)$	-	Error term

Other

A_k	-	Investment alternatives
$F(x)$	[%]	cumulative distribution function
$Hurdle$	[€/Wh]	Minimum revenue requirement for the arbitrage dispatch
$LB(t)$, $UB(t)$	[€/Wh]	Upper and lower bounds for the arbitrage dispatch
LF	[%]	Load Factor
p_i	[%]	Probability of outcome i
rg_{ik}	[€]	Regret for decision alternative A_k under scenario S_i
σ	-	Standard deviation
S_k	-	Sensitivity towards parameter k
S_i	-	Potential future states i
SC	[%]	Self-consumption
SS	[%]	Self-sufficiency
U_i	-	Uncertainty of parameter i
VaR_β	[€]	Value at Risk for the confidence level β

Chapter 1

1 Introduction

1.1 Context

Renewable electricity generation, especially from wind and solar, is growing with a fast pace around the world. In contrast, conventional technologies are facing increasing headwind, driven by environmental concerns about greenhouse gas emissions and air pollution. Furthermore, the expectation of rising fuel prices in the long-term as well as the internalization of external effects (such as taxes on CO_2 emissions) challenge the economics of thermal power plants. Contrary, renewable technologies are becoming increasingly competitive, driven both by technological advances as well as a decrease in the investment cost due to manufacturing improvements as well as economies of scale. Consequently, the contribution of electricity generation from renewable resources is on the rise. It is likely that this trend will continue with more governments implementing regulations to induce the increase of the share of renewables.

The energy roadmap of the European Union foresees a reduction in greenhouse gas emissions of 80% - 95% by the year 2050 as compared to 1990 levels [1]. A major contribution towards these savings is expected to come from the power sector. Until 2030, the power sector is expected to reduce its CO_2 emissions by 54% - 68% as compared to 1990. In order to achieve this goal, the contribution from renewables to total electricity generation needs to increase from 27.5% in 2014 [2] to at least 50% in 2030 [3].

However, this electricity generation paradigm change does not only require significant investments in renewable generation technologies, but has a range of further implications and far reaching consequences. Whereas conventional generation relied on a centralized system, renewable generation is usually much more distributed due to the availability of resources. Furthermore, most renewable resources depend on local, non-controllable weather conditions, and therefore cannot be dispatched when required. So far, the electric system has been designed around the assumption of load following, that is, generation will adapt to demand. With low shares of intermittent resources, fluctuations from their contribution can be compensated by traditional power plants. Hence, low shares of renewable generation can be easily integrated and its curtailment is rarely needed. However, with an increasing share of distributed and non-dispatchable units, this will become more and more challenging in the future clearly indicating that power systems have to evolve towards a larger flexibility both in expansion planning and operation phases.

Flexibility in the electric system can be provided by several options [4], [5]. One approach to address or at least mitigate the issue is to use demand-side management that includes strategies to shift loads from periods with low intermittent generation to periods with high intermittent generation. Thereby, the mismatch between demand and generation can be diminished at the cost of slightly reduced comfort at times. However, these measures are not restricted to reducing demand. Additional equipment like power-to-heat appliances can be easily dispatched when a generation surplus exists. In addition to increasing the flexibility of demand, also the generation of electricity can be closer aligned to the residual demand. For example, dispatching combined heat and power plants according to electric instead of thermal demand increases their value to the grid significantly. Furthermore, the mismatch between available generation and demand can also be further reduced by an increased exchange with neighboring grid zones or countries. However, this requires both sufficient interconnection capacity as well as suitable regulatory frameworks.

These efforts towards a ‘smart-grid’ will be able to mitigate many of the arising problems in the short-term and will allow a smooth transition to a more sustainable electricity system. Storage as another flexibility option has the major advantage of being able to act on both supply and demand side. In addition - depending on the implemented technology - it has very short ramping times and can therefore react quickly. With a further rising share of non-dispatchable renewable generation, storage can therefore guarantee the constant simultaneous balance between supply and demand by transferring energy from periods with an excess of renewable generation to periods with insufficient supply from renewables. Besides facilitating the integration of renewables in the system, storage devices are able to provide a range of further services which are required to ensure the stable and secure operation of the grid, such as the provision of ancillary services. In the long-term, storage can therefore deliver the missing link between a primarily renewable, non-dispatchable generation system and demand.

Despite their versatile capability and their technical appeal to solve a wide range of issues, storage systems apart from large-scale Pumped Hydro Stations (PHS) have not yet seen a widespread implementation. Over the past years, worldwide installed storage capacity grew annually only by about 2.7% [6]. In addition to technical, regulatory and political issues, this can be attributed to the missing confidence about the economics of storage [7].

1.2 Motivation

Currently, 97.5% of grid-connected storage capacity are large-scale PHS [6]. However, traditional power station operators are experiencing increasing economic pressure from shrinking margins caused by lower electricity wholesale prices, which are driven down by photovoltaic and wind feed-in with (almost) no marginal cost. Hence, financing for future storage installations needs to come from alternative sources, such as private agents or cooperatives.

The investment in a storage device requires the definition of a business case, which describes how the storage device will be operated in order to generate a profit. Such a business case must not only be realizable under the current legal and regulatory framework, but the operator must also be able to access the relevant revenue stream. This makes many potential opportunities uninteresting for private investors, as no immediate compensation for their provision is defined.

Previous research on storage has primarily focused on the deployment of large-scale systems connected to the transmission grid. Traditionally, the arbitrage of energy prices played a major role, which describes a strategy where energy is stored when prices are low and fed back into the grid when higher prices prevail. While this business case has been extensively covered in the literature (for example in [8]–[10]), previous research focused on large-scale installations at the transmission grid-level. Using small-scale storage devices in a distributed context requires the consideration of several additional factors in the dispatch, such as the limited cycle lifetime of battery systems. Furthermore, extensive negative or zero market prices as well as the introduction of shorter contract tenors are recent developments, which have only partially been reflected in the current state of the art.

In addition to arbitrage, the identification and definition of further business cases is required to attract investments in storage. Given the increasing share of distributed generation resources and rising electricity cost driven by fees and taxes, the installation of storage behind the meter to increase the self-sufficiency of consumers appears promising ([11], [12]). Furthermore, with an increasing share of fluctuating non-dispatchable resources in the generation mix as well as a decreasing capacity of traditional generators, the provision of ancillary services will gain in relevance and is an attractive opportunity for storage operators ([8], [9]).

By combining and integrating several applications, storage systems can theoretically serve more than just one purpose simultaneously and capture multiple value streams in parallel ([13]). While this has been widely suggested as a way to improve the economic performance of storage, little research has been done to look into the valuation of multi-purpose systems. Therefore, the formulation of a dispatch algorithm is required, which considers technical constraints as well as manages conflicting operational requests.

Based upon the proposed business case and the formulated dispatch algorithm, the storage device can then be evaluated from a financial point of view. The initial investment cost for small- to medium scale systems can typically be estimated accurately by either requesting commercial proposals to manufacturers or a price comparison of pre-configured systems. Contrary, the identification of benefits and the valuation of potential value streams of a storage system is much more complex and requires careful consideration of storage specific characteristics, such as the limitation of battery systems to both a calendric lifetime as well as a maximum number of cycles.

Wide-scale investments in storage systems will only occur once they become economic viable. However, the high complexity of the evaluation as well as the novelty of its application in a distributed context and the resulting lack in regulation makes it difficult to establish a clear value proposition for storage. Besides the complexity of valuation, uncertainty about the impact of future regulation and the sustainability of profits confirm investors in their wait-and-see attitude. While the application of a storage system might be economically interesting today, regulatory changes or a change of electricity price patterns might leave investors with lower than expected returns during the lifetime of the storage system. Therefore, many potential investors are still hesitating to adopt storage and are deferring their investment decisions.

Hence, the formulation of an evaluation framework, which also takes this uncertainty and the resulting financial risk into account, is required. While a wide set of such tools exists, suitable approaches must be selected and adapted to the storage context. Based thereupon, the impact of uncertain factors such as technical properties on the viability of the business case can be analyzed and included in the decision process. For business cases exposed to electricity market prices, the associated uncertainty should also be included in the analysis which means that the simulation of market prices is required.

Furthermore, previous research typically assumes perfect foresight, that is complete knowledge about future demand and generation. However, it remains unclear how much of this theoretical value can be recovered in a real installation. Therefore, an evaluation approach is required which does not only identify the theoretic optimum profits of a business case, but also provides an estimate of the profits that can be expected in reality.

While this uncertainty is common to many investment decisions, it becomes more complex for storage systems due to the potential reverse feedback that new installations might provoke. Once storage has been widely implemented, former benefits could disappear, such as pursuing arbitrage reduces price spreads and hence decreases available revenues. This not only makes additional investments less interesting from an economic point of view, but it also deteriorates the initial business case upon which an investment decision was taken. A complete investment evaluation therefore should not only consider uncertainty in the evaluation process, but should also estimate the deployment impact on the market and other agents as well as incorporate their estimated feedback reaction in the initial investment proposal. Therefore, an analysis of both the impact on the supply and demand balance as well as on market prices is needed.

1.3 Objectives

The goal of the research that was developed is to evaluate the economic benefits of distributed energy storage systems, which can be accessed by a private agent, determine the risks associated with an investment in such a system and analyze its impact on electricity markets. Based on the presented motivation and the identified gaps in the current literature, this research intends to address the following objectives:

- Definition of commercial business models for electric storage devices and formulation of the required dispatch algorithms in order to analyze their value proposition.
- Characterization of an evaluation framework, which takes uncertainty and the arising financial risk into account.
- Identification of additional value potential by providing multiple services simultaneously by a single storage device.
- Assessment of the impact of storage implementations on electric grid demand and electricity market prices.
- Identification of reciprocal feedback of storage implementations on the initial value proposal of the investment.

This research will focus on storage applications in a commercial context. Therefore, only business cases that can be accessed by a private agent will be considered. Furthermore, the focus will be on small-scale storage systems that can be deployed in a distributed manner, such that they can be installed behind the electric meter. Last, only electric storage devices will be considered.

1.4 Structure of the Document

This thesis is organized in seven chapters, which build upon each other.

The current (first) chapter gives an introduction to the topic of energy storage and its importance. Context, motivation, objectives and the structure of the document are presented.

Chapter two presents the current state of the art by means of a literature review. First, storage technologies are classified and their suitability is discussed. Following, an introduction to the different markets for electric energy is given. Thereafter, different business cases for storage systems are analyzed, including a review of several related areas such as ownership implications and the current regulatory framework. Furthermore, the economic evaluation of storage systems is considered. Last, existing work about the impact of energy storage systems on the electric system and energy markets is reviewed.

In chapter three, the business cases for three different commercial storage applications are presented: shifting of energy in a consumer setting with local generation resources in time, arbitrage of electricity prices and the provision of ancillary services. In addition, the co-integration of applications is considered. For each case, a dispatch model is formulated and an evaluation approach is specified dependent on the individual context of each application. Furthermore, for each case, a dispatch algorithm without foresight is formulated.

Following, in chapter four it is shown how uncertainty and the arising financial risk can be incorporated and considered in the evaluation. Therefore, several methodologies are presented and adjusted to the specific context of storage investments.

Chapter five analyses the impact of storage implementations on the electric demand seen by the grid. Therefore, the application of time shifting as well as arbitrage is considered. Based thereupon, it is estimated how the deployment of storage devices influences electricity prices.

In the sixth chapter, the three presented business cases are each applied to a case study. Furthermore, the co-integration of multiple applications is demonstrated. Each case is accompanied by an analysis, where further aspects beyond the economic viability are considered and the methodologies from chapter four are applied. Last, the combined impact from a wide-scale rollout of storage installations on grid demand is analyzed.

The final part of this document, chapter seven, summarizes the contributions of this research and recapitulates the most relevant conclusions. This document is completed by an outlook about opportunities for future work.

Chapter 2

2 State of the Art and Literature Review

Abstract

Chapter 2 provides an overview of relevant literature and establishes the current state of the art in the field of the economic evaluation of storage systems and their impact on electricity markets. Therefore, first a brief overview of available storage technologies with their characteristics, advantages and drawbacks is given. Thereafter, potential commercial applications for storage systems are discussed. Following, the literature about economic evaluation approaches is reviewed. At the end of this chapter it is addressed the current state of the art about the impact of energy storage systems on energy markets.

2.1 Energy Storage Systems

Electrical energy storage (EES) has recently experienced a strong increase in interest, driven by the growth of distributed energy resources and renewable energy sources. EES is based on processes which convert energy to a storable form, and convert it back to electricity when required. EES is considered as a complementary technology to distributed generation technologies and renewable energy resources, as it allows to balance load and the intermittent, variable generation as well as secures power supply and quality [14], [15]. The concept of EES was developed by the end of the 18th century by Alessandro Volta, who invented the first battery [16]. Since then, it has been refined and many further approaches to store electricity have been developed.

2.1.1 Classification

Storage systems for electrical energy can be broadly categorized into two groups: power and energy applications [17], [18]. Systems from the first group have typically high power ratings and very short reaction times. However, their energy capacity is usually limited. They are therefore mostly installed for power quality or reliability purposes. On the contrary, storage systems designed for energy applications can usually store energy for longer times, but lack the short-term power ratings and flexibility [14], [19]. While this classification allows a broad categorization, many storage technologies fall somewhere in between and can be counted to either group, depending on their particular design and configuration. Another wide-spread approach for the classification of storage is according to its scale of implementation (for example in [20]), ranging from small- to medium- to large-scale installations. However, this approach ignores that several storage technologies can easily be scaled to the desired capacity. Alternatively, EES can be classified according to how the energy is stored. In [20], the authors differentiate among devices using mechanical, electrical, electro-chemical and chemical storage. The following review of storage technologies will focus on electric storage technologies only, which are commercially available or in an advanced stadium of development. Table 2.1 provides a guide and overview of the discussed technologies in the following review.

Mechanical storage	Electrical storage	Electro-chemical storage	Chemical storage
▪ Pumped hydroelectric ▪ Compressed air ▪ Flywheels	▪ (Super-) Capacitors ▪ Superconducting magnetic energy storage	▪ Lead-acid ▪ Nickel-cadmium ▪ Nickel-metal hybrid ▪ Lithium-ion ▪ Sodium-sulfur ▪ Redox flow	▪ Fuel cells ▪ Power to gas

Table 2.1: Storage technologies (based on [20]**)**

2.1.2 Mechanical Storage

Mechanical storage systems use electricity to create mechanical energy, such as potential or kinetic energy. This energy can then be converted back to electric energy when required. Commercially available systems are pumped hydroelectrical storage systems, compressed air storage systems and flywheels.

Pumped Hydroelectric Storage

The most prominent large-scale storage technology is pumped hydroelectric storage (PHS). PHS converts electrical energy into potential energy by pumping water from a lower reservoir up to another reservoir at a higher elevation. Electricity is regained by the sequential release through a turbine. This technology is very mature, operates at an efficiency of 70-85%, has low self-discharge rates, allows the storage of comparably huge quantities of energy over long time periods and has a long lifetime of typically 50-60 years. It is mainly used for shifting energy from periods with low-demand to peak hours, but can also be operated for the provision of reserves [14], [20]. In the U.S., PHS constitutes 95% of installed storage capacity [21]. Despite being the most prominent storage technology, it only represents approximately 3% of global generation capacity [22]. Additional locations besides the already existing installations are limited in many regions. While efforts are ongoing to expand existing facilities, new installations are limited by favorable natural conditions and environmental concerns.

Compressed Air Energy Storage

Compressed air energy storage (CAES) systems also depend on appropriate natural conditions. While the technology itself is mature, with only two operating large-scale installations it cannot compete with the maturity level of PHS. Electric energy is used to compress air, which is stored in underground caverns. To recover the energy, the compressed air is released to drive a turbine in order to generate electricity. Two different system designs exist: diabatic, which requires the burning of gas to reheat the air, and adiabatic, where the heat from the compression process is recovered and later reused during the expansion process. Current designs therefore are usually based on the adiabatic process due to its increased efficiency (about 70% versus only about 50% for the diabatic design). Lifetime estimates range from 25-40 years. Due to their slow reaction time, CAES installations are usually used to store energy during periods with low demand and provide energy during peak hours. While CAES is theoretically capable of storing huge amounts of energy like PHS, the technology has not yet seen a widespread usage due to its lower efficiency and requirements for appropriate geologic formations [14], [15], [20], [22].

Flywheels

Flywheels store energy as rotational, kinetic energy by spinning a mass. To store energy, a motor is used to spin up the flywheel. To release energy, the flywheel is slowed down again and the same motor acts as a generator. Flywheels usually have magnetic bearings and operate in a vacuum to minimize friction. They have a high power density, an almost unlimited number of charge- and discharge cycles, quick reaction times and are environmentally friendly. While flywheels achieve efficiencies of up to 95%, they suffer from high standby losses due to friction. Furthermore, energy density is comparably low (discharge durations of a few seconds to a few minutes). Flywheels are a mature, commercially available technology and are typically used for frequency regulation and the provision of ride-through capability for short durations [14], [20], [23].

2.1.3 Electrical Storage

As opposed to mechanical storage systems, supercapacitors as well as superconducting magnetic storage systems do not use any intermediate form of energy and hence do not require converting the stored energy to electric energy.

Supercapacitors

Supercapacitors store electricity directly by accumulating positive and negative charges. Therefore, response times are very fast, as no conversion is required. In addition, supercapacitors have long lifetimes (8-10 years), high efficiencies (about 95%), high power densities (10 000 W/kg) as well as long cycle lifetimes. However, high self-discharge losses and low energy capacities limit their application potential to similar cases as flywheels. While first supercapacitors are already commercially available, development is still ongoing [15], [20], [23].

Superconducting Magnetic Energy Storage

Superconducting magnetic energy storage stores electricity in a magnetic field, generated by direct current flowing through a superconducting material. Besides requiring substantial energy itself for cooling and becoming superconducting, the technology is very cost intensive and generates strong magnetic fields. They have high efficiencies (about 97%), very quick reaction times with high charging- and discharging power ratings as well as a virtually unlimited cycle lifetime. As energy density is low, most installations of superconducting magnetic energy storage have been for voltage stability and power quality issues [14].

2.1.4 Electro-Chemical Storage

Electro-chemical storages are best known for their usage in household devices in the form of batteries. Batteries are EES that store electricity through a reversible chemical reaction. This reaction takes place in an electro-chemical cell, which usually consists of two electrodes and an electrolyte material. Depending on voltage and power requirements, these individual cells can be easily scaled / arranged to obtain the desired power and energy capacity [22]. Technological development of batteries over the last 25 years was mainly driven by demand for consumer electronics. Only in the last decade, research for suitable EES for electric vehicles advanced battery technologies for medium to large-scale systems as they are required for application in a smart-grid. Besides improvements of technical characteristics, huge progress was also made in their efficiency, reliability and in the cost for the required power electronics [19].

Lead-Acid, Nickel-Cadmium and Nickel-Metal Hybrid Batteries

Lead-acid batteries are the oldest battery type and a very mature and wide-spread technology. Their popularity stems from their versatility, low cost and high reliability. Lead-acid batteries have an efficiency of usually 65-80% and considerable self-discharge rates. Cell lifetime is typically 500 - 2 000 cycles. In addition, they usually require regular maintenance, have comparably low energy densities (30-50 Wh/kg), long charging times and can emit explosives gases. Lead-acid batteries are used in a wide range of applications, both in small-scale installations for power back-up as well as in large-scale installations for grid support [14], [15], [20].

As compared to lead-acid batteries, nickel-cadmium batteries have a longer life expectancy (2 000 - 2 500 cycles), a higher energy density (50-70 Wh/kg) as well as lower maintenance requirements [15], [24]. However, due to the toxic nature of cadmium, they were banned for most uses in the European Union. In addition, nickel-cadmium batteries should be fully discharged before the next subsequent charge cycle to avoid a “memory effect”, which reduces the battery capacity. Their usage in combination with intermittent energy resources therefore requires additional battery management techniques [14], [15].

Nickel-Metal hybrid batteries demonstrate an improved performance against lead-acid and nickel-cadmium batteries. In addition, they lack the environmental toxic components lead and cadmium. However, their 25-40% higher energy density must be weighed against their higher self-discharge rate, which makes them unsuitable for long-term storage [24], [25].

Lithium-Ion Batteries

Lithium-ion batteries are dominating the market for small, portable electronic devices. They have an even higher energy density (up to 2 000 Wh/kg), long lifetimes (more than 3 000 cycles), very low self-discharge rates, high power-ratings and reach efficiencies of 95%. Their main drawbacks are their high costs as well as strict operational limits [15], [24]. Due to their compelling characteristics, lithium-ion batteries are experiencing a strong increase in interest for usage in electric vehicles and small installations despite their high capital cost.

Sodium-Sulfur and Sodium-Nickel Batteries

Sodium-sulfur batteries require an operating temperature of about 300 - 350°C. Besides this demanding requirement and the associated high energy usage to keep the battery at this temperature, they exhibit many desirable features: a lifetime of 2 500 cycles, high power density (150 – 240 Wh/kg) and a good efficiency (75-90%) [15]. However, sodium-sulfur batteries have rather high capital cost. A competing battery based on sodium-nickel with similar characteristics is marketed as ZEBRA battery. Compared to sodium-sulfur batteries, ZEBRA batteries have improved operating limits at the price of lower power density (120 Wh/kg). Both battery types are currently manufactured by only one supplier each [14].

Flow Batteries

Like regular batteries, flow batteries store energy through a reversible chemical reaction. Their operation is however more comparable to a rechargeable fuel cell. A liquid electrolyte is pumped through a cell stack, where an ion exchange takes place, converting chemical energy to electricity and vice versa. As the liquid electrolyte can be stored externally, a flow battery can be efficiently scaled, both in terms of power (by adding additional cell stacks) as well as in terms of energy (increasing the volume of the electrolyte liquid). Flow batteries operate at ambient temperature and experience no self-discharge, but require a rather complex operating system as compared to regular batteries. They have lifetime expectancies of about 10-15 years, and are typically used for time shifting of energy. Several variants of flow batteries are being researched with slight technical variations. Commercially available representatives are vanadium redox batteries (reaching efficiencies of up to 85%) and zinc-bromine batteries (about 75% efficient) [14], [19], [20].

2.1.5 Chemical Storage

The storage of electrical energy in chemical form has seen a strong rise in interest, as it would allow storing energy in comparably huge dimensions and for longer timeframes than so far used large scale pumped hydro storage plants. Two related concepts have attracted most of the research and interest: conversion to hydrogen and synthetic methane.

Hydrogen

Hydrogen can be produced from water by electrolysis. It can then be mixed in small fractions into the existing natural gas network or stored in caverns or tanks. To achieve higher compressions, it can also be liquefied, however at a high energy effort. When energy is required again, the hydrogen can be used for example in combined heat and power plants or fuel cells to generate electricity. The biggest advantage of this method is its high energy density, low self-discharge rates, the versatile usage of the hydrogen both for long-term storage as well as for short-term regulation, scalability of generation and the expected long lifetime of installations. However, poor efficiencies (about 40%), security concerns about the storage of the highly explosive gas, high cost and the infancy of the technology currently still prevent a more widespread usage [14], [20], [22].

Synthetic Methane

The generated hydrogen can also be used to synthetically create methane. The advantage of synthetic methane over hydrogen is its equality to natural gas. Therefore, the existing natural gas infrastructure including the existing generation capacity can be used (unlike hydrogen, which can only be fed into the network in small fractions). However, efficiency is even lower due to the additionally required conversion and is currently only about 25% [20], [22].

2.1.6 Suitability

Kousksou et al. [25] provide a comprehensive review of the technical characteristics of different storage technologies and discuss their respective advantages. It is obvious that not all EES are suitable for implementation in a distributed, small-scale manner as required in a smart-grid application. PHS and CAES rely on geographical formations and are therefore site-specific. In addition, their size and the associated installation cost make them more suitable for utility scale storage applications. Flywheels, super conducting magnetic energy storage and supercapacitors have a very narrow operating profile, making them most suitable for power quality issues and frequency regulation. They lack the ability to provide energy over longer periods. Chemical storage systems are still in their infancy and require further research, before they become commercially available.

Battke et al. [26] therefore suggest that electrochemical batteries are the most promising technology for implementation and usage in smart-grids, as they offer fast response times, can be scaled to the desired capacity and can address both power and energy applications. Furthermore, they have almost no site specific requirements, are relatively compact in size and modular. This view is confirmed by further publications, such as [27], [28].

However, the most appropriate technology must be determined on a case by case basis. Depending on the specific application requirements and the charge / discharge profile, different storage characteristics are required [18], [29]. Additional criteria such as maintenance requirements, operating cost as well as regulatory or safety restrictions might further reduce the potential choices.

The authors of [18] suggest combining different technologies in a hybrid storage system. In a combined system of a battery and a supercapacitor, the latter would meet very short power requirements or peak demand in the order of several seconds, while the battery would be responsible for providing the energy with the required capacity. This would result in a lower number of battery cycles and therefore extend the lifetime of the battery.

2.2 Energy Markets

Transactions between two parties without involvement of a marketplace are called “over-the-counter”. They allow the individual negotiation of terms directly between the buyer and seller. However, identifying an interested counterparty is complex and oftentimes requires the involvement of a broker, which increases transaction cost. Furthermore, unwinding an existing transaction requires the consent of the counterparty. In addition, counterparty risk (the risk that the counterparty cannot fulfill the contract) is a concern especially for small counterparties and long-dated contracts. Exchanges offer a marketplace for standardized contracts. These lack the individual character of over-the-counter transactions, but among others offer higher liquidity, the possibility to unwind existing positions and to reduce counterparty risk.

The following introduction considers the German electricity market. It is restricted to relevant issues for the market participation of storage devices. First, the market for long-term contracts is discussed (Section 2.2.1), followed by the spot market which usually takes place on the day before delivery (Section 2.2.2). The balancing market considers the products available to the Transmission System Operator (TSO) to balance deviations (Section 2.2.3). Last, Section 2.2.4 provides an introduction to the modelling of electricity prices.

2.2.1 Forward Market

Contracts for electricity delivery with a maturity beyond the next day are offered by the European Energy Exchange.

Futures

Futures are standardized forward contracts for the settlement of electricity at some specified time. Quantity, price, delivery times and delivery period are agreed upon today, whereas the actual delivery and payment occur in the future. Underlying of the contracts are not immediate energy transactions, but energy indices reflecting the prices from the spot market. Phelix Base represents the unweighted average spot price for the combined German / Austrian market, Phelix Peak / Off-Peak the unweighted average price during peak / off-peak hours [30]. Usually, the contracts are financially settled, that is the difference of the traded contract to the then prevailing underlying price is compensated. However, holder of a contract can also ask for a physical delivery on the EPEX spot market. Offered delivery periods range from days to the complete year, with tradeable contract maturities up to six years from today for the annual contract. Minimum contract size is 1 MW [31].

Options

The European Energy Exchange also offers option contracts on electricity. Contrary to futures, these give the buyer the right to enter a contract, but are not an obligation. Hence, the buyer of an option pays a premium for this right, whereas the seller of the right receives the premium. At the maturity of the option contract, the buyer can then decide whether he wants to exercise the option and enter the underlying contract at the pre-specified conditions. Underlyings are the previously introduced Phelix Base Futures with monthly, quarterly and yearly maturity [31].

2.2.2 Spot Market

The short-term electricity market for Germany (as well as for Austria, France and Switzerland) is operated by the power exchange EPEX Spot. Transactions can be conducted in several standardized products. The day-ahead market allows market participants to fine-tune their energy purchases to expected demand and energy sales to available capacity. Finally, the intraday market provides the last opportunity to react to forecast errors of demand and renewable generation as well as to outtakes of generation capacity. In addition to hourly contracts, 15 minute intervals have been introduced as the shorter intervals allow market participant engaged in intermittent renewable energy generation (especially generation from photovoltaic systems) to more precisely trade their actual generation. In addition, ramps of thermal generation can be reflected more accurately [32].

Day-Ahead and Intraday Auctions

The day-ahead auction takes place daily at noon for physical delivery of electricity during the individual 24 hours of the following day. Prices can range from -500 EUR/MWh to 3 000 EUR/MWh, with minimum price increments of 0.1 EUR/MWh. Besides orders for individual hours, also block orders spanning several hours can be traded, for example for the hours 1-6 (‘Night’) or 19-24 (‘Evening’). Block orders are only executed when the price for all contained hours is matched. In addition to pre-defined blocks, trader can also link individual hours according to their requirements. Furthermore, market participants can also mark orders as exclusive, that is only one order of the specified group will be filled and the remaining orders cancelled. In addition to hourly contracts, at 3pm there also is an auction for all 15-minute intervals of the following day. In these auctions, prices can vary between -3 000 EUR/MWh to 3 000 EUR/MWh [33].

Auctions are conducted as blind auctions. Therefore, market participants submit their bids for the individual hours stating their reservation price and the associated quantity without knowing the orders from other market participants. After the deadline, the bids from all agents are aggregated to determine the overall supply and demand function. The uniform price for all executed orders is identified as the intersection between the two curves, where demand and supply balance. A more detailed explanation can be found in [33].

Continuous Trading

Besides the two daily auctions, electricity is also traded continuously allowing market participants to react promptly to changes in their demand or generation portfolio. Contrary to the auctions, orders are immediately executed once another party enters a matching order in the order book. Individual hours as well as 15 minute intervals can be traded until 30 minutes before delivery. The minimum price is -9 999 EUR/MWh, maximum price is 9 999 EUR/MWh. The minimum price increment is decreased to 0,01 EUR/MWh [33].

Delivery

The minimum trading amount for both the auctions as well as the continuous trading is 0.1 MW. All contracts are settled physically, that is contracts must be fulfilled by either consuming the contracted energy or by delivering the offered energy. Delivery zone is the grid of the four German Transmission System Operators. Contracts from the hourly day-ahead auctions can also be settled in the Austrian Power Grid. Hence, currently no price differentiation or market splitting exists across the four different system operator zones in the German power market [33].

Market Coupling

Purchasing electricity in a market with low prices and simultaneously selling this amount in a neighbouring electricity market, such as between France and Germany, is limited by the available cross-border transmission capacity. Therefore, between several market places routines for the optimal allocation of cross border transfer capacities exist. The so called market coupling ensures through implicit auctions that price differentials between markets are minimized and available capacity is optimally used. Energy is then transferred from the market with the lower price to the market, where a higher price prevails [34].

2.2.3 Balancing Market

Forecast errors for intermittent generation and demand as well as power plant failures might lead to deviations from the traded balance. It is the task of the transmission system operator to ensure a stable and reliable operation of the system by balancing generation and demand. Therefore, even more short-term instruments exist: primary control reserve, secondary control reserve as well as minute / tertiary control reserve, both for negative as well as positive deviations from the target frequency. The three services substitute each other in time, so that the preceding reserve becomes available again for additional corrections at a later point in time. Besides the three control reserves the TSOs can also make use of interruptible loads. A good overview of balancing services and an international comparison is published by Rebours et al., both for technical [35] as well as economic characteristics [36]. A more recent, but less complete overview is given by Rivero et al. [37]

In the German grid zone, all three reserves are procured by the four transmission system operators jointly through a public tender. The procured volumes are determined by a probabilistic approach based on the outtake probability of power plants, volatility of demand and historic requirements. In order to participate in the balancing market, agents must be prequalified. During the qualification process, among others the ability to meet the operational regulations as well as the provision of the contracted power is verified.

Due to its importance for the stability of the electric system, the balancing market is tightly regulated. On a European level, the balancing market is governed by the operation handbooks, regulations and grid codices of the European Network of Transmission System Operators for Electricity and the Agency for the Cooperation of Energy Regulators. On a national level, regulations are mainly defined in the “Electricity Grid Access Ordinance” (StromNZV) [38] and the “Law on the Energy Industry” (EnWG) [39]. Further details can be found in the regulations of the German regulator (Bundesnetzagentur) as well as in the contracts between the reserve provider and the TSO [40].

Primary Control Reserve

Primary control reserve [41] is automatically activated when the frequency deviates by more than +/-10 mHz from 50 Hz. The provision of required power is proportional to the deviation of the frequency, with full contribution required at 49.8 Hz / 50.2 Hz. The contracted power must be available within 30 seconds and must be continuously provided for periods up to 15 minutes. Contracts for primary control reserve are symmetrical, that is agents must provide both positive as well as negative power. The required volume is tendered weekly, participating parties must bid at least 1 MW. The provision of primary control reserve is compensated according to the individual bid (‘Pay-as-bid’) and the contracted power, independent of the usage.

For storage systems participating in the Primary Control Reserve, additional regulations apply [42]. These take into account that the available energy of a battery is limited. Thereafter, the contracted reserve power (both positive as negative) must be available for at least 30 minutes continuously. After a regulation event, the operator has two hours to return the storage system to a state of charge which allows again maintaining the 30-minute regulation. Therefore, the storage operator can participate in the regular continuous spot intraday market or exceed opposite reserve power requirements by up to 20% over the contracted power. Alternatively, he can also provide positive / negative power within the +/-10 mHz dead band, as long as the operation is reducing the deviation from 50 Hz [43].

Secondary Control Reserve

Secondary control reserve [44] is automatically activated by the TSO typically associated to the automatic generation control system that exists in each control area and must be available within five minutes. It is requested according to the merit order in the zone which is responsible for the frequency deviation. Secondary control reserve is tendered weekly for the peak- as well as for off-peak intervals individually for positive and negative power. Minimum size is 5 MW. Bids are selected according to the lowest power prices, for equal power prices by the lower energy price. A price for the contracted power (EUR/MW) is paid for the tender period, independent of the usage. For the actual use, an energy price is paid (EUR/MWh). Compensation is again according to the individual bids.

Minute / Tertiary Control Reserve

Minute control reserve [45] is manually activated by the TSO. It must be available within 15 minutes. It is procured through a daily tender, individually for positive and negative power for a 4-hour interval. Minimum size is 5 MW. Compensation is analogous to the secondary control reserve.

Table 2.2 provides an overview over the characteristics of the three reserve services. In order to reach the minimum size for participation, operators can pool several installations within the zone of a TSO.

Service	Tender	Interval	Power	Size	Activation	Compensation
Primary Control Reserve	Weekly	1 Week	Positive + Negative	1 MW	<30 sec automatic	Pay-as-bid: Power
Secondary Control Reserve	Weekly	1 Week, Peak / Off-Peak	Positive, Negative	5 MW	<5 Min automatic	Pay-as-bid: Power and Energy
Minute Control Reserve	Daily	6x4 h	Positive, Negative	5 MW	<15 Min manual	Pay-as-bid: Power and Energy

Table 2.2: Control Reserves

Non-Compliance with the Contract

In case of non-compliance with the contract, the compensation is reduced according to the non-availability of the contracted reserve [41], [44], [45]. In the case of repetitive non-availability, the compensation reduction according to the previous rule is multiplied by 10 for the primary and secondary control reserve. For the minute control reserve, penalties are imposed depending on the current market prices in order to avoid an opportunistic participation in the real-time markets. In the case of insufficient provision of power and repetitive failure, the penalty equals three times the missing power reserve multiplied with the day-ahead market price during the relevant period. In the case of insufficient reserve provision during an event, the penalty for the non-delivered energy equals the maximum of either the highest accepted bid for the provision of the reserve or three-times the day-ahead market price. In addition, the provider is liable for potential replacement cost. Furthermore, in case of repetitive failure to deliver the contracted reserve, the required prequalification for the tender participation can be withdrawn, effectively excluding the agent from further participation in the market.

2.2.4 Electricity Price Forecasting and Modelling

Research on electricity price forecasting and modelling is relatively recent due to the young nature of electricity markets, which came only into existence with the liberalization of power systems. Unfortunately, forecasting and modelling approaches from other markets cannot easily be transferred due to the different nature of products. Some of the attributes, which distinguish electricity from other commodities, are [46], [47]:

- the lack of economic storability for large quantities, which results in the requirement for a constant balance between supply and demand,
- strong seasonal and cyclic demand,
- inelastic demand and a
- oligopolistic supply side.

Due to these attributes, electricity prices exhibit several characteristic properties [47]:

- multiple seasonal patterns over the course of a year, a week and a day,
- mean-reverting behavior with a strong rate of reversion,
- high level of volatility,
- occurrence of spikes and jumps both up- as well as downwards and
- negative prices.

Forecasting and modelling of electricity prices is further complicated due to the large number of potential fundamental drivers and their varying influence [48]. In their literature review, Aggarwal et al. [46] identified 40 different influence factors, with the most common ones being previous day electricity prices, (historic) demand, available capacity, temperature and fuel prices.

Weron [48] reviews and discusses various approaches for electricity price forecasting. They find that nearly all previous studies employed an individual classification and suggest a subdivision of forecasting approaches into the following five categories:

- multi-agent models, which compromise all approaches simulating the actions of market participants;
- fundamental models, considering the interaction of physical and economic variables;
- reduced form models, which simulate electricity prices by means of their historic characteristic evolution;
- statistical models, which utilize statistical relations between demand and prices;
- computational intelligence models, which summarize all approaches capable of adapting to complex systems.

In reality, however, many publications relay on multiple techniques in parallel to improve forecast accuracy. Contrary to the other approaches, reduced form models are usually not employed for deriving accurate forecasts for a given point in time, but to replicate the typical behavior of electricity price evolution [48]. Hence, they are less suited for actual dispatch decisions but ideal for risk-management and financial evaluation purposes. The following discussion therefore focuses on this subset of forecasting models.

Bierbrauer et al. [47] compare the performance of several one- and two-factor models. Their results indicate that regime switching models outperform regular mean-reverting and jump-diffusion models. Keles et al. [49] confirm the result, concluding that a regime-switching approach is able to resemble the jumps most accurately and therefore delivers the best results. Both publications were looking at electricity prices from the EEX. However, performance of models can differ substantially across different markets [46]. Therefore, Weron [48] concludes his review saying that "[…] at least at this stage, it seems unlikely that there exists any one model that would systematically outperform other models on a consistent basis." [48]. This view is shared by Aggarwal et al. [46]. The comparison of different approaches is further complicated by the lack of a common evaluation framework as well as different error benchmarks [48].

So far, only a few papers about the modelling and forecasting of prices for the ancillary services market have been published. Weron [48] highlights that the price characteristics of ancillary service markets differ from the characteristics of the day-ahead market, notably a higher variability as well as more frequent and extreme spikes. Hence, individual models are required to capture these unique characteristics.

2.3 Business Case for Energy Storage Systems

2.3.1 General Aspects

Due to recent technical advances, increasing commercial availability and declining cost of EES systems, electricity generators as well as consumers are becoming increasingly interested in their application. However, many prospective investors are struggling to quantify the associated benefits in order to evaluate the storage device and determine its economic viability. Therefore, it is important to first understand the potential applications of storage and its value generation.

EES systems can be beneficial in numerous ways, depending on their performance characteristics and their usage. In discussions with 30 different stakeholders from relevant sectors, Grünewald et al. [5] collected more than 100 potential benefits associated with the presence of storage in an electrical grid. The majority of them was concerned with system operation, followed by cost, consumer benefits and security / resilience. Financial benefits from storage applications exist in the form of revenues, cost reductions or avoided cost [50].

According to [50], a specific purpose of storage is termed as “application”. However, there exists no consistent definition of applications in the literature and terminology varies widely across publications [26]. Eyer et al. [50] list 13 different storage applications, grouped into the three categories “Grid System” (for example bulk time shifting of energy, provision of ancillary services and several transmission grid applications), “End-user / Utility Customer” (for example individual time shifting of energy, demand charge management) and “Renewables” (for example capacity firming). Byrne et al. [51] suggest to classify storage applications in four categories: “Bulk Energy” (storage for electric energy time shift, such as arbitrage or renewable energy integration), “Transmission and distribution services” (storage for upgrade deferrals and voltage support), “Reserve services” (storage for provision of reserve and frequency regulation) and “Customer” (storage for power reliability and quality). Schoenung [28] differentiates between long- and short-duration storage applications, with either frequent or infrequent charge cycles.

Further potential applications are listed by the authors of [17], [21], [23], [26], [52]. The majority of them fall into one of the following categories:

- Short-term power supply: during a power outtake or scheduled maintenance, storage can act as uninterruptible power supply for short timeframes.
- Integration of renewables into the grid: storage devices can smooth the delivery of power as well as minimize power curtailment, thereby increase the value of renewables.
- Transmission and distribution upgrade deferral and substitution: storage installations can reduce the requirement for new infrastructure as well as increase the lifetime of existing devices by reducing peak loads.
- Time shifting: storage allows shifting energy consumption from expensive peak-periods to cheaper off-peak periods.
- Peak shaving: storage can reduce the maximum instantaneous power consumption from the grid.
- Ancillary services: storage devices have shown to efficiently provide spinning or capacity reserves and are already being used to ensure power quality and frequency control.
- Electric mobility: besides stationary usage, batteries can also be employed in mobile equipment. Most commonly, they provide the required energy in electric or hybrid vehicles.

2.3.2 Ownership

The liberalization of electricity markets enabled the participation of private agents. While both utilities as well as private agents are usually profit oriented, storage investments might be undertaken due to different motivations. When considering an investment, utilities typically also have a strong technical interest, such as infrastructure concerns or voltage regulation, which are usually of no concern for a private agent. Depending on the installed storage device and its primary purpose, further benefits beyond the intended usage could accrue [9], [10], [17]. However, some of those benefits are not explicitly recognized or compensated. Hence, not all benefits can be internalized and therefore the full value of storage cannot be accessed by all owners. The ability to accurately estimate the full theoretical value potential of a storage system varies according to the ownership.

Chang et al. [53] differentiate between merchant values, which are potential profits that can be captured by a private investor, customer benefits, which result in energy bill reductions, and societal benefits, which are system-wide cost reductions. Eyer and Corey [17] mention the integration of renewables, reduction of emissions from traditional load-following generation and improved utilization of grid assets as benefits which have a clear societal value, but which typically cannot be internalized. Sioshansi et al. [10] show that the installation of storage for arbitrage operations could generate welfare effects for customers, as the electricity cost for consumers would decrease if the diurnal spread is reduced by the deployment of storage. However, profits of generators would decrease as well as the profitability of the arbitrage strategy. Furthermore, the authors argue that storage systems could provide additional benefits such as deferred investment requirements or improved usage of existing transmission systems [10]. The way how a storage system is operated can also influence its societal value. Marra et al. [54] as well as Hollinger et al. [55] find that storage can help preventing overvoltage situations in low-voltage grids with a high PV penetration during peak generation periods, if the charging algorithm is amended. This is not only beneficial to the Distribution System Operator (DSO), as less investments are required, but also to society, as a higher share of photovoltaic generation can be integrated into the network and lower distribution usage fees will be paid by consumers. The authors of [56] suggest that a storage device installed at a consumer location can also provide backup power in case of a grid failure. While this certainly has a value to the client in case of a power loss, it is difficult to associate a financial value to it, as it is very case-specific and will depend on various factors such as the duration of the interruptions and the type of usage.

Depending on the regulatory framework, these external benefits can typically not be monetized by a private agent, as no market or price for them exists. The profitability threshold for private agents is therefore higher as compared to utilities, who might be able to capture some of these benefits and fully estimate the associated economic profit. The authors of [21] conclude that the consideration of all theoretical benefits would therefore increase the economic incentives and potential profitability and hence make storage more attractive. Eyer and Corey [17] follow these arguments. Even though the cost for a storage system may exceed the profits that can be internalized, from the perspective of society it might be beneficial as usually additional values can be realized. Lawmakers and regulators therefore play an important role in the development of the storage market.

In order to identify all potential benefits, Byrne et al. [51] suggest to first assess a baseline scenario without storage installations. Thereafter, storage installations should be included and all monetary benefits estimated. The remaining difference will be due to non-monetary benefits. However, according to the authors, such an approach would require the modelling of the complete electric network and hence becomes very complex.

2.3.3 Analyzed Applications

The following analysis will concentrate on those applications which are accessible to a private agent and which offer sufficient revenues that can be internalized. Therefore, only applications with direct monetary benefits to the investor or benefits for which a market or price exists will be considered.

Indirect benefits (such as a deferral of grid investments) or benefits for which no monetary value can be determined (such as power backup in case of a grid failure) will be neglected.

Based on above criteria, the following applications have been identified from the literature as commercial business cases for storage and will be reviewed in detail in the following sections:

- Storage for arbitrage purposes (Section 2.3.4)
- Storage for time shifting of energy at the consumer site (Section 2.3.5)
- Storage for the provision of ancillary services (Section 2.3.6)

Generally, a wide range of economic results was found in the reviewed literature. This appears to originate mostly from differing deployment contexts and technical as well as financial assumptions.

2.3.4 Arbitrage

Arbitrage describes a trading strategy where a market participant tries to exploit price differentials ([8]–[10], [13], [57]–[60]). Generally, arbitrage refers to the buying and selling of a product at different prices and can be applied to spatial and / or temporal scales. Spatial price differences can occur between two different market places, when electricity prices for a particular time period are lower in one market than in the other market. The trader can make a profit by purchasing at the cheaper market and simultaneously selling at the more expensive market. However, the difference must outweigh interconnection costs and losses to be profitable. Arbitrage can not only take place between different markets, but also between forward and spot markets for the same time period. Storage is only required for inter-temporal arbitrage. In this case, the trader would purchase energy, store it and sell it back at a later point in time. Arbitrage profits are therefore the revenues from selling energy to the grid (discharging the storage system) minus the cost for the previous charging cycle (purchasing energy from the grid), taking into account efficiency losses, self-discharge and capital cost for the storage system.

In commodity markets, the storability provides usually a natural link between spot and forward prices [61]. As electricity cannot be easily stored in adequate quantities, no such relation exists. The requirement of instantaneous balancing between supply and demand combined with the increased reliance on intermittent, variable energy resources such as PV and wind leads to volatility and price spikes. This fact, combined with the mean-reverting properties of electricity prices as well as periodic price behavior due to consumption patterns (diurnal, weekends), makes the electricity markets attractive for arbitrage considerations.

Looking at the prospects of additional PHS installations in Germany, Steffen [62] finds average annual potential revenues of 59 380 EUR per MW of installed capacity, ranging between 32 740 EUR and 88 230 EUR for the years 2002 - 2010 for the German market. However, given the high required investment cost, he concluded that the expected profits are not sufficient to justify a commitment by a typical utility. This view is shared by Kloess [63], who analyzed potential arbitrage profits in the Austrian market from 2007 - 2011 utilizing different technologies. He found declining revenues over the years. Pumped Hydro Storage was the most attractive storage system, but also did not break-even. Zakeri and Syri [64] looked at arbitrage in the Finnish market from 2009 - 2013. However, they found that none of the analyzed technologies was operating profitable and that annual profits show a high variability. According to their data, Pumped Hydro Storage was the most attractive technology with average potential benefits of 14 700 EUR per MW of installed capacity. The authors of [17] estimate an annual profit of 60 000 USD - 100 000 USD per installed MW, but they only look at one year of historical data, one market and assume perfect knowledge of prices. Yucekaya [65] looks at the application of CAES for arbitrage profits in the Turkish markets. He finds it is sufficiently profitable to justify an investment. He and Zachmann [60] are looking at arbitrage profits across three different markets, when varying the size of the storage system. They find a strong dependency on the size of the storage system, but none of their analyzed systems were able to break-even in three considered markets. Looking at arbitrage profits in the UK market, Barbour et al. [66] determine a significant variance in annual arbitrage revenues. While the authors did not calculate any cost, annual revenues dropped by 75% over the course of two years. High variations between annual profits were also found by Woo et al. [58]. Sioshansi et al. [10] determined intra-day price swings as major value driver. Bradbury et al. [57] look at arbitrage profits that can be obtained by different storage technologies in real-time energy markets, finding that not all technologies are suitable or profitable for arbitrage purposes. They see the biggest potential for PHS, CAES and ZEBRA batteries.

For markets with a high share of intermittent energy sources, forecasts might provide valuable insights for arbitrageurs [9], as peak and least cost periods can be more precisely defined. Furthermore, due to the required instantaneous balance between electricity supply and demand, unexpected negative deviations from the forecasted supply of energy would require the short-term scheduling of peaking generators to provide the shortfall in energy, which would most likely cause a rise in real-time prices. While this opportunity cannot only be exploited by storage operators, it would probably create advantageous conditions for the application of arbitrage in these particular markets.

2.3.5 Time Shifting of Energy

The term “time shifting” is broadly used in the literature to describe applications where storage is being employed to shift energy from one time to another. Contrary to arbitrage, time shifting applications are associated with energy consumption, where the system is typically installed at the consumer site. The primary interest is therefore not to benefit from price differentials, but typically to reduce the electricity bill.

In general there are two ways how grid-connected consumers can reduce their electricity bill [67]: reducing energy charges or reducing peak power demand, if a charge for the latter is applied. The first refers to shifting demand to hours when lower prices persist. Therefore, a storage system is charged during low-price periods from the grid. During periods with high grid charges, storage is then discharged to satisfy local demand. Contrary to demand side management, the consumption pattern therefore does not have to be changed. Peak power demand reduction refers to lowering the connection capacity required with the grid. Therefore, demand which exceeds a certain threshold is satisfied by discharging a storage system. The storage device is then recharged during times with lower demand to not exceed a certain power threshold.

For consumers with a local generation resource such as a photovoltaic installation, there exists another approach. Depending on the metering scheme, electricity from PV installations is typically fed into the grid at a more or less unattractive feed-in tariff, and must be later purchased back at a more expensive tariff. In that case, storage could be beneficial if the surplus generation, which was previously fed into the grid, is now stored for later self-consumption.

Time Shifting of Distributed Generation

The most widely considered case in the literature is the time shifting of locally generated energy for later consumption. Agents with own electricity production might be able to benefit from not feeding their excess electricity into the grid, but to store it for their consumption during later hours. This might be especially interesting for residential consumers with photovoltaic installations, as there is usually a significant spatial mismatch between generation and consumption of electricity over the course of a day [11], [12], [68]. A storage system would allow these “prosumers” [69] to align the generation from the PV system more closely with own demand, as excess generation which typically occurs during midday and afternoon could be stored for consumption during evening hours. The viability of such a strategy however depends highly on feed-in tariffs as well as electricity prices and related charges. However, if high retail rates apply and feed-in tariffs decrease, the installation of storage for self-consumption might be the economically most attractive application case for storage [11].

In this context, the concepts of self-consumption ratio and self-sufficiency are of interest [70]. The first describes how much of the locally generated electricity was consumed on-site (both for matching instantaneous demand as well as for storing), whereas the second one describes how much of demand was matched by local generation. For a system without storage, a rise in one figure usually leads to a reverse reaction of the other figure [71]: an increase in installed generation capacity typically increases self-sufficiency, whereas the percentage of self-consumed electricity will typically decline as more excess power will be fed into the grid. On the contrary, the installation of a storage device allows the storage of surplus generation for later consumption, thereby typically increasing both the self-consumption ratio as well as the self-sufficiency. Sizing of the installation therefore plays an important role. The determination of the optimum installation capacity has been analyzed for example by [11], [12], [72], [73].

The authors of [74] find that the self-consumption of PV generated electricity for a typical household can be increased from 20-40% to 40-96% by adding a storage device. Weniger et al. [73] confirm these numbers. They determined a self-consumption rate as well as a degree of self-sufficiency of about 30% for a single-family household, if 1 kW of PV capacity would be installed for every MWh of annual electricity demand. Installing a storage system with a capacity of 1 kWh per 1 MWh annual electricity demand increased these numbers close to 60%. Conducting a sensitivity analysis, they concluded that battery capacity beyond 1.5 kWh / MWh of annual electricity demand and above 2 kWh / kW of installed PV capacity only leads to insignificant improvements in self-consumption as well as self-sufficiency.

Weniger et al. [73] conclude that the installation of storage systems is not yet profitable. However, assuming rising grid electricity rates as well as declining equipment cost, they expect them to become the most cost effective solution in the long-term. Werner et al. [75] compare the cost for combined storage and photovoltaic systems for residential self-consumption for different countries. The authors state that the "Most attractive markets are those, with a large spread between PV and grid electricity cost." [75]. They identified Germany and Italy as the countries to first reach grid-parity. In other countries, like the U.S. or Japan, they found that it is more beneficial to install only a PV system. The potential of storage to reduce residential electricity costs is also analyzed by Braun et al. [12]. They are maximizing the self-consumption of electricity from a photovoltaic installation by installing a storage system, determining a break-even after 15-20 years. Wang et al. [68] find that the addition of a storage system to an existing PV installation can reduce the break-even time of the overall system by up to 30%.

Furthermore, storage devices could also help producers to not exceed feed-in limitations. Feed-in power limitations for PV installations are in the interest of policy makers and grid operators, as they relief the grid during peak feed-in hours and therefore allow accommodating more installations in the same network without reinforcements. However, storage installations for self-consumption are typically charged as soon as excess generation is available. Even though this operation policy maximizes self-consumption, it is not necessarily the optimal strategy, as the storage device might be fully charged before peak generation occurs. If there exists a feed-in limit, some energy might be lost as it can neither be stored nor feed-in. An economic optimal operation strategy should therefore not only consider maximizing self-consumption, but also minimize time during which feed-in is restricted [76].

Schmiegel and Kleine [77] evaluate the upper performance limit of a combined PV and storage installation for self-consumption in the German market, where feed-in restrictions (limitation of the maximum feed-in power in percent of installed capacity) apply. In this context, they found storage installations economic viable. Looking at the optimal dispatch algorithm, they concluded that the storage system is usually charged during the afternoon to avoid curtailment due to the feed-in restrictions, and not as soon as surplus generation from the PV installation is available during the morning. Weniger and Quaschning [78] assume a limitation of feed-in power to 50% of installed capacity, finding a reduction of total feed-in between 13.6% and 15.2%. These losses are reduced to

1.1% with a storage device (with a capacity of 1 kWh per 1 kW), when storage is only charged once the feed-in power limitation is exceeded. However, this would significantly impact the storage operation and reduce the amount of self-consumed electricity, as oftentimes the storage device would not be fully charged until the end of the day. Therefore, the authors suggest incorporating solar forecasts in the charging algorithm. Thereby, they are able to reduce the maximum feed-in power significantly, while still being able to fully charge the storage device to ensure a maximized self-consumption. Struth et al. [79] look at a system with a 60% / 70% feed-in limitation of peak-generation, identifying losses of 4.9% / 2.1%, when the storage device is charged once excess generation is available. According to their analysis, this figure can be reduced to 2.4% / 0.9% when the storage device is operated under a smart regime, considering weather and demand forecasts. However, self-consumption would drop from 54.1% to 52.6%. Moshövel et al. [76] elaborate the concept in more detail. Their model calculates a feed-in power-limit above which all energy is stored. This limit is defined with regards to the remaining battery capacity and expected remaining excess generation over the day, and constantly updated to account for forecast uncertainty. Looking at their results, the value of a good forecast becomes obvious. Considering a feed-in limit of 55.5%, maximizing self-consumption would achieve a self-consumption of 54%, but would also lose 6.5% of total generation. A forecast based on previous day’s data would achieve a self-consumption of 49.6%, with annual losses of 2.1%. In contrast, a perfect forecast would achieve a self-consumption of 53.2%, while only 0.1% of annual generation would be curtailed.

Most papers analyze the application for a single residential dwelling, whereas Parra et al. [80] analyze a storage device installed in a community. A similar approach is pursued by Zucker et al. [81], who assume that an aggregator is optimizing the interaction with the market. Besides a report by Willborn et al. [82] looking at the economic attractiveness of only a photovoltaic system for self-consumption, no publication was identified that considered a storage installation for commercial clients. The authors found that self-consumption of locally generated electricity is beneficial from an economic point of view for only some commercial clients. The attractiveness depends strongly on the tariff (especially taxes and network fees) that must be paid by the considered consumer.

While most authors look at lead-acid or lithium-ion batteries, Parra et al. [83] also consider hydrogen storage for self-consumption of electricity from PV generation. Despite its technical viability of increasing self-consumption over the mid-term (defined as three days), the authors find that the low efficiency of the process still penalizes the attractiveness of hydrogen storage. Furthermore, it can also not resolve the mismatch between lower generation and higher demand during winter-times, which is typically observed at higher latitude areas.

To increase the self-consumption of PV generated electricity, the authors of [72] consider storage as well as simultaneously apply active demand-side management. However, they conclude that the effect of demand-side management disappears with increasing storage capacity and become insignificant when the storage capacity exceeds typical daily demand.

Postponing the charging of a storage device could not only be of interest when reducing the maximum feed-in power, but also when considering the opportunity to sell excess generation to the market [78]. In many countries, distributed generation resources are still supported by feed-in tariffs, which will expire at some certain point in time. Thereafter, PV owners might be required to sell excess generation to the market. Based on solar yield and market price forecasts, excess PV generation could then be stored during hours with low market prices and sold to the market when prices are more favorable.

Time-of-Use Tariffs

Instead of charging the storage device with energy from local resources, energy can also be taken from the grid. Such an approach can be economic interesting if there are financial incentives such as under a time-of-use tariff. Under such a scheme, electricity prices during off-peak times are usually reduced at the cost of higher prices during peak-times. Consumers, who can shift some of their demand to the low-price periods can benefit from such a tariff. Given such a tariff, storage systems could be charged when off-peak prices apply. Local demand during peak-price periods would then be satisfied by discharging the storage devices [50]. Savings in the tariff must compensate both efficiency losses as well as investment cost for the storage device in order to be economically interesting.

Ahlert and van Dinther [84] consider storage in a residential setting, where energy is purchased during off-peak times and consumed locally during peak-times. In their optimistic case, such an application would be profitable. Dufo-López and Bernal-Agustín [85] look at a commercial client for the same application. They find that even a price difference between on-peak and off-peak prices of 0.135 EUR/kWh is not sufficient to make such an application profitable. They conclude that storage cost must decrease by a factor of 2-3 to break-even. Ahlert [86] states that benefits for a storage device typically increase with an increasing number of price blocks per day, as the storage device can be charged in timeslots with particular low tariffs. He finds savings of up to 17%. Carpenter et al. [87] analyze different pricing schemes. They conclude that time shifting can only be applied profitably under an extreme tariff, which offers strongly reduced off-peak prices. Carpinelli et al. [67] determine the optimal size of a storage installation at an industrial consumer site to reduce electricity cost. While they conclude that an installation would currently not be advantageous, they expect them to become so once investment cost declines. In a different paper, Carpinelli et al. [88] compare the storage economics for residential and commercial consumers. Considering a time-of-use tariff with three price levels and a maximum price spread of about 0.40 USD/kWh they determine a break-even point for the storage installation cost of 700 USD/kWh. Schmiegel [89] compares three electricity tariff regimes, considering residential consumers with a PV installation. The first tariff is a fixed rate, both for consumption as well as feed-in. The second tariff differentiates between day- and night, and the third tariff is variable along the year, depending on demand and supply in the grid. The author shows that an optimized storage operation can benefit from time-dependent tariffs.

Byrne and Verbic [90] analyze the economics of a residential battery storage system for price arbitrage in Australia. Their main objective is shifting electricity consumption to off-peak-times, when having access to a tariff with price differentiation for peak- and off-peak-times. Residual stored energy is feed back into the grid, if economic advantageous. Using Monte Carlo simulation to account for variable household demand, they find the application of batteries to shift load to off-peak times economically viable. Another idea is presented in [56]. The authors suggest that consumers with a storage installation could switch to a tariff giving the utility the right to curtail power for several times during a year. During these periods, power supply would be guaranteed by the storage device, with the benefit of having a reduced electricity tariff.

Peak Demand Charges

Storage devices can also be utilized to reduce peak power demand charges. Therefore, a local storage installation can provide power in order to level out demand peaks and reduce the maximum power demand from the grid [52].

In order to reduce peak demand of a distribution grid, [91] determined the required storage capacity which minimizes power fluctuations during the day. For their reference case they found a peak demand reduction of 29%. Purvins et al. [92] identified potential peak demand reductions of between 27-44% (47%, if a PV system is installed in parallel) for residential consumers in several European countries. Reductions in peak-demand are also found by Wang et al. [68].

Zheng et al. [93] conclude that peak shaving can be financially attractive for clients charged for their maximum power demand. Looking at residential consumers in the U.S. and several technologies, they determined annual cost reductions of up to 39%.

However, careful attention must be paid to the modeling as optimization takes place not for cumulative sums but for the maximum [94]. In addition, a reduction in the demand charge typically leads to an increase in energy charges, as the demand is only temporarily displaced and storage charge- and discharge cycle suffer from efficiency losses [50], [93]. Demand in other periods will therefore increase as compared to the initial state.

2.3.6 Provision of Ancillary Services

Another storage application that is interesting from a commercial perspective is the provision of ancillary services ([8], [9], [13], [59], [95]). Ancillary services refer to a range of services that are usually contracted by the Transmission System Operator to ensure the stability of the grid and the security of supply, such as control reserve (see Section 2.2.3).

Looking at the profitability of the provision of ancillary services by storage in the German market, Steffen [62] found especially attractive the provision of negative reserve power during the night. Average annual remuneration from 2008 - 2010 would have been 83 076 EUR / MW. Comparing these returns to potential revenues from pursuing arbitrage, the author found them to be more attractive. Zakeri and Syri [64] compared the revenues for the Finnish market. They also found the balancing market more interesting. However, the determined potential profits (on average, 43 200 EUR / MW annually) would still not be sufficient to cover cost and therefore justify an investment. They also found a high variability of returns over the analyzed timespan from 2009 - 2013. Kloess [63] finds that the provision of secondary reserve appears to be the most promising ancillary service in the Austrian market. However, due to the high penetration of pumped hydro storage, he concludes that revenues would likely be low and uncertain. He et al. [59] analyze the provision of tertiary reserve under a long-term contract in the French market, finding it highly attractive. Walawalkar et al. [9] compared the provision of ancillary services with an arbitrage strategy. While they determined higher profits, they also found them more uncertain.

Pesch and Stenzel [96] conclude in their analysis of the German market conditions regarding storage that for the provision of ancillary services by battery storage systems a change of the market framework is required to reduce capacity requirements as well as minimum operation time. Weber et al. [97] find revenues from the provision of ancillary services very interesting, but caution about their future availability due to potential market design changes. In addition, increasing competition both by more market participants as well as international cooperation in the procurement and utilization of ancillary services might decrease available revenues. Nailis et al. [98] also caution to rely on revenues from ancillary services. Due to the limited demand for such services and unsecure future development, they should be considered as additional, optional revenue in an investment analysis. This view is furthermore shared by [62], who expect diminishing revenues due to additional market participants.

Furthermore, as mentioned among others by [20], [99], [100], storage is just one potential provider of ancillary services and “does not hold a monopoly” [5] on them. It competes with other (potential) providers of flexibility, such as traditional generators or flexibility from demand-side-management. The recent popularity of electric vehicles provides additional agents, who could participate in the market for ancillary services [101]. Furthermore, storage systems are “energy-limited” [51], that is they have a limited energy capacity whereas traditional generation is only limited by fuel availability. On the contrary, storage systems are unique in their ability to provide as well as consume both active and reactive power. Furthermore, depending on the technology, their response times are very fast and accurate [51].

2.3.7 Integration of Multiple Value Streams

By combining and integrating several activities, storage systems could theoretically serve more than just one purpose and capture multiple value streams [8], [17], [21], [102]. Storage systems dispatched for example for arbitrage operations spent much time idle, waiting for the next charge- or discharge opportunity [10]. This time-span could be profitably used to provide additional services. Yet, most authors consider only an individual value stream in their analysis ([9], [10], [57], [58], [83], [90]). Sioshansi et al. [10] conclude that any analysis which considers only a single source of revenues “is likely to significantly underestimate the value and social benefits of energy storage". Xi et al. [103] even calls the consideration of multiple uses "critically important".

Therefore, by combining multiple value streams, agents can lower the profitability threshold for a storage system and achieve economic viability earlier. However, the combination of two or more value sources is complex as the interaction and interplay between different applications must be considered. As this will usually require tradeoffs, the results are subadditive [103]. In order to avoid "double-counting" [51] of benefits and an inflated valuation, the modelling and scheduling of the services becomes therefore even more important, as operational and regulatory requirements must be satisfied. Contractual obligations especially for ancillary services must be abided, as otherwise penalties might be imposed and future access to these markets might be limited. Furthermore, system services might have technical requirements and restrictions limiting the usage of the storage device for additional value streams [60], which must be considered in the evaluation.

Kazempour et al. [13] compare the economics of a sodium-sulfur battery and a PHS systems, when simultaneously participating in day-ahead energy markets for arbitrage as well as providing spinning reserves and regulation. Assuming perfect price foresight, the authors are able to combine the different value sources in their optimization, ensuring that the interdependence between the different strategies are observed. They find both storage technologies economic viable, with a financial advantage for PHS systems. However, they did not analyze the individual value streams in order to determine the added value of combining multiple services. He et al. [59] look at the potential profits of a CAES participating in both ancillary service markets (under a long-term contract as well as with short-term commitments) and doing arbitrage. They optimize the dispatch with known future prices, warranting the contracted services and complying with all operational constraints. The authors find a positive value contribution by participating in additional markets. Nonetheless, the overall result is slightly negative under their assumptions. Drury et al. [104] evaluate a CAES plant, which is pursuing arbitrage as well as providing ancillary services. They find that a CAES plant only pursuing arbitrage would not break-even, but becomes profitable if it is dispatched for both applications. Looking at several U.S. markets, annual arbitrage-only profits ranged from 15 000 USD to 120 000 USD per MW. Value added from the co-optimized operation averaged from 10 000 USD to 30 000 USD per MW and year. Keles et al. [105] simulate the dispatch of a CAES plant for both arbitrage and ancillary services. However, they used simulated prices instead of historical data. They find the application profitable (internal rate of return of 5.69%), but conclude that the return will not be lucrative enough for typical utilities. However, they applied a very conservative approach to evaluate the compensation for the provision of ancillary services. The authors do not provide a further break-down of value contribution by the two applications. The simultaneous implementation of arbitrage and provision of ancillary services is also analyzed by Kazempour et al. [106] as well as by Goebel and Jacobsen [107]. Both publications show that the majority of profits is generated by the provision of ancillary services, whereas the arbitrage operation is hardly breaking even.

Xi et al. [103] combine various applications step-by-step and evaluate the value added. In their reference case – pursuing arbitrage – they find a weekly revenue of 1.85 USD for a battery capacity of 11.2 kWh. Next, they included the provision of backup-energy in case of grid-failure. Therefore, a minimum battery charge level had to be maintained, which reduced the capacity available for arbitrage operations and hence had a slight negative effect (-0.01 USD) on weekly arbitrage revenues. However, this was more than offset by the estimated benefits of the provision of backup power (+0.20 USD). The authors also added the provision of ancillary services, which increased profitability strongly (+23.90 USD) at the cost of less profits from arbitrage operations (-0.60 USD). Their co-optimization of storage operations ensured that services are not simply stacked, but jointly incorporated and competing by their value contribution. However, they assumed that not providing ancillary service has no further consequences to the provider other than an associated penalty.

The vast majority of the existing literature is focused on combining arbitrage and the provision of ancillary services. Zucker et al. [81] consider a storage installation, which is time shifting PV generated electricity to avoid curtailment. By also incorporating arbitrage operations, they found a significant enhancement in profitability. Another approach is mentioned by [50], who suggest that storage employed to reduce demand charges can also easily be used to take advantage of time-of use tariffs and time shift some demand. Hollinger et al. [55] propose that storage systems installed for self-consumption of PV electricity can also provide a range of ancillary services. Another promising approach is the switching between strategies. For example, it might be worthwhile for a storage operator, who is usually providing ancillary services, to engage in arbitrage during times of high price volatility.

Loevenbruck [108] suggests to attach a priority to each application operating process to define a ranking in case of operational conflicts. If two applications are posing a request which cannot be fulfilled by the storage system due to technical limitations, the application with the lower value would then be withdrawn. Looking at two different system combinations, he finds that the loss of value due to the priority order is limited, but does not provide detailed insights. Furthermore, he remarks that the provision of ancillary services cannot easily be combined with arbitrage activities, as the latter originates on a regular basis large variations in the state of charge. Therefore, at times not sufficient capacity can be guaranteed to provide the contracted ancillary service.

He et al. [109] suggest to use a chain of auctions over different time horizons to sell the available energy and power capacity of the storage system to several actors. Furthermore, they present a coordination mechanism which ensures the technical and operational compatibility between the different uses. They find, that the aggregation of different value streams is possible from a technical perspective as well as identify a significant increase in value versus dispatching the storage only for one individual application.

2.3.8 Role of Aggregators

As the previous section indicates, storage owners might increase their revenues by participating in the market, for example small-scale storage systems deployed for time shifting of energy might benefit from simultaneously offering capacity in the ancillary service market. However, many installations do not fulfill the capacity requirement for a direct participation. A possible approach is the aggregation of many small storage installations to a pool, until sufficient capacity is available. Such a solution for example is foreseen in the regulations for provision of primary reserve control in the German grid area (see Section 2.2.3). The existing literature on aggregators for distributed storage installations is however very limited.

Zucker et al. [81] consider an aggregator, who is optimizing the interaction between photovoltaic generators, equipped with a storage system, and power wholesale markets. Their approach foresees, that the storage systems are dispatched by the aggregator according to price signals. The authors consider three different models: first, the aggregator dispatches storage in order to sell PV generated energy on the market at more favorable prices; second, the storage systems are dispatched in order to store otherwise curtailed energy; and third, storage is used to supply a portfolio of PV-equipped households. However, the authors focus on the economic evaluation and do not further elaborate the responsibilities of the aggregator.

Michiorri et al. [110] as well as Foggia et al. [111] consider a smart-grid demonstration project located in the south-east of France with a high share of PV installation. In order to address network congestion problems, primary objectives were a demand reduction during the winter, reduction of PV-induced overvoltage issues and in addition also the ability for islandic operations. To avoid reinforcement cost for the grid, the authors suggest a market design where both flexible loads as well as storage systems are considered to increase / decrease load. The storage systems however are not directly controlled by the DSO/TSO, but operated by storage aggregators, each of them managing a series of batteries of different capacities and technologies. On a periodic basis, the TSO/DSO would run a tender for which aggregators can submit bids depending on the available capacity and state of charge of their operated batteries. The TSO/DSO then selects from the submitted bids, minimizing its overall cost function and ensuring that grid constraints are not violated. While the authors propose an approach how a portfolio of storage systems can be managed by an aggregator, only active power as well as a dedicated usage for grid operations has been considered. As the economics of storage were not considered, no statement about its financial attractiveness can be made.

A range of researchers have looked at the aggregation of electric vehicles. Bessa et al. [112] provide an overview over the role of an aggregator of electric vehicles and how such an agent can interact with electricity markets. However, it becomes obvious that the transferability of results is limited due to restrictions resulting from the intended different primary usage of these storage systems (for example, a full state of charge in the morning is oftentimes required for electric vehicles) and their spatially uncertain and limited availability (such as an availability oftentimes only during the night). The participation of the aggregator in the ancillary services market however appears promising. In a different publication, Bessa et al. [113] analyze a scenario, where the aggregator buys electricity in the spot market and controls the charging of the electric vehicle. They find that this significantly reduces cost versus a strategy, where clients start charging once they return home. Above all, they find that the aggregator can generate additional benefits by participating with the fleet of electric vehicles in the ancillary services markets. These benefits can then be used to offer a subsidized electricity rate for the original charging process.

2.3.9 Investment Cost

Zakeri and Syri [114] look at the cost of different storage technologies, differentiating between capital and lifecycle cost. They summarize under capital cost not only the cost for the equipment, but also for planning, installing and connecting the storage system. Lifecycle cost represents all expenses that occur during the lifetime of the storage system, such as maintenance, replacement and disposal. In their review of actual costs for different storage systems they find a high variability in the literature. This is also found by Battke et al. [26]. In their comparative lifecycle cost review they state that even for similar application cases "[…] the resulting lifecycle costs still vary considerable.". A similar analysis, restricted to battery storage systems which are commercially available, was conducted by [71]. In their review of distributed energy generation technologies Allan et al. [115] find that the economics of installations cannot be generalized. Instead, they identified a strong sensitivity to the deployment context. Furthermore, they also highlight the wide range of used approaches to evaluate the projects.

The authors of [116] indicate that the cost for the battery constitutes about 50% of overall installation costs. Operation and maintenance cost for most systems are typically well below their capital cost (for example in [13], a sodium-sulfur battery is assumed to have variable costs of 1.3 – 4% of total capital cost per annum, with an estimated lifetime of 12-20 years).

2.3.10 Regulatory Framework

Anuta et al. [117] conclude their review of international regulatory frameworks for storage with several recommendations: first, the alignment of renewable and storage policy. Today, under most frameworks, no incentive for storage investment exists due to the feed-in priority as well as the compensation scheme of renewables. Second, the classification of storage as an additional asset class with very specific characteristics. The lack thereof makes storage being subjected to different charges, depending on whether it acts as generator or load, and oftentimes prohibits its usage by transmission system operators in unbundled markets. Furthermore, the introduction of standardized rules for the operation and usage of storage systems. Besides regulatory aspects, these authors mention a range of market design barriers. Currently, market participation rules are usually adjusted to traditional technologies but do not consider the individual characteristics of storage. Therefore, storage should be allowed to provide several services simultaneously. Ancillary service markets should adapt their requirement to consider storage providers and reflect the quality of service in their compensation.

Furthermore, price caps for market prices should be chosen carefully to still allow sufficient volatile prices to offer sufficient revenues when pursuing arbitrage.

Wilson and Hughes [118] find that most regulatory issues are a result from the missing fit into the traditional classification into generation, demand and transmission / distribution. Continuing with the existing framework requires a fine-tuning of existing regulation, but creates no additional complexity. Alternatively, these authors suggest expanding the classification framework to include specific services, such as a "frequency regulation classification". However, both approaches neglect that storage can provide multiple services, such as a system which pursues arbitrage and provides voltage support, effectively acting as load, generator and transmission facility at the same time. Besides regulatory issues, also competitive issues require an intervention by policy makers so that storage has "equal opportunity to compete in these markets against traditional providers". Today, oftentimes storage is not recognized as a potential provider of a service, technical requirements may exclude storage or the service is not adequately rewarded. Compensating primary frequency control providers not only for power, but also for speed and accuracy could be a step in this direction. These authors conclude that the regulator should ensure that "[…] the most cost-effective option […] is used" by removing "[…] barriers that prevent the fair competition of storage against traditional technologies." [118].

Regulatory and market barriers are also identified by Bhatnagar et al. [119] as key issues which must be addressed in order to allow storage systems access to markets. However, competing interests and complex amendments are delaying the process. Furthermore, these authors caution that market designs might require changes, as systems with low operating costs and high fixed / capital costs (such as most storage technologies) might drive prices in marginal cost based markets to zero. Besides the insufficient provision for the quality of the service provided in the primary control reserve market, these authors also mention the lack of transparent price signals, such as for example for the provision of black-start capability, as an entrance barrier for storage systems.

Schill et al. [4] recommend that policy makers should create the framework in such a way that storage can compete with other technologies and flexibility options on an even playground. Important aspects are for example a market place where storage can participate without discrimination. Price limitations (such as a set maximum or minimum price) or capacity auctions discriminate storage as they reduce the frequency and extent of price peaks. Markets for ancillary services should consider the characteristics of storage, for example for the required minimum capacity and maturity of contracts. In addition, regulations should be harmonized in order to not discriminate different storage technologies.

Krajačić et al. [120] state that "Faster market integration of new energy technologies can be achieved by use of proper support mechanisms that will create favorable market conditions for such technologies." Exemplary, they list feed-in tariffs, green certificates, tendering procedures and taxes as well as investment initiatives as examples for support schemes, which already have been implemented. In a different paper, Krajačić et al. [121] analyze different support options to recover the investment cost for a PHS. Considering the European electricity markets they conclude that "the differences in regulation and market operation and differing conditions on markets create an unstable framework for energy storage" [121]. Furthermore, they find that "there is a serious uncertainty as to how investment costs in energy storage would be recovered" [121]. Therefore, they recommend the introduction of a regulatory framework which gives investors some security about the recovery of their investment cost. They suggest that a supporting scheme should be linked to market prices to guarantee competitive operations.

Hauff and Rendschmidt [122] compare the legal framework and available support schemes for photovoltaic installations for self-consumption in several European countries. Their report shows a very nonhomogeneous situation within Europe, which in some countries favors the installation and in some countries creates a high regulatory burden. They identified barriers that result for example from a missing explicit regulation as well as incomplete market liberalization. The authors of [71] analyze the effect of a subsidy on the profitability of combined photovoltaic and storage installations for residential self-consumption. According to their data, subsidies improve the economic viability significantly. Otherwise, storage systems would only be interesting when expecting high price increases for grid electricity. However, the installation of an individual PV system is still the most cost-efficient investment in most cases.

Chang et al. [53] look at storage installations in Texas and find that currently neither private investors nor grid operators can yet capture sufficient benefits. Hence, investments remain lower than advisable from a societal perspective. In order to incentivize investments by grid operators, these authors therefore suggest to recover investment costs associated with system benefits through a regulated rate and "'auction off' the wholesale market value of distributed storage" [53], for example to a private party utilizing the storage for pursuing arbitrage. However, these authors do not discuss how the arising conflict of interest could be solved when storage is being utilized for more than one value stream (as discussed in 2.3.7).

Current Regulation in Germany

The following review describes the current treatment of storage under German law. The right for grid access by storage devices is granted in the "Law on the energy industry" (EnWG) §§ 17-19 [39]. Storage is not considered as an individual class besides generation, consumption and transportation, but instead regulations depend on the usage. When supplying energy to the grid, storage is subject to the same regulations as traditional generation technologies (EnWG §13 I) and can for example not be shut-down without regulatory notice (>10 MW) / permit (>50 MW) (EnWG §13a, 13b). When taking energy from the grid, storage installations are considered as final consumers of energy and therefore subject to the same taxes and fees as a regular consumer.

While in general the regulations for generation and consumption apply, several laws and ordnances regulate the financial implications of storage operations in specific and grant a range of exceptions [123], [124]:

- For the consumption of energy (the charging of the storage system), no grid fees are charged during the first 20 years for new installations (EnWG §118 VI 1). Additional fees, such as concession fees, are still due. Existing storage systems are relieved from grid fees for 10 years if either their power rating is increased by 7.5% or the storage capacity by 5%. Furthermore, grid fees can be reduced for intensive users by up to 90% according to the "Network tariffs regulation" (StromNEV $19 II 2) [125] and atypical users by up to 80% (StromNEV §19 II 1) in order to incentivize grid beneficial behavior.
- For the feed-in of energy from storage to the grid, no grid fees are due (StromNEV §15 I) [125].
- No renewable energy surcharge is due according to the "Renewable Energy Sources Act" (EEG 2014 §60 III) [126] if energy from the grid is stored and later feed back into the electricity grid. The surcharge is charged if electricity is stored for later self-consumption.
- If electricity generated by renewable sources is temporarily stored before it is fed into the grid, the subsidy is paid nonetheless (EEG 2014 §19 IV) [126]. Efficiency losses however are not compensated.
- No electricity tax according to the "Electricity tax law" (StromStG §9 I 2) [127] is due for the consumption, however the regulation applies only to PHS systems (StromStV §12 I 2) [128].

With regards to time shifting of energy by a final consumer, the major hurdle for a widespread usage of storage is system cost. Due to the subsidy program (discussed in the following section), the regulatory and legal framework has been clarified over the last years and only some detail questions remain. Technical guidelines for the connection and operation of small-scale distributed battery based installations are described in [129].

The business-case of arbitrage has been exploited by PHS for many years and hence it is not a novelty in the electric system. However, the current regulation lacks a harmonization across different technology options and hence creates an uneven playfield. The introduction of exchange-traded 15-minute contracts as well as their more extreme minimum / maximum price cap is a favorable development for storage systems.

Due to their quick reaction times, several storage technologies are well suited to provide Primary Control Reserve. This is also reflected in the current regulations, which were amended to allow a better integration of storage. However, current compensation only considers the provided power and not the quality of the provided service. Battery based storage systems, which oftentimes can provide power within fractions of a second, receive the same compensation as much slower thermal generation. Such a step, to more accurately reflect the speed and accuracy of delivered frequency control in the compensation, has for example already been implemented in the U.S. [130].

Due to their much higher power requirements as well as longer provision intervals, small- to medium-scale distributed storage systems are currently not able to participate in the Secondary and Minute Control Reserve markets. While storage systems would be well suited to provide voltage support as well as black start capabilities [119], currently no transparent market for them exists.

Sailer [123] concludes that initial efforts by policy makers and regulation authorities have already contributed to a clarification with regards to the usage of storage. However, there still exists considerable uncertainty in the laws and their interpretation. Furthermore, not many precedence cases exist in the judicature and as regulations are split across many laws and ordinances, it is complex to handle and difficult to build a consistent framework for the deployment of storage systems.

Subsidies in Germany

From 2013 until 2015, the national German development bank *Kreditanstalt für Wiederaufbau* offered a support scheme for storage installations either in combination with a new or existing photovoltaic system in Germany [131]. There was no restriction on storage technologies, but the maximum photovoltaic capacity was limited to 30 kW. Furthermore, the maximum feed-in was restricted to 60% of installed capacity (versus 70% for stand-alone photovoltaic installations). Additionally, storage providers had to disclose their communication interfaces and guarantee the storage performance for seven years. Applicants benefited from access to cheap financing and effectively received a grant of up to 30% of the storage installation cost. The program was extended in 2016, albeit at slightly more restrictive conditions. The grant has been reduced to 25% of the cost, further decreasing by three percentage-points every six months. In addition, the maximum feed-in was further reduced to 50% of installed photovoltaic capacity and the lifetime of the battery must now be guaranteed to be at least ten years. According to the associated scientific reporting, until March 2016 19 000 applications were approved, which represent about 50-60% of all installed storage systems [132].

Besides the subsidy program for small-scale combined storage / photovoltaic installations, several installations have also received substantial grants on a case-by-case basis by different entities. Since 2005, about 200 individual projects in Germany looking at electric storage have been supported with about 170 million EUR [4].

- WEMAG has started to operate a 5 MW / 5 MWh lithium-ion storage system in September 2014 with a total cost of 6.5 Mio. EUR. The investment was supported with 1.3 Mio. EUR (20%) by the Environmental Innovation Programme of the German Federal Ministry for the Environment [133].
- In combination with a PV park, a lead-acid based storage system with 1.5 MW / 1.9 MWh has been installed in November 2014. Total cost amounted to 1.3 Mio. EUR, however the project was supported by the European Regional Development Fund and the German state of Brandenburg with a grant of 0.4 Mio. EUR (31%) [134].

- Since March 2015, DREWAG has been operating a 2 MW / 2.7 MWh lithium-ion battery. Total investment cost was 2.7 Mio. EUR, of which 0.8 Mio. EUR (30%) were covered through a grant for pilot projects by the European Regional Development Fund and the German state of Saxony [135].
- Next to a wind park, a lithium-ion system with 10 MW / 10 MWh for a total cost of 12.8 Mio. EUR has been in operation since September 2015, supported with about 5 Mio. EUR (39%) by the European Regional Development Fund and the German state of Brandenburg [136].

All these projects were implemented with the intention to participate in the Primary Reserve Control market.

2.4 Economic Evaluation of Energy Storage Systems

In the previous Section 2.3, the state of the art of potential revenue streams for storage investments with a commercial background has been established. The current section will provide an overview of economic evaluation approaches, with a focus on the applicability to storage investments. Besides looking at valuation methods, the management and identification of uncertainty and risk as well as optimization methods are discussed.

2.4.1 Methodologies

The decision, whether a project should be implemented or abandoned, is usually made depending on an "investment criterion" [51]. The most commonly applied approaches found in the existing literature for the evaluation of storage devices were net present value and internal rate of return ([11], [13], [57]–[59], [62], [80], [90]). Alternatively, many papers also used Levelized Cost (for example in [26], [114]). Less often, the benefit-cost ratio (for example in [64]) or the payback period (for example in [90]) is calculated.

Net Present Value

Economic profitability of an investment project is commonly measured by its net present value (NPV), which is the difference between a project's present value and its cost [137]. The present value of a forecasted cash flow is a measure of today's value of future cash streams. The sum of all discounted cash flows – both revenues and costs – is the net present value. Economic theory dictates that an investment should only be undertaken if the NPV is positive, which is the case if future revenues exceed all cost under consideration of the time value of money.

Internal Rate of Return

Closely related to the calculation of the net present value is the determination of the internal rate of return (IRR). It is the projects discount rate for which the present value of all cash flows equals zero. The resulting rate is typically compared to the required return on capital or to alternative projects to determine if an investment is sufficiently profitable and should be pursued [51]. However, IRR can be ambiguous if cash flows have a reversal of sign during lifetime. Furthermore, IRR oftentimes provides a too optimistic view as it inherently assumes that interim cash flows are reinvested at the IRR [138].

Benefit-Cost Ratio

Related to the concept of net present value is the concept of the benefit-cost ratio. It is the ratio of the present values of benefits and cost, with numbers greater than one representing projects with a positive net present value. The figure is commonly used in project evaluations in the public sector [51].

Payback Period

Payback period is another popular evaluation criterion. It measures "[…] the number of years necessary to recover the project cost of an investment under consideration" [138]. Therefore, projects should only be accepted if their payback period falls below some defined threshold.

Levelized Cost

Specific to the evaluation of energy related projects is the concept of Levelized Cost of Electricity (LCOE) or Levelized Cost of Storage (LCOS), which is an estimate of the cost of a unit of energy that was produced or stored [26], [63], [64], [71], [80], [114], [139]. It is calculated by determining all expenses during the lifetime, discounting them to the base year and setting them in relation to the associated quantity of energy. As a normalized representation of cost (typically EUR/kWh, in order to compare capacity also EUR/kW [27]), the figure can easily be compared for projects that differ in scale or lifetime and gives an intuitive insight into the costs associated with a system. It is therefore used by several publications to benchmark different storage systems (for example in [26], [114]).

LCOS / LCOE can also be interpreted as revenue requirement to break-even [27]. When used as decision criterion in the case of self-consumption, LCOE must be below grid electricity cost in order to generate a financial return on the required upfront capital expenditure [140]. However, LCOS may vary strongly between applications and hence should be compared only for the same storage usage [26]. Furthermore, [51] suggests that the criterion should be used in conjunction with net present value when comparing mutually exclusive projects as it neglects the scale of investments alternatives.

Valuation Issues

When calculating the present value of an investment project, the choice of the discount factor plays an important role. Typically, the weighted-average cost of capital is used [141], which reflects the cost of capital for a company. Alternatively, if assessable, marginal cost of capital can be used. End-consumers typically require a much higher rate of return [138].

Investments with a higher uncertainty should be discounted with a higher rate to account for risk [137]. In his paper about the evaluation of energy efficiency investments, Thompson [142] argues that the discount rate for energy saving investments should be lower than the typically used discount rate. He reasons that with the energy saving investment the investor will face less uncertainty in the future with regards to the future development of energy prices, and hence the investment lowers his overall risk. By lowering the discount rate, the value of the investment would in turn be increased. Even though he is looking at investments in energy saving lighting technology, his reasoning is also applicable to the installations of storage installations for self-consumption, which would reduce energy supplied by the grid with uncertain future prices. Abadie [143] suggests that discount rates should be project specific in order to properly reflect the projects risks. Therefore, the author proposes to discount deterministic cash flows with the risk-free rate and stochastic cash flows with the rate implied in their futures market prices. This approach therefore requires a liquid market for the uncertain factors, which is typically only available for the most common underlying's and for short maturities.

In most installations, components will have a different lifetime expectancy. This could be overcome for example by assuming a residual value for system components with a longer lifetime [71]. Alternatively, replacement costs for components with a short life expectancy could be assumed [144]. As battery based storage systems degrade not only over their calendric lifetime, but especially due to cycling, Kloess [63] therefore depreciates them not linearly over time but with usage. However, both approaches suffer from the issue of requiring an estimate for future cost or values [138].

2.4.2 Uncertainty

Usually not all parameters and influence factors of an investment project are known with certainty beforehand. Hence, the evaluation of such a project and the following investment decision is conducted under uncertainty, which is however neglected in the previously discussed approaches given that they have deterministic nature. In their classification, Goh et al. [145] differentiate between data uncertainty and model uncertainty.

Model uncertainty describes the uncertainty that the prediction from the implemented model differs from the actual behavior that can be observed in reality, resulting for example from a lack of knowledge, complexity or imprecision. Model uncertainty is typically not discussed or considered. Barbour et al. [66] validate their dispatch scheduling algorithm by verifying it with some easily traceable price paths, such as a square wave for prices.

Data uncertainty results from parameters or predictions, which cannot be determined exactly, for example due to variability, ambiguity or imprecision [145]. Typical sources of data uncertainty in an investment evaluation are for example the evolution of electricity prices, the generation of non-dispatchable energy resources or the performance of technology [146]. Also cost and system parameters are linked to a high degree of uncertainty [114]. The outcome in a deterministic analysis does not consider these uncertainties, but assumes their realization with certainty. Using a deterministic approach, an investment evaluation affected by many uncertain assumptions is signaling a high confidence in the results, which does not exist in reality. Therefore, Goh et al. [145] recommend that "[…] the quantification of uncertainties is necessary to ensure the robustness and reliability of the decisions that are based on modeling results". Zucker et al. [102] review the profitability of storage systems, mostly pursuing arbitrage or providing ancillary services. They find widely varying results, ranging from 10 000 – 130 000 EUR / MW. The difference of more than a factor of 10 shows the great uncertainty associated with investments in storage and the high impact of the implementation context. Following, several approaches will be presented which are able to support the decision process to cope with uncertainty.

Sensitivity Analysis

The most prominent way to gain an understanding about the impact of different parameters is by conducting a sensitivity analysis ([64], [65], [73], [84]). Therefore, a parameter is changed over an estimated range and the obtained outcome is compared to the initial result. This procedure allows to determine the impact of the input parameters on the result and to identify to which parameters the result is more sensitive. Furthermore, it also gives an insight into the range of outcomes [138].

While usually only one parameter is changed at a time and the result recalculated, Hittinger et al. [139] first rerun their optimization routine before determining the impact on the result. Thereby, they reflect the opportunity of the decision maker to modify further system parameters when one decision variable such as investment cost changes. In order to evaluate the impact of two variables on the outcome, Yucekaya [65] runs his sensitivity analysis twice, with a change in one variable between the two runs.

Sensitivity analysis is typically applied to technical parameters to determine their influence. In this scope, the authors of [138] recommend to also asses the sensitivity of the discount and inflation rate, as the latter is usually associated with a high degree of uncertainty and the first one of major influence on the discounted cash flow analysis. Furthermore, [138] as well as [147] also recommend to run a sensitivity analysis with respect to the lifetime of the system, as it has major effects on all cash flows.

Scenarios

Some publications, for example [11], [80], develop multiple scenarios to improve their understanding on the impact of uncertainty. Therefore, a set of parameters representing a potential future state is selected and then the outcome deterministically evaluated. Compared to sensitivity analysis, several variables are simultaneously varied, accounting for their dependency and correlation. While this approach gives a better understanding of possible outcomes and to some extent also allows the consideration of flexible decisions, such as deferring an investment decision in time, results are still restricted to the selected cases. Furthermore, the determination of a worst-case-scenario is difficult, as variables will oftentimes be uncorrelated and their worst realization might not occur together [148]. Furthermore, as Goh et al. [145] mention, “scenario uncertainty is difficult to predict with confidence”, as usually only a limited number of scenarios – based on their perceived likelihood or representing a likely, best and worst case – are evaluated.

Monte Carlo Simulations

Another approach to consider uncertainty in the evaluation process is Monte Carlo Simulation [26], [114], [149]. In order to simulate possible outcomes, stochastic models of relevant uncertainty sources – such as electricity prices or renewable energy generation – are required as well as assumptions about the distribution of parameters such as efficiencies. In each simulation run of the Monte Carlo analysis, specific values of the input variables are then taken from their respective distribution and are simultaneously incorporated in the deterministic evaluation. After a sufficient number of repetitions, the resulting probability distribution of theoretical outcomes allows an interpretation about the uncertainty of the results and the range or likelihood of outcomes.

While Zakeri and Syri [114] assume that parameters are equally distributed in a certain range, Darling et al. [149] underlie their parameter with a distribution. Battke et al. [26] adopt a PERT distribution for their stochastic input parameter, which is according to them best suited for the expert estimates they used in their analysis. The authors of [138] recommend to consider correlation between parameters in the simulation.

In order to consider price uncertainty, Keles et al. [105] simulate price paths. Following, they run their optimization routine on each path to obtain the optimal dispatch. Evaluating each run, they obtain a distribution of the expected earnings. In his analysis of CAES systems for arbitrage, Yucekaya [65] runs 100 simulations on randomly generated price paths to obtain the standard deviation and 5% / 95% percentiles of potential profits in order to estimate the impact of uncertain parameters on the investment profitability. Battke et al. [26] conducted 10 000 runs with four stochastic input parameters to determine the mean LCOS as well as the interval in which 95% of all cost fall. They find a very high uncertainty in battery input parameters, with the 95% confidence interval spanning from 65% to 153% of mean cost. Furthermore, they identified a positive skew in their LCOS distributions.

Value at Risk

To determine the risk of investment portfolios, the application of the Value at Risk (VaR) concept is widespread in the financial industry. It is used to quantify the maximum loss that can be expected with a certain likelihood (confidence level) over a defined time horizon [150]. However, it can also be applied in a project evaluation context to estimate the likelihood that a certain investment falls short of a required return or to determine the return that can be at least expected with a certain likelihood [148]. Sadeghi and Shavvalpour [151] list three different approaches to obtain VaR in an energy context: historical simulation, which relies on an empirical distribution of historical data; Monte Carlo Simulation, which requires a model to calculate performance; and last, Variance-Covariance method which assumes that potential losses are proportional to the standard deviation of historical returns.

Jackson [148] demonstrates the application of the Value at Risk concept for an energy efficiency investment. Therefore, first a Monte Carlo Simulation is run which considers the uncertainty of several variables, such as electricity prices and operating performance on the investment outcome. The resulting probability density function of possible investment outcomes is then used to determine the likelihood of achieving a certain performance for a given confidence level. Applying the VaR concept therefore gives the decision maker an insight about the likelihood of certain outcomes, given the assumed uncertainty of the simulated variables.

Real Options Analysis

A further approach to consider uncertainty is the application of real option theory. Real option theory takes both uncertainty and flexible decisions into account and embeds it into the project valuation [137]. It is derived from classic financial option theory and applied to real assets, integrating rights or opportunities (but not obligations) to take flexible decisions with regards to a real asset. According to [146], “flexibility refers to the capability of managers to modify projects according to the evolution of uncertainty. This flexibility to adjust projects can enhance the projects worth […].”. Typical flexible decisions are the deferring or abandoning of investments, the option to switch operations or the option to grow. While more complex, a real options approach might therefore be more appropriate for valuing investments as the storage market and the regulation framework is still in its infancy and investment decisions would be associated to substantial uncertainty.

Martínez-Ceseña and Mutale [146] evaluate a hydropower project, considering the flexibility in the project design. By including this flexibility in the evaluation, they determine a 2% increase in net present value. Muche [152] applies Real Option theory to integrate the operating flexibility of a PHS. He finds that the PHS is more valuable when this flexibility is being considered and hence undervalued in a classic NPV valuation. Looking at a PHS investment for arbitrage, Fertig [153] found that using a real options approach would increase the value of the project by about 25% versus a traditional NPV analysis, as it would be worthwhile to defer the investment decisions. Moon [154] applies Real Options Theory to determine the optimal investment time for storage systems that pursue arbitrage. The author finds that it becomes more and more worthwhile to delay the investment with increasing volatility of the returns. Furthermore, it is shown that NPV valuation neglects this flexibility and hence undervalues projects. CAES systems are especially interesting when considering Real Options, as the gas turbine could also be dispatched without any stored compressed air during peak times [155].

2.4.3 Profit Driver

In their assessment of the economic viability of storage systems, many authors have also identified parameters with a high impact on revenues. Bradbury et al. [57] find that the profitability of a storage system is mostly determined by technical characteristics such as efficiency and self-discharge. Parra et al. [83] however mention that self-discharge does not play an important role for daily charging- and discharging cycles. Low investment cost and high efficiencies are identified as main profit driver by Ahlert and van Dinther [84]. Looking at the profitability of grid energy storage, Hittinger et al. [29] conclude that capital cost is the most important factor, followed by – depending on the pursued application – either power or energy limits. To improve the value proposition of storage systems, they therefore suggest focusing more on cost improvements, and less on improving the technical performance of storage systems. In their lifecycle cost review of battery storage system for different application cases, Battke et al. [26] find that the parameter with the highest impact on lifecycle cost is the energy-related capital cost of the system, followed by efficiency and calendrical as well as cycle life time. On the contrary, operation and maintenance costs have usually a minor impact. Barbour et al. [156] analyze arbitrage operations when negative prices occur. They find that less-efficient technologies are favored under these circumstances, as they will consume more energy to be fully charged. However, they conclude that this does not occur frequently enough to favor less-efficient technologies. Nonetheless, a small number of periods with negative prices increases potential revenues significantly.

Besides low investment costs, Woo et al. [58] conclude that the major driver for the profitability of an arbitrage strategy is a suitable electricity market. Furthermore, they also found considerable variations in annual profits. These results are confirmed by [8], [10], [60], who find significant variations between the profitability of different markets as well as significant variations between years. Sioshansi et al. [155] also identify a seasonal component for arbitrage profits as observable price spreads vary widely over the year depending on energy demand like electric heating or cooling. Drury et al. [104]

find significant differences not only between years, but also for different locations when pursuing arbitrage with CAES plants.

Steffen [62] highlights the importance of both the frequency of spot price fluctuations as well as of the difference between peak and base load prices for the profitability of arbitrage operations. The authors of [84] discuss the importance of the timely granularity of trading periods on realizable arbitrage profits. By choosing a suitable market with short intervals, higher profits can be obtained. For arbitrage operations, Walawalkar et al. [9] found that the price spread is the most important factor, followed by capital costs and then the efficiency of the storage device. However, their analysis was applied to a given system, neglecting the fact that in reality the capacity of the system or parameters in the operating strategy would also be decision variables when considering an investment in a storage system. Sioshansi et al. [10] looked at price spreads as well. They found, that the profitability of an arbitrage strategy is also influenced by natural gas prices. Due to the usage of gas power stations for peak generation, higher gas prices would effectively increase peak electricity prices, which would lead to increased arbitrage profits. In the specific case of a CAES power plant however, which requires natural gas during the generation process, Mokrian and Stephen [157] found a 50% decrease in arbitrage profits for a 30% increase in gas prices.

The authors of [71] compare the economic viability of some commercially available battery storage systems for self-consumption. Their results show that it is difficult to calculate an average case, as individual systems performed significantly better or worse than average. Looking at the Levelized Cost of Electricity, they found deviations of up to -38% / + 30% around average prices. Hence, the choice of the most cost-efficient system plays an important role in determining its profitability. Mulder et al. [11], looking at the economic viability of storage for increasing the self-consumption of PV generated electricity, identify remuneration tariffs, electricity prices and purchase costs as main factors. Parra et al. [80] highlight besides the efficiency the number of lifetime-cycles. In grids with power curtailments for local generation such as PV systems, [81] finds that the value of storage installed for time shifting of energy increases with decreasing feed-in limits. They also find that the profitability of arbitrage operations is reduced when the grid connection is limited, as the optimum timing cannot be realized.

In systems where storage capacity is independent from generation capacity, the size of both has to be aligned. Yucekaya [65] therefore runs a sensitivity analysis and modifies both parameters to determine the profit maximizing capacities. The same is also true when combining a local generation source with storage for increasing self-consumption. Weniger et al. [73] provide a good analysis of the importance of determining the optimal sizing.

Dufo-López et al. [158] analyze lifetime prediction models for storage systems. They conclude that the currently used models mostly predict longer lifetimes than the lifetimes that are observable in reality, which would result in a too optimistic economic evaluation. Disposal or recycling costs for storage systems are usually neglected in evaluations. From their review of several publications, Battke et al. [26] suggest that lead-acid and lithium-ion systems might even benefit as the included materials in the battery could be sold for a profit.

2.4.4 Optimization

Optimization methods are applied in the existing literature for two purposes: first, for determining the optimal system configuration. And second, for finding the profit-maximizing storage dispatch.

To determine the most cost-effective system configuration for a combined diesel, PV and battery storage system, Hittinger et al. [139] first use a simulated annealing approach to identify a promising configuration, followed by a search in all neighborhoods to identify a local optimum. Parameters for their search are the capacities of the system components. Tito et al. [159] look at a combined Wind, PV and storage installation. Their objective function does not only consider cost, but also security of supply. In order to consider uncertainty in the determination of the optimal installation size, Carpinelli et al. [67] suggest to use a process based on four steps. First, several installation alternatives and future states must be defined. Second, a probability (in their case, simply an estimate by the decision maker) must be assigned to each future state. Third, each installation must be evaluated for each future state. Last, decision theory is used to determine the optimal installation. Therefore, they evaluated three different objectives: minimization of expected cost, minimization of regret by the decision maker and a mix of both. In order to identify the optimal system, the authors used a genetic algorithm combined with a linear optimization. First, they identified the optimal time intervals to operate with a genetic algorithm. Following, liner optimization was used to define the optimal charge/discharge capacity.

The authors of [10] determined the optimal parameters for their storage system by varying a parameter and thereafter rerunning their analysis. They found among others that the capacity of a storage system engaging in arbitrage should be sized for about 4-8 hours of energy supply in order to maximize profitability. [17], [57] confirm this result. Bradbury et al. [57] find that a storage capacity of 4-5 hours can extract the majority of potential revenues and capacities above 10-12 hours are ineffective due to the daily periodicity of electricity prices. For arbitrage in the Finnish market, [64] determines six hours as optimal energy capacity for daily cycles. While a storage system with a higher capacity will oftentimes be able to produce higher total profits, marginal revenues will be reduced as the system can no longer exploit the maximum price spreads. Instead, charging and discharging operations must be extended to times when the price is no longer at or close to its minimum / maximum value [155]. He and Zachmann [60] conclude that determining the optimal size of a storage system for arbitrage has a strong impact on its value and must be made according to the target market. In addition, they highlight the importance of discharging power rates for arbitrage, as price peaks are usually of short durations whereas low prices for charging oftentimes last for several hours. Castillo-Cagiigal et al. [72] advise against oversized energy storage capacities. Not only will the installation be underutilized and capital cost be relatively high, but it will also consume unnecessary much energy to maintain fully charged due to higher losses from self-discharge.

The charging- and discharging cycles of the storage device are determined by its dispatch schedule. In order to find the profit-maximizing schedule, most authors use linear or non-linear (mixed) integer programming ([9], [10], [13], [57], [65], [84], [160]). Publications [12], [90], [161] are based on Monte-Carlo simulation, [58] uses a deterministic modelling tool. Ahlert and van Dinther [162] find that only simple models can be solved by using linear optimization, as they cannot incorporate state-dependent, variable cost such as usage-dependent depreciation charges. They suggest using dynamic programming models.

Drury et al. [104] use a mixed integer linear program to co-optimize net revenues of a CAES plant, which is both pursuing arbitrage and participating in the ancillary service markets. They run their optimization each for a two week-period, so that the storage device can pursue intra-day as well as inter-day opportunities. Keles et al. [105] use a linear optimization to evaluate their CAES dispatch for arbitrage and ancillary services. As the market for reserve power has a periodicity of four hours and energy is traded in hourly intervals they match each four hours of energy trading to one interval of reserve power provision in order to obtain a single optimization problem for both markets. However, due to the required computation time for their 1 000 runs on simulated price paths, they suggest to use a stochastic optimization model instead. Xi et al. [103] considered several applications in their co-optimization model, using stochastic dynamic programming and linear programming to determine optimal dispatch.

Barbour et al. [66] use an optimization routine based on Monte Carlo to determine the upper-boundary of arbitrage revenues. They reason their choice with the ability to also include time-dependent variables, such as storage self-discharge. Their algorithm explores the space and identifies feasible solutions in order to determine the optimal dispatch which maximizes revenues. Pesch and Stenzel [96] present a search algorithm which loops through all available data to identify the optimal dispatch.

According to Wright and Firth [163] , "[…] averaging data over periods longer than a minute is shown to under-estimate the proportions of both export and import.". Especially demand peaks are lost, when looking at data that was averaged over longer time intervals. While the mean remains unchanged, they find in their dataset that the 99^{th} percentile of load is reduced by -8% / -19% /-30% when looking at 5/15/30-minute data as compared to 1-minute data. Nähr and Rothert [164] discuss the required spatial resolution of data for simulation when looking at self-consumption of locally generated energy in a residential context. According to them, standard load profiles are not suitable to determine and optimize storage installations for self-consumption, as the averaging in such profiles reduces too many details. They found deviations of up to 50% in the achievable self-consumption of self-generated electricity. To ensure a realistic simulation, they recommend a spatial resolution of less than one minute.

Usually the dispatch of storage systems is optimized for cost minimization or profit maximization, neglecting the aversion of decision makers to risk. Moazeni et al. [165] therefore also consider a downside risk measure based on conditional value at risk in their objective function to include the aversion to market price risk. Applying their algorithm, they find a significantly reduced conditional value at risk (-9% at the 95% confidence interval) at the cost of a slight increase in operational expenses (+1%). A similar approach is followed by Fleten and Kristoffersen [166], which also identify a more stable profit distribution among scenarios. Another approach to consider risk for the dispatch of storage systems is proposed by Kazempour et al. [106]. The authors introduce an additional term in the objective function of their mixed integer programming problem, which represents a risk-based monetary penalty (with variance of historical data as risk-measurement) and is weighted according to the risk-aversion of the decision maker. Furthermore, as the request for ancillary services delivery is uncertain, the authors use probabilistic model. To fulfill all power requests, the minimum level of energy that must be hold available is continuously adjusted in their problem formulation. To consider the realization of uncertain variables over time, the optimization is conducted daily for a seven day forecast window.

2.4.5 Perfect Knowledge and Forecasts

Whereas in an actual implementation the dispatch decision must be made without previous knowledge of future prices, most authors use deterministic models and assume perfect price foresight in the optimization of their operation algorithm. The impact of uncertainties affecting future prices on the profitability of the dispatch has been a matter of concern for several researchers as suggested in [10], [66], [77], [104], [160], [167]. Some of these authors argue that if future electricity prices were known free of uncertainty, that is, if perfect knowledge was available in advance, then the profitability would be maximum because the most adequate decisions regarding charging and discharging of the storage devices for each time period would be selected. Consequently, deviations from this optimium dispatch schedule would compromise profitability and result in reduced revenues. Therefore, Drurey et al. [104] call the simulated profits under perfect knowledge an "upper bound" on profitability. However, as the boundary is based on the optimization of historical data, this approach can only provide a guidance for expected, future profitability.

Ahlert and van Dinther [161] compare results under knowledge of future prices with more or less uncertain forecasts. Despite having a negative impact on profits, they conclude that storage systems can still be economically dispatched under uncertainty. Graves et al. [8] argue that, while an arbitrage implementation would not be able to perform as good, the "disparity is likely to be small, as it is only at the marginally attractive prices that errors are likely to be made" [8]. This assumption is confirmed by Sioshansi et al. [10], who found that at least 85% of the potential theoretical value can be extracted due to the predictable nature of price behavior. Woo et al. [58] as well as Lund et al. [168] have similar results, finding that without perfect knowledge of future prices, profitability of a trading strategy drops by less than 20%. However, these findings might be influenced by a regular diurnal pattern in electricity demand and prices. If price behavior would become more erratic due to the contribution of fluctuating renewable resources with a less predictable pattern, bigger deviations might become common.

Using linear programming, Dunbar et al. [167] first determine arbitrage revenues under perfect foresight. Thereafter, they assume inaccurate forecasts with increasing percentage errors to analyze the impact on optimal revenues. Their results show that “revenue reduces at an increasing rate with increasing forecast error” [167]. According to their data, a forecast with 90% accuracy could achieve about 98% of optimal revenues, whereas a 70% accurate forecast would only reach about 80% of optimal revenues. Xi et al. [103] find that an optimal policy for provision of ancillary services is relatively insensitive to accurate forecasts, whereas “arbitrage profits are more sensitive to accurately estimating energy price patterns” [103]. Furthermore, they find models for arbitrage less computational expensive than models for ancillary services. Therefore, they suggest spending more efforts on improving forecast accuracy for arbitrage applications.

Drury et al. find a bigger drop in arbitrage profitability if future prices are unknown [104]. They first determine an upper bound on profits by optimizing the dispatch under perfect foresight. Following, they determine a lower bound on profits by assuming a simplistic dispatch algorithm. In their case, they optimize on previous weeks’ data, which would be known by then, and operate according to this dispatch schedule. Looking at several markets in the United States, they find that revenues from the provision of ancillary services are not very sensitive to the assumption of having perfect price knowledge due to relatively constant prices. Contrary, arbitrage revenues become significantly reduced (up to -37%) when the dispatch algorithm cannot benefit from the most extremes in peak- and off-peak prices. Peterson et al. [169] find a decrease in profitability by 49% between a two-week back-casting approach and having perfect information. However, they were looking at using electric vehicles for electricity arbitrage, and had only a limited timespan per day available for their arbitrage operations. Zakeri and Syri [64] utilize previous days prices as forecast for the current day. They find that below 70% of theoretical maximum profits can be achieved, but also highlight the dependency of this number of the storage characteristics and operation algorithm. Khani and Zadeh [160] find that about 70% of ideal revenues can be realized by using a backward-looking approach in the Ontario power system. By considering pre-dispatch prices published by the TSO, they are able to increase profits by about 5%.

To reduce the impact of price forecast, Walawalkar et al. [9] first determine an optimal charging- and discharging schedule for their arbitrage operation by analyzing future data. The implementation is then based on the implementation of this schedule, which always operates at the same times of the day. Therefore, the authors are still utilizing future data, but are implicitly only assuming knowledge about the future diurnal price pattern. A similar approach was adopted by Sioshansi et al. in [10] (and also in [155], [169]), who however optimized only on the trailing previous two weeks. Thereby, their algorithm behaves in a much more reactive way. The authors indeed find slightly varying dispatch schedules over time, due to seasonal effects. Both papers mention, that they would expect increased revenues by considering forecasts. The disadvantage of these approaches is the reliance on predictable patterns, which might become distorted through the increasing share of renewable generation.

Lund et al. [168] buy and sell energy at a predetermined distance away from an average price, which is either based on the previous 24 hours or a price prognosis for the upcoming hours. Even though He et al. [59] also relied on perfect foresight in their optimization, these authors suggest to derive a deployable trading algorithm from the optimized dispatch by analyzing its profile for daily and weekly patterns for future work. In addition, they suggest accounting for seasonal aspects, fossil energy prices as well as further economic parameters.

Muche [170] suggests to apply stochastic programming models to cope with price uncertainty for arbitrage. As hourly prices at the European Energy Exchange are not revealed hour by hour but in one step after the auction process is completed, the author models first daily prices and then derives hourly prices from them, assuming a deterministic daily pattern. Based on the modelled price forecast, the optimal dispatch is determined using an optimization model. Looking at PHS, he finds a weekly planning interval superior to a daily one as among others the weekend consumption pattern can be considered and be optimally exploited. Furthermore, he concludes that simpler models perform better due to a more robust forecast. In order to reduce the dependency on historical data for the development and testing of arbitrage trading strategies, Zucker et al. [102] suggest to use stochastic models to generate synthetic price tracks. Furthermore, these models could be modified to incorporate potential changes to market structure, like the disappearance of the mid-day peak on sunny days, to assess the impact of such a change on storage profitability. Another approach to reduce the dependency on historical data would be to optimize the trading strategy on only a part of the available data and verify the results on the remaining data.

Schmiegel and Kleine [171] look at self-consumed photovoltaic energy of private households. They find that knowledge about future generation and consumption would increase the value of a storage system only slightly. A simple charging- and discharging strategy without perfect knowledge fell behind by only 5-7%. Wang et al. [68] develop algorithms to forecast PV generation and residential load forecasts for their storage controller, simultaneously minimizing peak load and total electricity cost under a dynamic energy pricing model. Their scheme is separated in two levels, a primary tier performed in accordance with the billing period, and a subordinated level compensating prediction errors. They find that the addition of a storage device reduces the break-even time of the combined system. Ahlert and Block [172] look at residential consumers who charge their storage device from the grid during low price periods for later consumption. They look at the economic impact of price forecast accuracy on the optimal scheduling of the storage system. Therefore, they assume imperfect load and price forecasts and compare their results to an operation schedule model with perfect foresight. Assuming a 10% Mean Absolute percentage error for their forecasts, they find that overall savings decline from 17% (operation with perfect knowledge) to 15%. Furthermore, these authors also discuss the optimal forecast period. They find that for short forecast periods the algorithm behaves myopic and does not exploit inter-daily charging- and discharging opportunities. On the other hand, if the forecast period becomes too long, accuracy declines and again the algorithm performs worse. They find a forecast period of one day as optimal, however they did not discuss the relevance of storage capacity on this finding.

2.5 Impact of Energy Storage Systems on Electricity Markets

Storage devices pursuing arbitrage or providing ancillary services are inevitably connected to the grid. Therefore, their interaction with the electricity markets should be considered in their evaluation as well, as any potential reaction couplings might affect their economic value proposition.

Therefore, first the impact of storage devices on the supply and demand balance is considered. Even though storage devices do not generate or consume electricity (neglecting efficiency losses), they shift energy in time and therefore change the demand profile seen by the rest of the grid. Thereafter, the impact of storage installations on electricity prices is considered. Last, the market potential for storage devices is reviewed.

2.5.1 Impact on Electricity System Load

Parra et al. [83] find that storage for residential self-consumption will shave most demand peaks during summer and spring time. Santos et al. [173] look at the potential impact of PV equipped residential storage installations on grid demand in Portugal. According to their findings, storage devices are able to significantly reduce power exchange with the grid by reducing peak demand or feed-in power. Hollinger et al. [55] estimate that an increase in residential storage installations for self-consumption would lead to a more steady residual load seen by the grid, if the storage devices are operated in a grid beneficial way.

Carpenter et al. [87] find that storage applied for time shifting of residential grid demand can create new demand peaks, when the reaction of agents to price signals is identical and market penetration of storage devices is sufficiently high. Nyamdash and Denny [174] identify in their case study an increase in net-demand during the night, when storage devices would be charged. The discharge of the storage device during the day then reduces peak-demand. Their resulting charging profile shows a strong concentration on a few hours during the night, whereas discharge occurs more distributed, with two peaks around noon and in the early evening.

2.5.2 Impact on Market Prices

Most reviewed and mentioned publications assume prices to be exogenous input factors and model the operation of storage devices as price takers (for example in [81], [156], [170]). In reality, however, every storage operation would obviously influence the supply and demand balance and therefore market prices.

Sioshansi et al. [10] considered the potential impact of a large-scale storage device which is pursuing arbitrage on electricity prices. By using linear regression, the authors find a strong relationship between electricity demand and electricity prices. The coefficient of determination can be further increased if seasonality is considered by estimating the parameters for shorter time-frames. The authors find that pursuing an arbitrage strategy would smoothen the electricity prices. Previously high prices during discharge times (peak hours) would be reduced, whereas the charging during low-price periods would increase prices (off-peak hours).

Kondziella and Bruckner [175] analyze the effect of introducing storage capacity on the example of the German market. Therefore, they first determine power supply scenarios for 2020 and 2030 to consider the increasing contribution of renewable energy sources (assumed to be 40% in 2020 and 65% in 2030), which allows them to simulate and analyze future price behavior. Following, storage capacity is introduced, which is exclusively applied for arbitrage. This model enables the authors to analyze potential future price behavior with and without the presence of storage. They find that without the presence of additional storage price spreads will more than double on average versus current levels. In addition, they find that price patterns will change. Due to the contribution of solar, the mid-day peak will disappear, with prices significantly below the morning and evening peak. This might open up additional potential for arbitrage as there will not only be a diurnal charge-discharge opportunity, but two charge-discharge cycles per day. Furthermore, negative prices will occur more frequently due to excess-contribution from renewables on weekends. When considering the addition of storage, they find that spreads tighten again; however, even when doubling the currently available storage capacity in Germany, price spreads would stay slightly above current levels.

Nyamdash and Denny [174] analyze the impact of large-scale storage installations on the electricity price. Therefore, they simulate the dispatch of the overall electric system (in their case, for Ireland) in order to consider all constraints such as ramping times. They find that the presence of storage changes the economic dispatch decision. During the night, baseload generation as well as electricity imports are increased. Generation by peak-load generators, which had previously been held available for the provision of reserves, was substituted by the storage systems. Baseload generators also showed a higher utilization during the day, as no spare units had to be held in reserve, which was now provided by PHS. Overall, they identified a slight increase in prices during off-peak hours, which was more than offset by price reductions during peak-hours. Therefore, total production costs decline due to the higher utilization of baseload generators and less frequent generation by peak-plants.

Gast et al. [176] demonstrate that storage has a smoothing effect on prices and therefore reduces volatility. Their simulation results show that the occurrence of both very high as well as very low prices is reduced. Hollinger et al. [55] analyze the impact of residential combined PV and storage systems for self-consumption in Germany. They expect an overall decrease in electricity prices.

He et al. [109] also consider the impact, that their arbitrage operation would have on market prices, in their own dispatch decision by including a factor, which reflects the sensitivity of market prices to changes in supply / demand. In a second paper [177], the authors estimate the impact of a 400 MW storage device pursuing arbitrage in the French day-ahead market (typical volume of 5 000 – 7 000 MWh) to be 1.40 EUR.

2.5.3 Market Potential

The economic potential for storage pursuing arbitrage is limited due to a saturation process, as the introduction of additional capacity decreases price spreads through their operation. Hence, the revenue potential is deteriorated for current as well as further installations [175], [176], [178], [179]. Sioshansi et al. [10] expect that this would lead to an equilibrium, as decreasing potential arbitrage profits would disincentive additional market entrants. According to Borenstein et al. [180], “arbitrage opportunities can persist in reasonably functioning financial markets if capital restrictions, limited information, and other more explicit barriers to trading limit the number of traders.”.

Eyer et al. [50] present a generic process to estimate market potential. First, the technical market potential should be estimated, which is the maximum amount given technical constraints. In an energy context, the upper bound is typically defined by peak electric demand. Next, the maximum market potential should be estimated. These should take for example regulations into account. Last, the market size can be estimated as a fraction of the maximum potential. Market potential estimates for different applications in the U.S. can be found in [50] and [17].

In their study about a future electricity market design for Germany, the authors of [178] mention that flexibility options like demand side management or grid enhancements reduce price volatility as well as high price spikes and the occurrence of negative prices. Overall, this would result in more steady prices that would negatively impact the revenue expectations of storage operations pursuing arbitrage.

Peterson et al. [169] state that first movers in ancillary service markets can potentially make attractive earnings. However, they expect a quick saturation of the market. As mentioned in chapter 2.3.6, this view is shared by a range of authors.

The development of storage capacity is not the only influence factor on electricity prices and the further market potential for storage. It will likely be accompanied by among others a further growth of renewable generation, which will also have an impact on prices. Nicolosi and Fürsch [181] argue that the projected growth of wind generation will increase price volatility. As the marginal cost of wind generation is negligible, the increase of wind generation has a reducing effect on day-ahead spot prices. Over the long-term, this would crowd out baseload plants. As these depend on a high utilization, their profitability is strongly reduced due to the low cost electricity provided by wind. The residual demand (after the consideration of wind) has to be met by peaking plants, whose share would increase. This again would lead to more volatile electricity prices with cheap prices during times of high wind speeds, and high prices during times of little wind. Depending on its magnitude, this effect might become more distinct than the diurnal effect. This might open up additional business opportunities for storage, but would also require the definition of new scheduling algorithms, that are currently predominantly based on the regular periodicity of prices. Sioshansi et al. [155] argue that storage devices are not impacted by the overall price level. For arbitrage operations, only the price spread but not the absolute price matters. In markets with high shares of renewable production, storage could therefore be still used for arbitrage between renewables that bid at zero in the market and baseload power plants like coal stations.

2.6 Conclusion

This chapter details the current state of the art about the economic evaluation of energy storage systems and their impact on electricity markets. Despite many excellent contributions, there remains a wide array of questions which require further research to advance in the understanding of the economic viability and impact of distributed storage devices. In the context of this thesis, the following issues will be considered in more detail.

Deployment Context

Most of the previous research on commercial applications has focused on the installation of large-scale storage systems such as PHS or CAES in the traditional electricity grid. Research about the application of storage in a distributed, smart-grid context to achieve economic profits is still in its infancy. As among others the access to financial markets and the scale of operations differ widely, available revenue streams will diverge and existing results cannot easily be transferred. Furthermore, ownership issues must be considered. Private agents with purely commercial interests have only limited access to storage benefits, as certain applications generate benefits which can only be captured by utilities or grid operators.

Implementation of Storage Operations

The majority of publications rely on perfect knowledge about the future to schedule operations. To actually deploy storage, scheduling formulations must cope with uncertainty, such as unknown market prices or variable demand. Furthermore, applications have typically been considered individually. However, there is consensus that the integration of multiple value streams will lower the threshold for economic viability, requiring additional research about their interaction and potential combinations.

Economic Evaluation

Another aspect which requires additional research efforts is the economic evaluation process. Most authors pay close attention to the modelling of the storage device and its technical implementation, but neglect the financial valuation. One of the most significant factors is the determination of a discount factor, which is typically not discussed despite its huge impact on the outcome. Also, little consideration is usually given to the evolution of the framework, for example electricity rates, as well as the impact of external factors, such as taxes. Last, very few publications have been concerned with how storage investments could be incentivized or what influence subsidies might have.

Uncertainty

As the deployment of electric storage in smart-grids is still in its infancy, common valuation methods like NPV or IRR are not able to consider the related uncertainty. Methods like the Real Options approach or Value at Risk might be helpful to better understand and incorporate the risks, but their application to storage requires further research. Furthermore, many authors use sensitivity analysis to identify the most relevant parameters. However, most authors do not further proceed with the gained insights. A better understanding of the impact of uncertainty and approaches to handle it would certainly be beneficial to investors.

Impact on Electricity Markets

Just like the wide-scale deployment of distributed photovoltaic systems and wind generators is influencing electricity market prices, so will likely occur with the introduction of storage. However, research about the impact on electricity prices and further implications is in its very beginning and requires further efforts in multiple directions. So far, most authors considered storage in their evaluation as an isolated system, without being impacted or having an impact on markets. However, an increasing number of storage installations will likely have an influence on electricity markets and therefore also on their own revenue proposal. An understanding about such a process would not only be beneficial to potential investors to recognize a market saturation, but it would also give policy makers a better understanding about the consequences of storage growth.

This literature review confirms with the conclusion of Xi et al. [103]. They determined gaps in the existing literature in the co-optimization of multiple storage uses, the disregard of price and system uncertainty in many analysis and the missing consideration of small-scale and distributed storage. This thesis and the accompanying publications are addressing these gaps and will provide further insights into the economic evaluation of storage systems and their impact on electricity markets.

Chapter 3

3 Financial Evaluation of Commercial Storage Applications

Abstract

Chapter 3 discusses the financial evaluation of commercial storage applications. Therefore, first a general abstract model for the simulation of storage operations is presented, which will be adapted for each application. Following, a framework for the evaluation of storage systems as well as key financial indicators are discussed. Thereafter, the application of storage for time shifting energy in a consumer setting, for pursuing arbitrage profits as well as for the provision of ancillary services by an investor is presented. Furthermore, the simultaneous application of storage for multiple purposes is discussed. For each application, the business case is introduced in detail, followed by the presentation of an operation process for the storage dispatch and a discussion of the evaluation approach.

3.1 Simulation of Storage System Operations

This first section provides a high-level simulation approach for electrical storage systems, which serves as a basis for the more detailed implementations of the individual applications. Section 3.1.1 provides some general guidelines for the simulation. In 3.1.2, the characteristics and technical limitations of storage systems are presented.

3.1.1 Framework

Simulations will be done in discrete time steps of constant length. Table 3.1 summarizes the relevant parameters.

Symbol	Unit	Description
t	-	Index
Δt	-	Fraction of an hour between two time steps
T	-	Number of total time steps

Table 3.1: General simulation parameter

Index t refers to the time and the associated variables are assumed to be unknown before. Time *t=0* refers to the instant in time where the investment is undertaken. The simulation then starts at *t=1* and ends at the simulation horizon *t=T*. The simulation time step Δt is expressed in fractions of an hour. The constant time step is required to convert between power and energy values as well as to aggregate instantaneous load or generation of each time step [W] into energy units [Wh]. Ramp rates and response times are not considered. Furthermore, power is assumed to be constant during Δt.

The number of hours, days or years over the evaluation horizon can be determined according to equations (3.1) - (3.3).

$$T^{hours} = T \times \Delta t \quad \textbf{(3.1)}$$

$$T^{days} = \frac{T \times \Delta t}{24} \quad \textbf{(3.2)}$$

$$T^{years} = \frac{T \times \Delta t}{8760} \quad \textbf{(3.3)}$$

All simulations will only consider active power. Furthermore, technical constraints beyond the ones which are presented in the following are not considered. As a general convention, all power flows with a negative sign represent a load to the specified system, and all power flows with a positive sign represent energy supplied by the specified system. Parameters are assumed to be constant over the evaluation period. Hence, it is assumed that system performance does not degrade over time. Furthermore, all installations are assumed to have an availability of 100%.

Subscripts of variables or parameters are used to refer to different systems such as a storage system, a PV installation or a grid connection. Superscripts further differentiate between different meanings of a variable or parameters, such as the differentiation between operating and fixed costs.

3.1.2 Storage Device

Table 3.2 summarizes the relevant parameters and variables of a storage device, which are considered for its simulation.

Symbol	Unit	Description
$E_{Storage}^{Capacity}$	[Wh]	Nominal capacity of the storage device
$E_{Storage}(t)$	[Wh]	Current charge of the storage device
$P_{Storage}^{Out}(t)$	[W]	Power supplied by the storage device (> 0)
$P_{Storage}^{In}(t)$	[W]	Power absorbed by the storage device (< 0)
$P_{Storage}^{Capacity}$	[W]	Maximum charge or discharge power
$\eta_{Storage}$	[%]	Roundtrip efficiency of the storage device
$\eta_{Storage}^{In}$	[%]	Charging efficiency of the storage device
$\eta_{Storage}^{Out}$	[%]	Discharging efficiency of the storage device
$\delta_{Storage}$	[%]	Depth of discharge of the storage device
$\phi_{Storage}$	[%]	Self-discharge per hour of the storage device
$L_{Storage}^{Calendric,\, Cycle,\, Operating}$	[a, -, h]	Calendric lifetime (in years), cycle lifetime (in equivalent full cycles) or operating lifetime (in hours)
$N(t)$	[#]	Number of equivalent full charge- and discharge cycles
$SoC(t)$	[%]	State of charge

Table 3.2: Operational parameters and variables of a storage device

To simulate the operation of a storage device, the charge- and discharge power flows have to be taken into account. Hence, the charge of the storage device $E_{Storage}(t)$ equals the charge of the previous period under consideration of powers flows and the length of the time period, as indicated by equation (3.4).

$$E_{Storage}(t) = E_{Storage}(t-1) - \Delta t \times \left(P_{Storage}^{In}(t) + P_{Storage}^{Out}(t)\right) \qquad \textbf{(3.4)}$$

However, charge- or discharge processes are typically not 100% efficient. Equation (3.5) describes the roundtrip efficiency of a storage device, that is the energy which can be recovered in relation to the energy which was used to charge the storage device. As the efficiency of some technologies differs between the charging- and discharging process, charging efficiency $\eta_{Storage}^{In}$ and discharging efficiency $\eta_{Storage}^{Out}$ will be differentiated. Their product equals the roundtrip efficiency.

$$\eta_{Storage} = \frac{\sum P_{Storage}^{Out}(t)}{-\sum P_{Storage}^{In}(t)} = \eta_{Storage}^{Out} \times \eta_{Storage}^{In} \qquad \textbf{(3.5)}$$

The efficiency is assumed to be constant and therefore independent of the power flow as well as of the state of charge of the storage device. The charge of the storage device in period t can then be calculated as shown by equation (3.6).

$$E_{Storage}(t) = E_{Storage}(t-1) - \Delta t \times \left(P_{Storage}^{In}(t) \times \eta_{Storage}^{In} + P_{Storage}^{Out}(t) \big/ \eta_{Storage}^{Out}\right) \qquad \textbf{(3.6)}$$

Storage devices are limited in their operations by their technical capacities. Therefore, a range of constraints must be observed. First, power flows both for charging (equation (3.7)) as well as discharging (equation (3.8)) cannot exceed the power rating. It is assumed that maximum charge- and discharge rates are identical and independent of the current state of charge.

$$0 \geq P_{Storage}^{In}(t) \geq -P_{Storage}^{Capacity} \tag{3.7}$$

and

$$0 \leq P_{Storage}^{Out}(t) \leq P_{Storage}^{Capacity} \tag{3.8}$$

Second, the storage device cannot be charged beyond its capacity. Hence, the level of charge cannot exceed the storage device's capacity as indicated in equation (3.9).

$$E_{Storage}(t) \leq E_{Storage}^{Capacity} \tag{3.9}$$

In addition, the storage device can also not be discharged below a certain threshold in order to avoid damages and prolong the lifetime of the storage system, according to equation (3.10). This lower charge limit is also referred to as depth of discharge and it corresponds to the relation of the effective capacity regarding the nominal capacity.

$$E_{Storage}(t) \geq E_{Storage}^{Capacity} \times \delta_{Storage} \tag{3.10}$$

The State of Charge, *SoC*, of the storage device is the ratio of the currently available energy for discharge in relation to the total capacity, as indicated by equation (3.11). In order to avoid damaging the storage system, it must remain above the depth of discharge.

$$SoC(t) = \frac{E_{Storage}(t)}{E_{Storage}^{Capacity}} \tag{3.11}$$

The number of storage cycles over a certain time horizon provides an insight on how intensively a storage device has been used. A full cycle refers to a discharge to the maximum depth of discharge followed by a charging operation up to the full capacity. However, as frequently storage devices are not fully discharged or brought back to a full state of charge, equivalent full cycles are considered. An equivalent full cycle accounts for all charge- and discharge operations by accumulating the power flows. The number of equivalent cycles is then calculated by equation (3.12).

$$N(t) = \frac{\sum_{n=1}^{t} \left(P_{Storage}^{Out}(n) - P_{Storage}^{In}(n)\right) \times \Delta t}{2 \times E_{Storage}^{Capacity} \times (1-\delta)} \tag{3.12}$$

Installations typically have a limited lifetime L, which can be restricted by a calendric age $L^{Calendric}$, by operating hours $L^{Operating}$ or – specifically for some storage technologies – by a certain number of charging- and discharging cycles L^{Cycle}. For some systems, several restrictions apply simultaneously. In these cases, the installation is assumed to be at the end of its lifetime once the first limit is reached. For example, an electro-chemical battery is assumed to be no longer functional as soon as it reaches either its calendric lifespan or its designed number of lifetime cycles. While the batteries would not stop operating beyond that moment, their performance starts to degrade noticeable.

3.2 Evaluation Methodology

Section 3.2 presents the required methodology for the economic evaluation of a storage system. First, in 3.2.1, the different cost and revenue sources are introduced. Following, Section 3.2.2 presents the economic evaluation framework.

3.2.1 Cost and Revenues

Table 3.3 provides an overview over the relevant financial parameters. The symbol € refers to a monetary unit, and not necessarily to the currency Euro. All costs are defined as negative numbers. For an entity investing in storage, costs typically result from two sources: cost related to the installation, and cost related to the exchange of energy with the grid during the lifetime.

Symbol	Unit	Description
C^{Invest}	[€]	Investment cost
C^{Fixed}	[€/a]	Fixed cost
$C^{Variable}$	[€/Wh]	Operating cost
$R(t)$	[€/Wh]	Electricity market price
$R^{Import}(t)$, $R^{Export}(t)$	[€/Wh]	Import (/consumption) and export (/feed-in) tariff for electricity
$R^{Regulation}(t)$	[€/W]	Compensation for the provision of reserve control
$LCOS$	[€/Wh]	Levelized Cost of Storage

Table 3.3: Parameters for the financial evaluation

The dominant cost factor for most small-scale storage systems is the initial investment expense C^{Invest}. The annual cost that occurs regardless of system usage such as maintenance or insurance expenses are described by C^{Fixed}. Last, $C^{Variable}$ refers to cost that occurs due to the system usage.

Besides the cost related to the system installation, the cost for the exchange of energy with the grid is of interest. Consumers are typically charged according to a tariff $R^{Import}(t)$, which can be time-dependent. Network fees are assumed to be included in this tariff. Feed-in of locally generated electricity is compensated according to $R^{Export}(t)$. Commercial entities can participate directly in the electricity market at the current market price $R(t)$. Providers of ancillary services are rewarded according to $R^{Regulation}(t)$.

As discussed in the previous section, the lifetime of many battery systems is restricted by two limits: the calendric aging as well as a usage based wear down. Once one of these limits is reached, the storage system is considered at the end of its usable life. The levelized cost of storage (LCOS) relates the investment cost of the storage system to the energy that the storage can provide over its cycle lifetime. Therefore, it gives an insight into the cost of storing and providing a unit of energy. The levelized cost can be determined using equation (3.13).

$$LCOS = \frac{C_{Storage}^{Invest}}{L_{Storage}^{Cycle} \times E_{Storage}^{Capacity} \times (1 - \delta_{Storage})} \quad \textbf{(3.13)}$$

As a normalized figure independent of storage dimensions, the levelized cost then allows for an easy comparison between technologies and system configurations. LCOS can also be interpreted as a depreciation charge or as an average revenue hurdle.

3.2.2 Evaluation

As this document is concerned with the economic evaluation of storage, only monetary benefits and cost are considered. Externalities, both positive as well as negative, are disregarded. Table 3.4 summarizes the parameters and metrics, which will be discussed in this section.

Symbol	Unit	Description
$CF(t)$, $CF_{Loant}(t)$	[€]	Cash flow, cash flow from financing
NPV	[€]	Net present value
r_{Loan}	[%]	Interest rate for debt financing
T_{Loan}	-	Debt tenor in time steps
$Loan$	[%]	Amount of loan in percent of the investment amount
r_{Equity}	[%]	Required return hurdle for equity
irr	[%]	Internal rate of return

Table 3.4: Financial evaluation

The cash flow in t=0 represents the investment cost as indicated by equation (3.14).

$$CF(0) = -C_{Storage}^{Invest} \tag{3.14}$$

However, oftentimes not sufficient data for a complete evaluation over the lifetime of the storage system is available (that is if the timespan of the simulated data is less than the calendric lifetime of the analyzed storage system). In that case, the investment cost can be considered proportionally according to the limiting factor of cycle or calendric lifetime of the storage system as indicated by equation (3.15).

$$CF(0) = -C_{Storage}^{Invest} \times max\left(\frac{N}{L_{Storage}^{cycle}};\frac{T^{years}}{L_{Storage}^{calendric}}\right) \tag{3.15}$$

However, the net present value based on this value is difficult to interpret, as it represents the value of the storage system over a certain timespan. In addition, the time-value of money is not properly accounted for. The ideal approach therefore corresponds to assume that historic prices repeat themselves and extend the existing price time series by repeating it. Then, a full evaluation over either the calendric or cycle lifetime with proper accounting of the time value of money can be conducted.

In the periods following the initial investment, the cash flows *CF(t)* are determined by the fixed cost, which are distributed evenly over the time steps, as well as the cost / revenues for the energy exchange with the grid. However, the formulation is highly specific to the context and will therefore be individually defined for each application. As an illustration, equation (3.16) shows the outline of the formulation for a private consumer with local generation.

$$CF(t) = -\Delta t \times \left(\frac{C^{Fixed}}{8760} + [...] \times C^{Variable} + [...] \times R^{Import}(t) - [...] \times R^{Export}(t)\right) \tag{3.16}$$

Equation (3.16) shows clearly that the benefit of a storage system not necessarily comes from the revenues generated, but can also result from a cost reduction, for example due to less energy taken from the grid.

Besides the cash flows resulting from the operation of the storage system, cash flows from financing must also be taken into account, if the project is (partly) funded by a loan. These are determined by three components as indicated in the next paragraphs.

First, the principal payment during the investment stage, depending on the percentage *Loan* of the initial investment amount which is refinanced (equation (3.17)).

$$CF_{Loan}(0) = Loan \times C^{Invest} \tag{3.17}$$

Second, the redemption of the loan over its tenor T_{Loan}. It is assumed that the loan is repaid in constant rates at every time step as indicated by equation (3.18).

$$CF_{Loan}(t) = -T_{Loan}^{-1} \times Loan \times C^{Invest} \qquad for\ t < T_{Loan} \tag{3.18}$$

Third, the interest payments on the outstanding loan, depending on the interest rate r_{Loan}. Again, it is assumed that interest is paid at every time step t, until the loan is redeemed (equation (3.19)).

$$CF_{Loan}(t) = CF_{Loan}(t) - Loan \times C^{Invest} \times (1 - \frac{t}{T_{Loan}}) \times \frac{r_{Loan} \times \Delta t}{8760} \qquad for\ t < T_{Loan} \tag{3.19}$$

Based on the determined cash flows CF and CF_{Loan}, the net present value can then be determined according to equation (3.20). The net present value (NPV) reflects the difference between benefits and costs of a project, considering the yield expectation of the investor and therefore its time value of money. It is obtained by discounting all cash flows with the cost of capital r_{Equity}.

The NPV therefore reflects the economic value of storage to an investor. A positive NPV will provide first guidance to a potential investor if the investment might be worthwhile. Contrary, if the NPV is negative, the return falls short of the required return rate r_{Equity}.

$$NPV = \sum_{t=0}^{T} \frac{CF(t) + CF_{Loan}(t)}{(1 + r_{Equity})^{\frac{t \times \Delta t}{8760}}} \tag{3.20}$$

The internal rate of return (*IRR*) shows which rate of return a project delivers, irrespective of the capital structure. It can be obtained by solving equation (3.21) for *irr*.

$$0 = \sum_{t=0}^{T} \frac{CF(t)}{(1 + irr)^{\frac{t \times \Delta t}{8760}}} \tag{3.21}$$

3.3 Time Shifting of Energy

As elaborated in the literature review in Section 2.3.5, one of the most promising commercial applications for storage is the time shifting of energy at the consumer level. This section will provide a framework to evaluate the application of storage in this context.

Section 3.3.1 will lay out the business case in more detail. Section 3.3.2 will explain the different components of the system and their interaction. Section 3.3.3 presents a simple operation mechanism, which does not require any foresight. Following, in Section 3.3.4, a MIP is presented which minimizes the operation cost for a given system. The optimal system configuration can be obtained by the search routine presented in 3.3.5. Finally, 3.3.6 details the approach to evaluate the value of storage dispatched for time shifting. The presented framework will be applied to a case study that is detailed in Section 6.1.

3.3.1 Business Case

The goal of time shifting is to move electricity from periods when it is cheap or sufficiently available to periods when it is more expensive. Therefore, the storage system is charged when electricity can be obtained at low cost or when there is excess local generation. During periods with higher prices or insufficient local generation, demand is then satisfied by discharging the storage system instead of taking electricity from the grid.

A related idea to time shifting at the consumer level is demand-side management. However, these two concepts differ substantially. Demand side management tries to shift demand from periods with high prices or scare local generation to periods where lower prices persist or sufficient local generation is available. Therefore, it requires a change of consumption behavior, which is not necessary when utilizing a storage system instead.

The storage system can either be charged by a local generation resource or from the grid. The most widespread distributed small-scale generation resources are photovoltaic (PV) installations and combined heat and power plants (CHP). The generation of a photovoltaic system is location specific and can only be slightly influenced by modifying the orientation of the panels. Contrary, cogeneration units can be actively dispatched. However, especially for small-scale installations such as in multi-family houses, they are typically dispatched according to thermal requirements from heating and hot water demand. In that case, the generation can be considered analogous to the PV panels as extrinsic. Consequently, there will oftentimes be a temporal mismatch between electricity generation and demand. Local excess electricity generation is typically fed into the grid. When demand exceeds generation at a later point in time, it is again taken from the grid. As the consumption tariff is typically above the feed-in remuneration, it would be economic interesting for the client to store the electricity instead of feeding it into the grid for later self-consumption. Time shifting of local generated electricity is therefore only economic interesting if no net-metering exists and the feed-in tariff is below the consumption tariff. Otherwise, storage will not be able to add value.

The mismatch between electricity generation and demand can also be reduced by actively dispatching the CHP plant depending on the electric load. However, this requires also taking the thermal balance into the consideration. In order to capture the potential total value of a storage system, therefore, a more integrated view is required, which takes the overall energy supply of a building into account. This necessity is underlined by the increasing popularity of heat pumps, which in addition to CHP plants further connect the electric and thermal subsystems. Therefore, in order to consider the complete set of options available to a house owner, not only the electric but also the thermal system will be modeled. Besides the electrical storage system, therefore also a thermal storage system will be considered. Last, to further complete the available set of small-scale energy systems, solar-thermal installations as well as a traditional gas boilers will be considered as heat sources.

Instead of relying on excess local generation to recharge the storage system, it can alternatively also be charged from the grid under a time-of-use tariff. Time-dependent or dynamic tariffs are offered to incentivize consumers to shift their demand to periods when electricity can be generated more inexpensive. Typically, these periods fall into the nighttime when there is less overall demand and hence generation is cheaper due to the merit order effect. Storage can then be charged during low-price periods and satisfy local demand during high-price periods.

The following sections will not only provide the required methodology to evaluate both usage cases individually under different scenarios, but also co-integrated. Furthermore, the proposed evaluation approach allows considering arbitrary combinations of system components and capacities in order to identify the profit maximizing configuration.

3.3.2 System

The notation of all additional system components will be analogous to the denomination of the electrical storage system. Hence, all power flows will be denoted by $P(t)$, with the subscript indicating the system and the superscript indicating the direction of power flow. Heat flows will be denoted by $H(t)$. The installed capacity will be denoted by $P^{Capacity}$ / $H^{Capacity}$, with the subscript indicating the system.

The following local generation resources will be considered:

- the electric generation of the photovoltaic system ($P_{PV}(t)$)
- the simultaneous provision of power ($P_{CHP}(t)$) and heat ($H_{CHP}(t)$) from a CHP unit
- the conversion of electric ($P_{HP}(t)$) to thermal ($H_{HP}(t)$) energy by a heat pump
- the provision of heat by a solar-thermal installation ($H_{ST}(t)$)
- as well as the provision of heat by a traditional gas boiler ($H_{GB}(t)$)

In addition, the following energy flows will be integrated:

- the local demand for both power ($P_{Load}(t)$) as well as heat ($H_{Load}(t)$)
- the exchange of electricity with the grid ($P_{Grid}^{Export}(t)$ and $P_{Grid}^{Import}(t)$)
- the charging and discharging of the electrical storage system ($P_{Storage}^{In}(t)$ and $P_{Storage}^{Out}(t)$)
- last, the heat provision and absorption from the thermal storage ($H_{ThStorage}^{Out}(t)$ and $H_{ThStorage}^{In}(t)$)

Table 3.5 lists all considered systems as well as it indicates their associated power or heat flows. By definition, all variables associated with a (+) sign are considered to be sources of power or heat and hence must be positive. Contrary, all variables associated with a (-) sign are sinks and must be negative at all times.

	Power	**Heat**
Demand	$P_{Load}(t)$ (-)	$H_{Load}(t)$ (-)
PV	$P_{PV}(t)$ (+)	-
CHP	$P_{CHP}(t)$ (+)	$H_{CHP}(t)$ (+)
Heat pump	$P_{HP}(t)$ (-)	$H_{HP}(t)$ (+)
Solar thermal	-	$H_{ST}(t)$ (+)
Gas boiler	-	$H_{GB}(t)$ (+)
Electric grid	$P_{Grid}^{Import}(t)$ (+) / $P_{Grid}^{Export}(t)$ (-)	-
Storage	$P_{Storage}^{Out}(t)$ (+) / $P_{Storage}^{In}(t)$ (-)	$H_{ThStorage}^{Out}(t)$ (+) / $H_{ThStorage}^{In}(t)$ (-)

Table 3.5: Available systems as well as power and heat flows

To ensure the balance of the electric system, equation (3.22) must hold at every time *t*. Any mismatch in power can always be balanced with the grid.

$$P_{Load}(t) + P_{PV}(t) + P_{CHP}(t) + P_{HP}(t) + P_{Grid}^{\text{Import}}(t) + P_{Grid}^{\text{Export}}(t) + P_{Storage}^{Out}(t) + P_{Storage}^{In}(t) = 0 \tag{3.22}$$

In an analogous way, the balance of the thermal system is described by equation (3.23).

$$H_{Load}(t) + H_{CHP}(t) + H_{HP}(t) + H_{ST}(t) + H_{GB}(t) + H_{ThStorage}^{Out}(t) + H_{ThStorage}^{In}(t) = 0 \tag{3.23}$$

The further denomination of the thermal storage system follows the electric device. While the electrical storage system is denominated with the subscript *Storage*, the subscript *ThStorage* will refer to the thermal storage system. The calculation of the stored energy $E_{ThStorage}(t)$ follows equation (3.6), the state of charge is limited in an analogous way to equations (3.9) and (3.10). The heat exchange is limited during each period by equivalents to equations (3.7) and (3.8).

The classification of cost into C^{Invest}, C^{Fixed} as well as $C^{Operating}$ also applies to the different systems, again with the subscript referring to each individual system.

- The investment cost for photovoltaic installations C_{PV}^{Invest} not only includes the panels, but also the required power electronics as well as the installation cost. Typical fixed cost C_{PV}^{Fixed} corresponds to insurance fees as well as regular cleaning and inspection. There is no variable cost.
- For a CHP plant, the investment cost C_{CHP}^{Invest} is dominated by the unit cost, however installation and integration into the building is also a major investment cost component. Fixed cost C_{CHP}^{Fixed} will include maintenance contracts for regular inspection intervals and insurance. Variable operating cost $C_{CHP}^{Variable}$ is primarily the fuel cost, but also related costs such as lubricants or filters.
- Heat pumps, which are air-based, are typically easy to install. Hence, the investment cost C_{HP}^{Invest} is mainly driven by the unit cost. Fixed cost C_{HP}^{Fixed} in the form of maintenance efforts and regular inspection are typically rather low. Besides the demand for electricity, which is considered by $P_{HP}(t)$, there is no additional variable cost.

- Similar to photovoltaic installations, solar thermal systems are commonly installed on the roof and require additional attachment and wiring investments besides the system itself. Total investment cost is C_{ST}^{Invest}. Fixed cost C_{ST}^{Fixed} is usually very low, no operating cost exists.

- Frequently, a gas boiler will be installed in combination with a cogeneration unit in order to cover peak heat demand. The unit cost drives the total installation cost C_{GB}^{Invest}. Fixed cost C_{GB}^{Fixed} is low and mostly due for regular maintenance, variable cost $C_{GB}^{Variable}$ is determined by fuel cost.

When jointly optimizing the energy supply of a building, no division of cost between heat and electricity is required. However, when considering both individually, costs must be separated. While for most systems cost can be clearly identified and assigned to either the provision of electricity or heat, this assignment is no trivial task for cogeneration units due to their simultaneous provision of both electricity and heat. As cogeneration units are typically installed in combination with a gas boiler for the provision of peak demand, the cost can be compared to a stand-alone solution, where the gas boiler covers the complete heat demand. In both cases, the cost for the provision of heat should be identical. The increase in overall cost can then be attributed to the generation of electricity. Therefore, as the cogeneration unit is in addition to the regular gas boiler and does not reduce the cost of heat supply, investment cost for the CHP plant will typically be assigned to the provision of electricity. Fuel cost is considered proportionally to the split of electricity and heat output. However, as the CHP unit will for example reduce the operating hours of the gas boiler and hence likely extend its lifetime, the separation remains fuzzy.

Figure 3.1 shows a simplified representation of the power and heat flows. Electricity generation resources, photovoltaic and combined heat- and power plants provide electricity to serve local demand. The electrical storage system can both provide or absorb power, as well as the interconnection with the grid. The connection with the heat system stems from both the cogeneration unit, which simultaneously also produces heat, as well as the heat pump, which requires electricity. Further heat sources are a solar-thermal installation as well as a boiler. Temporal deviations between heat generation and demand are matched by a thermal storage.

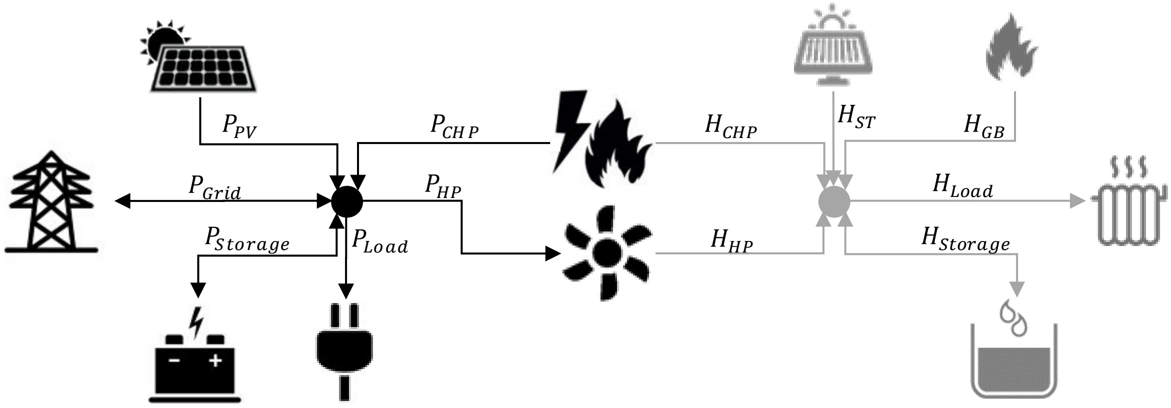

Figure 3.1: Simplified representation of power and heat flows

In this chapter, only clients without access to the wholesale market are considered. Hence, they have a commercial contract with a retailer and are charged according to a tariff scheme $R^{Import}(t)$. The tariff can either be a flat-price tariff, where the electricity taken from the grid costs the same at all times. Alternatively, $R^{Import}(t)$ can be a time-of-use tariff, differentiating between peak- and off-peak periods. However, more complex schemes are possible and might provide additional incentives for generators and distribution companies as well as consumers.

Electricity that is fed into the grid will be compensated according to the feed-in tariff $R_{PV}^{Export}(t)$ or $R_{CHP}^{Export}(t)$. In the case of a combined PV and CHP installation it will be assumed that the generation of the system with the lower feed-in tariff will be preferentially locally consumed. Furthermore, feed-in of PV generated power might be limited to a certain fraction of installed power ($P_{PV}^{\max\ feed-in}$) to accommodate more installations in the network and incentivize grid-beneficial behavior. In a simple installation, this can be accomplished through a limit in the PV controller. In the presented case, however, it should refer to the connection between consumer and grid, therefore also considering local demand and storage charging.

3.3.3 Operation Schedule

Before the storage system can be evaluated, its dispatch and interaction with the other systems must be defined. Therefore, an algorithm is required which describes when the storage device is charged or discharged. The operation of the storage depends on the pursued objective of the storage investors. As this thesis is concerned with the economic evaluation of storage, the maximization of profits or the minimization of cost is the chosen objective. However, further objectives, such as the maximization of autarky or self-sufficiency, exist and require a different operation of the storage system.

In this section, a simple operation schedule, which does not rely on any external information besides the current power and heat flows, is described. It assumes the installation of a storage system for a grid-connected consumer together with a PV system and a cogeneration unit, which is dispatched according to thermal demand in a residential context. Hence, electric energy is delivered only as a byproduct and might be available during times, when no immediate demand exists. Generation, which exceeds instantaneous demand, will be primarily used for charging the storage device or otherwise be fed into the grid. Contrary, demand that exceeds current generation is first satisfied by the storage system. Only when the storage system is discharged, deficit energy is taken from the grid.

As the dispatch of the cogeneration is driven by the demand for heat, the complete thermal system needs to be considered as well as previously discussed. Therefore, a solar thermal installation, the cogeneration unit as well as a gas boiler will be considered. In addition, a thermal storage device will be integrated, which can be charged from either surplus solar thermal generation or from the cogeneration unit. In order to limit the degrees of freedom and the resulting complexity, the heat pump will not be considered for this operation schedule.

As the electric dispatch depends on the thermal dispatch due to the dependency of the cogeneration unit, for each time step first the thermal system is considered, before the dispatch for the electric system is determined. Figure 3.2 shows the simplified operation over one time step. Equations (3.24) - (3.34) translate the process into a set of mathematical formulations, linking the state-dependent variables in time.

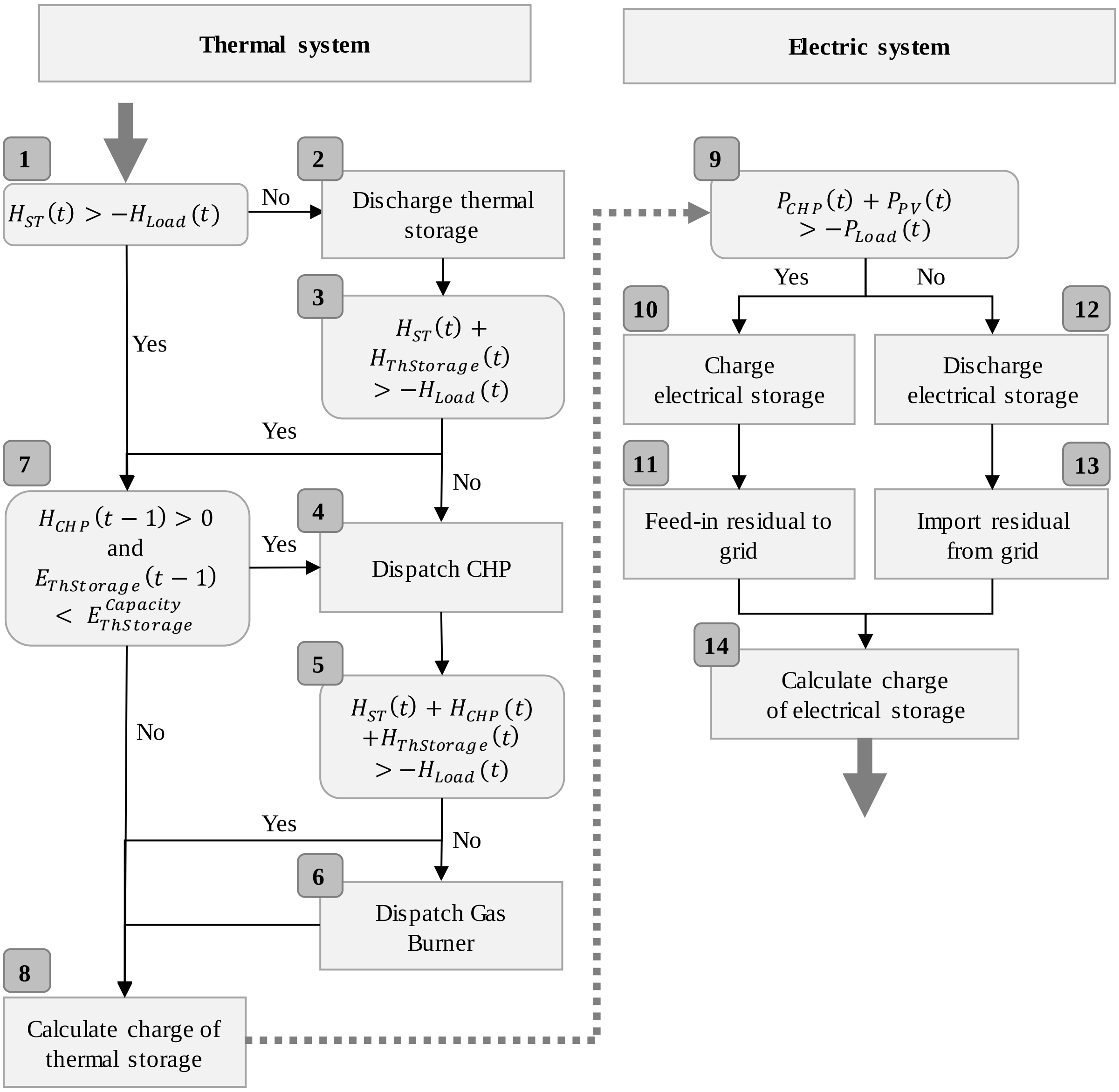

Figure 3.2: Simplified representation of one time step of the operating algorithm

First, the model will determine (step {1} in Figure 3.2) if solar thermal generation $H_{ST}(t)$ is sufficient to satisfy the heat demand $H_{Load}(t)$ during period t. If the solar thermal installation does not provide sufficient heat, the thermal storage will be discharged (step {2}), observing its current state of charge as well as the capacity of the heat exchanger as indicated by equation (3.24).

$$H_{ThStorage}(t) = \max\left(0; \min\left\{\begin{matrix} -H_{Load}(t) - H_{ST}(t) \\ E_{ThStorage}(t-1) \times (1 - \Delta t \times \phi_{ThStorage}) \times \Delta t^{-1} \\ H_{ThStorage}^{Capacity} \end{matrix}\right.\right) \tag{3.24}$$

If the available heat ($H_{ST}(t) + H_{ThStorage}(t)$) is still less than demand ($H_{Load}(t)$) (step {3}), the cogeneration unit will be dispatched according to equation (3.25) (step {4}).

$$H_{CHP}(t) = H_{CHP}^{Capacity} \tag{3.25}$$

A subsequent check, if the heat provided ($H_{ST}(t)$ + $H_{ThStorage}(t)$ + $H_{CHP}(t)$) now satisfies demand ($H_{Load}(t)$) *(step {5})*, determines the dispatch of the gas boiler (step {6}) as given by equation (3.26).

$$H_{GB}(t) = \max(0; -H_{Load}(t) - H_{ST}(t) - H_{ThStorage}(t) - H_{CHP}(t)) \tag{3.26}$$

Furthermore, if the cogeneration unit had been dispatched the previous period and the thermal storage is not yet fully charged, it will be kept running to minimize start-/stop cycles (step {7}).

Equation (3.24) was only an intermediate calculation to determine the required heat generation from the cogeneration unit and the gas boiler. In order to determine the new charge level of the thermal storage device (step {8}), the potential charging from the solar thermal installation and the cogeneration unit must also be considered. Equation (3.27) determines the heat charge/discharge amount of the thermal storage which ensures the balance of heat flows.

$$H_{ThStorage}(t) = -H_{Load}(t) - H_{ST}(t) - H_{CHP}(t) - H_{GB}(t) \tag{3.27}$$

Finally, the new charge level of the thermal storage device is calculated as given by equation (3.28), taking the self-discharge into account.

$$E_{ThStorage}(t) = E_{ThStorage}(t-1) \times (1 - \phi_{ThStorage}) - H_{ThStorage}(t) \times dt \tag{3.28}$$

Based on the thermal dispatch of the cogeneration unit, the power generation for each time period t can be determined according to the ratio of the heat and power generation capacity as indicated by equation (3.29).

$$P_{CHP}(t) = H_{CHP}(t) \times \frac{P_{CHP}^{Capacity}}{H_{CHP}^{Capacity}} \tag{3.29}$$

Following, the local balance of the electric system is determined (step {9}) by comparing generation from the photovoltaic system $P_{PV}(t)$ and the cogeneration unit $P_{CHP}(t)$ with demand $P_{Load}(t)$. If local electricity generation exceeds instantaneous demand, a surplus exists that can be used to charge the electrical storage system (step {10}). On the contrary, if demand is greater than current generation, it can be satisfied by discharging the storage unit (step {12}). However, when charging / discharging the system, its technical limitations have to be observed.

The charging-power of the storage system for each period ($P_{Storage}^{In}(t)$) is determined by the minimum of the local power balance of load and generation from PV and CHP, the remaining capacity of the storage system (considering the efficiency of the charging operation) and the power limit (equation (3.30)). The outer minimization furthermore ensures that only charging operations are assigned.

$$P_{Storage}^{In}(t) = \min\left(0; -\min\left\{\begin{array}{c} P_{PV}(t) + P_{CHP}(t) + P_{Load}(t) \\ \left(E_{Storage}^{Capacity} - E_{Storage}(t-1)\right) \times \left(\Delta t \times \eta_{Storage}^{In}\right)^{-1} \\ P_{Storage}^{Capacity} \end{array}\right.\right) \tag{3.30}$$

Contrary, the discharging-power of the storage system ($P_{Storage}^{Out}(t)$) is determined by a lack of local generation versus demand, the remaining charge of the storage system (considering the discharge efficiency and the depth of discharge) as well as its power limit (equation (3.31)).

$$P_{Storage}^{Out}(t) = \max\left(0; \min\left\{\begin{array}{c} -\left(P_{PV}(t) + P_{CHP}(t) + P_{Load}(t)\right) \\ \left(E_{Storage}(t-1) - E_{Storage}^{Capacity} \times \delta_{Storage}\right) \times \eta_{Storage}^{Out} \times \Delta t^{-1} \\ P_{Storage}^{Capacity} \end{array}\right.\right) \quad \textbf{(3.31)}$$

Surplus from local generation, which cannot be charged into the storage system due to its power limit or because it would exceed storage capacity, is fed into the grid (step {11}). Contrary, any shortfalls that cannot be provided by the battery are satisfied from the grid (step {13}). The exchange with the grid is therefore determined as the residual of the previously defined power flows, which balance the electrical system (equations (3.32) and (3.33)).

$$P_{Grid}^{\mathrm{Import}}(t) = \max\left(0; -P_{Load}(t) - P_{PV}(t) - P_{CHP}(t) - P_{Storage}^{Out}(t) - P_{Storage}^{In}(t)\right) \quad \textbf{(3.32)}$$

$$P_{Grid}^{\mathrm{Export}}(t) = \min\left(0; -P_{Load}(t) - P_{PV}(t) - P_{CHP}(t) - P_{Storage}^{Out}(t) - P_{Storage}^{In}(t)\right) \quad \textbf{(3.33)}$$

Last, based on the charging- and discharging power flows from equations (3.30) and (3.31), the resulting energy level of the electric storage device is calculated (step {14}) according to equation (3.34), taking the efficiency of the storage system into account.

$$E_{Storage}(t) = E_{Storage}(t-1) - \Delta t \times \left(P_{Storage}^{In} \times \eta_{Storage}^{In} + P_{Storage}^{Out} \big/ \eta_{Storage}^{Out}\right) \quad \textbf{(3.34)}$$

3.3.4 Optimal Dispatch Problem

The previous section presented a simplified operation schedule for an electric storage device, which only reacts passively to the current power and heat flows. The integration of several dispatchable resources, time-of-use tariff schemes and the consideration of the thermal system make it difficult to obtain the cost minimizing operation schedule. Therefore, a mixed integer program (MIP) formulation is used to determine the optimal storage dispatch. A mixed integer problem aims at optimizing an outcome that is described and restricted by linear relationships, where some of the variables can only assume integer values. These relationships describe the functionality of the represented system in a simplified model. The obtained schedule after solving the problem is forward-looking. Following the argumentation in the existing literature (see Section 2.4.5), this represents a lower bound on cost / upper bound on profitability, as in reality future information is unknown and forecasts typically contain errors leading to sub-optimal dispatch decisions.

A general formulation of the storage dispatch process and the required technical framework was presented in Section 3.1. The integration with the electric and thermal system increases the complexity of the model significantly. Therefore, in order to replicate the complete system by linear relations, a range of simplifications are implemented:

- Self-discharge ϕ is neglected for the electrical storage system. For commonly installed battery storage systems (such as a lithium-ion battery) which are dispatched daily, the resulting losses are minimal and can be ignored.

- Contrary, thermal-storage systems suffer from significant daily self-discharge. Hence, it is important to consider this effect in the problem formulation, as shifting thermal energy over longer timeframes is severely impacted by the accumulating self-discharge losses.
- As no conversion process for heat is required during thermal storage, the efficiency of that process is assumed to be 100%. Therefore, no split into two separate vectors $H_{ThStorage}^{In}(t)$ and $H_{ThStorage}^{Out}(t)$ is required. Rather, it is assumed that $H_{ThStorage}(t) > 0$ represents heat supplied and $H_{ThStorage}(t) < 0$ heat absorbed by the thermal storage system.
- Storage operations have no immediate variable cost.
- The power exchange with the grid is split into $P_{Grid}^{Import}(t)$ (electricity taken from the grid, ≥0) and $P_{Grid}^{Export}(t)$ (energy injected, ≤0). A further subdivision of feed-in power into $P_{Grid}^{Export\,PV}(t)$ (feed-in of PV generated power) and $P_{Grid}^{Export\,CHP}(t)$ (feed-in of CHP generated power) is required to differentiate between different feed-in tariffs $R_{PV}^{Export}(t)$ and $R_{CHP}^{Export}(t)$ for PV- and CHP-generated electricity.
- The power-output $P_{CHP}(t)$ of the cogeneration unit can be modulated from $P_{CHP}^{CapacityMin}$ up to $P_{CHP}^{Capacity}$ at constant efficiency.
- The power from photovoltaic generation $P_{PV}(t)$ considered in the formulation can be less than the actual generation $P_{PV}^{*}(t)$. This can for example be realized by setting a sub-optimal set point in the solar controller. This restriction can be required to follow the feed-in limitation of PV installations to $P_{PV}^{\max\ feed-in}$.
- Analogous, the considered heat $H_{ST}(t)$ from a solar-thermal installation can be less than the available generation $H_{ST}^{*}(t)$.
- The considered consumption tariff must exceed the feed-in remuneration and must be positive at all times ($R^{Import}(t) > R^{Export}(t) > 0$). Otherwise, the problem formulation must be extended in order to avoid simultaneous import and export of electricity with the grid, which might be financially advantageous in the objective function but impossible from a technical viewpoint.
- Time-value of money is not considered in the dispatch optimization. As the individual decisions are of a short horizon and the storage device is typically cycled frequently, this effect can be neglected. However, in the following evaluation of cash flows, which are based on the previously taken dispatch-decisions, the effect is considered.

The problem is described by equations (3.35) - (3.56). The objective is the maximization of the gross margin, that is the difference between the revenues and cost, by determining the optimal dispatch and operation schedule for the system components (equation (3.35)). Revenues are determined by the feed-in of energy from both the photovoltaic system as well as the cogeneration unit. Cost result from energy taken from the grid as well as consumption of fuel for the cogeneration unit and the gas boiler.

Objective:

$$\max \Delta t \times \sum_{t=1}^{T} \begin{pmatrix} -P_{Grid}^{Import}(t) \times R^{Import}(t) - P_{Grid}^{Export\,PV}(t) \times R_{PV}^{Export}(t) - P_{Grid}^{Export\,CHP}(t) \times R_{CHP}^{Export}(t) - \ldots \\ P_{CHP}(t) \times C_{CHP}^{Variable} - H_{GB}(t) \times C_{CHP}^{Variable} \end{pmatrix} \quad \textbf{(3.35)}$$

In order to determine the value maximizing dispatch, the following decision variables must be defined:

- the dispatch of the cogeneration unit, resulting in the provision of power $P_{CHP}(t)$ as well as heat $H_{CHP}(t)$ in the ratio of their respective capacities,
- the exchanges with the grid ($P_{Grid}^{Import}(t)$, $P_{Grid}^{Export\,PV}(t)$ and $P_{Grid}^{Export\,CHP}(t)$),
- the operation of the storage systems, both for the electric storage ($P_{Storage}^{Out}(t)$ and $P_{Storage}^{In}(t)$) as well as the thermal storage system ($H_{ThStorage}(t)$),
- the dispatch of the gas boiler ($H_{GB}(t)$),
- the consideration of non-dispatchable resources based on the available generation ($P_{PV}(t)$ and $H_{ST}(t)$) and
- the dispatch of the heat pump ($H_{HP}(t)$), which results in a demand for power ($P_{HP}(t)$).

Besides the capacities and technical limitations of the installed systems, the demand for electricity ($P_{Load}(t)$) as well as heat ($H_{Load}(t)$) must be given. Furthermore, the generation of non-dispatchable resources ($P_{PV}^{*}(t)$ and $H_{ST}^{*}(t)$) must also be known. Last, as the efficiency of heat pumps depends on the outside temperature and therefore varies over time, the coefficient of performance $CoP(t)$ (describing the ratio of units of heat output for each unit of power) must be provided. The cost for the system installations are independent of the decision variables and therefore not considered in the optimal dispatch decision.

Subject to:

The system is constrained by a range of limitations. First, power demand and supply must be balanced at all times, as shown by equation (3.36).

$$\begin{aligned} &P_{Grid}^{Import}(t) + P_{Grid}^{Export\,PV}(t) + P_{Grid}^{Export\,CHP}(t) + P_{Storage}^{In}(t) + P_{Storage}^{Out}(t) + P_{PV}(t) + P_{CHP}(t) + \ldots \\ &\qquad P_{HP}(t) + P_{Load}(t) = 0 \end{aligned} \quad \textbf{(3.36)}$$

The power generation of the cogeneration unit is limited to its capacity. Furthermore, electric output of the CHP can only be modulated to a certain extend and cannot fall short of a lower limit. Therefore, a binary decision variable $z(t)$ is introduced, which controls if the cogeneration unit is on ($z(t) = 1$) or off ($z(t) = 0$). Equation (3.37) ensures, that the lower limit is observed, when the CHP is activated. The maximum output is limited by (3.38) to the nominal capacity of the cogeneration unit.

$$-z(t) \times P_{CHP}^{CapacityMin} + P_{CHP}(t) \geq 0 \quad \textbf{(3.37)}$$

$$-z(t) \times P_{CHP}^{Capacity} + P_{CHP}(t) \leq 0 \quad \textbf{(3.38)}$$

Similarly, the power considered from the photovoltaic system cannot exceed the currently available generation (equation (3.39)).

$$0 \le P_{PV}(t) \le P_{PV}^{*}(t) \tag{3.39}$$

The exchange with the grid is governed by equations (3.40) – (3.43). First, energy taken from the grid must be a positive number as described by equation (3.40).

$$0 \le P_{Grid}^{Import}(t) \tag{3.40}$$

According to equation (3.41), feed-in of energy generated by the cogeneration unit cannot exceed current generation.

$$P_{CHP}(t) + P_{Grid}^{ExportCHP}(t) \ge 0 \tag{3.41}$$

Analogous, the feed-in of energy generated by the photovoltaic system cannot exceed the current power provided by the installation (equation (3.42)).

$$P_{PV}(t) + P_{Grid}^{ExportPV}(t) \ge 0 \tag{3.42}$$

Furthermore, feed-in of power generated by a photovoltaic installation might be limited by a feed-in restriction, as shown by equation (3.43).

$$-P_{PV}^{\max\ feed-in} \le P_{Grid}^{ExportPV}(t) \le 0 \tag{3.43}$$

The charge- and discharge operations of the storage device are limited by its power rating. In order to ensure that no simultaneous charge- and discharge operations occur an additional binary decision variable *y(t)* is introduced. Otherwise, simultaneous operations could be chosen by the algorithm in order to increase the electric load due to the resulting efficiency losses. It is assumed, that for periods with *y(t) = 0*, only discharging can occur (equation (3.44)). Contrary, for *y(t) = 1*, the storage device can only be charged (equation (3.45)).

$$0 \le P_{Storage}^{Out}(t) \le P_{Storage}^{Capacity} \times (1 - y(t)) \tag{3.44}$$

$$-P_{Storage}^{Capacity} \times y(t) \le P_{Storage}^{In}(t) \le 0 \tag{3.45}$$

Besides the power limitation, the storage device is also energy limited. The state of charge cannot exceed the energy capacity (equation (3.46)) nor can it fall below the minimum depth of discharge (equation (3.47)).

$$\sum_{n=1}^{t} P_{Storage}^{In}(n) \times \eta_{in} \times \Delta t + \sum_{n=1}^{t} P_{Storage}^{Out}(n) \times {}^{1}\!/_{\eta_{out}} \times \Delta t \le 0 \tag{3.46}$$

$$\sum_{n=1}^{t} P_{Storage}^{In}(n) \times \eta_{in} \times \Delta t + \sum_{n=1}^{t} P_{Storage}^{Out}(n) \times {}^{1}\!/_{\eta_{out}} \times \Delta t \ge -E_{Storage}^{Capacity} \times (1 - \delta_{Storage}) \tag{3.47}$$

Besides the electricity related constraints, the heat system is also considered. Foremost, heat generation and demand must balance at all times (equation (3.48)).

$$H_{CHP}(t) + H_{ST}(t) + H_{GB}(t) + H_{HP}(t) + H_{Storage}(t) + H_{Load}(t) = 0 \quad \textbf{(3.48)}$$

Given the chosen power output of the cogeneration unit, its heat generation is defined through the constant ratio of the respective capacities, as shown by equation (3.49).

$$H_{CHP}(t) = P_{CHP}(t) \times \frac{H_{CHP}^{Capacity}}{P_{CHP}^{Capacity}} \quad \textbf{(3.49)}$$

Equation (3.50) limits the heat considered of the solar thermal installation to the actual generation.

$$0 \le H_{ST}(t) \le H_{ST}^{*}(t) \quad \textbf{(3.50)}$$

The heat generated by the gas boiler (equation (3.51)) is limited to its rated capacity.

$$0 \le H_{GB}(t) \le H_{GB}^{Capacity} \quad \textbf{(3.51)}$$

Choosing the output of the heat pump defines the required power $P_{HP}(t)$ depending on the coefficient of performance (equation (3.52)), which varies with the outside temperature:

$$P_{HP}(t) = -\frac{H_{HP}(t)}{CoP(t)} \quad \textbf{(3.52)}$$

Furthermore, equation (3.53) limits the power demand of the heat-pump to its capacity rating.

$$-P_{HP}^{Capacity} \le P_{HP}(t) \le 0 \quad \textbf{(3.53)}$$

The charge-/discharge rate of the thermal storage is limited according to equation (3.54).

$$-H_{ThStorage}^{Capacity} \le H_{ThStorage}(t) \le H_{ThStorage}^{Capacity} \quad \textbf{(3.54)}$$

The state of charge of the thermal storage system is limited by its capacity (equations (3.55) - (3.56)), considering the self-discharge ϕ of the system.

$$\sum_{n=1}^{t} H_{ThStorage}(n) \times \Delta t \times (1 - \Delta t \times \phi_{ThStorage})^{t-n} \le 0 \quad \textbf{(3.55)}$$

$$\sum_{n=1}^{t} H_{ThStorage}(n) \times \Delta t + (1 - \Delta t \times \phi_{ThStorage})^{t-n} \ge -H_{ThStorage}^{Capacity} \quad \textbf{(3.56)}$$

By selectively setting the capacity of individual system components to zero, the optimal dispatch for a wide range of potential configurations can be analyzed.

3.3.5 Optimal System Configuration Problem

The optimization problem presented in the previous Section determines the optimal dispatch for a given system configuration. However, an investor considering an investment in storage is typically faced with the decision to determine the cost minimizing system configuration. This is typically no longer a linear / mixed integer problem:

- Investment cost do not increase linearly with capacity, as oftentimes economies of scale can be observed, such as for system planning, installation or power electronics.
- Usually, only certain capacity values are commercially available.
- Subsidies are oftentimes not linear and might have a range of further restrictions.

While the simple operation schedule from Section 3.3.3 and the mixed integer program from Section 3.3.4 provide the (cost minimizing) dispatch for a given system configuration, an additional process is required to determine the optimal system configuration.

This optimization problem is described by equations (3.57) - (3.60). The assumed objective is the maximization of the net present value of the project (equation (3.57)). Decision variables are the capacities of the system components. The dispatch for a chosen configuration is then determined by the dispatch problem described in the previous Sections 3.3.3 and 3.3.4. Based thereupon, the net present value can be determined (as described in the following Section 3.3.6).

Typically, the investment amount will be constrained by a given budget, as shown by equation (3.58). An increase in capacity for one system will oftentimes require a tradeoff and a reduction in some other capacity. Furthermore, installed capacities might only assume some discrete values, which are commercially available (equation (3.59)). Last, the capacity of system components can be limited to a certain range, as indicated by equation (3.60), for example due to limited roof space for photovoltaic installations. If a specific system already exists or should be excluded, its capacity value can also be enforced to a certain value in the search process this way.

Objective:

$$\max NPV \tag{3.57}$$

Subject to:

$$C_{Storage}^{Invest} + C_{ThStorage}^{Invest} + C_{HP}^{Invest} + C_{GB}^{Invest} + C_{ST}^{Invest} + C_{PV}^{Invest} + C_{CHP}^{Invest} \leq budget \tag{3.58}$$

For each system: commercial availability **(3.59)**

$$x_{\min} \leq P_x^{Capacity} \leq x_{\max} \tag{3.60}$$

To determine the NPV maximizing system configuration, Simulated Annealing will be used. Simulated Annealing is a probabilistic metaheuristic, which was proposed by Kirkpatrick et al. [182] to find the global minimum of a function which may have several local minima. Its general manner of operation follows the physical process of slowly cooling a solid material, whereby the atoms or molecules will arrange themselves in an energy minimizing configuration. The underlying idea of the algorithm is to admit worse solutions during the process in order to move away from local minima. Over time, the probability of accepting a worse solution decreases. Therefore, one of the big advantages of this approach is that it can move away from local optima to explore different areas of the search space. In addition, the search process can be easily adapted to a specific problem. However, the algorithm does not necessarily identify the global optimum but if an adequate closing criterium is used and a sufficiently slow lowering process of the temperature is adopted good quality solutions are in general obtained.

Algorithm 1 describes the general process of this search routine. After establishing a starting point describing an initial system configuration (Step 1), its net present value is calculated (Step 2) by determining its optimal dispatch (as described in Section 3.3.4). After that, a random search point in the neighborhood of the current location is chosen (Step 3) and again its NPV is calculated (Step 4), by rerunning the optimal dispatch problem for that specific system configuration. If the net present value of the new explored solution is higher than the NPV of the current location, the search point is accepted unconditionally as new starting point for further searches (5a). In addition, it may also be accepted (with declining probability over time, as the temperature of the Simulated Annealing simulation decreases) if its NPV is lower (5b). Otherwise, it is rejected and the current location is kept (5b). Steps 3-5 are repeated, until an acceptable solution has been identified. In addition, after each iteration the temperature of the simulation is reduced by a pre-specified cooling factor, which reduces the likelihood of accepting a worse solution.

Algorithm 1: High-level overview of the Simulated Annealing process to determine the optimal system configuration

1. Generate a random start point
2. Calculate its NPV
3. Generate a random search point in the neighborhood of the current location
4. Calculate the NPV of the new search point
5. Compare the NPV of the new search point and the current location
    a. Move to the new solution if the NPV is higher
    b. Otherwise: move to the new location with a decreasing likelihood or reject it
6. Repeat steps 3-5, until an acceptable solution has been identified

A real implementation of this search process requires some additional steps and parameters. As the process might move away from previously identified optimal solutions, an additional step will be implemented to ensure that the best solution found is remembered. The search process stops when a certain number of iterations were completed without improving the current best solution by at least a predefined amount usually defined by a percentage. Furthermore, the choice of the parameters plays an important role. The initial acceptance probability must be high enough to allow the search routine to move to different areas of the search space, but not too high to avoid a complete random evaluation.

Figure 3.3 shows the proposed optimization process for a storage system deployed for time shifting of electricity. The goal of the optimization process is determining the NPV-maximizing system configuration, given a range of restrictions. The mixed integer program presented in 3.3.4 solves the optimal dispatch for a given system configuration. Based thereon, the NPV for the analyzed system configuration is calculated. This process of determining the cost minimizing dispatch and the calculation of the NPV is embedded in the higher-level Simulated Annealing algorithm which is searching for the optimal system configuration having the highest NPV.

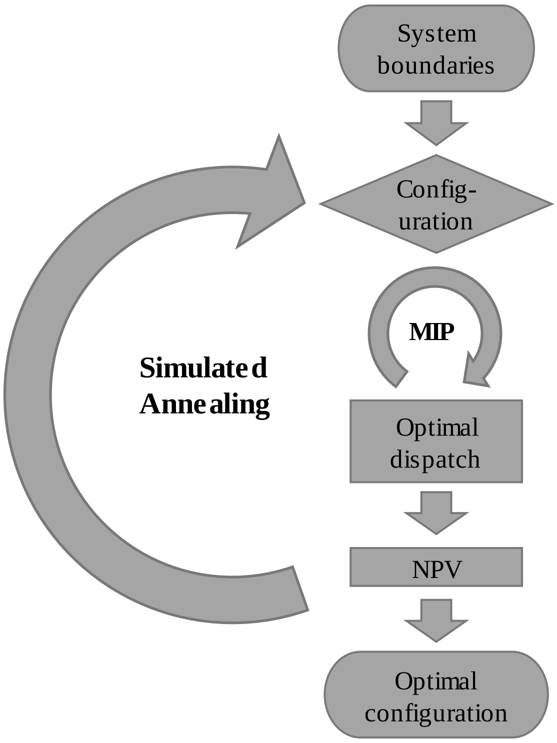

Figure 3.3: Flowchart of the optimization process

3.3.6 Evaluation

Based on the obtained dispatch from the optimization problem (3.35) - (3.56) and assuming that fixed cost are split evenly over the evaluation period, the resulting cash flow can then be calculated by equation (3.61).

$$CF(t) = -\alpha - \beta(t) - \Delta t \times (P_{Grid}^{Import}(t) \times R^{Import}(t) + P_{Grid}^{Export\,PV}(t) \times R_{PV}^{Export}(t) + P_{Grid}^{Export\,CHP}(t) \times R_{CHP}^{Export}(t)) \qquad \textbf{(3.61)}$$

In this expression, α represents the allocation of the fixed annual cost to each time step, as indicated by equation (3.62).

$$\alpha = \left(C_{Storage}^{Fixed} + C_{ThStorage}^{Fixed} + C_{CHP}^{Fixed} + C_{PV}^{Fixed} + C_{GB}^{Fixed} + C_{HP}^{Fixed} + C_{ST}^{Fixed}\right) \times \frac{\Delta t}{8760} \qquad \textbf{(3.62)}$$

The variable cost from operation is summarized as *β(t)*, as shown by equation (3.63).

$$\beta(t) = \Delta t \times \left(\sum_{x=Storage,\,CHP,\,PV} C_x^{Variable} \times P_x(t) + \sum_{x=ThStorage,\,ST,\,GB,\,HP,\,CHP} (C_x^{Variable} \times H_x(t) \right) \qquad \textbf{(3.63)}$$

As the lifetime of system components will regularly diverge from the evaluation horizon (for example due to insufficient data), their initial investment cost will be considered proportionally according to their calendric lifetime. Investment cost of storage systems will be considered according to either their calendric or their cycle lifetime, whichever factor is limiting their lifetime expectancy. The calculation is given by equation (3.64).

$$CF(0) = -\sum_{x=PV,CHP,HP,GB,ST,ThStorage} C_x^{Invest} \times \frac{T^{years}}{L_x^{calendric}} - C_{Storage}^{Invest} \times \max\left(\frac{N(T)}{L_{Storage}^{cycle}}; \frac{T^{years}}{L_{Storage}^{calendric}}\right) \tag{3.64}$$

In reality, the lifetime of system components regularly diverges from each other. Hence, after some time some systems will reach their end of service and either are no longer operational or must be replaced. Alternatively, a terminal residual value for the remaining components could be estimated. While the replacing of system components introduces additional complexity in the dispatch schedule and requires very long evaluation horizons, the estimation of terminal values introduces additional uncertainty due to the required value appraisals. Therefore, equation (3.64) implicitly assumes that systems can be bought or replaced with arbitrary lifetime expectations.

Based on the determined cash flows (equations (3.61) - (3.64)), the net present value can then be calculated according to the procedure presented in Section 3.2.2.

Generally, the application of storage is only beneficial if the savings exceed the cost of storage, including efficiency losses. In the case of a time-of-use tariff, the savings enabled by a storage installation are determined by the difference between the valley price of the time-of-use tariff and the flat price of the regular, undifferentiated tariff considering efficiency losses. Storage in such a setting can only be beneficial, if the price differential of the offered tariff scheme is sufficiently high (equation (3.65)).

$$LCOS \leq R^{Import}(flat) - \frac{R^{Import}(valley)}{\eta_{Storage}} \tag{3.65}$$

For local generation, the base assessment criterion is the difference between feed-in remuneration and consumption tariff, as shown by equation. (3.66). The levelized cost of the storage system must be lower than the overall cost of feeding-in and later taking the electricity from the grid, considering efficiency losses. However, for example feed-in restrictions move this statement in favor of storage. In fact, electricity that had to be regulated down due to feed-in restriction was previously inevitably lost for the investor. However, if it can be stored for later self-consumption, the relative cost of that amount of energy would be zero. Overall, the lower the feed-in tariffs or the higher the consumption tariff, the more attractive storage is.

$$LCOS \leq R^{Import} - \frac{R^{Export}}{\eta_{Storage}} \tag{3.66}$$

In order to assess the economic value of a storage system, first a reference case is evaluated to establish a baseline for further comparison. Under the reference case, the consumer takes all electricity from the grid. Local heat demand is exclusively satisfied by a gas boiler, which is co-installed with a small thermal storage, such that the gas boiler does not need to be dimensioned to cover peak demand. The required capacity can be easily identified by employing the Simulated Annealing search process and restricting the capacity of all other components to zero. Based on the obtained configuration the reference value $NPV_{Reference}$ can then be calculated by means of equations (3.61) - (3.64) and (3.20).

The economic benefit of a particular configuration can then be determined by comparing its NPV to the reference case. Obviously, this approach can not only be used for a comparison with the reference case, but also between different system configurations. Furthermore, the value contributed by electrical storage to a certain system configuration can be easily established by comparing the net present value with and without the presence of a storage device.

Besides the financial evaluation, a range of indicators (see Table 3.6) provide additional insights into the operation and utility of storage. As normalized figures, they allow an easy assessment and comparison among different system configurations.

Symbol	**Unit**	**Description**
SC	[%]	Self-consumption
SS	[%]	Self-sufficiency
LF	[%]	Load Factor

Table 3.6: Indicators for the evaluation of storage systems

The self-consumption describes the relation between locally generated energy and the amount of energy thereof which was locally consumed (either immediately or for storage charging), as indicated by equation (3.67).

$$SC = 1 + \frac{\sum_{t=1}^{T}\left(P_{Grid}^{Export\,CHP}(t) + P_{Grid}^{Export\,PV}(t)\right)}{\sum_{t=1}^{T}\left(P_{CHP}(t) + P_{PV}(t)\right)} \tag{3.67}$$

Equation (3.68) calculates the self-sufficiency, which describes how much of local demand was satisfied by local sources such as local generation or battery discharge.

$$SS = 1 + \frac{\sum_{t=1}^{T} P_{Grid}^{Import}(t)}{\sum_{t=1}^{T} P_{Load}(t)} \tag{3.68}$$

The load-factor describes the relation between peak and average usage of a grid connection as indicated by equation (3.69).

$$LF = \frac{max(P_{Load}(t))}{mean(P_{Load}(t))} \tag{3.69}$$

3.4 Arbitrage of Energy Prices

While the business case introduced in the previous section is concerned with reducing the cost of energy for a consumer, the application presented in this section is concerned with pursuing a profit by benefitting from temporal electricity price differentials. Section 3.4.1 explains the business case in more detail. Section 3.4.2 introduces the problem of determining the optimal dispatch under perfect foresight, that is with knowledge of future prices. Therefore, a mixed integer program is formulated. The assumption of knowledge about future prices is relaxed in 3.4.3, where a dispatch algorithm is presented based on historical electricity prices. Last, Section 3.4.4 provides a framework for the evaluation of the business case. The approach will be applied to a case study in section 6.2.

3.4.1 Business Case

Arbitrage describes a storage operating strategy where energy is taken from the grid when prices are comparably low and fed back into the grid during higher price periods. The profits of such a strategy are therefore determined by the price spread, that is the revenues from selling energy at a high price (discharging the storage system and feeding energy into the grid) minus the cost for previously buying the energy at a lower cost (charging the system by taking energy from the grid). Therefore, arbitrage operations benefit from high volatility with frequent swings to both high and low prices.

Traditionally, storage plants were oftentimes operated in a diurnal pattern. During the night, storage plants were charged and thereby increased the utilization of thermal base load generators. On the following day, the storage system was discharged during peak demand periods, reducing the required generation capacity. Due to the merit order effect and regular demand patterns, this type of operation was easy to schedule.

The strong increase of non-dispatchable, renewable generation is however changing this pattern. With further increasing shares of renewable generation and a simultaneous reduction in traditional thermal generation, electricity prices are becoming more volatile. In times of excess of renewable generation, prices drop. Contrary, during times with little renewable generation, prices increase. The more pronounced price spread provides the required incentives for additional storage investments to absorb energy during low-price periods and provide energy during peak times.

3.4.2 Optimal Dispatch Problem

In order to determine the profit maximizing dispatch of a storage system pursuing arbitrage, a range of assumptions are required. They follow the assumptions established for the optimal dispatch problem for time shifting of energy (see Section 3.3.4): the split of variables representing power flows into in- and out-flows, the disregard of the time-value of money for the optimal dispatch, the disregard of self-discharge as well as no immediate variable operating cost.

The assumed objective of the operator is the maximization of profits, as indicated by equation (3.70). The decision variables are the charging and discharging quantities, $P_{Storage}^{In}(t)$ and $P_{Storage}^{Out}(t)$. They are multiplied with the respective market prices in order to obtain the associated revenues and cost. However, as the lifetime of most storage systems is limited by a maximum number of cycles, a hurdle rate (*hurdle*) is implemented in the objective function in order to permit only those operations, where the net revenue exceeds a predefined threshold. The lower the rate, the more frequently the storage system will be dispatched and hence the shorter will be its expected lifetime. As all energy used for charging the storage device is taken from the grid and all energy obtained from discharging is fed back into the grid, the exchange with the grid $P_{Grid}^{Import}(t)$ as well as $P_{Grid}^{Export}(t)$ are indirectly also defined.

<u>Objective:</u>

$$max\ \Delta t \times \sum_{t=1}^{T} (P_{Storage}^{In}(t) \times R(t) + P_{Storage}^{Out}(t) \times (R(t) - hurdle)) \qquad \textbf{(3.70)}$$

Equation (3.71) ensures that the storage device is not discharged too low, and (3.72) restricts the charge to the effective capacity of the storage device. Equations (3.73) and (3.74) restrict power flows to the rating of the storage device, and equations (3.75) together with (3.76) ensure the correct sign of the power flow variables.

Subject to:

$$\sum_{t=1}^{T}\left(P_{Storage}^{In}(t)\times\eta_{Storage}^{In}\times\Delta t\right)+\sum_{t=1}^{T}\left(P_{Storage}^{Out}(t)\times\frac{1}{\eta_{Storage}^{Out}}\times\Delta t\right)\leq 0 \tag{3.71}$$

$$\sum_{t=1}^{T}\left(P_{Storage}^{In}(t)\times\eta_{Storage}^{In}\times\Delta t\right)+\sum_{t=1}^{T}\left(P_{Storage}^{Out}(t)\times\frac{1}{\eta_{Storage}^{Out}}\times\Delta t\right)\geq -E_{Storage}^{Capacity}\times\left(1-\delta_{Storage}\right) \tag{3.72}$$

$$P_{Storage}^{Out}(t)\leq P_{Storage}^{Capacity} \tag{3.73}$$

$$P_{Storage}^{In}(t)\geq -P_{Storage}^{Capacity} \tag{3.74}$$

$$P_{Storage}^{Out}(t)\geq 0 \tag{3.75}$$

$$P_{Storage}^{In}(t)\leq 0 \tag{3.76}$$

All relationships are linear and therefore linear programming (LP) can be used to identify the optimal dispatch.

Negative Prices

For markets where negative prices can occur, the above formulation however might lead to undesired and in reality impossible operating schedules. If during a certain hour negative prices occur, the storage device would typically be discharged beforehand and then charged again during the period with the negative prices, effectively being compensated for consuming energy. However, if negative prices persist over several periods, the storage device will be fully charged at one point and no further energy can be taken from the grid, even though it is economically advantageous. Under the above model, the device would then be charged and discharged during the same period, generating a profit as the discharged energy would be less than the charged energy due to efficiency losses.

This can easily be demonstrated by a small numerical example, as shown in Table 3.7. Initially, the storage device is discharged. During the first period, the storage is not yet charged as lower prices will prevail in the following periods. In periods two and three, market prices are negative and hence the storage device is charged at its power rating. Considering efficiency losses, the storage device is charged to 95% at the end of period three. The undesired effect can be observed in period 4. Being fully charged, the storage device is now simultaneous charging and discharging. As the operations takes place at less than 100% efficiency and the market price is negative, a positive cash flow is generated.

t	*R(t)*	$P_{Storage}^{In}(t)$	$P_{Storage}^{Out}(t)$	$E_{Storage}(t)$	*CF(t)*
1	+1	0	0	0	0
2	-1	-0.5	0	0.475	0.500
3	-1	-0.5	0	0.950	0.500
4	-1	-0.5	0.404	1	0.096
5	+1	0	0.5	0.474	0.500

Table 3.7: Dispatch from the LP with simultaneous charge- and discharge operations[1]

[1] Assumed parameters: $\Delta t = 1h$; $E_{Storage}^{Capacity}=1kWh$, $P_{Storage}^{Capacity}=0.5kW$, $\eta_{Storage}^{In}$ / $\eta_{Storage}^{Out}$=95%, $\delta_{Storage}$=0%

As the obtained solution is infeasible in reality, the above model does not reflect reality well when negative prices occur and hence must be extended to prevent simultaneous charge- and discharge operations.

In order to restrict the solution of the problem to either charging- or discharging during any time period t, an additional decision variable *y(t)* is introduced. The variable is binary, and hence turns the optimization problem into a mixed integer programming (MIP) problem. It is assumed that *y(t) = 1* for charging operations and *y(t) = 0* for discharging operations. Constraints (3.73) and (3.74) must be replaced by equations (3.77) and (3.78):

$$P_{Storage}^{Out}(t) \leq P_{Storage}^{Capacity} \times (1 - y(t)) \quad \textbf{(3.77)}$$

$$P_{Storage}^{In}(t) \geq -P_{Storage}^{Capacity} \times y(t) \quad \textbf{(3.78)}$$

When *y(t) = 1* (charging), equation (3.77) in combination with (3.75) enforce $P_{Storage}^{Out}(t)$ to 0. Conversely, equations (3.78) and (3.74) limit $P_{Storage}^{In}(t)$ to 0 whenever *y(t) = 0* (discharging). Consequently, simultaneous charging- and discharging-operations can no longer occur. Table 3.8 shows the optimal dispatch, considering the amended constraints.

t	*R(t)*	$P_{Storage}^{In}(t)$	$P_{Storage}^{Out}(t)$	$E_{Storage}(t)$	*CF(t)*
1	+1	0	0	0	0
2	-1	-0.5	0	0.475	0.500
3	-1	-0.5	0	0.950	0.500
4	-1	-0.053	0	1	0.053
5	+1	0	0.5	0.474	0.500

Table 3.8: Dispatch from MIP with correct operations under negative market prices[1]

Figure 3.4 compares the computation time to determine the optimum dispatch over a certain time horizon, considering both the linear programming as well as the mixed integer programming approach. While for short horizons the difference is negligible, the computational effort increases significantly for longer optimization periods.

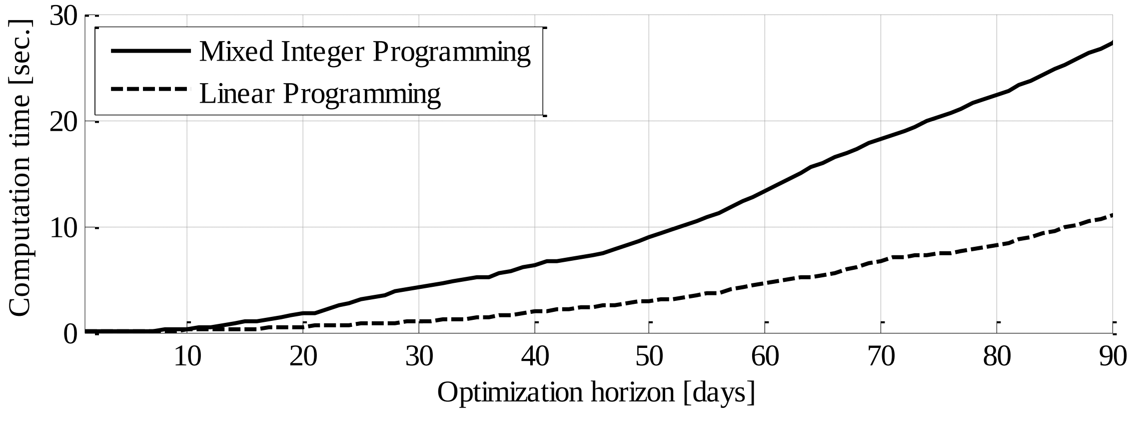

Figure 3.4: Comparison of computation time for linear and mixed integer programming

Hurdle Rate

Before the linear / mixed integer program can be solved, the hurdle rate required in the objective function (see equation (3.70)) must be defined. The objective of the operator is assumed to be the maximization of profits. While revenue opportunities (the sequence of low and high prices) are defined by the market, the operator must decide which opportunities to pursue and which not. This threshold is defined by the hurdle rate.

If the operator decides to pursue all opportunities (a hurdle rate of 0), the storage system will be charged and discharged frequently and its lifetime will be limited by its cycle lifetime, if such a limit applies to the considered storage system. While maximizing the profitability in the short-term, the operator will miss out on additional opportunities after the end of the cycle lifetime and before the theoretical calendric lifetime limit. Contrary, if the operator decides to pursue only those opportunities which offer a very high revenue, the storage system will be cycled only very infrequently and the lifetime will be limited by the calendric aging. Consequently, the storage system could have been dispatched more frequently and realized additional revenues without affecting the lifetime.

Hence, the hurdle rate should be sufficiently high to ensure that the lifetime of the storage system is not significantly cut short by frequent operations with low revenues. On the other hand, the threshold should not be so high that only very few dispatches are done. The balance is therefore reached if the storage system has at the end of its calendric lifetime also reached its cycle limit (see equation (3.15)).

Usually, however, it will be more difficult to identify the hurdle rate which maximizes value, especially when considering the time value of money, financing cost as well as fixed annual cost. As the determination of the lifetime of the storage system is non-linear (the minimum of the cycle- and calendric lifetime), the identification of the optimal hurdle rate cannot easily be integrated into the linear / mixed integer program.

Analogous to the procedure in the case of time shifting of Energy (Section 3.3.5), therefore a metaheuristic will be used to identify the profit maximizing hurdle rate. Based on the previous consideration, that a storage system should perform best if the cycle lifetime equals the calendric lifetime, it will be assumed that the search problem is of convex nature. Therefore, an iterative search routine resembling a hill climb has been devised, which will cycle through the narrowing search space and will iteratively move closer to the maximum. A high-level overview of the procedure is given in Algorithm 2.

Algorithm 2: High-level overview of the iterative search routine to determine the hurdle rate which maximizes net present value

1. Define an initial search space
2. Determine *n* equally spaced search points within the search space
3. Solve the linear / mixed integer program for each search point and determine the associated NPV; stop the procedure once the NPV starts to deteriorate
4. Identify the maximum NPV of the search points
    a. if the identified point is at either end of the search spectrum: define the new search space from the end of the spectrum to the adjoining point
    b. otherwise, the new search space is defined by the two adjoining points
5. Repeat steps 2-4 until the search interval becomes smaller than a defined threshold

Initially, the search space must be defined. The lower bound should bet set a zero, as for storage systems with no or a very high cycle lifetime limit it might be optimal to dispatch them at every possible opportunity. The upper end should be set sufficiently high, so that the storage system gets only dispatched infrequently and the depreciation is dominated by the calendric aging. Following, the search space is divided and *n* equally spaced search points are determined, which are thereafter evaluated one by one. Therefore, the linear / mixed integer program is solved to determine their net present value. This search is stopped once a deterioration in the net present value is observed. The new search space is now defined by the two adjoining search points around the point, which resulted in the highest NPV. Alternatively, if the maximum NPV was found at either end of the search spectrum, the space between the limit and the adjoining search point will be the new search space. The overall search process is repeated until a sufficiently precise solution has been found.

In an implementation, additional precaution has to be taken against getting stuck in plateaus. This might happen when a very low or very high hurdle rate is analyzed, which would result in the storage system either getting dispatched very frequently or not at all. As long as the hurdle rate is not changed significantly, the storage system will not be dispatched and the NPV stays unchanged. Therefore, the search routine should continue in such a case either until a better NPV has been found or it reaches the end of the search space. Furthermore, saving intermediate results helps to reduce search time as it avoids recalculation of the corner points of the search spectrum.

In order to determine the profit maximizing arbitrage dispatch for a storage system, the above search routine will be included, which iteratively solves the dispatch for different hurdle rates until the profit maximizing threshold has been identified.

3.4.3 Dispatch without Perfect Foresight

The presented approach neglects the fact that future prices are revealed step by step and are not known beforehand, when determining the dispatch. In order to obtain a more realistic idea of expectable profits, two simple operation algorithms will be implemented. As the forecast of market prices is a study field of its own and available forecasts are typically error-prone, the algorithm will be based on two observable behaviors of electricity prices: first, electricity prices are mean-reverting. After periods of higher or lower prices, they tend to return to their means. Second, electricity prices follow cycles, as the electricity demand is a repeating pattern. Based on recent prices, the presented dispatch algorithm determines lower / upper price boundaries, which are relatively cheap / expensive in historical comparison. The dispatch decision is then made dependent on the current price in relation to the upper and lower boundary.

The implemented operation algorithm of the first proposed algorithm (‘A’) is shown in Figure 3.5. In order to determine the dispatch for a given day, the algorithm first determines which prices are relatively cheap and which prices are relatively expensive based on historical data in order to set lower and upper boundaries. Therefore, the outer loop is executed once and the following steps performed. First, the distribution of historical price data is determined. Therefore, a recent timespan with a similar demand pattern should be considered. The length of the chosen period should be long enough such that extreme prices do not completely distort the distribution, and short enough that demand changes over time are registered. Second, the extreme prices are determined and based thereupon an upper and lower boundary defined. Prices above respectively below the boundary should occur frequently enough to allow the storage device to charge and discharge within the selected period, considering its power limit. On the other hand, they must be sufficiently far away from each other to permit a profitable operation. Following, the dispatch for a given day can be simulated. Therefore, for every hour it is checked if the price is below the defined lower boundary. In that case, the storage device is charged during that hour if there is still capacity available. If the price for a given hour is above the upper boundary, the storage device is discharged. It is assumed that charge- and discharge operations occur at the maximum power rating. The operation of the storage device is described by equations

(3.6) - (3.10). This process is then repeated for all days during the evaluation period. Finally, the cash flows can then be calculated in order to determine the net present value of the project.

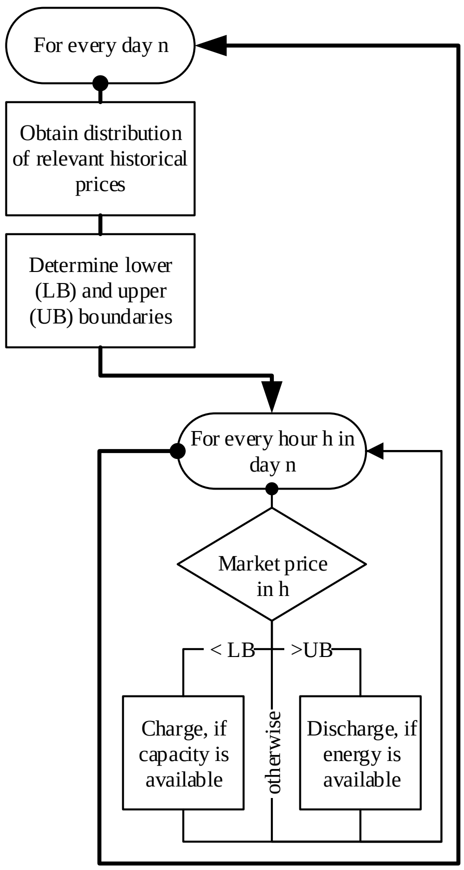

Figure 3.5: Flow Chart of the arbitrage dispatch algorithm 'A' without perfect foresight

In addition, a second approach ('B') is implemented, which reacts more dynamically. It takes into account that prices themselves are volatile and can remain at depressed or increased levels over longer times. Furthermore, it considers that price volatility itself is not static.

Therefore, first the average price $\overline{R}(t)$ (equation (3.79)) as well as the price volatility (defined by the standard deviation, equation (3.80)) over the most recent *n* intervals is calculated.

$$\overline{R}(t) = \frac{1}{n} \sum_{i=t-n}^{t-1} R(i) \tag{3.79}$$

$$\sigma(t) = \sqrt{\frac{1}{n-1} \sum_{i=t-n}^{t-1} (R(i) - \overline{R}(t))^2} \tag{3.80}$$

The upper and lower bounds *LB(t)* and *UB(t)* are then defined by a multiple (denominated by *x*) of the standard deviation *σ(t)* away from the recent average price $\overline{R}(t)$, as shown by equations (3.81) and (3.82).

$$LB(t) = \overline{R}(t) - x * \sigma(t) \tag{3.81}$$

$$UB(t) = \overline{R}(t) + x * \sigma(t) \tag{3.82}$$

The dispatch based on these boundaries is then analogous to the dispatch of the first algorithm 'A'.

The choice of the parameters for both algorithms (for the lookback period as well as for the determination of the boundaries) can easily be optimized by rerunning the above algorithm with different parameters, until the profit maximizing parameters have been identified. However, as historical price patterns will most likely not repeat themselves in the future, care must be taken to avoid an over-fitting to historical data. Rather, a robust solution – parameters, where a small change in their value does not change the outcome significantly – should be chosen. Furthermore, as price spikes are typically rather short-lived and low price periods might persist over longer periods, boundaries do not necessarily have to be symmetrical.

The presented approaches could also be easily implemented: a limit order to purchase below the lower boundary, and a conditional limit sell order above the upper boundary, which is only executed if the previous buy order had been executed. As the proposed approaches are rather simplistic and make no use of additional information besides historical data, it is assumed that they represent a lower bound for profits from arbitrage. While there exists no mathematical justification for this assumption, profitability could most likely be increased by using a more sophisticated approach and considering forecasts. The upper bound is assumed to be set by the previously presented linear / mixed integer programming dispatch with perfect knowledge of future prices, following common practice in the existing literature (see Section 2.4.5). However, as both bounds are based on historical data, they only provide an indicative range for future profits.

3.4.4 Evaluation

Fundamental condition for the profitable pursuing of arbitrage is a sufficiently large spread between the buying and selling price, which at least must exceed efficiency losses.

$$LCOS \leq R(selling) \times \eta - R(buying) \tag{3.83}$$

A full assessment obviously needs to consider further factors. The approaches presented in the two previous sections allow the investor to fully evaluate a potential project and provide him with an upper and lower boundary for the expected profitability. The cash flows resulting from the dispatch can be calculated by equations (3.84) and (3.85), taking into account both energy-related revenues and cost as well as fixed cost of the storage system:

$$CF(t) = -\alpha + \Delta t \times \left(P_{Storage}^{In}(t) \times R(t) + P_{Storage}^{Out}(t) \times R(t) \right) \tag{3.84}$$

$$\text{with } \alpha = C_{Storage}^{Fixed} \times \frac{\Delta t}{8760} \tag{3.85}$$

The calculation of the net present value then follows the procedure discussed in Section 3.2.2.

3.5 Provision of Ancillary Services

Besides time shifting of locally generated energy and pursuing arbitrage, another promising commercial application for storage is the provision of ancillary services, such as reserve control. Section 3.5.1 introduces the business case. Following, Section 3.5.2 elaborates the bidding problem and presents a strategy for which no foresight is required. Finally, in 3.5.3, the evaluation is discussed. In Section 6.3, the framework will then be applied to the German case.

3.5.1 Business Case

An approximate balance between electricity demand and generation is determined in the day-ahead spot market. However, in order to ensure a stable operation of the electric system, the TSO has to constantly balance demand and generation in real-time. These imbalances might result from failures, generation over-/undersupply (for example from non-dispatchable renewables) or from wrong demand estimates. Furthermore, the dispatch of generation in the spot market leads to increasing imbalances at the hour and since recently also at the 15-minute marks. These imbalances in active power result in deviations from the nominal grid frequency. An increase in load leads to a decrease in frequency, while lower consumption leads to a rise in frequency. To stabilize the frequency and guarantee the safe operation of the grid, the TSO therefore needs to be able to increase as well as decrease generation when required. Therefore, he relies on different, interacting control reserves, which have previously been introduced in Section 2.2.3.

The provision of Primary Control Reserve seems most interesting for small- to medium scale storage systems. While large-scale pumped hydro storage systems successfully participate in the secondary and tertiary control reserve, energy requirements currently still present a substantial entry barrier for smaller systems. In addition, the technical characteristics of many storage systems fit the requirements for primary reserve control very well: many storage systems are able to deliver power quicker and more accurate than traditional generators, even though this is (not yet) accounted for in the compensation. Furthermore, storage systems can be in standby and provide both negative as well as positive reserve, whereas traditional generators must already be running in order to provide negative control reserves. Besides control reserves, a range of further ancillary services exist (such as voltage support or black-start capabilities). However, as currently no transparent market exists for them, they will not be further considered. As the provision of reserve control is strictly regulated due to its importance for system stability, and hence individual rules apply in different grid zones, the German case will be considered.

In Germany, the power is contracted through a public tender according to EnWG §22 [39] by the TSO. In order to provide primary reserve control, operators and the particular system must be pre-qualified. During this process, among others, it is verified that the system can provide the contracted power within the required reaction time. According to §6 of the master agreement for the provision of primary reserve control [41], the service must be provided at all times over the entire contracted time period. However, as small-scale storage systems are limited by their energy capacity, they are therefore effectively excluded from participating in the market for primary reserve control. In order to ensure equal access independent of the technology, the existing regulation has been amended such that battery systems can participate in the tender if they are able to provide the contracted power for a duration of at least 30 minutes continuously, both for negative as well as positive regulation [42].

During the prequalification of a storage system for primary reserve control, therefore not only the provision of the contracted power needs to be demonstrated, but the storage device also must demonstrate that it has sufficient energy capacity. Storage systems, which suffer from energy capacity degradation, must maintain sufficient capacity over their lifetime at all times, otherwise the prequalification expires. However, capacity degradation will not be further considered in the following analysis.

If the complete power capacity of the storage system ($P_{Storage}^{Capacity}$) is contracted, the available energy capacity (considering the depth of discharge as well as charge- and discharge efficiencies) must be sufficient for a charge- or discharge duration of 30 minutes. The minimum required energy capacity is therefore given by equation (3.86).

$$E_{Storage}^{Capacity} \geq \frac{0.5 \times P_{Storage}^{Capacity} \times \left(\eta_{Storage}^{In} + {}^{1}\!/\!_{\eta_{Storage}^{Out}} \right)}{(1-\delta_{Storage})}. \tag{3.86}$$

Equation (3.87) determines the minimum state of charge which the storage device must keep in order to be able to provide the contracted power for 2x15 minutes.

$$E_{Storage}(t) \geq E_{Storage}^{Capacity} \times \delta_{Storage} + \frac{0.5 \times P_{Storage}^{Capacity}}{\eta_{Storage}^{Out}} \tag{3.87}$$

Furthermore, there must be sufficient energy capacity available for being charged consecutively for 2x15 minutes, as defined by equation (3.88).

$$E_{Storage}(t) \leq E_{Storage}^{Capacity} - 0.5 \times P_{Capacity}^{Storage} \times \eta_{Storage}^{In} \tag{3.88}$$

After a regulation incident, the operator has two hours' time to return the storage device to a state of charge limited by (3.87) and (3.88) [42]. Therefore, the operator can either purchase (/ sell) the deficit (/ excess) energy in the continuous intraday market, exceed the contracted power by up to 20% if a regulation event occurs in the opposite direction or provide negative / positive control service also within the dead band [43]. Furthermore, [42] explicitly mentions the possibility to provide the regulation service by a pool of agents, which makes it attractive to small-scale, distributed storage systems.

3.5.2 Dispatch and Bidding Problem

Contrary to the case of arbitrage or time shifting, the owner of the storage has no influence over the dispatch of the system. Instead, the storage system is (automatically) dispatched according to frequency deviations from 50 Hz (see Section 2.2.3). Therefore, no dispatch operation algorithm is required for the evaluation. However, it is the responsibility of the storage operator to ensure that the storage system is returned to a state of charge so that the system can again provide positive / negative power for 30 minutes after the storage system had been activated.

The compensation for the provision of primary reserve control $R^{Regulation}(t)$ is determined by a weekly pay-as-bid auction, where the agents with the lowest bids are selected until sufficient power has been contracted. For the time period *t*, bids *i* will be denominated by $R_i^{Regulation}(t)$ in ascending order. In order to maximize revenues, market participants are therefore faced with the issue of identifying the marginal price $R_{max}^{Regulation}(t)$, which is still accepted by the TSO. Initially, perfect foresight will be assumed to determine the maximum profits which could have been obtained. Therefore, the marginal price from each auction will be considered.

In a second step, a backward looking approach will be implemented in order to determine the value of foresight and which profits realistically can be expected. Historically, prices for the provision of reserve control are based on the opportunity cost of regular baseload generators. Revenues from the provision of reserve control must be sufficiently attractive to incentivize operators to withhold some capacity from the energy market. Therefore, prices have been much more stable than in the energy market, where the marginal price is being traded. Therefore, a viable strategy appears to simply bid at a quantile of the accepted bids of the previous tender (see Figure 3.6). The bid would have been accepted, if it is lower than the maximum accepted bid for the considered period. Obviously, the higher the chosen quantile, the higher the potential revenues but also the higher the likelihood, that the bid is not accepted, if the overall price level has declined since the last auction.

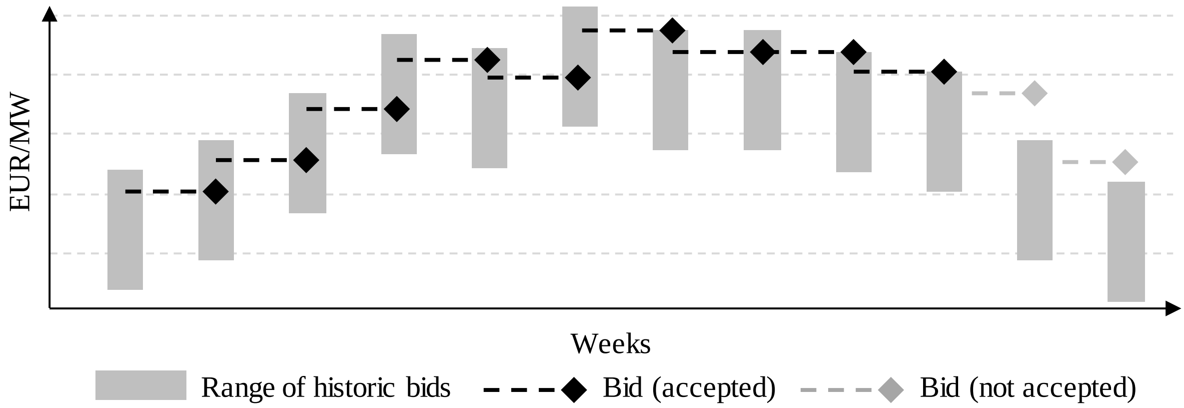

Figure 3.6: Schematic representation of the bidding process based on historical results

3.5.3 Evaluation

Revenues equal the contracted power times the compensation price. Recurring costs are defined by fixed cost. For each week t (hence, $\Delta t = 168$), the resulting cash flows can therefore be determined by equation (3.89).

$$CF(t) = R^{Regulation}(t) \times P_{Storage}^{Capacity} - C_{Storage}^{Fixed} \times \frac{\Delta t}{8760} \tag{3.89}$$

The lifetime of battery based storage systems is limited by its calendric aging, as less than 100 equivalent charge-cycles can be expected per annum [183]. Hence, depreciation charges are determined by the calendric lifetime. The investment cost to be considered for the evaluation therefore depends on the simulation horizon, as calculated by equation (3.90).

$$CF(0) = -C_{Storage}^{Invest} \times \frac{T^{years}}{L_{Storage}^{calendric}} \tag{3.90}$$

The net present value can then be determined as discussed in Section 3.2.2.

The required weekly average revenues to offset depreciation cost can be estimated by equation (3.91), giving a first guidance to the required revenues.

$$\overline{R^{Regulation}(t)} > \frac{C_{Storage}^{Invest}}{L_{Storage}^{Calendric} \times 365.25/7} \tag{3.91}$$

3.6 Co-integration of Applications

Last, the co-integration of applications is considered, where a storage system is dispatched to provide multiple services simultaneously. Thereby, several value streams can be captured in parallel, which might further increase the value proposition of storage. The considered business case is explained in more detail in Section 3.6.1. Following, in 3.6.2, the dispatch problem is formulated as mixed integer program, based on the formulation of the time shifting business case. Last, Section 3.6.3, provides a framework for the evaluation of the business case. The framework will be demonstrated in a case study that will be presented in 6.4.

3.6.1 Business Case

Storage is oftentimes praised for its versatility, among others due to its ability to both provide and absorb power. A widely suggested idea in the existing literature to increase the value of storage systems (see Section 2.3.7) is to provide several services simultaneously by stacking multiple applications. By combining and integrating several activities, storage systems could theoretically serve more than just one purpose simultaneously and capture multiple value streams in parallel. For example, during periods, where the storage device is otherwise underutilized, it can be used for the provision of ancillary services. However, it remains unclear, how multiple applications can be simultaneously implemented from an operational perspective, as technical constraints must be observed and conflicting operational requests must be managed.

To validate the concept of stacking multiple applications to increase the value of storage, the presented business case will aggregate three simultaneous services. Therefore, a storage system located at a consumer installation will be dispatched for time shifting locally generated energy (analogous to Section 3.3) as well as participate in the tender for the provision of reserve control with some of its capacity (see Section 3.5). Furthermore, it is assumed that clients must pay for the capacity of their grid interconnection. Besides the dispatch for the time shifting and the provision of control reserve, the storage system will in addition be dispatched to minimize the required grid capacity (‘peak shaving’), as previously discussed in the literature review in Section 2.3.5. Therefore, the storage system will typically be charged during periods with low grid demand. Contrary, during those times, when the demand from the grid exceeds a certain threshold, the storage device will be discharged to reduce the demand seen by the grid. The required capacity and therefore the actual cost can thereby effectively be reduced.

3.6.2 Optimal Dispatch Problem

The underlying storage implementation is based on the formulation presented in Section 3.3. However, besides considering the local power and heat flows, the storage dispatch process also takes into account the potential revenues from the provision of reserve control as well as the potential savings from reducing the required grid connection capacity. Therefore, the dispatch process must not only allocate the optimal capacity to each service, but must also consider the resulting operational requirements and technical restrictions. Furthermore, the formulation must ensure that no conflicts in the storage dispatch arise, such as an energy requirement from the contracted primary reserve control which cannot be fulfilled due to a depleted storage system.

In order to determine the operative dispatch, which considers the requirements and constraints of all services simultaneously and at the same time maximizes the storage value, the mixed integer program described in Section 3.3.4 is extended. Two additional decision variables are implemented for the provision of reserve control and for the grid connection capacity. Furthermore, the problem formulation is extended by a range of restrictions to ensure non-conflicting operability.

Provision of Ancillary Services

The tendered capacity for the provision of reserve control is denominated $P_{Regulation}^{Capacity}(t)$ and must be constant over each tender period. The compensation per time step is given by $R^{Regulation}(t)$.

In order to integrate the provision of primary reserve control in the MIP from the time shifting business case, the objective function (equation (3.35)) must be extended by the revenues from the provision of reserve control, as shown by the last term of equation (3.92).

$$\max \Delta t \times \sum_{t=1}^{T} \begin{pmatrix} -P_{Grid}^{Import}(t) \times R^{Import}(t) - P_{Grid}^{Export\,PV}(t) \times R_{PV}^{Export}(t) - P_{Grid}^{Export\,CHP}(t) \times R_{CHP}^{Export}(t) - \ldots \\ P_{CHP}(t) \times C_{CHP}^{Variable} - H_{GB}(t) \times C_{CHP}^{Variable} + P_{Regulation}^{Capacity}(t) \times R^{Regulation}(t) \end{pmatrix} \quad \textbf{(3.92)}$$

Equation (3.93) ensures that the tendered power for the regulation service is constant over each tender period.

$$P_{Regulation}^{Capacity}(t) - P_{Regulation}^{Capacity}(t-1) = 0 \;\; for\; t = 2,3,\ldots \;\; of\;\; each\; tender\;\; period \quad \textbf{(3.93)}$$

In addition, the tendered power cannot exceed the maximum capacity of the storage device (equation (3.94)).

$$0 \le P_{Regulation}^{Capacity}(t) \le P_{Storage}^{Capacity} \quad \textbf{(3.94)}$$

Furthermore, the resulting power flow $P_{Regulation}(t)$ must be considered in the balance of power (equation (3.95))

$$\begin{aligned} &P_{Grid}^{Import}(t) + P_{Grid}^{Export\,PV}(t) + P_{Grid}^{Export\,CHP}(t) + P_{Storage}^{In}(t) + P_{Storage}^{Out}(t) + P_{PV}(t) + P_{CHP}(t) + \ldots \\ &\qquad P_{HP}(t) + P_{Load}(t) + P_{Regulation}(t) = 0 \end{aligned} \quad \textbf{(3.95)}$$

Equations (3.44) and (3.45), which limit the power flows of the storage device to its capacity and ensure that no simultaneous charge- and discharge operations occur, need to be modified so that sufficient power capacity is available at all times for the regulation service, both absorbing and providing power (equations (3.96) and (3.97)).

$$0 \le P_{Storage}^{Out}(t) \le \left(P_{Storage}^{Capacity} - P_{Regulation}^{Capacity}(t)\right) \times (1 - y(t)) \quad \textbf{(3.96)}$$

$$-\left(P_{Storage}^{Capacity} - P_{Regulation}^{Capacity}(t)\right) \times y(t) \le P_{Storage}^{In}(t) \le 0 \quad \textbf{(3.97)}$$

Last, equations (3.46) and (3.47), which restrict the current state of charge to the energy capacity limits of the storage device, must also be adjusted to ensure that both sufficient energy as well as spare capacity is available at all times. Under the current German regulation, as outlined in Section 2.2.3, the storage device must be able to provide the contracted power for up to two consecutive 15-minute intervals, both for absorbing as well as providing power. This is enforced by equations (3.98) and (3.99), considering efficiency losses and the depth of discharge as well.

$$\sum_{n=1}^{t} P_{Storage}^{In}(n) \times \eta_{Storage}^{In} \times \Delta t + \sum_{n=1}^{t} P_{Storage}^{Out}(n) \times \eta_{Storage}^{Out}{}^{-1} \times \Delta t \leq -P_{Regulation}^{Capacity}(t) \times {}^{0.5}\!/_{\Delta t} \quad \textbf{(3.98)}$$

$$\sum_{n=1}^{t} P_{Storage}^{In}(n) \times \eta_{Storage}^{In} \times \Delta t + \sum_{n=1}^{t} P_{Storage}^{Out}(n) \times \eta_{Storage}^{Out}{}^{-1} \times \Delta t \geq \ldots \quad \textbf{(3.99)}$$
$$- E_{Storage}^{Capacity} \times (1 - \delta_{Storage}) + P_{Regulation}^{Capacity}(t) \times {}^{0.5}\!/_{\Delta t}$$

Peak shaving

In order to integrate the peak shaving business case into the mixed integer program, the objective function is further extended by the additional decision variable $P_{Grid}^{Capacity}$ for the required connection capacity. It is assumed that the total cost for the interconnection increases linearly with the required capacity according to $C_{Grid}^{Capacity}$. Therefore, the original objective function (3.35), which was modified for the provision of reserve control by (3.92), is again modified by the cost for the interconnection, as indicated by equation (3.100).

$$\max \Delta t \times$$
$$\sum_{t=1}^{T} \begin{pmatrix} -P_{Grid}^{Import}(t) \times R^{Import}(t) - P_{Grid}^{Export\,PV}(t) \times R_{PV}^{Export}(t) - P_{Grid}^{Export\,CHP}(t) \times R_{CHP}^{Export}(t) - \ldots \\ P_{CHP}(t) \times C_{CHP}^{Variable} - H_{GB}(t) \times C_{CHP}^{Variable} + P_{Regulation}^{Capacity}(t) \times R^{Regulation}(t) \end{pmatrix} - \ldots \quad \textbf{(3.100)}$$
$$T^{years} \times P_{Grid}^{Capacity} \times C_{Grid}^{Capacity}$$

Given the chosen capacity limit of the grid interconnection $P_{Grid}^{Capacity}$, it must be ensured that the energy taken from the grid does not exceed the threshold. Therefore, constraint (3.40) must be amended as shown by equation (3.101).

$$0 \leq P_{Grid}^{Import}(t) \leq P_{Grid}^{Capacity} \quad \textbf{(3.101)}$$

The required grid capacity should then be equivalent to the maximum demand over the considered time period (3.102).

$$P_{Grid}^{Capaciy} = \max_{t} P_{Grid}^{Import}(t) \quad \textbf{(3.102)}$$

According to the problem formulation, the energy fed into the grid is not subject to the capacity restriction. Furthermore, the limit is constant over time.

3.6.3 Evaluation

The evaluation follows the approach presented under the time shifting business case (Section 3.3.6), which already considers all storage related cost.

However, the calculation of cash flows needs to be extended in order to consider the revenues from the provision of reserve control, which are given by $P_{Regulation}^{Capacity}(t) \times R^{Regulation}$. Therefore, equation (3.61) is extended by the additional revenues to equation (3.103).

$$\begin{aligned} CF(t) = & -\alpha - \beta(t) - \Delta t \times (P_{Grid}^{Import}(t) \times R^{Import}(t) + P_{Grid}^{Export\,PV}(t) \times R_{PV}^{Export}(t) + \ldots \\ & P_{Grid}^{Export\,CHP}(t) \times R_{CHP}^{Export}(t) + P_{Regulation}^{Capacity}(t) \times R^{Regulation}(t)) \end{aligned} \quad \textbf{(3.103)}$$

Furthermore, equation (3.62), which defines the fixed cost allocation for each time step, must be extended by the cost for the required grid capacity $P_{Grid}^{Capacity} \times C_{Grid}^{Capacity}$, which was not considered in the time shifting business case, as shown by equation (3.104).

$$\alpha = \frac{\Delta t}{8760} \times \left(C_{Storage}^{Fixed} + C_{ThStorage}^{Fixed} + C_{CHP}^{Fixed} + C_{PV}^{Fixed} + C_{GB}^{Fixed} + C_{HP}^{Fixed} + C_{ST}^{Fixed} + P_{Grid}^{Capacity} \times C_{Grid}^{Capacity} \right) \quad \textbf{(3.104)}$$

The individual revenue streams of the stacked applications are most likely sub-additive due to the interaction of their operations. With one service dispatching the storage for some usage, the available capacity is reduced for all other applications. For example, the tendered capacity for the provision of reserve control is no longer available for the time shifting of energy. In order to determine the value added by the individual applications, their revenue streams will be segregated. Therefore, first, the NPV of several different configurations will be determined:

- $NPV_{Baseline}$, which describes the NPV of the system configuration without dispatching the storage system. Therefore, the power capacity $P_{Storage}^{Capacity}$ of the storage system is enforced to be zero.
- NPV_{TS}, where the storage system is dispatched for time shifting. To disregard the value associated to the other two applications, $P_{Regulation}^{Capacity}(t)$ is enforced to be zero at all times. The cost for the grid interconnection $C_{Grid}^{Capacity}$ are neglected in the objective function of the optimization routine, but considered in the later financial evaluation.
- NPV_{TS+RC}, which considers the value from storage for time shifting and the provision of reserve control. Therefore, $C_{Grid}^{Capacity}$ is set to zero in the MIP when determining the dispatch schedule.
- NPV_{TS+PS}, which takes the value from storage for time shifting and peak shaving into account by enforcing $P_{Regulation}^{Capacity}(t)$ to zero at all times.
- $NPV_{TS+RC+PS}$, reflecting the joint value from all three applications (time shifting, provision of reserve control and peak shaving) by solving the MIP as described in the previous Section 3.6.2.

Following, the value contribution from the individual applications can be determined by comparing the NPV of the different system configurations. The presented approach therefore does not only allow to determine the overall value of a storage investment, but also to break down the value contribution and the resulting revenue streams to the stacked applications.

Chapter 4

4 Uncertainty and Risk of Storage Investments

Abstract

Chapter 4 incorporates the inevitable uncertainty affecting assumptions and parameters in the evaluation process of storage systems. Several approaches to assess the uncertainty and the resulting risk are introduced and discussed.

4.1 Introduction

Uncertainty describes the fact that the future is unknown and cannot be predicted with accuracy. The potentially negative consequences on the economic profitability of an investment is called risk.

As described under the literature review in Section 2.4.2, uncertainty can among others result from model uncertainty or parameter uncertainty. Model uncertainty describes the uncertainty if the model does not reflect reality in an accurate way. Differences between reality and model output typically come from a lack of knowledge about the underlying process, simplifications or implementation errors. Parameter uncertainty results from imperfect knowledge about the future behavior of parameters that serve as model inputs.

The existing uncertainty limits the confidence of decision makers in the output of the model. While an analysis of uncertainty can still not predict the future and guarantee a certain outcome, gaining a better understanding about the extent uncertainty affects modeled results and its drivers as well as providing some boundaries of potential outcomes increases confidence in the model predictions. Furthermore, it supports the decision maker to select investment alternatives which have an acceptable level of uncertainty and / or minimize risk. In other words, uncertainty analysis helps decision makers to take robust decisions, that is decisions about which they would feel least regret if the future evolves unfavorably compared to the assumed evolution of uncertain input factors.

To ensure that the model behaves as expected, the dispatch algorithms detailed in Chapter 3 are tested against some easily traceable paths in Section 4.2. Section 4.3 then introduces the concept of sensitivity analysis, which allocates the uncertainty in the output of the evaluation result to different input uncertainties. Following, Section 4.4 discusses scenario analysis, which enables the decision maker to evaluate different evolution paths of uncertain parameters, considering the interaction of multiple uncertain parameters. Thereafter, Section 4.5 introduces the concept of Monte Carlo simulation, which is used to simulate price paths as well as to simulate parameter uncertainty. Based thereon, in Section 4.6 the measurement Value at Risk is presented, which allows to calculate loss probabilities and to determine a probability based worst-case. Last, Section 4.7 discusses several techniques for decision making under uncertainty.

The application of the various techniques is demonstrated in several case studies in chapter 6.

4.2 Model Verification

To ensure that the models are properly formulated and implemented, the dispatch algorithms are validated against some easily traceable data. The dispatch problems are formulated in Matlab R2014a and following solved by Gurobi 6.0.

4.2.1 Time Shifting of Energy

In order to verify the ordinary dispatch process presented in Section 3.3.3 as well as the optimal dispatch problem from Section 3.3.4, synthetic time-series for heat and electric demand ($P_{Load}(t)$ and $H_{Load}(t)$) as well as generation from solar technologies ($P_{PV}(t)$ and $H_{ST}(t)$) were assumed. Furthermore, a simple system configuration was assumed:

- Electric storage with a capacity of $E_{Storage}^{Capacity}$= 10 000 Wh
- Thermal storage with a capacity of $E_{ThStorage}^{Capacity}$= 10 000 Wh
- Cogeneration unit with a power- and heat-capacity of $P_{CHP}^{Capacity}$ = 2 000 W and $H_{CHP}^{Capacity}$ = 4 000 W
- A gas boiler with a capacity of $H_{GB}^{Capacity}$ = 10 000 W

Figure 4.1 shows the result from the ordinary dispatch process. The upper pane displays the power flows from the electric system, the middle pane the heat flows from the thermal system and the lower pane the resulting charge levels of the storage systems.

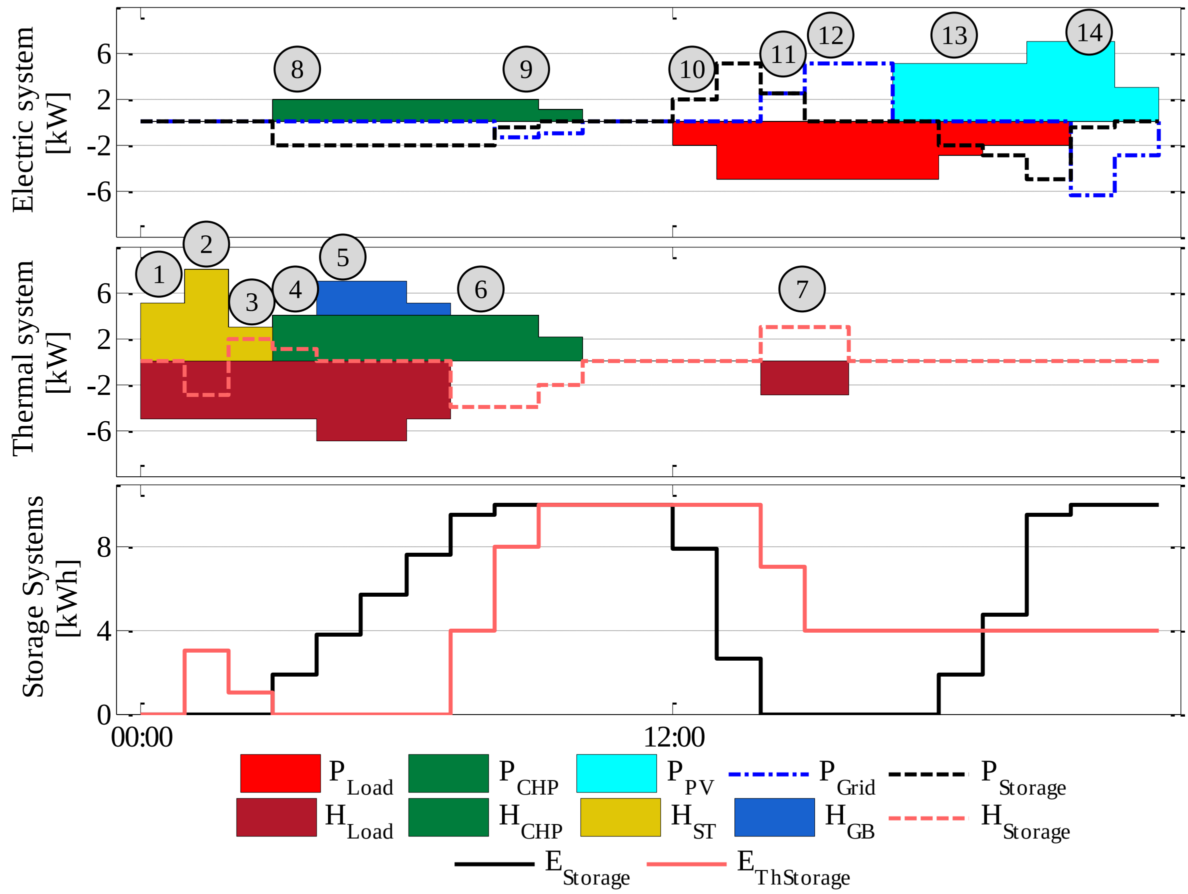

Figure 4.1: Power and heat flows from the ordinary dispatch for time shifting

Initially, only the heat system is analyzed to verify its correct implementation. The following list refers to the numbering shown in Figure 4.1 and explains the heat flows:

1. Supply from the solar thermal installation (H_{ST}) satisfies the heat demand (H_{Load})
2. Supply from H_{ST} exceeds H_{Load}, hence the thermal storage is charged
3. Insufficient supply from H_{ST}, hence discharge of the thermal storage
4. Cogeneration unit is dispatched to provide heat (H_{CHP}), as thermal storage is not sufficient and no solar-thermal generation is available
5. As heat supply from the CHP is not sufficient, the gas boiler (H_{GB}) is dispatched in addition
6. Cogeneration unit is kept running until the thermal storage is fully charged to minimize the number of start-/stop-cycles
7. H_{Load} is met by discharging the thermal storage

Following, the electric system is also considered:

8. The power generation from the cogeneration unit (P_{CHP}) exceeds current electric demand (P_{Load}) and hence is used to charge the electrical storage system
9. Once the electric storage is fully charged, the residual is fed into the grid
10. Electricity demand is met by discharging the storage device
11. As the demand exceeds the stored energy, additional energy is taken from the grid

12. Once the electric storage is depleted, all energy is taken from the grid
13. Surplus generation from the photovoltaic installation, which exceeds current demand, is used to charge the storage device
14. Once the storage device is fully charged, all surplus generation is fed into the grid

Despite its simplicity, the algorithm ensured that demand was satisfied at all times and provided a result according to expectations.

Analogous, the result from the optimal dispatch process (Section 3.3.4) for the same time series and the same system configuration is analyzed. However, to keep the analysis manageable, heat pumps as well as differentiated electricity tariff schemes are neglected. Figure 4.2 show the resulting dispatch from the mixed integer program.

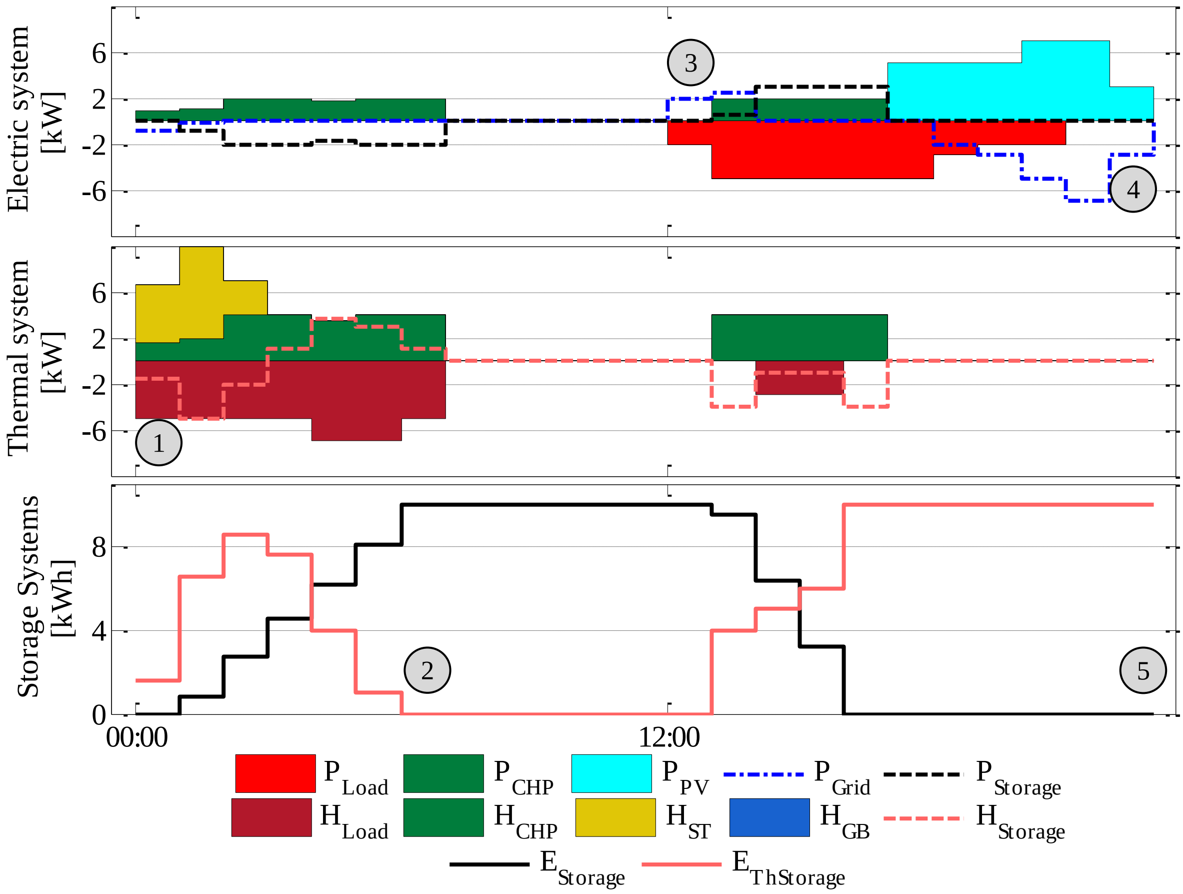

Figure 4.2: Power and heat flows from the optimal dispatch for time shifting

Compared to the dispatch from the ordinary process (see Figure 4.1), several differences can be identified:

1. The cogeneration unit is dispatched from beginning on to immediately charge the thermal storage to avoid running the gas boiler during subsequent periods
2. The thermal storage is completely discharged in order to free capacity to run the cogeneration unit when there is demand for electricity
3. Most of the electricity demand can be met locally by the electrical storage system and running the cogeneration unit

4. + 5. Excess generation from the photovoltaic installation is fed into the grid as well as the electric storage device is completely discharged at the end, as any residual is not considered in the financial evaluation. Furthermore, it can be concluded that the generated electricity from the cogeneration unit is more worthwhile than the accompanying heat, as the thermal storage remains fully charged at the end of the evaluation horizon as the generated heat is no longer required.

A more in-depth analysis was performed to ensure the correctness of both dispatch processes as well as their correct implementation.

4.2.2 Arbitrage of Electricity Prices

Following the methodology in the previous section, the dispatch resulting from the MIP problem (Section 3.4.2) as well as from the two backward-looking approaches (algorithm ‘A’ and ‘B’ in Section 3.4.3), which are solely relying on historic information, is verified.

The dispatch resulting from the MIP problem is verified by an artificial price curve, shown in the upper pane in Figure 4.3. In addition, the resulting charge- and discharge signals are shown by markers. The lower pane displays the resulting energy level in the storage system. Initially, the storage device is discharged. As prices during the next few time slots will be higher, the storage device is immediately charged ((1) in Figure 4.3), before it is discharged at peak prices (2). Over the following cycles, the storage device is always charged at the valley prices (for example at (3)). The subsequent discharge always occurs as expected at the peak prices (for example at (4)). The breakdown into several charging-/discharging steps is caused by the power limitation of the storage system. As can be seen by the charging at (5) and discharging at (6), the operation does not necessarily occur at the maximum prices, but also exploits local extrema in the price.

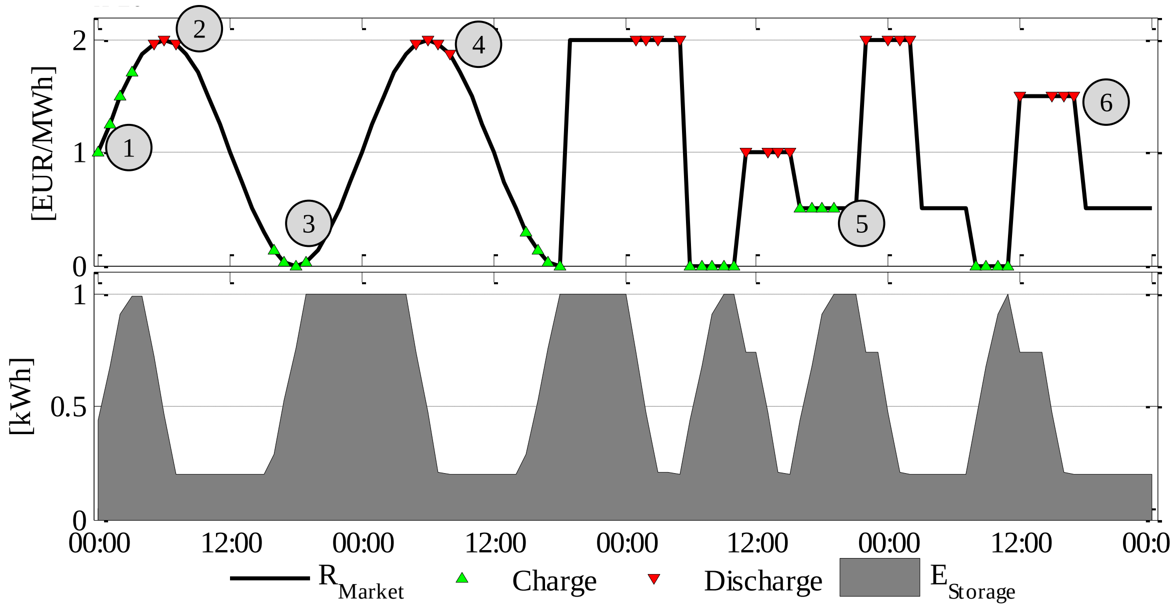

Figure 4.3: Arbitrage dispatch with perfect foresight

Figure 4.4 shows the arbitrage dispatch resulting from algorithm ‘A’, which only utilizes historical data to determine operations. In this case, a sinusoidal price curve is assumed, with its extremes at zero and two. The upper and lower boundary for the dispatch were assumed to be at the 25% / 75% quantile of considered historical data, hence at 0.29 / + 1.71 ((1) and (2) in Figure 4.4). Once the price falls below the lower boundary, the storage device is charged up to its full capacity (3). In reverse, the storage is discharged once the price exceeds the upper boundary (4). Hence, contrary to a forward looking dispatch, not always the best decisions are taken. Exemplary, the storage device is discharged at (5) even though higher prices are available some time steps later. Also, it would be beneficial to charge the storage device at (6) and discharge it again at (7). However, not only these beneficial opportunities are not used, but also costly decisions are taken. For example, the storage device is charged at (8), even though much lower prices are available immediately afterwards.

Furthermore, Figure 4.4 also shows how the lower and upper boundaries adjust to the price volatility. After the period with stable prices (6), the boundaries contract. They return again to their previous state at the very end of the considered period.

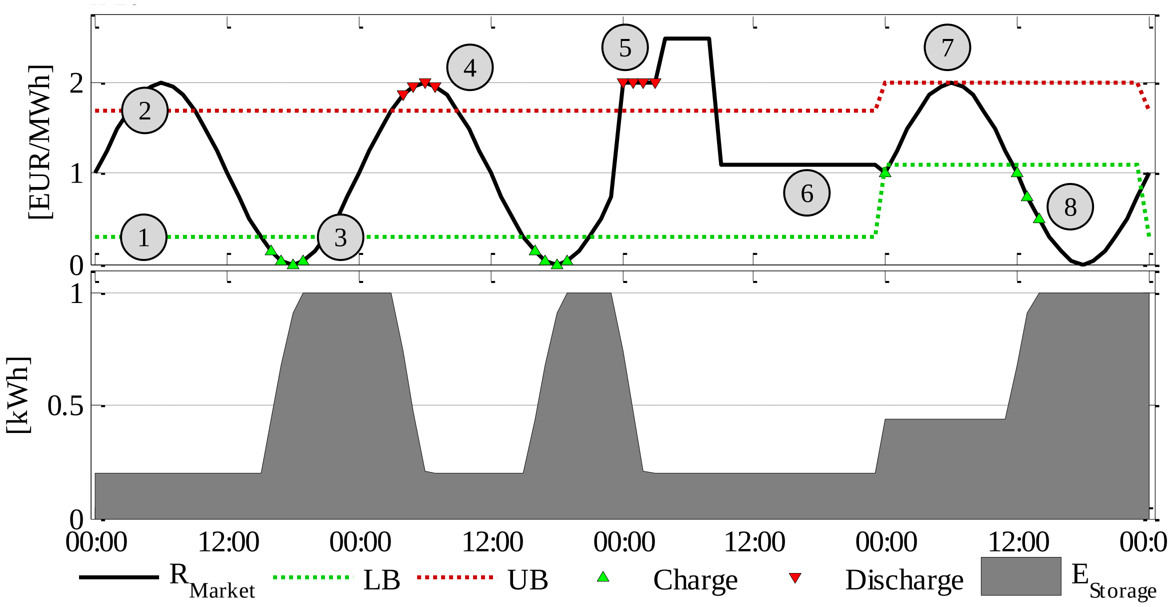

Figure 4.4: Arbitrage dispatch without perfect foresight (algorithm 'A')

Last, the dispatch of algorithm 'B' is considered. Using the same price path as for algorithm 'A', the difference between the resulting dispatches can be easily compared. In this case, the storage is charged at significantly higher prices (1), with the subsequent discharge occurring at relatively low prices (2). At (3), the discharge also occurs not at the peak price. However, as (4) is relatively cheap compared to recent prices, the storage device is charged. It is again discharged at the next price increase (5). Furthermore, the widening and narrowing of the boundaries based on recent volatility can be observed at (6).

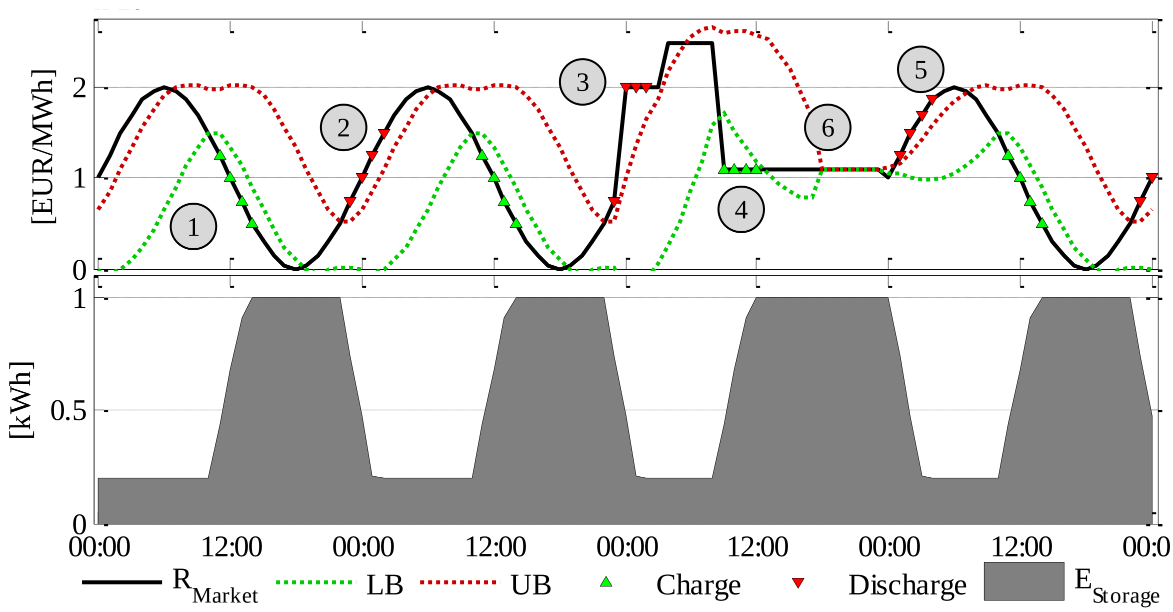

Figure 4.5: Arbitrage dispatch without perfect foresight (algorithm 'B')

The dispatch of all three approaches was as expected and thereby verifies the correct formulation and implementation of the models. In addition, it also showed the inferiority of the algorithm 'A' and 'B' versus the dispatch originating from the MIP problem. While the MIP determines the most advantageous times for charging- and discharging, algorithm 'A' and 'B' will oftentimes operate at less optimal times. The value of having perfect information about the future price development as compared to relying only on historical data to defer charge- and discharge decision is easily recognizable in this simplified context.

4.2.3 Co-integration of Applications

Last, the dispatch from the MIP for the co-integration of applications is verified, which was presented in Section 3.6.2. As the problem formulation is based on the business-case of time shifting, which has been verified in 4.2.1, only the modified electric system will be considered without any local generation resource present.

Therefore, the following assumptions have been taken:

- Capacity of the storage device $E_{Storage}^{Capacity}$ is 20 kWh, with $\delta_{Storage}=20\%$ and $P_{Storage}^{Capacity} = 10\,000$ W
- Tender period for the provision of reserve control is four time steps
- $R^{Regulation}(t)$ was assumed to be 0.01 EUR per kW and hour
- $R^{Import}(t)$ is assumed to be 0.30 EUR / kWh
- $C_{Grid}^{Capacity}$ was assumed to be 75 EUR per kW and year
- For the heat supply, only a gas burner is installed which is instantaneously dispatched to satisfy any heat demand.
- All power demand is satisfied from the grid.

Figure 4.6 shows the assumed energy demand as well as the resulting dispatch. The following list refers to the numbering shown in the graph:

1. Provision of reserve control. However, not all the available power is tendered as the storage device is charged from the grid at the same time
2. As a response to the provision of reserve control, reduction in the available capacity of the storage device
3. Discharging of the storage device to reduce the required demand from the grid
4. No reserve control is provided, as it is more beneficial to use the existing power capacity of the storage device in order to avoid higher grid demand and the resulting payments
5. Peak electricity demand can be provided by the grid without increasing the required grid capacity. Hence, all storage power capacity is available for providing reserve control.
6. No control reserve is provided as otherwise sufficient energy would have to be kept available in the storage device. However, any remaining energy at the end of the optimization horizon is without value. Under the taken assumptions, the value of this energy is greater than the revenues from the provision of reserve control and hence the storage is discharged to satisfy demand instead of dispatched for provision reserve control.

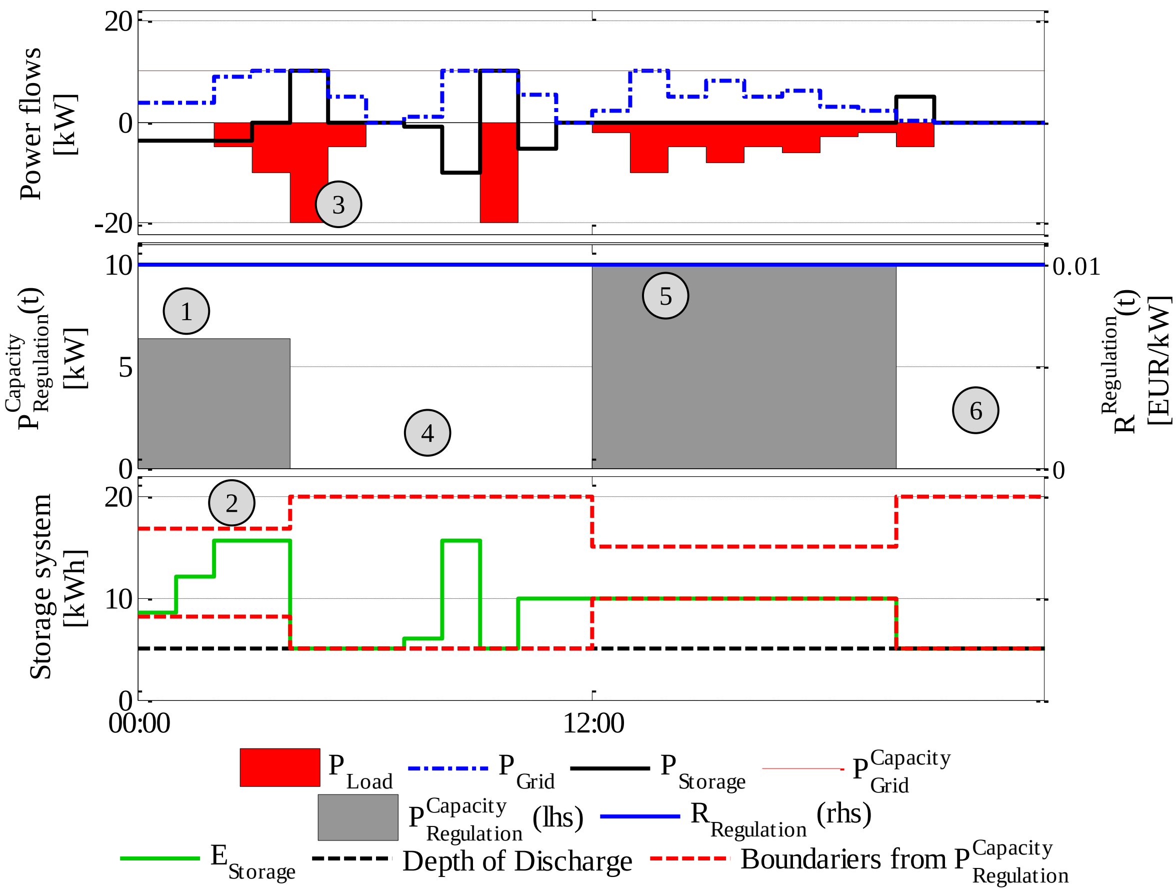

Figure 4.6: Joint dispatch for time shifting, provision of control reserve and peak shaving

A thorough check of the power- and heat dispatch of the individual system components was successfully conducted in Section 4.2.1, which showed that the implementations are in line with the mathematical formulation.

4.3 Sensitivity Analysis

The basic purpose of a sensitivity analysis is to determine how sensitive the output of a model is to changes in the uncertain model inputs. By conducting a sensitivity analysis, the decision maker gains valuable insights into the importance of various assumptions as well as into the robustness of the results provided by the model. Furthermore, it improves the understanding of the relationship between model parameters and the result. Last, a sensitivity analysis allows the decision maker to identify the most sensitive inputs, which are the parameters with the highest contribution to the uncertainty. Additional efforts can then be spent on validating the assumptions behind the variables with the highest impact in order to increase the confidence in the results.

Most commonly in the literature (see Section 2.4.2), one input is changed at a time, referring to one starting or reference point. Calculating the objective function again, the impact of the variable can then be determined. Holding all other variables constant, the sensitivity S_k of the output to variable x_k can be calculated by equation (4.1).

$$S_k = \frac{\delta NPV}{\delta x_k} \tag{4.1}$$

Typically, x_k is varied by a specified percentage value. However, the analysis should be conducted for several values of the same input variable, as the relation between the change in the output and the change in input variable is not necessarily linear. Ideally, the range of considered values for the change in the varied input parameter should reflect possible changes during the lifetime of the storage system. Alternatively, if such data is available, the distribution function of the parameter can be considered, increasing / decreasing the parameter by multiples of their standard deviation. While this approach requires an estimate of the parameter distribution and neglects its distribution shape, it simplifies the comparison of the impact of different parameters on the output and associates the sensitivity with a likelihood of occurrence.

In an actual implementation of a storage installation, the dispatch would be amended in order to incorporate the changed information and consider the changed system configuration. Therefore, the dispatch optimization routine must be rerun in each case, which makes it computational expensive due to the required repetitions for the many parameters included in the presented models.

Figure 4.7 shows an illustrative sensitivity plot for several input parameters, where only one parameter was changed at a time. A steeper line indicates a parameter for which a small change results in comparably larger changes in the outcome, that is with a higher sensitivity. Flatter lines represent parameters to which the outcome is rather insensitive.

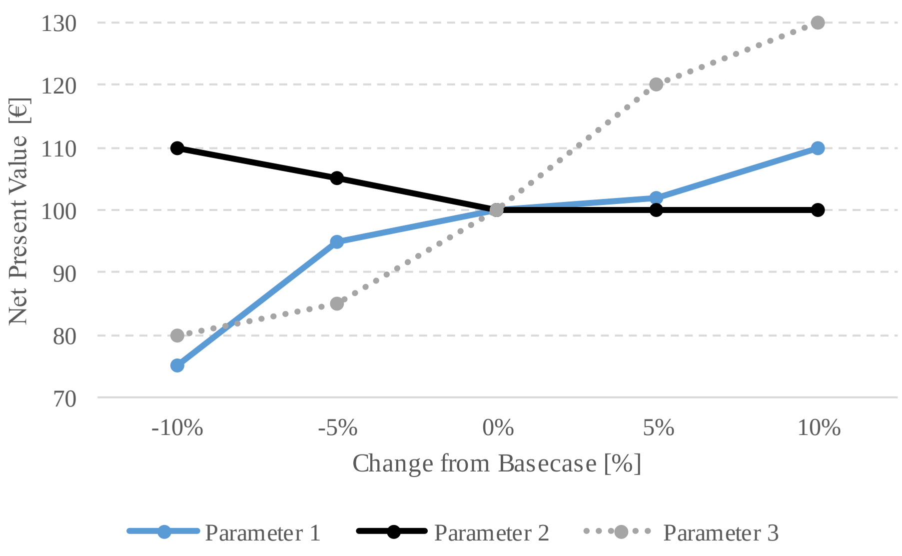

Figure 4.7: Exemplary sensitivity plot of variable parameters

4.3.1 Input Parameters

Based on the formulation of the storage models, the following technical parameters should be considered in a sensitivity analysis:

- Storage capacity $E^{Capacity}_{Storage}$
- Power limits $P^{Capacity}_{Storage}$ and efficiency $\eta_{Storage}$ of the storage device
- Generation capacity $P^{Capacity}$ of PV or CHP installations
- Lifetime limits $L^{Calendric, Cycle, Operating}_{System}$ of all installed systems

The depth of discharge will not be considered in the sensitivity analysis, as decreasing it is equivalent to increasing the storage capacity, which is already considered. In addition, the self-discharge of electrical storage systems will not be included in the analysis, as the parameter is not considered in the presented models.

Furthermore, the impact of the following financial parameters will be studied:

- Investment, fixed and variable cost (C^{Invest}, C^{Fixed} and $C^{Variable}$)
- Discount rate r
- Consumption and feed-in tariffs $R^{Import}(t)$ and $R^{Export}(t)$

The above list disregards market prices $R(t)$, as simply shifting them up or down would not consider the complexity behind. Therefore, a parametric model for market prices would be required, whose parameters could then be modified in order to assess their impact on the validity of storage investments.

4.4 Scenario Analysis

Sensitivity analysis typically only looks at the effect of a change in one variable, keeping everything else constant. While this assumption might be viable for small changes in the considered variable, larger changes in one variable would likely also have an impact on some other variables. While sensitivity analysis can be extended to consider correlation between different variables, the integration of their interaction as well as their analysis becomes already for just a few variables very complex. Using only sensitivity analysis, it is therefore difficult to analyze the outcome of different evolutions or define worst cases, as the worst case for each individual parameter will typically not occur jointly. Furthermore, the change in parameters is usually assumed to be constant in time. Contrary, in reality, an evolution can be frequently observed, such as a gradual worsening of efficiency over time. In order to estimate the impact of larger changes as well as to consider parameter interaction on the outcome and assess their consequences, scenario analysis can be used. Scenario analysis captures the evolution of all variables to a future state and therefore is able to measure the "joint impact of various uncertainties" [184] as well as to integrate different evolution paths of parameters in order to provide a "script-like characterization of a possible future." [185].

Typically, a prediction of the future state exists, reflecting the evolution path which is considered most likely. Usually, this path has been used for the previous financial analysis as well as a starting or reference point in the sensitivity analysis. This 'baseline' evolution and its financial evaluation will be used as reference for all other scenarios. Figure 4.8 illustrates the evolution of two different scenarios compared to the baseline prediction.

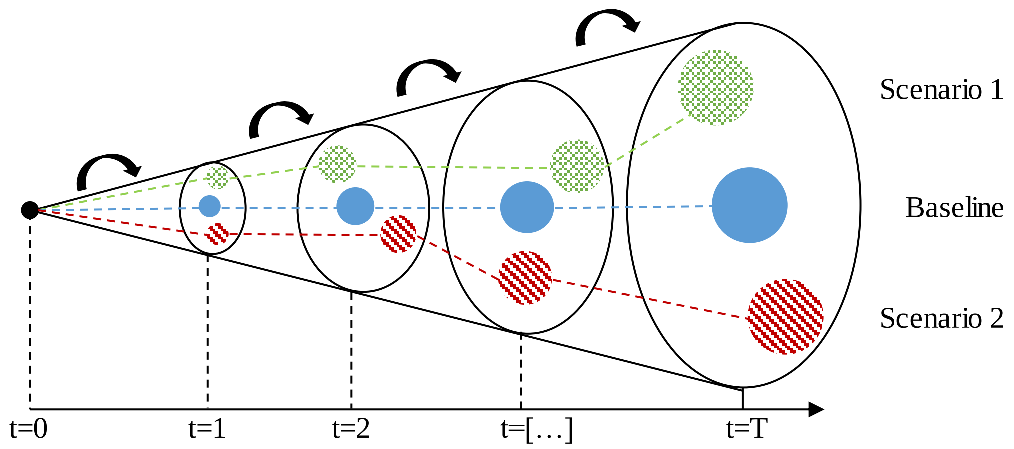

Figure 4.8: Scenario funnel

Scenario analysis does not predict a specific future outcome, but analyses different evolution paths towards different final states, which reflect credible instances of input parameters affected by uncertainty. By evaluating the different evolutions, scenario analysis therefore helps to identify situations which adversely affect the profitability of a storage system. Furthermore, its application allows to identify system configurations which are least affected by adverse future outcomes thus leading to more robust decisions in the sense that the decision maker would feel less regret when adopting them.

One of the major weaknesses however remains: Schoemaker [184] explains in his paper how people tend to overestimate the likelihood of what in their judgement are favorable outcomes and underestimate the impact of negative influences. Scenario analysis can only help in the decision process if realistic unbiased assumptions are taken.

4.4.1 Uncertainties

Table 4.1 lists the uncertainties U_i, which have been identified as major drivers for the business cases described in Sections 3.3 - 3.6 and which might experience severe changes over the evaluation time horizon.

Symbol	Description
U_1	Wholesale market price
U_2	Consumption tariff
U_3	Compensation for electricity feed-in
U_4	Compensation for ancillary services
U_5	Price fluctuations

Table 4.1: Uncertain factors

The following list provides an insight into the driver of each uncertainty:

- U_1: The wholesale market price for electricity is determined by supply and demand and hence underlies a wide range of influence factors. Major drivers for its future development are - among others - the installed capacity of dispatchable and non-dispatchable generators, commodity prices and the demand for electricity.
- U_2: Consumption tariffs are influenced by the development of the wholesale market price. However, as the market price constitutes only a part of the total cost to consumers, the tariff is influenced by further factors, such as infrastructure cost for the networks, the cost for the provision of ancillary services or subsidies for feed-in tariffs.
- U_3: The compensation for electricity feed-in is determined by policy makers. Their future development depends for instance on environmental goals, the development of technologies and their cost as well as the development of electricity cost for consumers.
- U_4: Prices for the compensation of ancillary services are determined by a tender and hence driven by supply and demand. The demand is set by the TSO in relation to overall electricity demand and stability concerns, considering for example the share of non-dispatchable, fluctuating generation from photovoltaic and wind resources. Supply for ancillary services depends on generation capacity availability and the development of wholesale prices (higher prices make participation in the spot market more attractive), regulatory aspects as well as the market entrance of further participants, such as storage operators or virtual power pools.
- U_5: Last, market price fluctuations are - among others - influenced by the overall price level as well as the development of installed capacities of non-dispatchable resources.

After the identification of uncertainties, their interdependency must be estimated in order to obtain internally consistent scenarios. Table 4.2 provides a qualitative estimate, showing the causal connection between the individual uncertainties. A positive / negative relation is indicated by a ‘+’ / ‘-‘. If no or no constant relationship can be established, the relation is marked with a ‘o’. Importantly, the relation between variables is not necessarily reciprocal. Furthermore, as shown in the previous list, the dependencies are not singular, but every uncertainty is driven by a variety of factors.

Reaction

Cause	U_1	U_2	U_3	U_4	U_5
U_1		$+^{(a)}$	$-^{(b)}$	$+^{(c)}$	$+^{(d)}$
U_2	$-^{(a)}$		$-^{(e)}$	$o^{(f)}$	$o^{(g)}$
U_3	$-^{(b)}$	$+^{(e)}$		$o^{(h)}$	$o^{(h)}$
U_4	$o^{(c)}$	$+^{(f)}$	$o^{(h)}$		$o^{(h)}$
U_5	$o^{(d)}$	$+^{(g)}$	$o^{(h)}$	$o^{(h)}$	

Table 4.2: Qualitative estimate of the causal connections of uncertainties

The superscript in Table 4.2 indicates the appendant explanation:

a) A rise in wholesale prices would most likely lead to a rise in consumption tariffs, as retailers would try to pass on their additional cost. Contrary, a rise in consumption tariffs (due to a rise in additional tariff price components, such as taxes) could even lead to a decrease in wholesale prices due to lower demand for electricity.

b) Furthermore, an increase in whole-sale prices might lead to a reduction in feed-in tariffs, as new technologies would require less financial support to become financially viable and policy makers might consequently reduce the feed-in compensation. Contrary, a change in feed-in tariffs would only have limited impact on wholesale-prices on the short-term, as most generators benefiting from feed-in tariffs such as photovoltaic or wind generators are bidding at their marginal cost of zero. However, on the long-term, attractive feed-in tariffs might result in higher investments and hence an increasing market share of generators that bid at zero, resulting in a likely decrease in market prices.

c) In addition, a rise in market prices would make selling energy more attractive than providing ancillary services. Therefore, compensation for the provision of ancillary services has to increase to ensure that sufficient capacity is provided. Due to the comparatively small market size, an increase in the tender for the provision of ancillary services would lead only to marginal changes in the wholesale market.

d) An increase in market prices would increase absolute price fluctuations, whereas a higher volatility would not necessarily lead to higher prices.

e) A significant increase in the consumption tariff (for instance, due to rising market prices) might make policy makers inclined to lower the overall electricity cost to consumers by reducing feed-in tariffs. An increase in feed-in tariffs would be passed on to consumers and hence lead to an increase in consumption tariffs.

f) An increase in consumption tariffs would have no direct impact on the tender for ancillary services, whereas an increase in the compensation for the provision of ancillary services would be passed on to consumers and hence lead to an increase in consumption tariffs.

g) Furthermore, an increase in consumption tariffs would have no impact on price fluctuations. On the contrary, a higher price fluctuation would likely lead to higher consumption tariffs, as retailers would demand a higher compensation for their increased risk.

h) No direct causal relationship is assumed between feed-in tariffs, the compensation for the provision of ancillary services or price fluctuations.

However, when analyzing the causal connection in a real setting, further influence factors must be observed and the dependency cannot be simplified to a one-dimensional association.

4.4.2 Scenario Construction

Amer et al. find that a wide variety of approaches for scenario creation exists and that planning is a “fairly practitioner driven approach” [186]. Generally, the infinite number of potential future states resulting from the combination of particular instances of each individual input data must be first reduced to a limited number of possible, representative outcomes, which can then be evaluated. Besides determining realistic boundaries for all variables, their relationships and interdependencies must be considered in order to ensure that the outcome is realistic. Furthermore, each scenario should be internally consistent, plausible as well as relevant [184]. To evaluate the value of a storage device not only the final state is of interest, but also the evolution path, as they will have an impact on the intermediate cash flows.

In their literature review of scenario planning, Amer et al. [186] find that typically 3-5 scenarios are considered as sufficient by most authors. While a higher number might be able to depict the future in more detail, the process becomes more complex and time-consuming, which does not necessarily yield better results. Furthermore, scenarios should “describe generically different futures rather than variations on one theme” [184].

In the following, the expected development of the listed uncertainties will be discussed. Furthermore, four scenarios will be presented. These reflect the opinion of the author, and are, as previously discussed, subjective in nature.

Baseline

The expected overall development is based on the current legislation and regulation framework. Feed-in tariffs will be further reduced by policy makers as a reaction to decreasing investment cost for established technologies such as photovoltaic and wind generation as well as to counter the high cost of electricity for final consumers. Despite the decrease in feed-in remuneration, the market share of renewable generators will further increase, due to both further decreasing investment cost and technological advancements. Therefore, wholesale prices during periods with high renewable generation will further decline, closer to the marginal cost of many renewable technologies of zero. However, this will be compensated by short periods with more extreme prices demanded by peak generators, when insufficient renewable generation will be available. On average, wholesale prices will therefore remain unchanged, however price fluctuations will increase. Increased competition in the ancillary service market, for instance from storage operators and distributed, virtual power plants from cogeneration units, will be offset by less traditional generators participating in the market, resulting in an unchanged compensation for the provision of ancillary services. Consumption tariffs will remain unchanged. Further developments such as for example an increase in investment cost for network extensions to integrate more renewable generators in addition to the more volatile wholesale prices counteract the cost reduction from the declining charges for the subsidy of renewable.

U_1 **Wholesale market price**	***U_2*** **Consumption tariff**	***U_3*** **Feed-in tariff**	***U_4*** **Ancillary services**	***U_5*** **Price fluctuations**
o	o	-	o	+

Table 4.3: Baseline: expected development of uncertain variables

Scenario 1: Strong Increase in Distributed Generation

Scenario 1 assumes a strong increase in distributed generation as a reaction of many consumers to the increasing spread between high electricity cost and decreasing cost for distributed generation technologies, such as small-scale cogeneration units and photovoltaic installations. Contrary to the baseline, therefore, more generation will be installed at the consumer site to achieve a higher self-sufficiency. This leads to less demand for electricity at times with sufficient local generation, where consumers will satisfy the majority of their demand locally. However, during periods with little local generation, many consumers will still rely on the grid for their electricity demand, driving market prices up. Therefore, whole sale price will be on average unchanged, however will become more volatile. Despite lower feed-in tariffs, the cost for electricity taken from the grid will increase for consumers, driven by the effects of grid defection. Compensation for ancillary services will decrease as a reaction to more distributed generators providing such services, for example from small-scale cogeneration units coupled in virtual power pools.

U_1 Wholesale market price	U_2 Consumption tariff	U_3 Feed-in tariff	U_4 Ancillary services	U_5 Price fluctuations
o	+	-	-	+

Table 4.4: Scenario 1: development of uncertain variables

Scenario 2: Strong Increase in Renewable Generation

Scenario 2 discusses the effects of a policy implemented to increase the efforts against climate change. Therefore, policy makers will increase feed-in tariffs in order to incentivize additional investments in renewable technologies. As a result, wholesale prices will further decline, whereas price volatility will increase sharply. With a significantly lower number of thermal generators running, the cost for the provision of ancillary services will increase. Consumption tariffs will increase significantly due to the high cost from the feed-in tariffs as well as increased cost from ancillary services and further aspects, such as increased network costs to accommodate the rising share of renewables.

U_1 Wholesale market price	U_2 Consumption tariff	U_3 Feed-in tariff	U_4 Ancillary services	U_5 Price fluctuations
-	+	+	+	+

Table 4.5: Scenario 2: development of uncertain variables

Scenario 3: Return to Old Paradigm

Scenario 3 assumes a return to the old paradigm of electricity generation, primarily from thermal generation due to concerns about the security of supply and increasing cost. Feed-in tariffs would therefore be eliminated. Wholesale prices would increase, as less and less generators with marginal cost of zero would participate. Volatility would decrease as a reaction to less volatile generation resources. Compensation for ancillary services would increase in line with the increases of the wholesale market price. Overall, the cost for consumers would remain unchanged, as higher cost for the purchase of energy from the wholesale market and a higher compensation for ancillary services would be offset by lower subsidy cost for feed-in tariffs, a lower profit margin for retailers due to their reduced risk and less required investments for the extension of the network.

U₁ **Wholesale market price**	***U₂*** **Consumption tariff**	***U₃*** **Feed-in tariff**	***U₄*** **Ancillary services**	***U₅*** **Price fluctuations**
+	o	-	+	-

Table 4.6: Scenario 3: development of uncertain variables

Scenario 4: Increased Demand from Electric Vehicles

Last, Scenario 4 assumes a significant increase in electricity demand – mostly during the evening and the night – from the charging of electric vehicles. In order to satisfy the demand, more traditional thermal generators are built. Wholesale prices will increase slightly, as frequently the marginal bid will then be offered by a thermal station and the relative market share of renewables bidding at zero decreases. Compensation for ancillary services will decrease significantly, as it will be provided by pooled electric vehicles. Consumption tariffs will decrease slightly, as the reduction in network cost more than offsets the increasing wholesale prices. Price fluctuations are reduced, as the bidding curve becomes more stable and less dependent of intermittent resources. Feed-in tariffs are further reduced as under the baseline case.

U₁ **Wholesale market price**	***U₂*** **Consumption tariff**	***U₃*** **Feed-in tariff**	***U₄*** **Ancillary services**	***U₅*** **Price fluctuations**
+	-	-	-	-

Table 4.7: Scenario 4: development of uncertain variables

4.4.3 Evaluation of Scenarios

In order to evaluate the impact of the different scenarios, the NPV should be determined for each evolution case ($NPV_{Baseline}$, $NPV_{Scenario\ 1}$, …). The horizon of the evaluation should span the lifetime of the storage system in order to consider all cash flows. As the evolution of different variables impacts the cycle lifetime and might induce different dispatches, an individual assessment for each scenario is required. However, as the system configuration cannot be changed ex post, the same configuration must be assumed in all cases.

The resulting cash flows and net present value under each scenario can then be analyzed for their absolute value, their deviation from the base line as well as best and worst cases. While scenario analysis cannot identify which scenario will occur, it can help to estimate the potential impact on the validity of the project. It is the task of the decision maker to judge how likely such a scenario is and if the investment can still be justified if a particular scenario will in fact occur.

4.5 Monte Carlo Simulation

Monte Carlo simulation is a widespread computational method using repeated statistical trials to obtain an approximate solution or an expectation value for high-dimensional problems [187]. In addition, it can also be applied to gain an understanding about the distribution of outcomes, which will be the primary objective in this case. The resulting distribution of potential outcomes can then be analyzed in order to assess the uncertainty of an investment decision. The concept is therefore related to scenario analysis, but considers a much broader range of possible (random) alternatives. However, Monte Carlo simulation does not only show which outcomes are more or less likely, but also provides a probability assessment of an outcome.

In order to implement a Monte Carlo simulation, first assumptions about the distribution or evolution processes of uncertain parameters or variables are required. Next, for each simulation run random samples are taken from the specified distribution as inputs to the valuation process and the NPV is determined. This step is repeated numerous times to obtain a distribution of possible outcomes. With an increasing number of conducted simulations, the average outcomes will converge to an expected result.

Monte Carlo simulation enables the integration of multiple sources of uncertainty. The following two sections will detail two aspects: first, parameter uncertainty, such as storage efficiency or lifetime and second, uncertainty about the development of future electricity prices.

4.5.1 Parameter Uncertainty

The evaluation process of a potential investment project usually requires assumptions about several parameters, which are typically associated with varying degrees of uncertainty. By using Monte Carlo simulation and repeatedly taking samples from the probability distributions of the unknown parameters, which reflect their associated uncertainty, a distribution of outcomes can be created which reflects the initial uncertainty in the input parameters [149].

Battke et al. [26] as well as Zakeri and Syri [114] conduct extensive literature reviews about parameter uncertainty of storage systems. The choice of the parameters to be considered as uncertain variables in the Monte Carlo simulation should be made depending on the selected storage technology and the deployment context. Exemplary, the following parameters will be considered:

- Cyclic and calendric lifetime of storage systems is influenced by the application context as well as external factors. Operating a system constantly close to its specification limit might for example degrade the system prematurely and reduce its lifetime expectation. However, also under regular usage, storage systems experience deviations from their nameplate lifetime.

- Storage efficiency varies widely between different technologies, but even nameplate efficiencies for the same technology show significant variations between different manufactures. In addition, realized efficiency can be affected by many factors, such as current state of charge, charging or discharging power or temperature. While some of the later effects could be partly incorporated in a more sophisticated model, there remains significant uncertainty which can be easily considered in a Monte Carlo simulation.

- Maintenance cost will vary strongly depending on the implemented technology. While for some technologies little maintenance is required and the associated cost can be reasonably forecasted, other technology might require more uptake efforts, which are typically rather uncertain due to unforeseen repair cost.

Parameters, which are uncertain during the evaluation process but will become known before the project has been committed, should be excluded. These are typically investment and financing cost, which are oftentimes uncertain during the evaluation phase but become known before the project is actually committed and are therefore certain parameters for the final investment decision.

In addition, in a Monte Carlo simulation, the interdependent relationship between the realizations of variables can be considered, both for positive as well as negative correlation. For example, an undetected manufacturing fault of a storage device might lead to higher maintenance cost, occurring jointly with a lower efficiency and a lower lifetime expectation.

4.5.2 Price Simulation

Besides parameter, a major source of uncertainty are future electricity prices. The implementation of a model for the simulation of electricity prices is of interest for two reasons:

- First, to gain a better understanding about the range of outcomes when evaluating a business case under uncertain prices
- Second, to identify the impact of a change in the price process on a business case, such as an increase in future price volatility, a more pronounced seasonal pattern or a generally higher price level.

In the existing literature, a wide range of modeling approaches has been discussed. Section 2.2.4 provides a general overview. In this document, additive decomposition will be used to break the price process into three components [47], [49], [152], [188]:

- $X(t)$: deterministic process for trend and seasonality
- $J(t)$: price jumps
- $S(t)$: stochastic residuals

Each component is described by a mathematical model, whose parameters are estimated from historical data. For the demonstration of the calibration process, historical hourly data of the years 2011-2015 for the German day-ahead market has been considered [189].

To simulate prices based on the calibrated process, the additive decomposition is reversed. All three components are modelled individually, and aggregated at the end to obtain the simulated price path.

Trend and Seasonality

In a first step, the long-term trend as well as seasonal cycles are identified from the historical time series. The trend describes the long-term evolution of prices towards an overall higher / lower level. Seasonal cycles refer to the periodic repetition of price behavior. This can typically be found simultaneously on several time resolutions. The following seasonal patterns will be considered:

- annual period: long-term patterns over the year, influenced by changing demand and supply along the year
- weekly period: prices typically show a weekly pattern, driven by varying demand along the week and especially the weekends
- daily period: supply and demand and therefore also prices vary considerably within a day. Demand is typically much higher during the daytime and in the evening as compared to the night. Furthermore, solar generation is also only available during the daytime

These periodic behaviors resemble oscillations with different frequency, which can be decomposed into sine- and cosine-functions. The trend of the time series is assumed to be linear. With t as index variable representing days, the deterministic trend and seasonality component $X(t)$ can be modeled by equation (4.2).

$$\begin{aligned} X(t) &= \alpha_0 + \alpha_1 t + \ldots \\ &\alpha_2 \cos(\tfrac{2\pi t}{365}) + \alpha_3 \sin(\tfrac{2\pi t}{365}) + \alpha_4 \cos(\tfrac{4\pi t}{365}) + \alpha_5 \sin(\tfrac{4\pi t}{365}) + \ldots \\ &\alpha_6 \cos(\tfrac{2\pi t}{7}) + \alpha_7 \sin(\tfrac{2\pi t}{7}) + \alpha_8 \cos(\tfrac{4\pi t}{7}) + \alpha_9 \sin(\tfrac{4\pi t}{7}) + \ldots \\ &\alpha_{10} \cos(2\pi t) + \alpha_{11} \sin(2\pi t) + \alpha_{12} \cos(4\pi t) + \alpha_{13} \sin(4\pi t) \end{aligned} \quad \textbf{(4.2)}$$

α_0 is a constant, reflecting a permanent offset of prices. α_1 is the coefficient of the linear trend. Parameters α_2 - α_5 are the coefficient for long-term cycles that occur over the course of a year. Coefficients α_6 - α_9 reflect the weekly cycle of prices, and α_{10} - α_{13} price patterns within a day. The parameters can easily be estimated from historical data using linear regression.

Figure 4.9 shows for an exemplary period both the historic price as well as the estimated seasonal process. The weekly as well as the daily cycle can be easily identified.

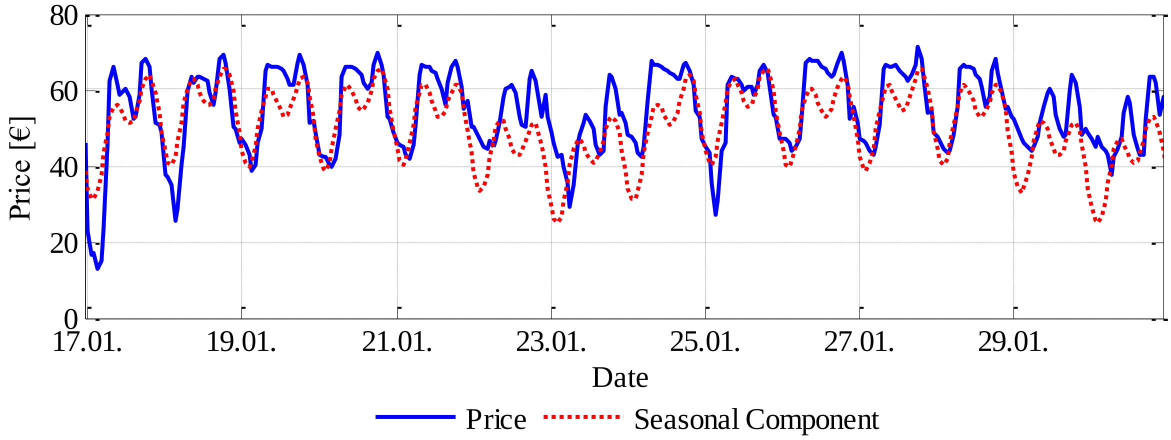

Figure 4.9: Historic market prices and estimated seasonal process

Figure 4.10 shows the distribution of residuals after the seasonal component has been removed from the time series. The residuals have a mean of 0, but are slightly skewed to the left.

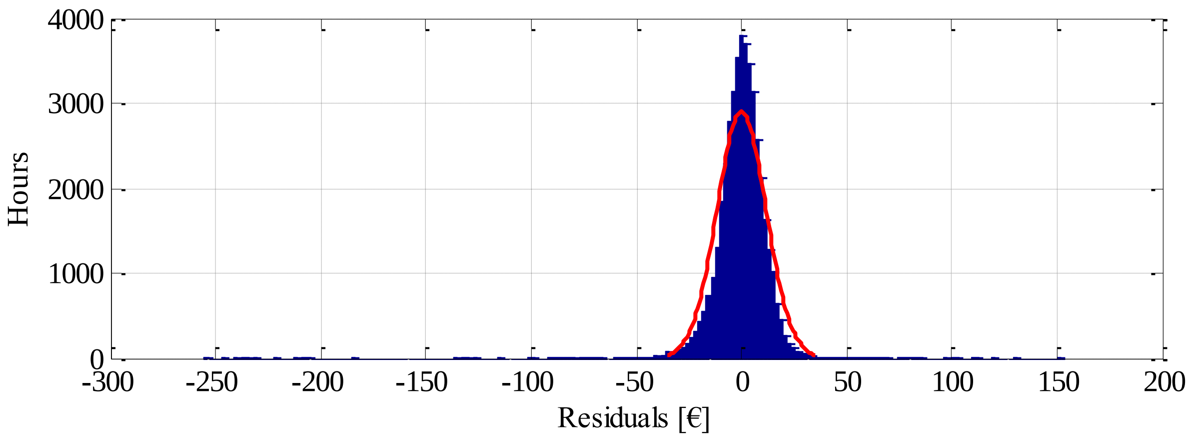

Figure 4.10: Distribution of price residuals after removal of the seasonal component

Jumps

After the identification of the seasonal component and its removal from the time series, in a next step price jumps are removed. Therefore, first the standard deviation (σ) of the remaining time series is calculated. Following, all prices outside the confidence interval (-4σ, $+4\sigma$) are considered as jumps and removed from the time series

These two steps are repeated until no more prices lay outside the confidence bands. Figure 4.11 shows this process exemplary for the first three iterations.

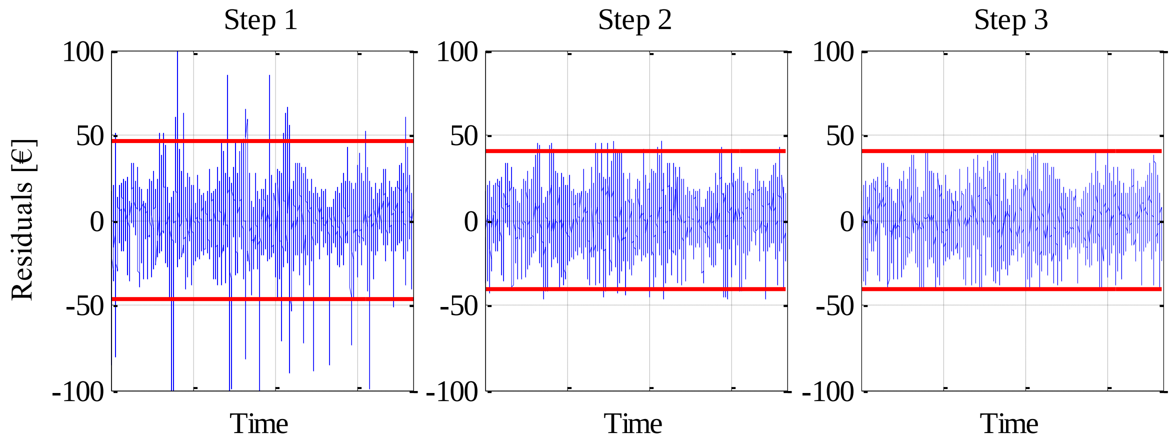

Figure 4.11: Process to remove jumps from price series over three iterations

The distribution of the removed jumps can be seen in Figure 4.12. The jumps occurred both on the up as well as on the downside, with few jumps reaching extreme values. Hence, in the forthcoming simulation, jumps will be modeled by an exponential distribution (with parameters λ_{jump_up} and λ_{jump_down}), which is shifted up / down (by α_{jump_up} and α_{jump_down}) to match the empirical data. Their occurrence is assumed to be independent and governed by their empiric probability (δ_{jump_down} and δ_{jump_up}).

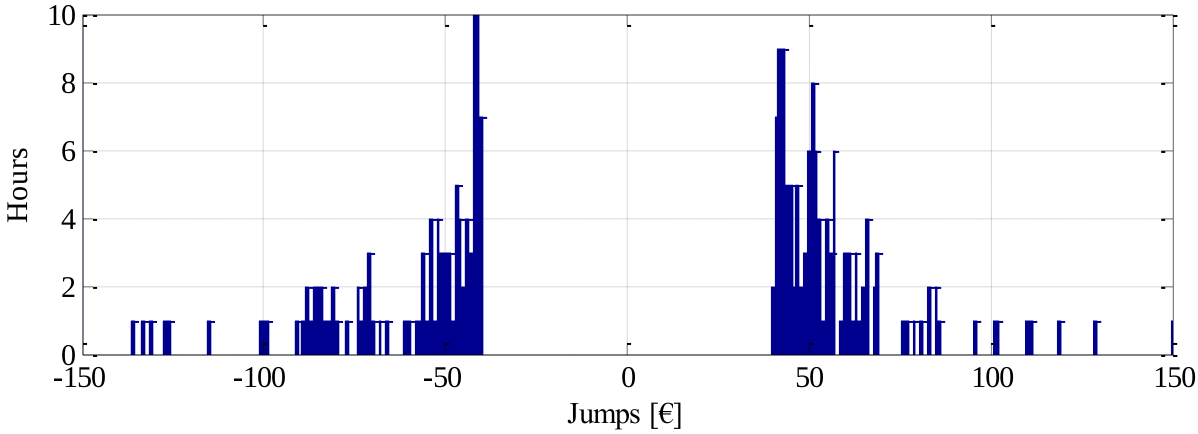

Figure 4.12: Distribution of price jumps

Weron [48] suggests, that price spikes show a seasonal pattern and are more likely to occur during high price periods. However, the author also acknowledges that the scarcity of occurrence makes the identification of relations and integration into a model problematic. Hence, for the sake of simplicity, the jump component will be modeled independently as detailed in equation (4.3).

$$J(t) = (\alpha_{jump\_up} + \exp(\lambda_{jump\_up})) \times j_{up} + (\alpha_{jump\_down} + \exp(\lambda_{jump\_down})) \times j_{down} \quad \textbf{(4.3)}$$

with $j_{up} = 1$ with probability δ_{jump_up}, otherwise $j_{up} = 0$

with $j_{down} = 1$ with probability δ_{jump_down},, otherwise $j_{down} = 0$

Stochastic Residuals

The residuals of historic prices after removing both the seasonal component as well as price jumps are shown in Figure 4.13.

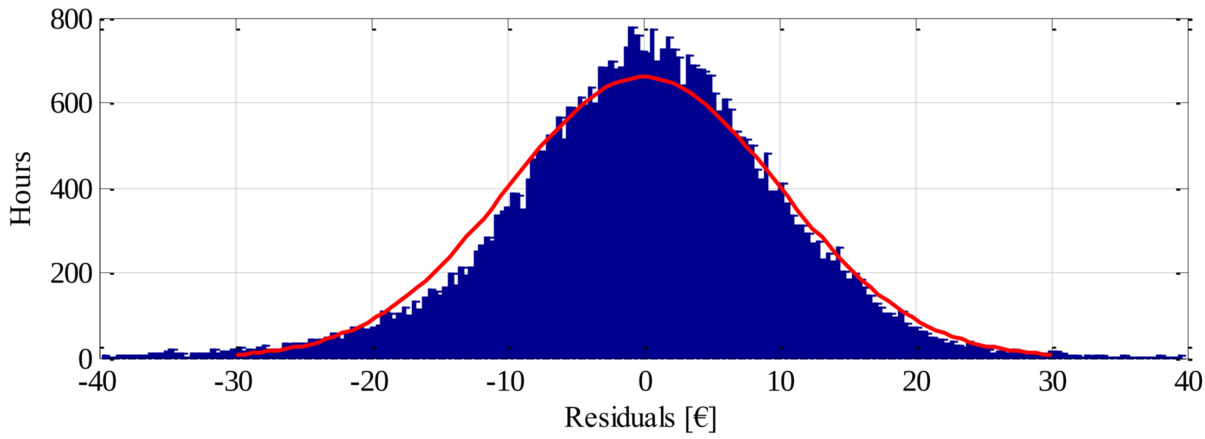

Figure 4.13: Distribution of price residuals after removal of the seasonal components and price jumps

They are assumed to be normally distributed in the following. In addition, the residuals also display strong autocorrelation, as can be seen from Figure 4.14

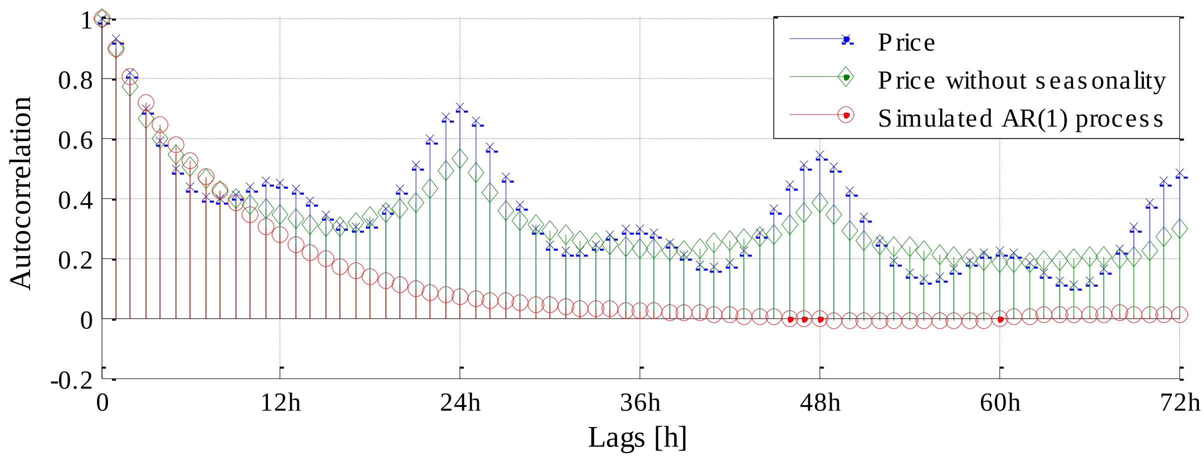

Figure 4.14: Autocorrelation of electricity prices and its components

In order to incorporate the mean-reverting behavior as well as the autocorrelation into the model, an autoregressive model of first order (AR(1)) [190] was chosen to simulate the stochastic residuals, as shown by equation (4.4).

$$S(t) = \alpha \times S(t-1) + \varepsilon(t) \quad \textbf{(4.4)}$$

The error term $\varepsilon(t)$ is normally distributed, with a mean of zero and a standard deviation of σ_ε. While empirical evidence suggests that volatility is not constant, integrating heteroscedasticity into the model does not necessarily lead to better accuracy [48]. For the sake of simplicity, constant volatility is therefore assumed. Both σ_ε as well as the coefficient α can then easily be estimated from historical data by using linear regression. In order for the process to be mean-reverting, α must be <1.

Figure 4.14 displays the autocorrelation of the original time series, the autocorrelation after removing seasonality as well as the autocorrelation of the simulated AR(1) process. It is obvious that there is considerable autocorrelation in the original data with different cycles, which was reduced by removing seasonal pattern.

Simulation

In order to simulate a price path, the required parameters have to be estimated as detailed on the previous pages. This is most easily accomplished by analyzing historical data. However, care must be taken as considering long time periods might underestimate recent changes in price patterns. Contrary, only considering a short time frame might give too much importance to a period with a not relevant price behavior. Furthermore, parameters can also be adjusted to reflect possible future scenarios, for example an increased likelihood of price jumps or an expected increase in volatility.

Using equations (4.2) – (4.4), the individual processes for the seasonal component, the jump component and the stochastic component can be modeled. In a final step, these processes are added up to obtain the simulated price, as shown by equation (4.5).

$$R(t) = X(t) + J(t) + S(t) \tag{4.5}$$

The process can then be repeated to create multiple price evolution paths. Figure 4.15 shows exemplary three simulated price paths. The simulated prices clearly exhibit the required characteristics of electricity prices, that is seasonal cycles, jumps and mean reversion.

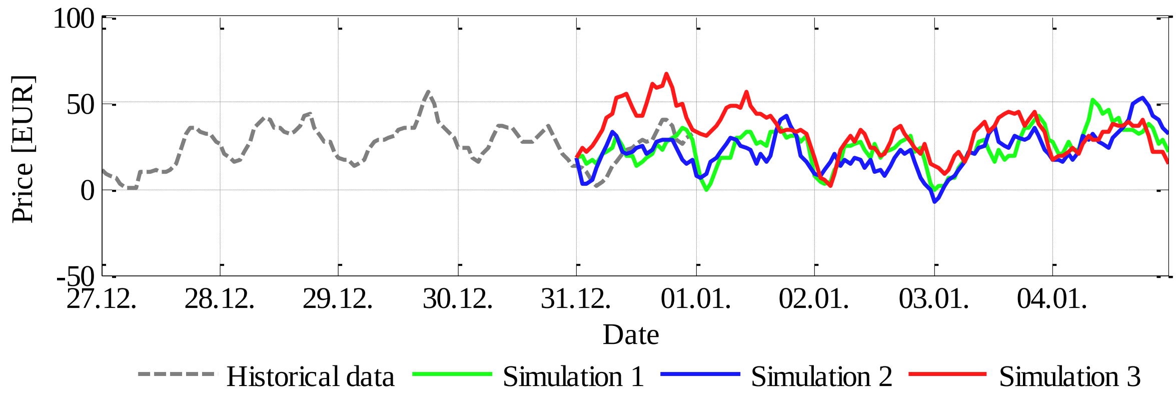

Figure 4.15: Historic price data and price simulation

The resulting price duration curve is displayed in Figure 4.16, confirming the overall good fit of the simulation process.

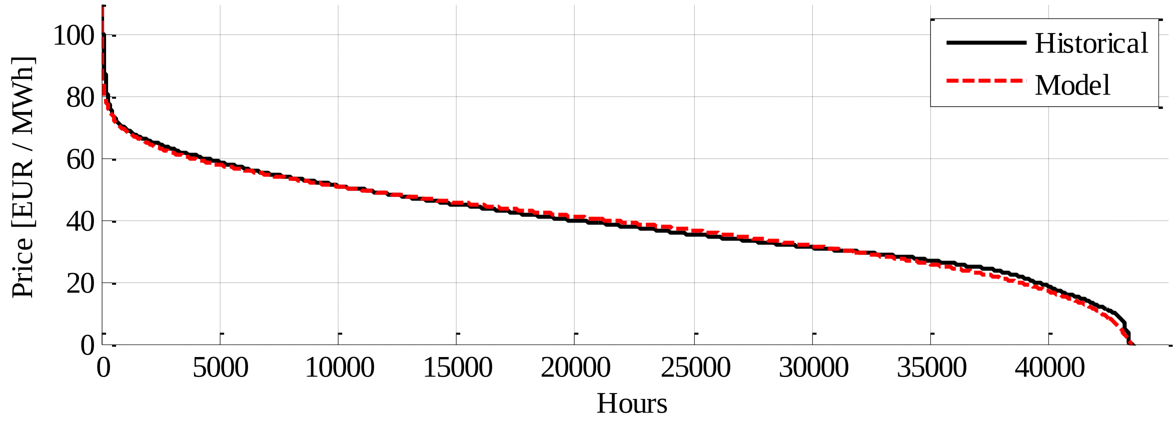

Figure 4.16: Price duration curve

4.6 Value at Risk

While Monte Carlo simulation provides a good impression of the range of potential outcomes and therefore of the financial uncertainty associated with an investment undertaking, it does not provide a measurement for the associated risk. Therefore, the concept of Value at Risk (VaR) is introduced. Value at Risk quantifies the risk, based on the previously obtained probability density function of possible investment outcomes. It provides an estimate of a threshold which will not be exceeded with a certain probability β over a defined time horizon. Therefore, it enables decision makers to assess the outcome of an investment and estimate the worst case in all but extreme events. For the so called confidence level β, values of 95% - 99% are common.

VaR therefore provides an estimate of potential adverse outcomes that can be expected under regular conditions, neglecting tail events. Based on the cumulative distribution function $F(x)$ from the previous Monte Carlo Simulation, the Value at Risk VaR for the confidence level of β is defined according to equation (4.6) [190]:

$$VaR^{\beta} = \inf \{x \mid F(x) \geq 1-\beta\} \quad \textbf{(4.6)}$$

Hence, the Value at Risk for the confidence interval β is simply the $(1\text{-}\beta)$ - quantile of the cumulative distribution function. It represents the threshold, under which the NPV will only fall in $(1\text{-}\beta)$% of all realizations. The considered time horizon is defined by the horizon of the underlying Monte Carlo simulation.

Alternatively, one can determine the probability of an outcome worse than a specified threshold (a predefined value for VaR) from the cumulative distribution [190], as shown by equation (4.7).

$$p_{VaR} = \Pr[x \leq VaR] = F(VaR) \quad \textbf{(4.7)}$$

Figure 4.17 shows exemplary the determination of the VaR from the cumulative probability function for a confidence level of 90%.

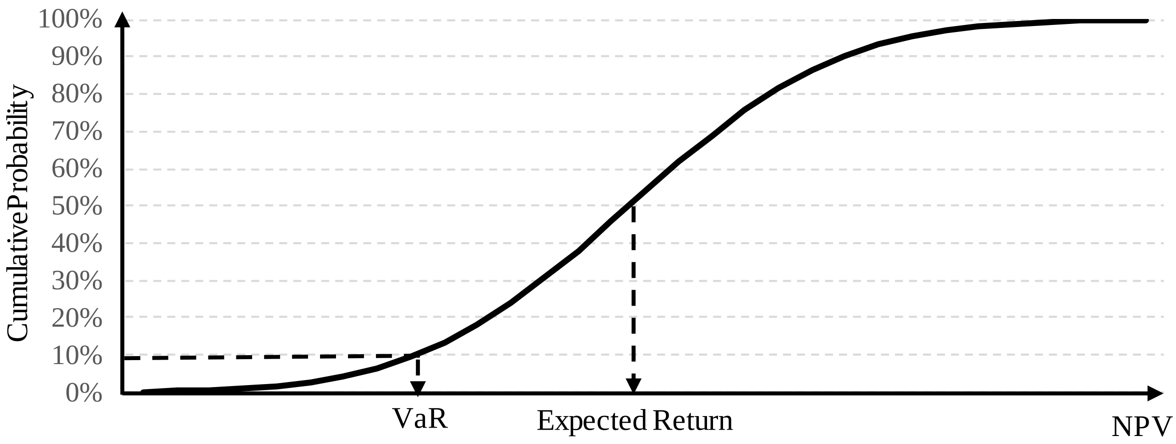

Figure 4.17: Schematic representation of the Value at Risk

Using the VaR concept gives the decision maker an insight about the likelihood of certain outcomes, given the assumed uncertainty of the simulated variables in the Monte Carlo Simulation. It enables the decision maker to take a decision based on his willingness to accept a certain loss and his ability to write off the project in case it fails or does not achieve the expected result. Risk-averse managers therefore will prefer projects with a lower uncertainty and hence with a lower VaR.

The major drawback of the VaR concept is the requirement for a (oftentimes complex) model in order to run the underlying Monte Carlo Simulation. In addition, many assumptions are required, both for the market price process as well as for parameters and their correlation. In addition, VaR does not specify the risk beyond the confidence level and hence does not inform about tail risk. Care is also needed when using Value at Risk for several projects, as the measure is not additive. Instead, the correlation between the projects must be considered in the evaluation in order to calculate a joint Value at Risk.

4.7 Decision Making under Uncertainty

While sensitivity analysis (Section 4.3), scenario analysis (Section 4.4), Monte Carlo simulation (Section 4.5) and Value at Risk (Section 4.6) provide valuable insights into the uncertainty of storage investments and the resulting financial risk, they do not provide a guideline for the decision maker whether he should invest at all or which alternative to choose. This process of selecting an option out of several alternatives (doing nothing, investing into a particular project or another) is called decision making.

If the decision maker is pursuing only one objective (such as the maximization of profits), the process of decision making is usually a (simple) optimization problem. However, in order to include uncertainty into the consideration of the decision making process, usually several objectives have to be considered simultaneously. Oftentimes, this results in a conflict of interest between the different objectives.

In the following, two approaches how uncertainty can be integrated into the decision making process will be discussed. First, scenario analysis will be considered in order to determine the system configuration, which performs best according to the decision maker's preferences across several future scenarios. Second, an approach to consider the results from a Monte Carlo simulation and the resulting Value at Risk in the evaluation of a storage installation is presented. For both cases, several preference functions are formulated and discussed.

4.7.1 Using Scenario Analysis

Uncertainty can be considered in the project evaluation by integrating scenario analysis into the decision making process. Typically, a project is evaluated based on the expected evolution of external factors. Thereby, however, it is neglected that future events are uncertain and potentially deviate from expectations. Scenario analysis can be integrated into the decision making process by the following four steps [67]:

1. In a first step, potential future states ("Scenarios") S_i must be defined as discussed in Section 4.4. In addition, the decision maker needs to assign an occurrence probability p_i (for example, his subjective estimate) to each scenario.
2. Second, possible investment alternatives A_k must be specified. These alternatives refer to different system configurations and / or system operation schedules.
3. Third, each investment alternative A_k is evaluated under each scenario S_i, by determining the optimal dispatch and calculating its net present value NPV_{ik}.
4. Following, the optimal investment alternative based on the decision maker's objective and his preferences towards risk can be identified.

This process is outlined in Figure 4.18.

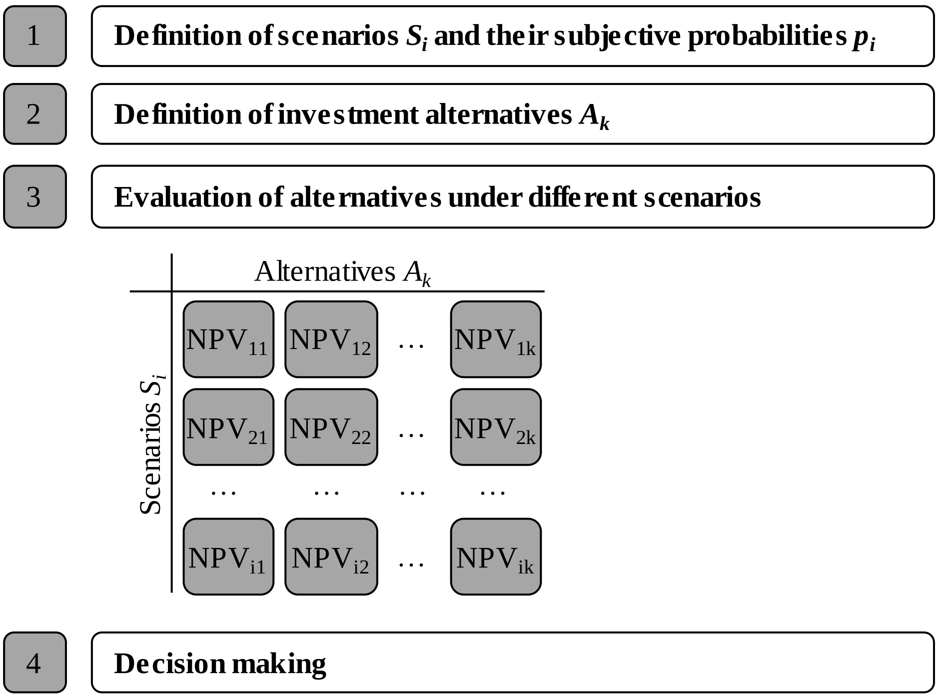

Figure 4.18: Decision making process using scenario analysis (based on [67]**)**

The last step differs according to the objectives of the decision maker and the degree of his aversion to risk. The following objectives will be discussed hereafter:

- the maximization of the expected profits,
- the minimization of potential losses,
- the minimization of regret felt by the decision maker in case other alternatives perform better
- and last, the avoidance of variability.

The expected result $\overline{NPV}_k$ for investment alternative A_k across all N scenarios and considering their occurrence probability is defined by equation (4.8).

$$\overline{NPV}_k = \sum_{i=1}^{N_i} NPV_{ik} \times p_i \tag{4.8}$$

The variability of results σ_k, expressed as the probability weighted standard deviation, is given by equation (4.9).

$$\sigma_k = \frac{\sqrt{\sum_{i=1}^{N_i} p_i \, (NPV_{ik} - \overline{NPV_k})^2}}{N_i} \tag{4.9}$$

Maximization of the Expected Result

A common approach to determine the optimal investment alternative is to choose the profit maximizing system configuration for the expected evolution of variables. Uncertainty can be easily integrated into the decision making process by looking at expectation values across the defined scenarios, considering their likelihood of occurrence in the evaluation. The investment alternative which maximizes the expected profits is chosen. This accounts for the fact that the best solution for the expected scenario does not necessarily perform well across a wider range of potential futures. The optimal alternative can be determined from the probability weighted result of the investment alternative under each scenario, as shown by equation (4.10).

$$A_{Opt} = \max_k \overline{NPV}_k \tag{4.10}$$

While the approach is suitable for repetitive decision problems, it neglects the variability of results. Therefore, an alternative with highly variable results across different scenarios might be preferred over a steadier, but slightly worse alternative.

Minimization of Potential Losses

Instead of maximizing the (expected) profitability, a strongly risk-averse decision maker might prefer the investment alternative which minimizes his losses when adverse conditions occur. The system configuration which generates the lowest losses under its individual worst case scenario is selected, as indicated by equation (4.11).

$$A_{Opt} = \max_k \left\lfloor \min_i NPV_{ik} \right\rfloor \tag{4.11}$$

The drawback of this approach is that the decision making is based on a single value, which for example might occur only with a very low probability and would otherwise lead to good results.

Minimization of Regret felt by the Decision Maker

Regret represents the opportunity loss compared to the best performing alternative for each scenario. Once the future realizes, the best alternative can be determined in hindsight and hence the regret a decision maker has about having invested in a particular alternative. This approach minimizes the "anger" a decision maker would experience about taking a sub-optimal investment alternative in the past.

First, the regret matrix rg_{ik} for every decision alternative A_k under all scenarios S_i is determined [67], as indicated by equation (4.12). Therefore, the best decision for every scenario is identified in hindsight and following the opportunity loss for all other alternatives calculated. This procedure is repeated for all scenarios.

$$rg_{ik} = NPV_{ik} - \max_k NPV_{ik} \tag{4.12}$$

Following, the alternative with the lowest maximum regret is chosen, considering their probability of occurrence.

$$A_{Opt} = \max_k \left[\min_i rg_{ik} \times p_i \right] \tag{4.13}$$

While the approach might be of interest for risk-averse decision makers, extreme values might distort the result as in the case of the minimization of potential losses.

Avoiding Variability

By avoiding alternatives with a high variability in the results, the decision maker reduces the uncertainty associated with the investment decision. Equation (4.14) considers the ratio of the results to their variability for each alternative, hence maximizing the expected result per unit of variability.

$$A_{Opt} = \max_k \left[\frac{\overline{NPV}_k}{\sigma_k} \right] \tag{4.14}$$

By integrating the variability into the process, more steady results are favoured. However, as the approach does not consider extreme values it might prefer alternatives, which suffer from extreme losses under selected scenarios but show otherwise stable results.

4.7.2 Using Monte Carlo Simulation and Value at Risk

The decision making process can also be based on the results from a Monte Carlo Simulation and the accompanying Value at Risk measure. Compared to the procedure based on Scenario Analysis, no individual scenarios must be defined and the assignment of probabilities to each scenario is not required. In addition, a much broader range of future evaluation paths is considered in a Monte Carlo Simulation. However, the requirement for a model together with the definition of parameters and assumptions makes the process more complex, sensitive to erroneous assumptions and liable to implementation errors.

Analogous to the decision making process using scenario analysis, Figure 4.19 illustrates the process when using Monte Carlo Simulation and the resulting Value at Risk figure. In a first step, a model for the simulation is required. Following, several investment alternatives A_k have to be defined. Theoretically, a metaheuristic search routine could be used to identify the optimal system configuration according to the preferences of the decision maker. However, in order to reduce the complexity and the required computational efforts, instead of optimizing across all potentially possible system configurations, only a discrete number of alternatives will be considered. Following, for each alternative a Monte Carlo Simulation is run. The resulting distribution can then be used to determine the Value at Risk for each investment alternative. Based thereupon, a decision can be taken.

The following objectives will be considered:

- maximization of the expected result (under consideration of a risk budget),
- the minimization of the probability to lose money and
- a balanced approach, which maximizes profit but also takes risk into consideration according to the decision makers preference function.

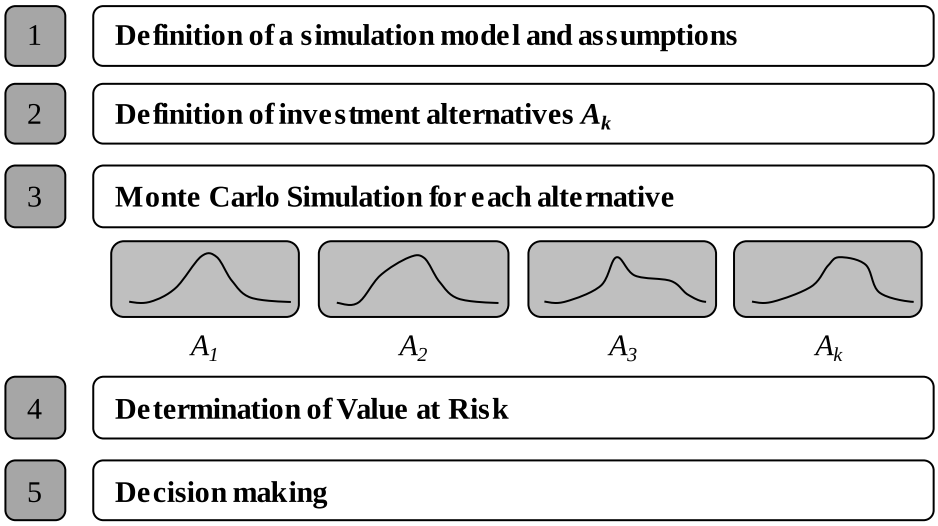

Figure 4.19: Decision making process using Monte Carlo Simulation and Value at Risk

The expected result $\overline{NPV}_k$ across all N simulation runs for an alternative A_k is defined by equation (4.15).

$$\overline{NPV}_k = \frac{1}{N} \times \sum_{i=1}^{N} NPV_{ik} \tag{4.15}$$

Based on the distribution of outcomes (NPV_{ik}), the cumulative distribution Function $F_k(x)$ can be determined for each alternative A_k. Following, the Value at Risk VAR_k^{β} with confidence interval β can be calculated according to equation (4.6).

Maximization of the Expected Result (limited by a Risk Budget)

Analogous to the maximization of the expected result using scenario analysis (subsection 1 in 4.7.1), the same approach is applicable when using Monte Carlo Simulation. The investment alternative with the highest expectation value can be determined by equation (4.16).

$$A_{Opt} = \max_k \overline{NPV}_k \tag{4.16}$$

Risk averse decision makers can easily limit the risk undertaken by only accepting alternatives, whose Value at Risk is above a certain threshold L. Equation (4.17) constraints the objective function (4.16) to those solutions, where the NPV will not fall below L with a probability of β.

$$VaR_k^{\beta} >= L \tag{4.17}$$

Considering only the expectation value in the decision making process neglects the impact of uncertainty. While the approach of restricting the viable solutions to a specified risk budget is straight forward and easily comprehensible, it suffers from one of the major drawbacks of the Value at Risk approach. As the concept does not transfer any information about the shape of the distribution and therefore the tail risk, no statement can be made about the magnitude of the losses beyond the chosen confidence interval.

Minimization of Loss Probability

The Value at Risk approach can also be used to estimate the probability that a certain outcome will realize. A decision maker might have an interest in minimizing the probability of a loss. He therefore prefers the investment alternative which has the lowest probability of resulting in an outcome with a negative NPV. Based on equation (4.7), the optimal investment alternative can therefore be determined by equation (4.18).

$$A_{Opt} = \min_k \left[F_k(0) \right] \qquad \textbf{(4.18)}$$

This approach suffers as well from the drawback mentioned in the previous case. While a decision maker might minimize the probability of suffering a loss, the magnitude of the potential losses beyond the confidence interval might significantly exceed other alternatives. In addition, no information about the expected returns is considered.

Balancing Return and Risk

In order to achieve a balance between potential returns and risk undertaken, a weighting can be assigned by the decision maker according to his preferences. A decision maker with a low risk aversion will focus more on achieving a higher return, whereas risk averse decision maker will prefer an alternative with lower potential losses. The weight ω describes the decision maker preference for higher returns, ω*-1* his risk aversion.

The objective function is given by equation (4.19). For a given weight, the higher the net present value and the Value at Risk (and hence the lower the potential losses), the higher the likelihood of acceptance.

$$A_{Opt} = \max_k \left[\omega \times \overline{NPV}_k + (1-\omega) \times VAR_k^{\beta} \right] \qquad \textbf{(4.19)}$$

By considering both return and risk in the objective function, the decision maker can clearly state his preferences. However, the previously mentioned critics towards Value at Risk remain. Furthermore, the weight ω must be selected, which requires an objective evaluation of the decision makers' preference function.

Chapter 5

5 Impact on Electricity Markets

Abstract

Chapter 5 looks at the potential impact from a wide-scale storage rollout on the electric system. After an introduction to the issue and its importance (Section 5.1), potential changes in demand will be analyzed (Section 5.2). Thereafter, the resulting impact on market prices will be discussed (Section 5.3). Last, consequences and potential feedback reactions of storage implementations will be discussed (Section 5.4).

5.1 Introduction

So far, this document has looked into the economics of storage on a micro-scale, considering an individual installation. A thorough evaluation however would be incomplete without considering the potential impact of storage installations on the electric system and the resulting feedback reactions on the initial business case. Therefore, this chapter determines the aggregated impact of numerous storage installations dispatched for either time shifting or arbitrage on the electric grid and estimates the resulting consequences on electricity market prices. As the provision of ancillary services has no immediate impact on electricity markets, the related business case will not be considered in this chapter. Based upon the obtained results, it will be concluded which impact a wide-scale rollout of storage devices has and whether the introduced change is affecting the viability of storage.

Based upon the description and formulation of the business cases for time shifting of energy (Section 3.3) and arbitrage (Section 3.4), a range of potential changes in electricity demand can be identified:

- Storage dispatched for time shifting of locally generated energy reduces the total demand seen by the grid. In addition, compared to a stand-alone PV system, less energy is fed into the grid. Hence, the overall interaction with the grid is reduced substantially. Furthermore, in addition to the changes in absolute demand, there is a temporal shift in demand.
- Contrary, arbitrage increases the overall demand seen by the grid as storage operations suffer from efficiency losses and hence every charge- / discharge cycle represents a net demand. The temporal shift in demand seen by the grid is evoked by price signals.

Section 5.2 will analyse and quantify these changes as well as discuss their implications in detail.

Based on these results, an approach will be developed in Section 5.3 to estimate the resulting impact of storage installations on electricity prices. Therefore, first a relation between market prices and electricity demand will be established. Following, the feedback reaction of market prices on the changed electricity demand is estimated.

The results are relevant and of interest to a wide range of stakeholders:

- Storage investors themselves. Agents pursuing arbitrage might see their current opportunities disappear once a sufficient large number of market participants are exploiting them. Final consumers using storage to reduce their grid demand and the resulting fees might suffer from new tariff structures, which might be introduced as a reaction to the changed usage of the electric grid.
- Grid operators are faced with a change in demand patterns as well as a range of new agents, which are acting both as load and generation. Furthermore, technological innovations and the shift to smart-grids increase the uncertainty and provide additional facets which must be handled by the operator to ensure a stable operation of the network.
- While traditional generators are already faced with increased pressure from generation with zero marginal cost, the decision to invest in new capacity should also consider the increasing presence of storage. Besides influencing market prices, storage also affects the demand for baseload and peak generation.
- Last, regulators and policy makers have to find solutions to cope with a range of potential issues, such as the reduced tax income due to less energy taken from the grid by consumers deploying storage for time shifting locally generated energy.

The developed methodology will be applied in a case study in Section 6.5, which considers the deployment of storage systems for time shifting locally generated energy in the German context. Assuming a storage deployment rate, the aggregated impact on the electric system and potential prices changes are determined. While such an analysis requires a wide range of assumptions, it provides a high-level understanding of the consequences of storage investments.

5.2 Impact on Electricity Demand

As the impact of storage on grid demand varies with the purpose for which the device is dispatched, two applications will be analyzed.

First, the consequences from dispatching storage for time shifting locally generated energy will be considered. However, as the impact differs according to the implementation, three cases will be distinguished: the refitting of an existing PV installation with a storage system, a new PV installation equipped with a storage system as well as a new combined system with a cogeneration unit, a PV installation and a storage system.

Second, the impact of storage devices dispatched for arbitrage will be considered. Here, it will be differentiated between storage systems with a low and a high power to energy ratio. This is not directly a technical limitation, but could also result from co-integrating arbitrage operations in a storage system primarily dispatched for other purposes and using spare capacity to benefit from price differentials.

5.2.1 Time Shifting

In order to estimate the impact from time shifting locally generated electricity on the grid, assumptions about residential electricity demand as well as about the generation from the photovoltaic systems and the cogeneration unit are required. Based on the assumed load and generation profiles, the dispatch of the storage device as well as the resulting exchange with the grid will be determined using the MIP detailed in Section 3.3.4. The change in grid demand can then be determined by comparing the exchange with the grid under both system configurations. In order to take the varying generation level of the photovoltaic system and the cogeneration unit into account, the impact will be determined over a three-month period both for the summer and winter time. In addition, for each case different storage capacities will be considered to analyze the sensitivity towards the installed capacity.

Electricity demand is characterized according to standard load profiles specified by the German Federal Association of the Energy and Water Industry [191]. These profiles reflect the typical electric load patterns for different consumer groups. For the implementation of the described approach and the following analysis, the residential load profile is assumed. The electric demand differs according to the day of the week as well as the season. Figure 5.1 shows the residential load profile for a day during winter as well as during summer, assuming an annual demand of 1 MWh as reference. The demand for electricity is significantly higher during the day than during the night. It has a distinct peak at about seven pm, which is especially pronounced during the winter. Two further peaks exist, one during the morning and one during the early afternoon. Overall, demand during winter exceeds summer demand by more than 40%. Furthermore, consumption during weekends is slightly higher than during the week days.

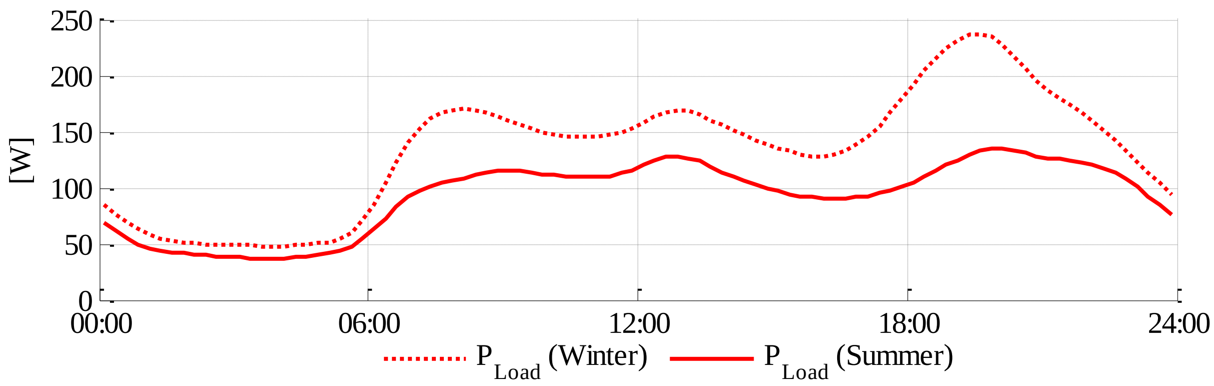

Figure 5.1: Standard load profile for residential consumers during a workday

Generation data for the photovoltaic system is based on [192], assuming an annual generation of 910 kWh per 1 kW installed capacity. The distribution of power generation from the CHP unit is according to the heat demand defined in [193]. Surplus generation from both systems can be fed into the grid and is compensated at a fixed rate. However, feed-in of generation from the photovoltaic system is assumed to be limited to 70% of the installed capacity.

Figure 5.2 shows the average generation data for both systems during a day in winter and summer for an installed capacity of 1 kW. Generation from the photovoltaic systems depends upon the available solar radiation and therefore exhibits a strong variability. Electric generation from the cogeneration unit is linked to the thermal demand and therefore also depends on the time of the year. However, over the day, generation is assumed to be constant. Contrary to the demand, there is no difference between the different days of the week.

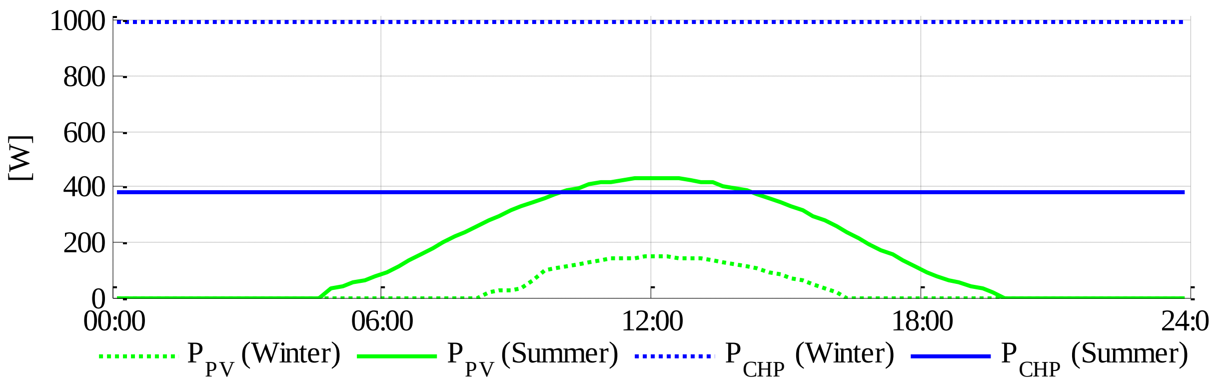

Figure 5.2: Generation profile for photovoltaic systems and cogeneration units

To simplify the analysis, the effective capacity of the storage device is assumed to equal its nominal capacity (hence, the depth of discharge $\delta_{Storage}$ is 0%). Furthermore, the assumed power rating is equal to half of the effective capacity, hence $P_{Storage}^{Capacity} = 0.5 \times E_{Storage}^{Capacity}$.

The power flow $P_{Grid}(t)$ summarizes for each interval the exchange with the electric network, both for energy taken from the grid ($P_{Grid}^{Import}(t)$) as well as for energy fed into the grid ($P_{Grid}^{Export}(t)$). Positive numbers represent a net import of energy over the period, while negative numbers represent a net feed-in. The impact of the analysed case – that is the difference to a pre-established reference – will be denoted by $\Delta P_{Grid}(t)$. A positive number consequently reflects a net demand to the grid, either due to an increased amount of energy taken from the grid or less energy exported to the grid. Vice versa, negative numbers represent a net supply to the grid, induced by either less energy taken from the network or an increased feed-in.

New PV Installation

First, the case of a new combined photovoltaic and storage installation is considered. Whereas previously the consumer has taken all energy from the grid, local demand is now preferentially satisfied from the photovoltaic system and the storage device. Hence, locally generated electricity is first used to match immediate demand. Surplus generation is stored for later self-consumption, and further excess generation is fed into the grid. If load exceeds instantaneous generation, the storage device is discharged to satisfy demand. After it is depleted, additional demand is satisfied from the grid. The resulting exchange with the grid is compared to the case in which the consumer takes all energy from the grid.

Figure 5.3 and Figure 5.4 show the energy exchange of a residential consumer with the grid, assuming an annual energy demand of 1 MWh, a photovoltaic system with 1 kW capacity and a storage system with 1 kWh effective capacity (abbreviated as 1 kW / 1 kWh in the following to facilitate reading). Hence, total annual generation of the photovoltaic system would fall slightly short of the annual electricity demand. The days are not in consecutive order, but sorted according to their daily cumulative sum. Hence, their serial order is lost and therefore the presentation of the energy shifted in time. However, the interpretation is much facilitated, as the overall trend can be easier recognised.

During the winter, as shown in Figure 5.3, demand is typically satisfied by taking energy from the grid. However, around noon, despite the high demand during that time, energy taken from the grid is close to zero on many days due to the availability of some solar generation. As shown by the uppermost ten rows, on several day generation even exceeds local consumption and – after charging the storage device – some surplus generation is fed into the grid. Nighttime demand was satisfied during about one-third of all days by discharging the storage device, resulting in no power demand from the grid.

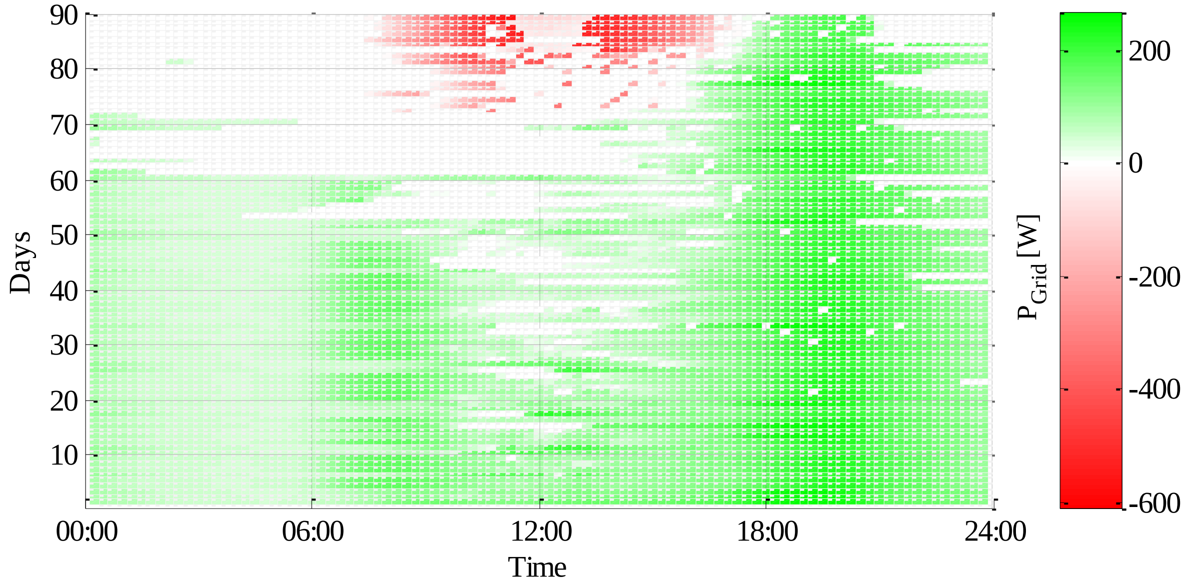

Figure 5.3: Energy exchange of a residential consumer with the grid during the winter (1 kW / 1 kWh)

Figure 5.4 shows the same analysis for the summer months. However, in this case, on most days feed-in of power clearly exceeds demand from the grid. Only during about ten days (bottom rows) demand is primarily satisfied from the grid. Contrary, on most days, there is a significant feed-in of power from the photovoltaic system during the hours with high solar radiation. Demand during the evening and night is satisfied on most days from discharging the battery, such that almost no energy is taken from the grid during hours with no local generation.

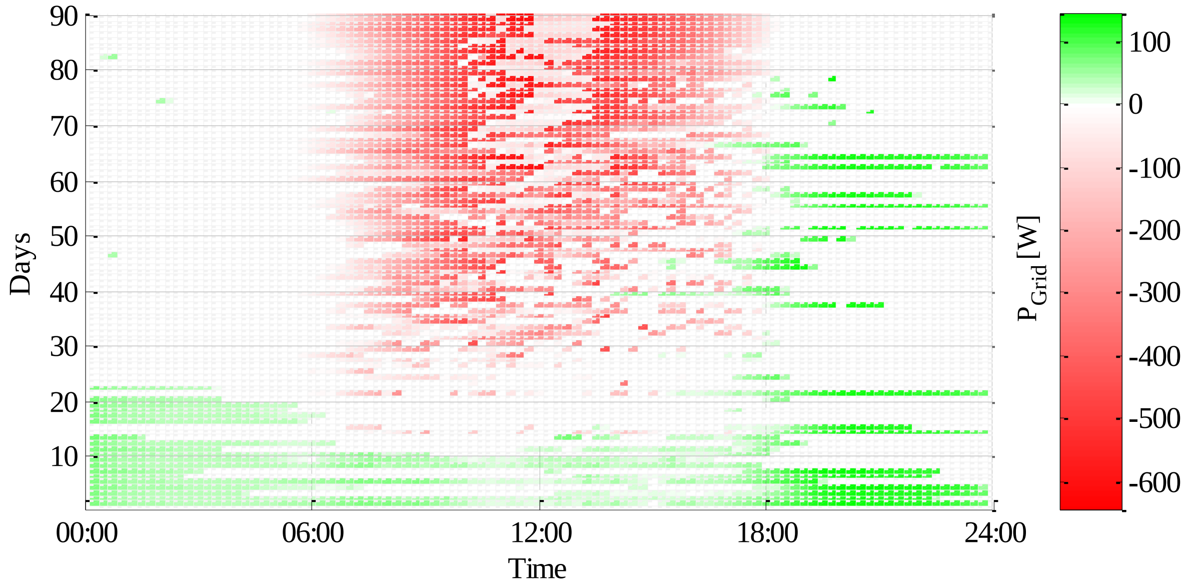

Figure 5.4: Energy exchange of a residential consumer with the grid during the summer (1 kW / 1 kWh)

Based upon the power flows with the grid, the change in demand can be determined by comparing the energy exchange with the initial situation with no photovoltaic system and no storage system present. Figure 5.5 shows the resulting average change in demand during the winter. Besides the initially assumed and previously discussed installation of the storage device with 1 kWh effective capacity, two additional configurations are considered to study the influence of different storage capacities.

For a system with a reduced storage capacity (in this case, 0.5 kWh), the impact on the grid exchange would be slightly larger around noontime, as less local generation would be used to charge the storage device and hence the feed-in of surplus energy would be higher. Consequently, as less energy would be shifted in time, the impact during the night would be reduced as comparably more energy is still taken from the grid. The impact of a larger storage device (2 kWh) is the reverse: more local generation surplus is consumed to charge the storage device and hence the impact on the grid is reduced. However, as more demand is then satisfied during the night from discharging the storage device, impact on grid demand is consequently increased when no immediate generation is available.

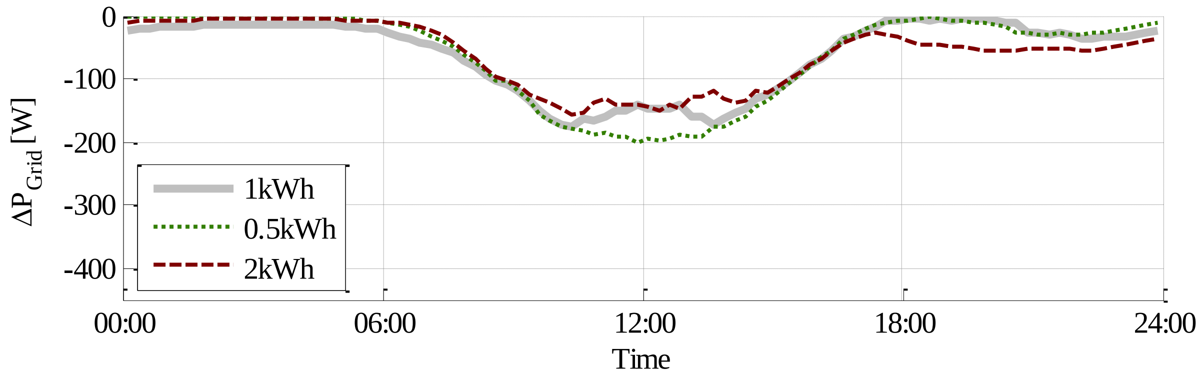

Figure 5.5: Average change in demand of residential consumers during winter (1 kW / 1kWh)

The same analysis for the summer months is shown in Figure 5.6. Due to the more intense and longer availability of solar radiation as well as the overall lower demand (see Figure 5.1), the impact on the power exchange with the grid is significantly increased in summer as compared to the winter months. Otherwise, the same conclusions from the impact during the winter apply also for the summer period.

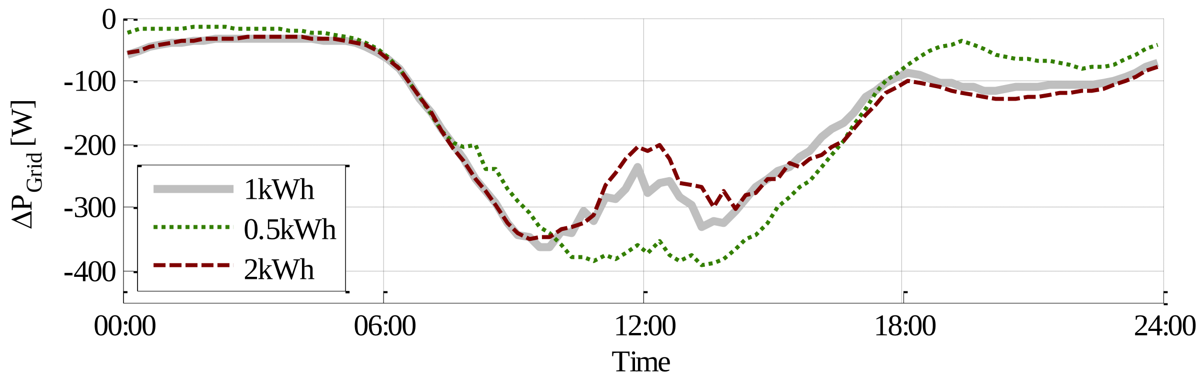

Figure 5.6: Average change in demand of residential consumers during summer (1 kW / 1kWh)

Overall, the impact from a combined photovoltaic and storage installation shows a strong seasonal component due to the availability of generation from the photovoltaic system. The impact during the night is limited to the previous demand due to the non-availability of local generation. During the day, local generation can lead to a significant feed-in of energy.

During the winter, the impact on most days is restricted to a slight demand reduction during noontime. Only on a few days, there is a significant impact when sufficient surplus generation is available such that it is being fed into the network. Contrary, during summer months, the previous consumer becomes a net-generator of energy. On most days, almost no energy is taken from the grid as demand is satisfied either immediately from the photovoltaic system or from discharging the storage device. In addition, during the daytime, significant amounts of surplus generation are being fed into the grid.

New PV & CHP Installation

Second, the installation of a cogeneration unit in addition to the photovoltaic system and the storage device is considered. Besides the electric demand of 1 MWh, the consumer is assumed to have a thermal demand of 1.5 MWh. As in the previous case, the installation of a photovoltaic system with a capacity of 1 kW is assumed. In addition, a cogeneration unit with a thermal output of 250 W and an electric output of 115 W is considered (1 kW / 115 W / 1kWh). The unit is dimensioned in such a way, that at the rated output it would operate during 6 000 hours. The expected continuous electric generation over the winter months is 115 W, and about 30 W during the summer period.

Figure 5.7 shows the resulting power flows during the winter. During most days, there is very little energy exchange with the grid. On about 20 days however (shown by the bottom rows), some residual demand is still satisfied by taking energy from the grid. This case is therefore distinctively different to the case of installing only a photovoltaic system, where energy was taken from the grid on most days during the winter. In addition, during daytime due to the simultaneous generation of the cogeneration unit and the photovoltaic system, significantly more local generation surplus exists, which increases the amount of energy fed into the grid.

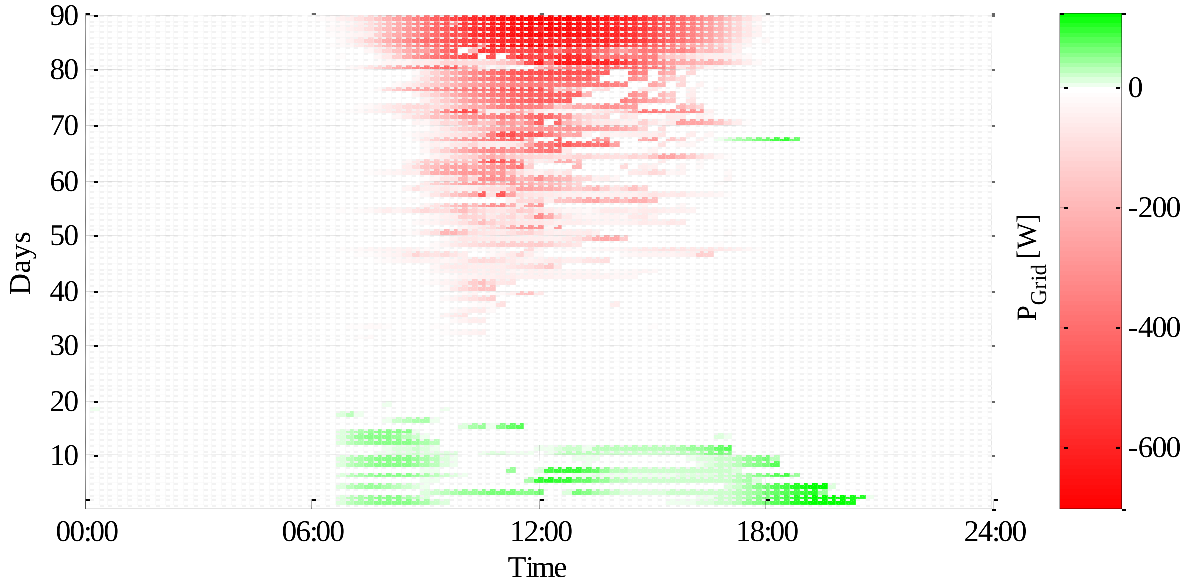

Figure 5.7: Energy exchange of a residential consumer with the grid during the winter (1 kW / 115 W / 1 kWh)

The exchange with the grid is very similar during the winter as compared to the summer, as shown by Figure 5.8. The lower generation from the cogeneration unit is slightly overcompensated by the photovoltaic yields, leading to an overall higher feed-in. There is a local generation deficit only on about 10 days. Contrary, the previous consumer becomes a net producer on more than 70 days over the three-month period.

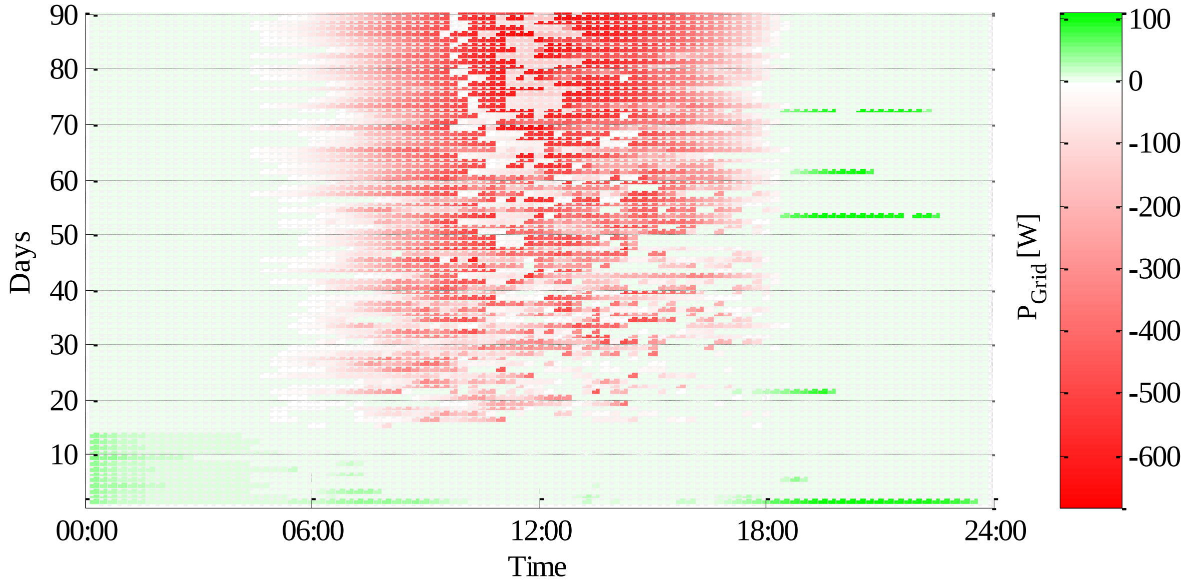

Figure 5.8: Energy exchange of a residential consumer with the grid during the summer (1 kW / 115 W / 1 kWh)

The average impact on the grid demand is shown in Figure 5.9 for the winter period. As there was very little interaction with the grid and almost all demand was satisfied locally, it is more or less the inverse of the load profile (see Figure 5.1). However, around noon time, there is typically some surplus generation from the photovoltaic system, which is fed into the grid. Due to the constant generation of the CHP unit, 1 kWh of storage capacity apparently is sufficient to time shift photovoltaic generation to cover the majority of local demand. Further increases to the storage capacity have very little impact on the exchange with the grid. Even smaller capacities (0.5 kWh) appear to be sufficient as the impact on the grid interconnectivity is almost unchanged.

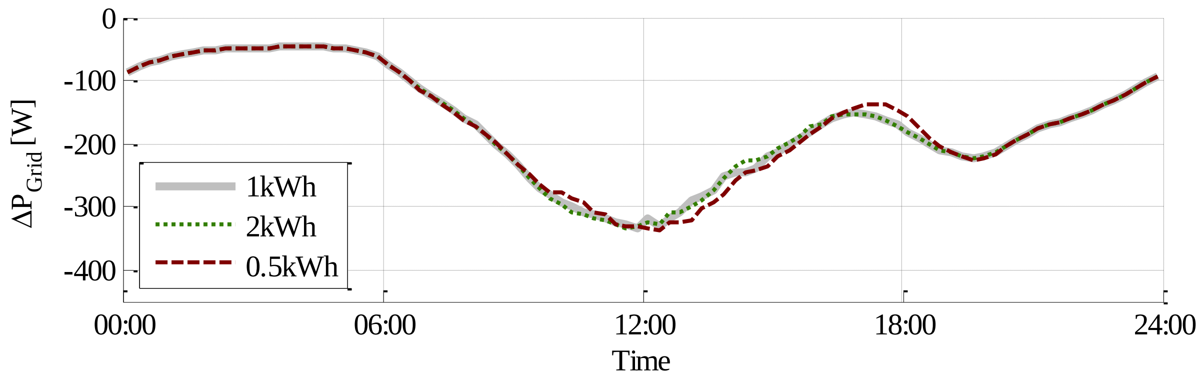

Figure 5.9: Average change in demand of residential consumers during winter (1 kW / 115 W / 1 kWh)

During summer, more surplus generation from the photovoltaic system is available, resulting in a more pronounced feed-in during the daytime. Smaller storage capacities show a slightly reduced impact on the grid connection, whereas larger storage capacities beyond 1 kWh do not lead to an increased impact.

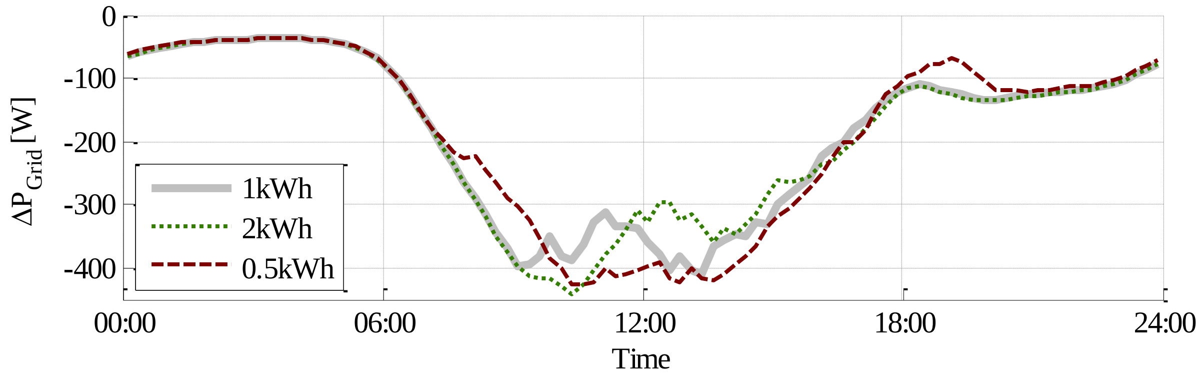

Figure 5.10: Average change in demand of residential consumers during winter (1 kW / 115 W / 1 kWh)

Overall, the impact is comparable to the installation of only a photovoltaic system with a storage device. However, in this case, due to the higher thermal demand during the winter and the consequent higher output of the cogeneration unit, the impact during the winter is also significantly increased. Furthermore, the capacity of the storage installation had less impact as compared to the previous case as most demand during the nighttime has already been satisfied from the cogeneration unit and hence less energy had to be shifted in time.

Refitting of Existing PV Installation

Last, the refitting of an existing photovoltaic installation with a storage device is considered. Therefore, an existing PV installation (1kW) is complemented with a 1kWh storage device (1kW + 1kWh) Many residential consumers have already installed a photovoltaic system, motivated by either attractive feed-in compensation for surplus generation and / or high consumption tariffs. With decreasing storage costs and installations reaching the end of the guaranteed feed-in premiums, the installation of a storage device might be economically interesting. Hence, compared to the previous two cases, the reference is now a consumer who is already using a photovoltaic system. Impact on the electricity demand seen by the grid is therefore only due to the time shifting operations of the storage device. A part of the energy, which was previously fed into the grid, is now stored and used for consumption during those times, when otherwise energy was taken from the grid.

The resulting power exchange with the grid is therefore identical to the case in which a new photovoltaic system together with a storage device is installed (see Figure 5.3 and Figure 5.4). However, due to the different reference case, the impact on the grid differs. Figure 5.11 and Figure 5.12 show the resulting change in power flows with the grid.

In the winter period (Figure 5.11), the addition of a storage device has only little impact on most days, with no or minimal changes of the power exchange with the grid. During those days where previously surplus generation was fed into the grid, the energy is now primarily stored for later self-consumption during the evening and the night. Consequently, feed-in into the grid during the daylight hours as well as demand from the grid during the nighttime are both reduced.

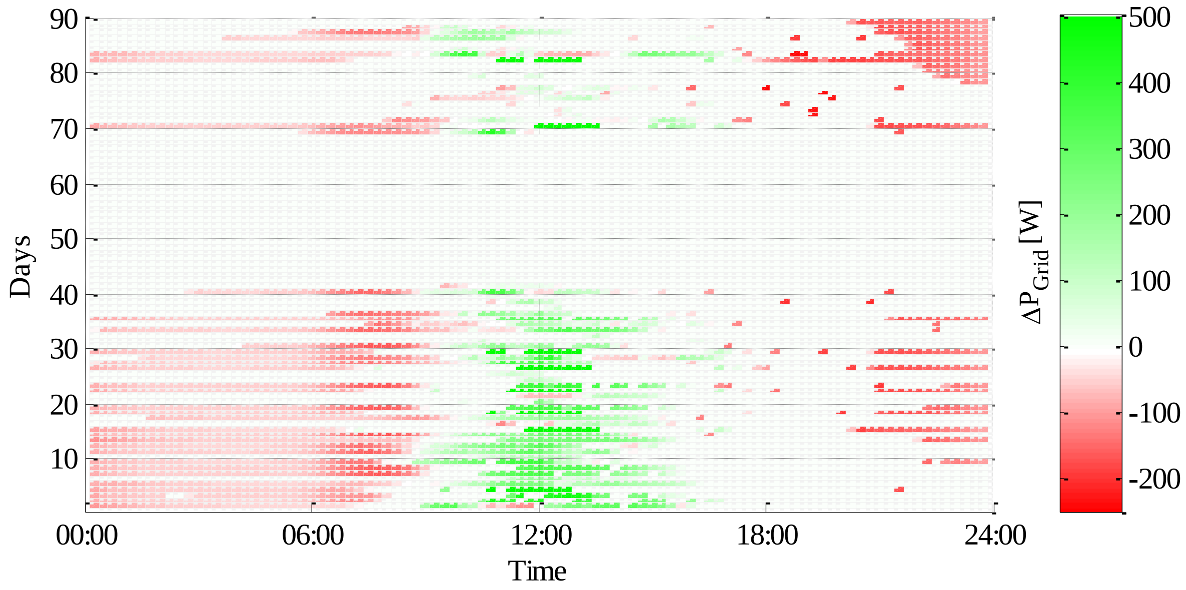

Figure 5.11: Impact on the power exchange with the grid during winter (1kW + 1kWh)

The same effect, however on almost every day and more pronounced, can be observed during the summer (Figure 5.12). The effect is facilitated by the fact that electricity demand during the summer is lower as compared to the winter and solar generation is available during more hours.

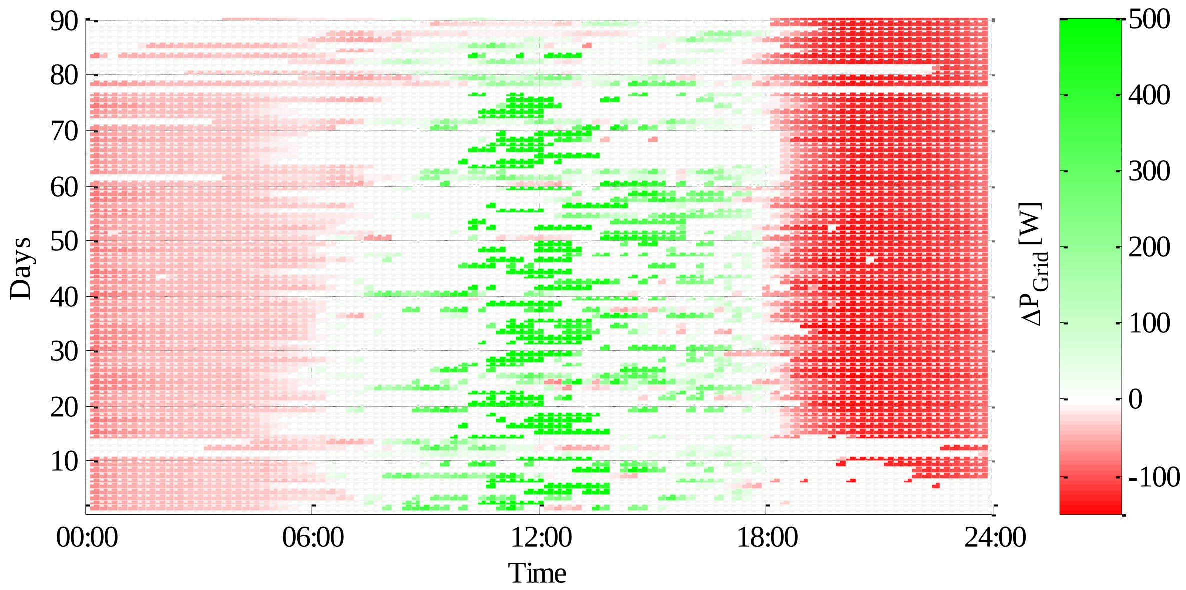

Figure 5.12: Impact on the power exchange with the grid during summer (1kW + 1kWh)

Contrary to the installation of a new combined photovoltaic and storage system addressed in the previous section, the refitting causes changes to the grid demand in both directions. The average impact on the grid demand is shown by Figure 5.13 for the winter period. During daytime, the addition of a storage device and the resulting charging operations reduce the feed-in of power. Contrary, during nighttime, demand from the grid is reduced as it is satisfied locally by discharging the storage device. As expected, with increasing storage capacity (in this case, a doubling to 2 kWh), the effect becomes more pronounced.

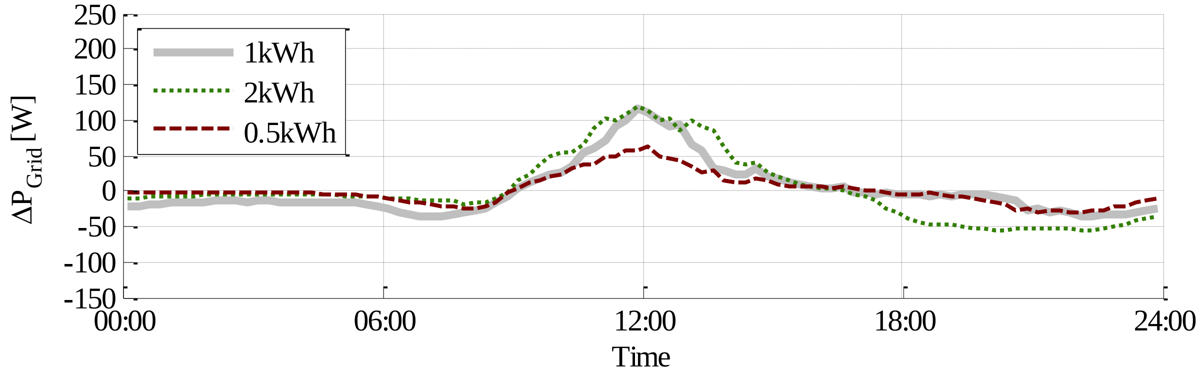

Figure 5.13: Average change in demand of residential consumers during winter (1kW + 1kWh)

The analogous analysis for the summer period is shown by Figure 5.14. Due to the overall higher solar radiation, the impact is more pronounced.

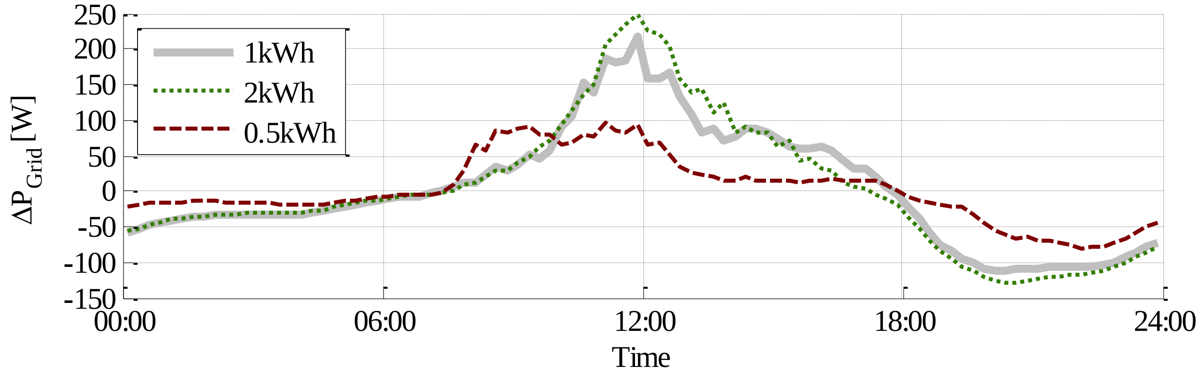

Figure 5.14: Average change in demand of residential consumers during summer (1kW + 1kWh)

Overall, the refitting of existing solar installations with a storage device does not have a large impact on the exchange with the grid during the winter time as most local generation is immediately self-consumed and little energy was previously fed into the grid, which is now time shifted for usage during the night. The effect is more pronounced during the summertime, when more surplus generation from the photovoltaic system is available. However, as compared to the case of a new installation (see Figure 5.5 and Figure 5.6), the impact remains limited. In addition, while in the previous cases the impact on grid demand was always negative, in this case the net demand seen be the grid actually increases during daytime due to the lower photovoltaic feed-in.

5.2.2 Arbitrage

In order to estimate the impact from arbitrage operations on the electricity demand seen by the grid, a hypothetic agent pursuing arbitrage will be simulated and analyzed. The storage device is operated according to the MIP presented in Section 3.4.2. The dispatch is driven by market price signals, hence storage acts as demand if prices are relatively low and as generation once prices are relatively high.

Due to the inefficiencies of all storage technologies (see Section 2.1 in the literature review), storage operations are associated with energy losses. Hence, overall it can be expected that the net demand for electricity increases. To analyze the impact of arbitrage on grid demand, the operations of the storage device will be related to the total load seen be the electric network.

To determine the optimal dispatch, historic prices of 1-hour contracts for the German grid zone over the year 2014 [189] have been considered. Total load is based on [194]. Two storage systems will be considered. The first system has a low power to energy ratio (0.25 kW with 1 kWh effective capacity), the second system has a high power to energy ratio (1 kW with 1 kWh effective capacity). Minimum profit hurdle for the dispatch algorithm was assumed to be 10 EUR.

Figure 5.15 shows the charge- and discharge power flows depending on the total load of the network. Accordingly, most charging operations occur at times with a relatively low overall load level. Contrary, the storage device is more frequently discharged during periods with high overall load. Hence, storage acts typically as generation when overall demand is high and as load when overall demand is low. Even though the overall volume transferred is higher in the case of the storage device with a high power rating, the distribution of charging and discharging operations in relation to the total load is almost identical for both power capacities.

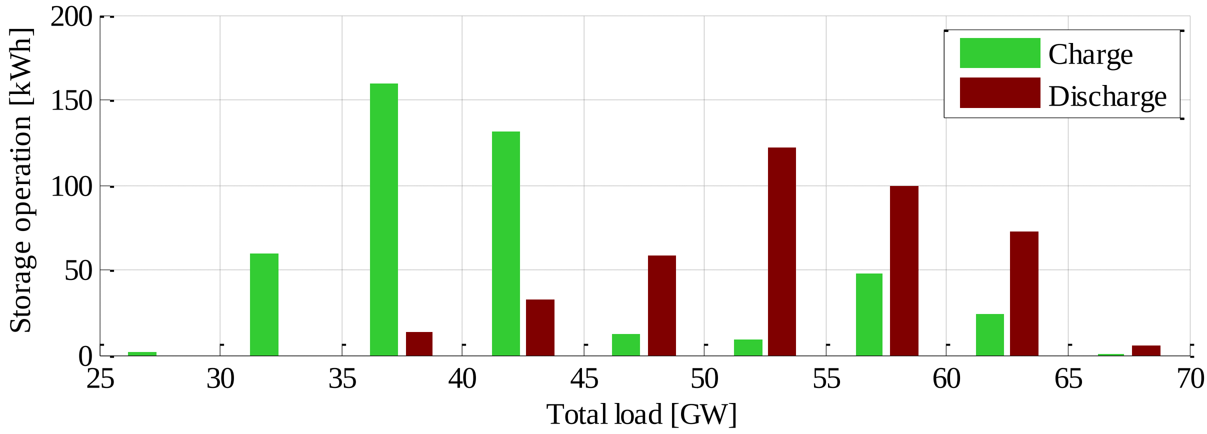

Figure 5.15: Relation of storage operations and total electric load

The temporal distribution of storage operations is shown by Figure 5.16 for the storage system with a low power rating. Most frequently, storage dispatched for arbitrage would be charged from midnight to the early morning hours and hence would increase the demand seen by the grid during those times. In addition, some charging typically also occurs during the early afternoon. Discharging operations, which would be seen as generation by the grid, typically occur during the morning as well as evening hours.

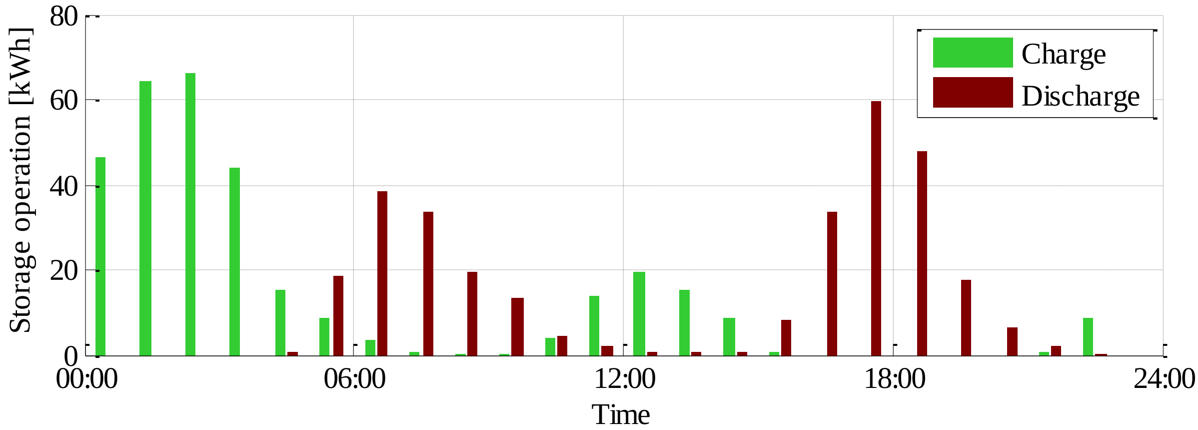

Figure 5.16: Temporal occurrence of storage operations (low power system)

The same analysis is shown by Figure 5.17 for the storage system with a higher power rating. While the overall pattern is unchanged, the total volume of shifted energy is higher. Furthermore, charging and discharging operations occur more concentrated during shorter time periods. Accordingly, most charging operations occur from 01:00 until 03:00 and increase the demand seen by the grid. The majority of energy provided back to the grid by discharging the storage device occurs from 07:00 to 08:00 in the morning as well as from 17:00 to 19:00 in the evening.

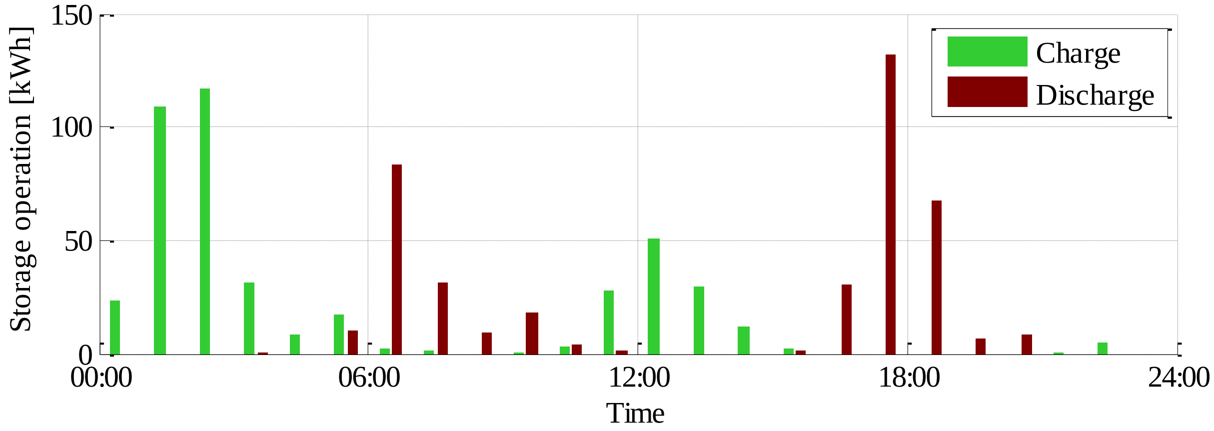

Figure 5.17: Temporal occurrence of storage operations (high power system)

Overall, storage systems dispatched for arbitrage purposes therefore have a stabilizing effect on the total load seen by the grid. Most charging operations, which increase the demand for electricity seen by the grid, occur during times with a low load level. Contrary, most discharging operations which provide energy back to the grid, occur during times with an elevated load level.

Furthermore, the charging- and discharging operations also show a clear temporal pattern. As a consequence from arbitrage operations, load seen by the grid would typically increase from midnight till the early morning hours and around noon. Contrary, energy would be provided from storage and decrease net-load during the morning and evening hours.

5.3 Impact on Electricity Prices

The analysis so far assumed that all agents act as price-takers and hence have no impact on market prices. However, given the results from the previous section, the presence of storage clearly influences the supply and demand balance of the electricity market. Hence, it is unlikely that prices remain stable given a wide-scale rollout of storage. In this section therefore, it will be analyzed how the dispatch of storage influences market prices.

In a first step, the sensitivity of market prices to changes in electricity demand and supply is established. Following, the impact from the storage applications for time shifting and arbitrage on market prices will be analyzed, building on the results from Sections 5.2.1 and 5.2.2.

5.3.1 Market Resilience

Market resilience refers to the change in market prices caused by an in- or decrease in either supply or demand. It therefore reflects the price sensitivity with regards to the quantity. In order to determine the market resilience, two methods will be discussed:

- First, a top-down approach. By means of a regression analysis the relation between market prices and overall load will be determined.
- Second, a bottom-up approach. An analysis of the order book allows resembling the price-finding process of the market auction, taking additional bids or offers into account.

While the second approach provides more detailed insights, the required data is not always available. Furthermore, the first approach provides a more intuitive and general interpretation.

Price-Load Relationship

The first approach assumes a linear relationship between demand and market prices, that is electricity prices respond in a predictable fashion to changes in load due to the merit order of generating capacity in the considered market.

To determine the relationship and its coefficients, a linear regression was conducted using least-squares to fit a model to historic data from the year 2014 [189]. The prediction variable for the regression analysis is the electricity demand $P_{Load}(t)$, the response variable is the market prices $R(t)$. The obtained model with the best fit is given by equation (5.1)[2].

$$R(t) \approx -17.66 + 0.00096 \times P_{Load}(t) \tag{5.1}$$

Hence, for every MWh increase in load, the model predicts the market price to rise by 0.00096 EUR. Figure 5.18 shows the historical data as well as the estimated linear relationship.

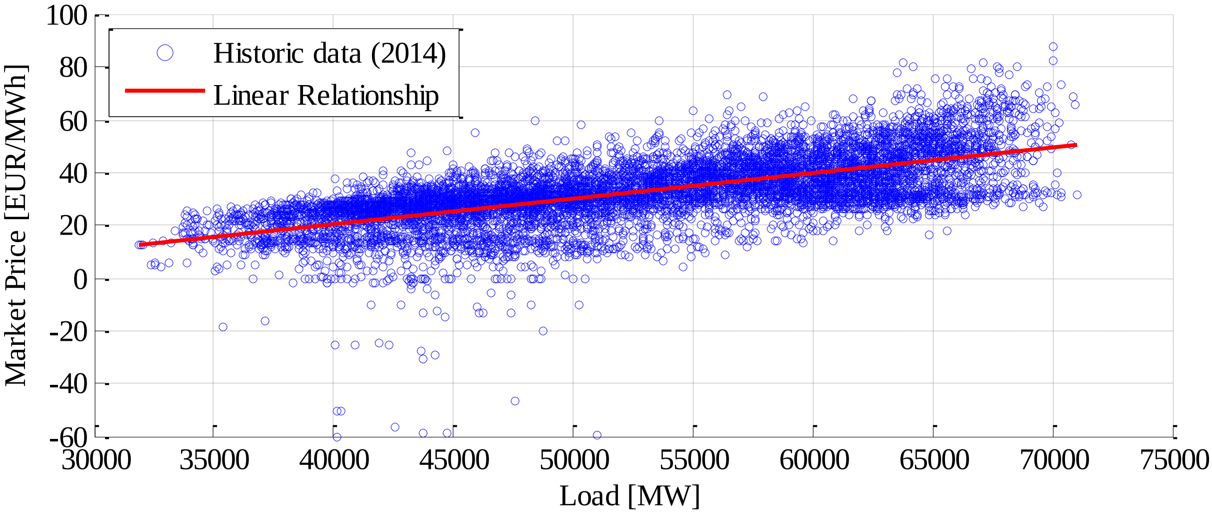

Figure 5.18: Linear regression considering load

While the model is able to predict the relation at a statistical significant level, the coefficient of determination (R^2) is only 0.428. This figure indicates how much of the variability of the market price $R(t)$ can be explained by the linear regression model. The higher R^2 is, the better the variability is explained by the model, with $R^2 = 1$ implying a perfect prediction.

The distribution of residuals, that is the difference of the actual outcome versus the predicted outcome, is shown by Figure 5.19. The standard deviation of the residuals is 9.66. As compared to a normal distribution, the data shows significantly larger tails as well as is skewed. Hence, one of the underlying fundamental assumptions of linear regression models – a normal distribution of errors – clearly does not hold.

[2] As power is traded in MWh and to facilitate reading, all references in this section are to MWh and not to Wh

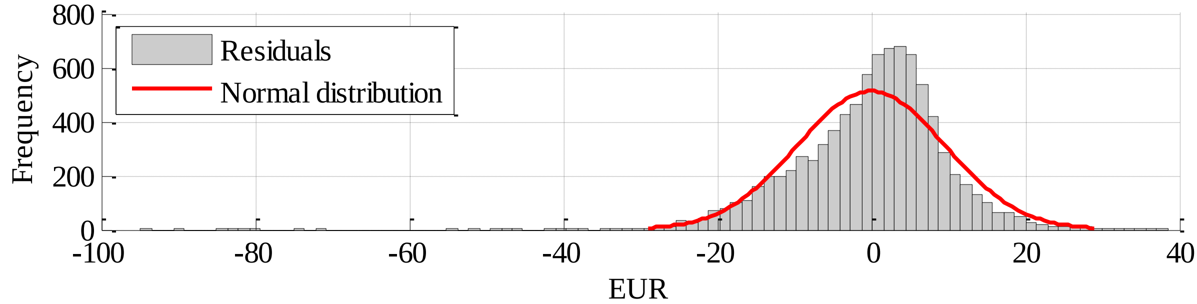

Figure 5.19: Distribution of residuals from the linear regression considering the load

The predictive quality of the model can be improved by considering the contribution of photovoltaic and wind generation, which have no marginal cost and typically bid at zero in the market. Hence, assuming an unchanged demand, during times with high generation from one of the two resources prices can be expected to decline.

Furthermore, after an initial estimate of coefficients, 388 data points were identified as outliers and removed from the dataset. Therefore, the individual influence of each data point on the outcome of the regression was determined using Cook's distance [195], excluding all data points with a value above three times the mean value.

The obtained model from the linear regression is shown by equation (5.2), displaying a significantly better fit to the underlying historic data ($R^2 = 0.804$).

$$R(t) \approx -19.21 + 0.00118 \times P_{Load}(t) - 0.00084 \times P_{PV}(t) - 0.00117 \times P_{Wind}(t) \qquad \textbf{(5.2)}$$

As expected, generation from photovoltaic and wind reduces the expected market price. The predicted reduction in market prices from wind generation ($-0.00117 \times P_{Wind}(t)$) offsets the price increasing effect of demand ($+0.00118 \times P_{Load}(t)$). The predicted impact of solar generation ($-0.00084 \times P_{PV}(t)$) is slightly less pronounced.

Figure 5.20 shows the predicted market price from equation (5.2) against the residual load, that is the load after considering the contribution from wind and solar. The improved relation versus the initial model (shown by Figure 5.18) is obvious.

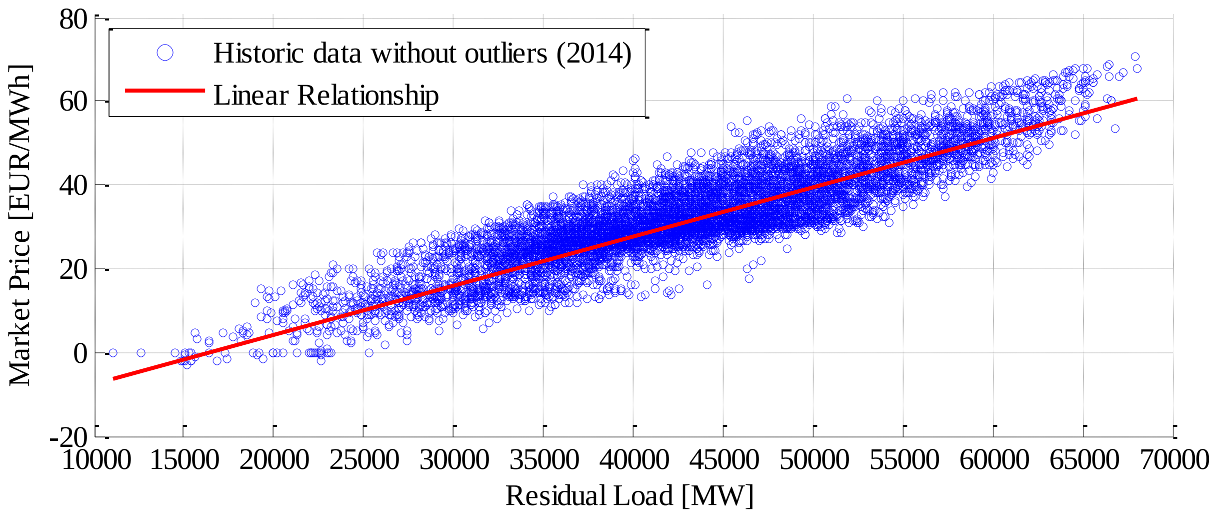

Figure 5.20: Linear regression considering residual load

The distribution of the unexplained residuals is shown by Figure 5.21 and closely resembles a normal distribution. The standard deviation of residuals is reduced from 9.66 to 5.12.

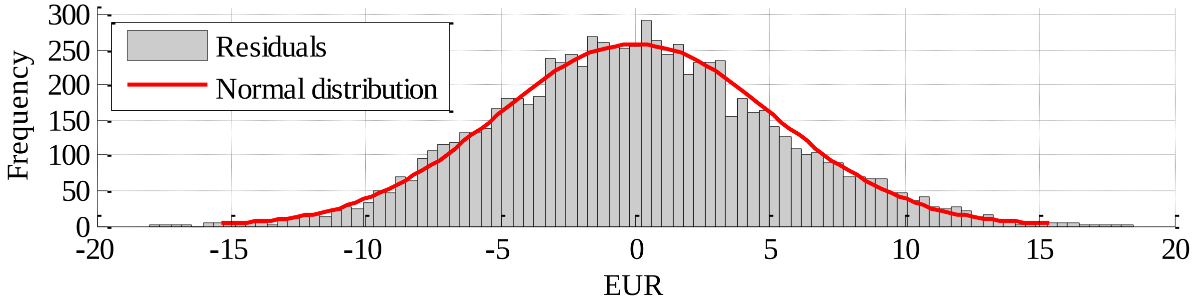

Figure 5.21: Distribution of residuals from the linear regression considering the residual load

Last, in Figure 5.22, the residuals from both approaches are compared to each other as well as to their normal distributions. It is obvious, that the residuals from the second approach follow a normal distribution much closer. Furthermore, as all outliers have been removed from the data for the second case, no extreme deviations can be identified in the tails.

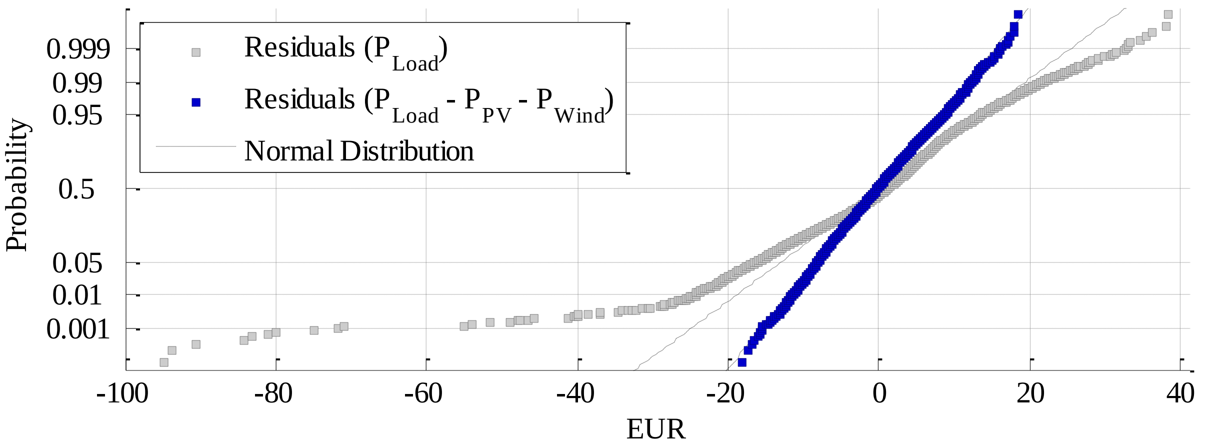

Figure 5.22: Comparison of residuals from the two models versus their normal distributions

The accuracy of the regression model can be further improved, for example by determining the linear relationship on a monthly basis. However, as the intention is not to predict the absolute value of market prices but only to identify the impact of a change in load, the accuracy of the model is assumed to be sufficient.

While the approach is easy to implement and does not require data beyond historic prices and demand, it suffers from several disadvantages: first, the sensitivity is assumed to be constant, that is independent of the considered hour or the load level. Second, a change in sensitivity is reflected only slowly over time, once sufficient new data points are considered in the regression analysis. Last, the increasing cross-country flow of energy caused by market coupling further distorts the relation.

Aggregated Bid and Offer Curves

The second approach considers the order book, which contains the bids from consumers as well as the offers from generators for electricity. All submitted orders are aggregated to build a supply and a demand curve, reflecting the relationship between price level and quantity of energy. Hence, the curves show the willingness of both agents to generate / consume electricity at a certain price level. The price-quantity relation, at which supply and demand are in equilibrium, represented by the intersection of the two curves, is the market clearing price.

Figure 5.23 shows the supply and demand curves for a particular hour. The supply curve is upward sloping, indicating the increasing willingness of generators to produce more the higher the price is. Conversely, the demand curve is downward sloping, reflecting the decreasing demand if electricity becomes more expensive. In this example, the market would clear at 29.96 EUR/MWh with a total demanded / supplied amount of 32 331 MWh.

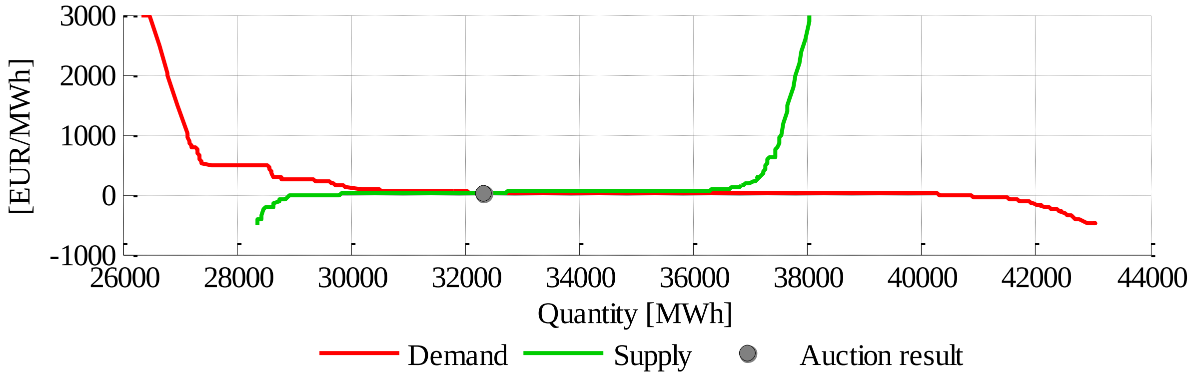

Figure 5.23: Aggregated supply and demand curve

A reduction in demand shifts the demand curve to the left, leading to a lower market price. Conversely, an increase in demand shifts the demand curve to the right, resulting in a higher price. The same argumentation applies for the supply curve. An increase in generation shifts the curve to the right and hence results in a lower market price, whereas a decrease shifts the supply curve to the left and leads to higher market prices.

Exemplary, Figure 5.24 shows the impact of a reduction in grid demand on the market price, based on the initial supply and demand curves shown in the previous figure. In addition, the demand curve with the reduced demand (-500 MWh) is shown, shifted to the left by the magnitude of the demand change. The new intersection with the supply curve is both at a lower amount as well as at a lower price.

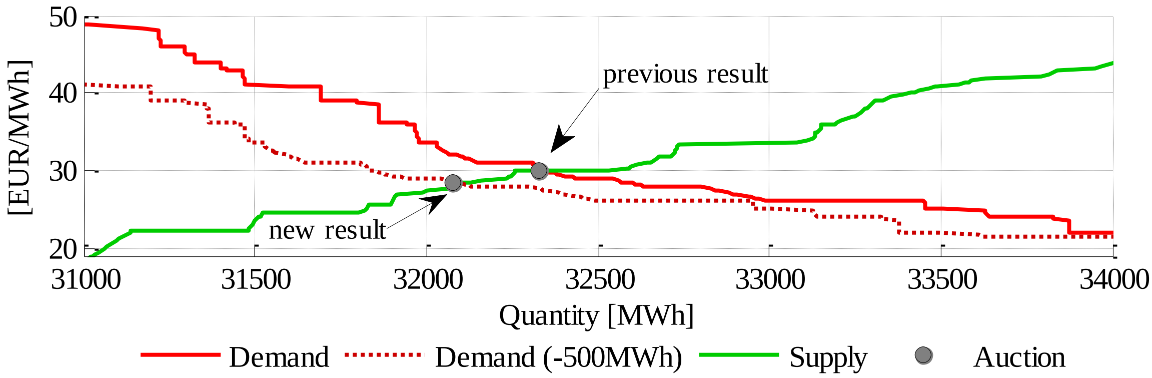

Figure 5.24: Impact of a demand change on the auction result

The impact of a storage device on market prices can now be determined by shifting the respective bidding curve by the induced impact from the stage system and determine the resulting change in market price.

In the following the sensitivity of the market price towards changes of ± 10 / 50 / 100 MWh will be analyzed. Figure 5.25 shows the average impact of a change in demand on the market price along a winter day. The impact is clearly less pronounced during the nighttime as compared to the daytime, but otherwise rather constant. Furthermore, the impact across the shown demand changes is relatively linear.

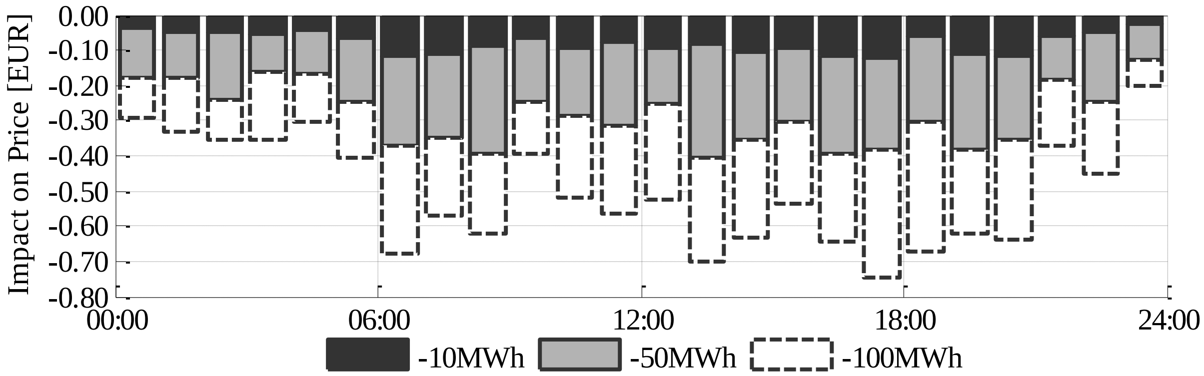

Figure 5.25: Average, cumulative impact of demand reductions on market prices in winter

The same analysis is shown by Figure 5.26 for a typical day in summer. The impact of a demand reduction is overall less pronounced and almost no differences between day- and nighttime exist.

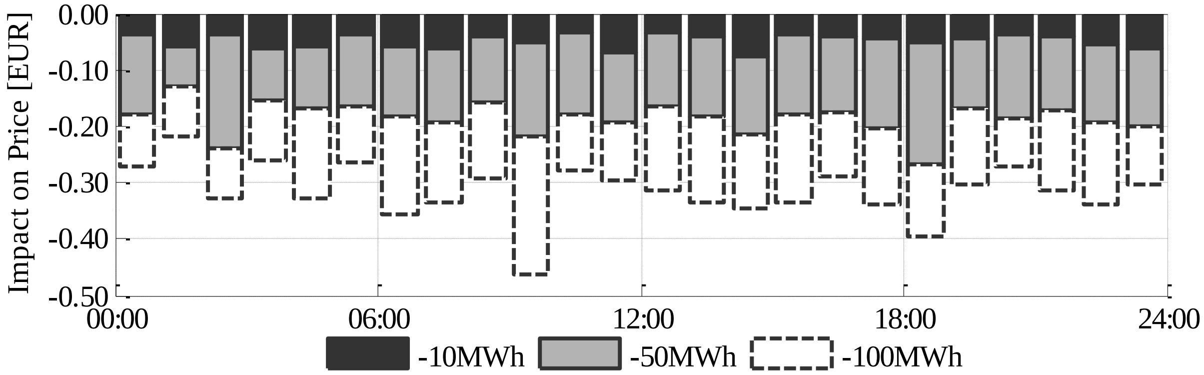

Figure 5.26: Average, cumulative impact of demand reductions on market prices in summer

The impact from demand and supply changes on the market price varies over time. Figure 5.27 summarizes the impact over a year. Typically, bid and offer curves have a smooth slope at the intersection and hence price changes are marginal. However, at times more extreme reactions occur.

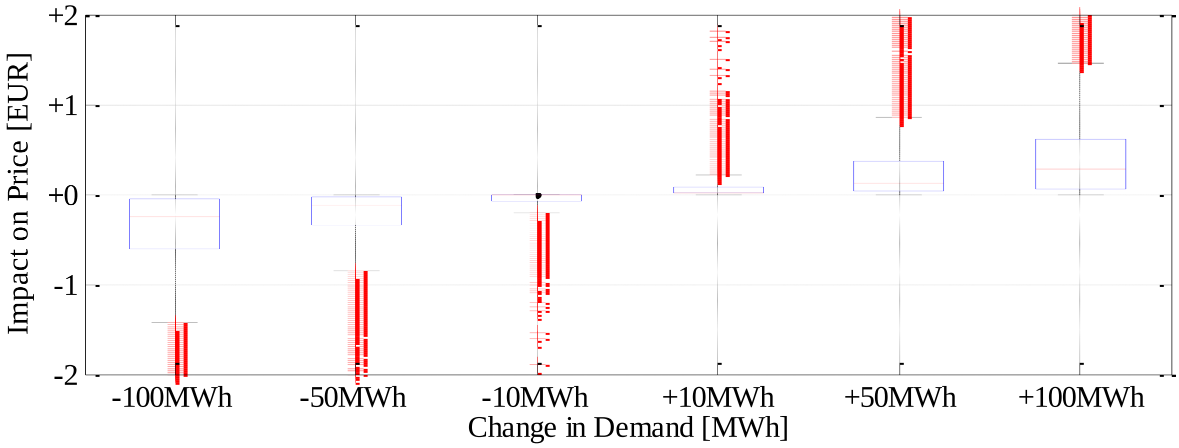

Figure 5.27: Impact of demand and supply changes on market prices[3]

[3] In this document, datasets are several times shown by a boxplot, which allow to easily compare distributions. The top / bottom of each box represents the 25th / 75th percentile of the distribution, the line in the middle highlights the median. The vertical line above / below the box extends to the data points which are not yet considered outliers (within 1.5 times the interquartile range). Data points beyond this range are marked with '+'.

Last, Figure 5.28 shows the relation between the impact from a demand shift by +10 MWh and +50 MWh. While the relationship is not clearly defined ($R^2 = 0.48$), a linear regression model predicts that the market price rises only 1.7 times if the demand increases fivefold.

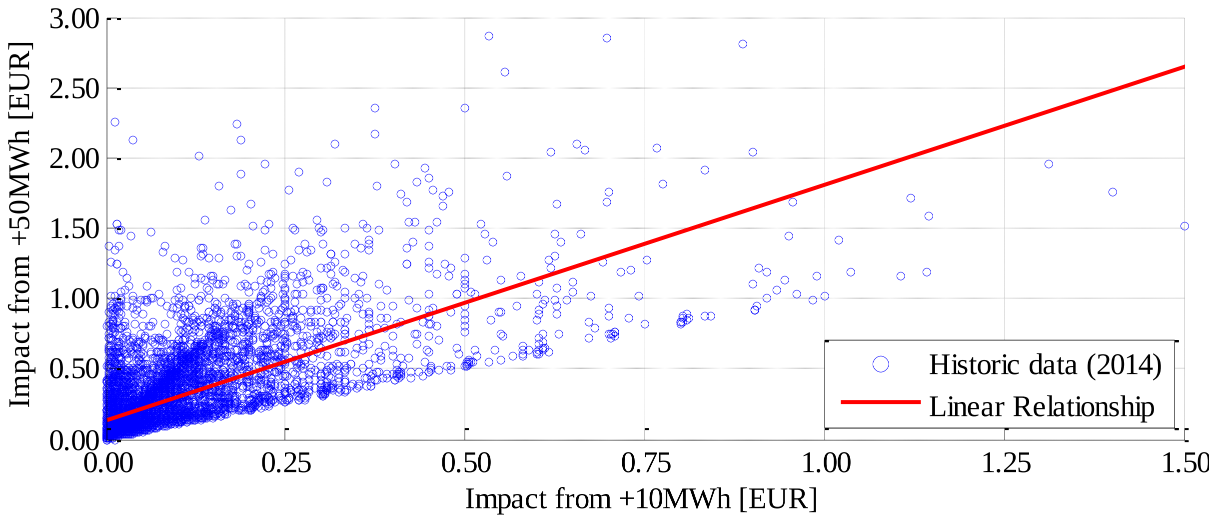

Figure 5.28: Relation between price sensitivities

No relation between the price sensitivity and the overall demand or the price level could be identified.

In reality, further deviations beyond the analysed shift in supply and demand curves might occur and influence prices, driven by two effects [196] as follows: first, the interaction between coupled markets is not taken into account. Second, price-dependent block orders or other complex order types, are not properly considered. The effect of these could only be incorporated by rerunning the dispatch algorithm of the market operator, requiring detailed knowledge about the order book.

5.3.2 Time Shifting

Based upon the analysis in Section 5.2.1, which determined the changes in the power exchange with the grid from time shifting operations, this section will estimate the resulting price changes. Therefore, the changes in the power demand or supply are considered in the aggregated bid and offer curves in order to determine the resulting market prices. These are then compared to the initial time series.

New PV Installation

The installation of new photovoltaic systems combined with storage devices for time shifting locally generated energy decreases the overall price level slightly (Table 5.1), both due to the feed-in of excess local generation as well as the lower demand for grid energy. The volatility of market prices, measured by their standard deviation, as well as the range of market prices, indicated by their 1%- and 99%- quantile, remain more or less unchanged.

		Installed storage capacity		
	Reference	**100 MWh**	**500 MWh**	**1 000 MWh**
Mean	32.76	32.72	32.58	32.43
Standard deviation	12.78	12.77	12.76	12.76
99% quantile	65.05	65.04	64.96	64.95
1% quantile	0.11	0.11	0.10	0.08

Table 5.1: Impact of new PV and storage installations for time shifting on market prices

Figure 5.29 shows the distribution of market price changes along the day. During the night, only slight price reductions can be observed. Previous demand is frequently satisfied locally from discharging the storage device, resulting in lower market demand and hence lower prices. During the day, more extreme price reductions can be observed. Not only is the demand reduced and hence the associated bidding curve shifted to the left, but also local excess generation is fed into the grid, resulting in a simultaneous right-shift of the supply curve. While the effect is limited on most days, on some days extreme price reductions can be expected. During the evening, the effect is again less pronounced. Previous demand is now locally covered by discharging the battery. Compared to the night, the observed price reductions are slightly higher due to the higher intensity of the reduced demand.

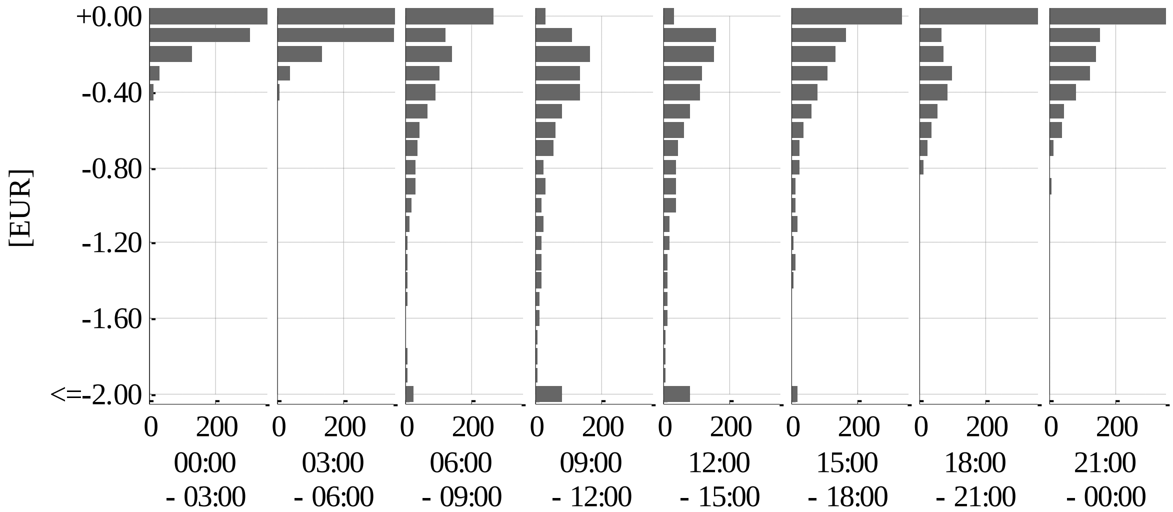

Figure 5.29: Change of market prices along the day

New PV & CHP Installation

Installing a CHP unit in addition to the photovoltaic system and the storage device further decreases market prices (Table 5.2), almost doubling the previously observed impact. While the standard deviation as well as the distribution of low prices (1% quantile) remain more or less unchanged, there is a more pronounced reduction of high market prices (99% quantile), which can be traced back to the presence of the cogeneration unit.

		Installed storage capacity		
	Reference	**100 MWh**	**500 MWh**	**1 000 MWh**
Mean	32.76	32.68	32.45	32.18
Standard deviation	12.78	12.76	12.70	12.66
99% quantile	65.05	65.03	64.56	63.92
1% quantile	0.11	0.11	0.10	0.06

Table 5.2: Impact of new PV, CHP and storage installations for time shifting on market prices

The chronological breakdown of the distribution of price changes (Figure 5.30) is similar to the case of installing only a photovoltaic system and a storage device. However, overall the impact is more pronounced, with fewer occurrences of no or very little impact. This is especially noticeable during the evening and night hours, where previously most often no impact on market prices was observed. Considering a cogeneration unit in addition, now during most hours a small reduction in market prices can be identified.

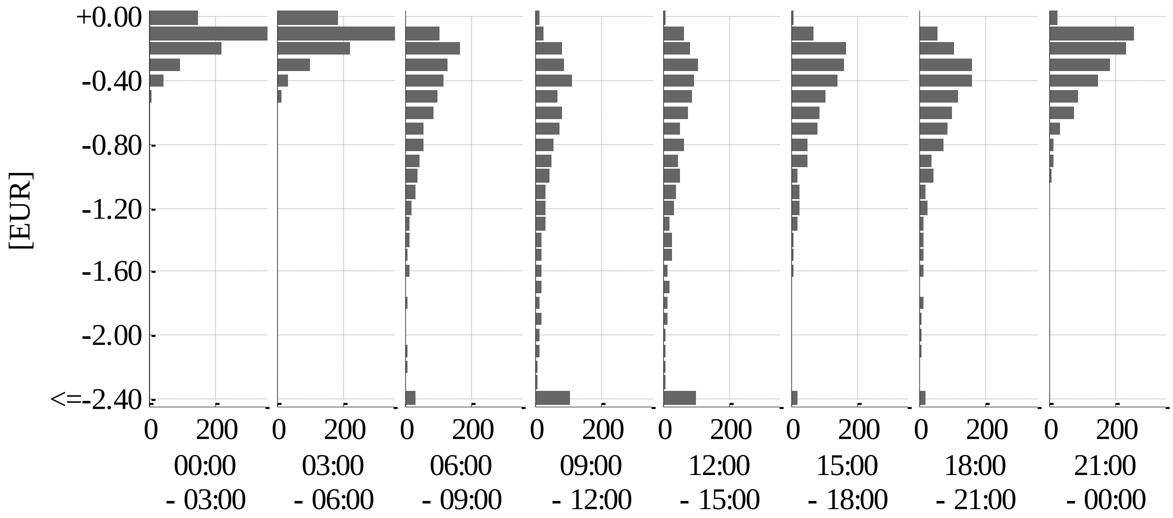

Figure 5.30: Change of market prices along the day

Refitting of Existing PV Installation

The analysis of the consequences from refitting an existing photovoltaic installation with a storage system has shown (Section 5.2.1) that demand seen by the grid will at times increase. Consequently, also the impact on market prices will be two-sided. This is contrary to the previously considered cases of installing a photovoltaic system (and a cogeneration system) in combination with a storage system, which always have a negative impact on prices.

Table 5.3 shows the resulting statistics of the market prices. Accordingly, refitting an existing PV installation with a storage device has a slightly positive impact on market prices. Overall, however, the impact is limited, leading to only marginal changes of the price series.

		Installed storage capacity		
	Reference	**100 MWh**	**500 MWh**	**1 000 MWh**
Mean	32.76	32.77	32.77	32.79
Standard deviation	12.78	12.78	12.78	12.79
99% quantile	65.05	65.10	65.10	65.24
1% quantile	0.11	0.11	0.11	0.11

Table 5.3: Impact of refitting existing PV installations with storage on market prices

The impact on market prices is chronologically summarized by Figure 5.31. During the hours with high solar radiation (late morning and early afternoon), the market price will at time increase. Energy, which was previously fed into the grid, is now locally used to charge the storage device. Hence, less power is supplied to the market, shifting the supply curve to the left and hence increasing the market price. While most often prices will remain unchanged, at times there is a significant impact. During the evening and the night, the impact on market prices is typically negative, as previously energy had to be taken from the grid which is now supplied by the storage device.

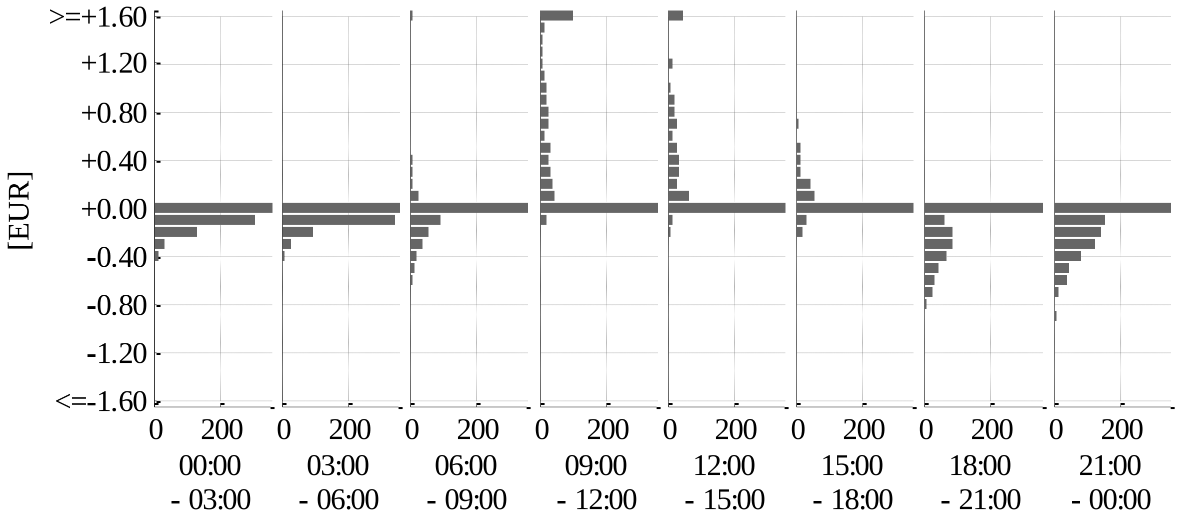

Figure 5.31: Change of market prices along the day

5.3.3 Arbitrage

In order to determine the impact from arbitrage operations on market prices, the dispatch algorithm presented in Section 3.4.2 was applied to the historical prices, as described in 5.3.1. Following, the impact on supply and demand for multiple installed capacity levels was established. Based on the shifted supply and demand curves, an analysis of the resulting change in market prices was conducted.

Figure 5.32 shows the impact of arbitrage operations on market prices exemplary over several days. The storage dispatch operations are marked by a triangle. As previously demonstrated, these operations result in an increase in demand during times with low market prices, resulting in a price increase, shown both for a dispatched storage capacity of 500 MWh and 1 000 MWh. Contrary, supply is increased when relatively high prices prevail, resulting in a decline of market prices. As expected, the higher the dispatched capacity, the higher the impact.

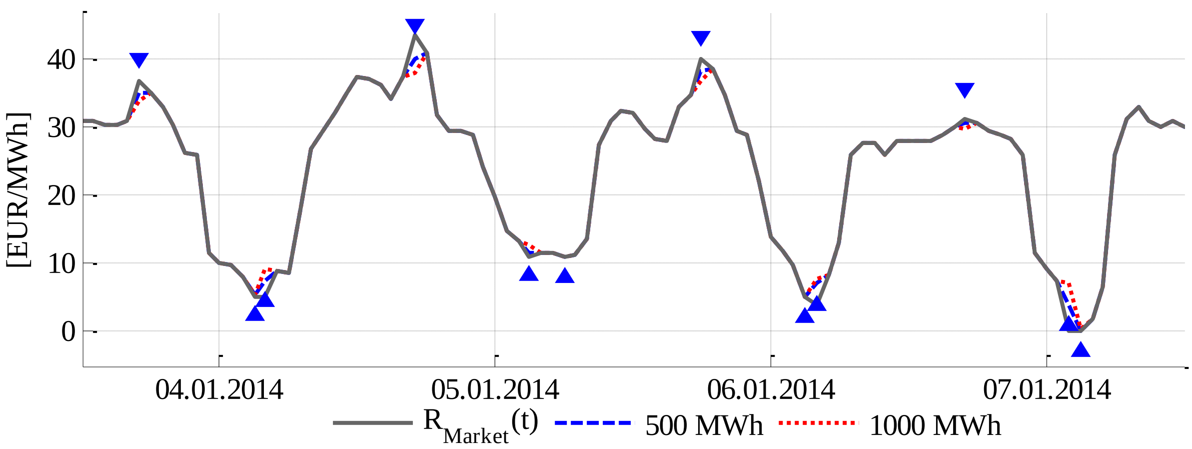

Figure 5.32: Impact of storage dispatched for arbitrage on market prices

Table 5.4 summarizes the statistical attributes of the original time series as well as of the price series under the impact of the arbitrage dispatch. As expected, the volatility measured by the standard deviation decreases the more storage capacity pursues arbitrage operations. Likewise, the price range as indicated by the 99% and 1% quantiles, is also reduced. Hence, less extreme prices both on the up- as well as on the down-side occur. Furthermore, overall, the price level also slightly decreases the more storage capacity is dispatched for arbitrage.

		Installed storage capacity		
	Reference	**100 MWh**	**500 MWh**	**1 000 MWh**
Mean	32.76	32.76	32.72	32.69
Standard deviation	12.78	12.70	12.47	12.24
99% quantile	65.05	64.91	63.96	62.98
1% quantile	0.11	0.13	1.82	2.30

Table 5.4: Impact of arbitrage operations on market prices depending on the aggregated capacity

Figure 5.33 shows the relation between the initial market price as well as the market price under the impact of storage devices with an aggregated capacity of 1 000 MWh dispatched for arbitrage. Accordingly, most prices remain unchanged. However, market prices above 65 EUR / MWh will typically be reduced. On the other hand, low prices below 0 EUR / MWh generally slightly increase, even though the relation is not as clearly visible as for high prices.

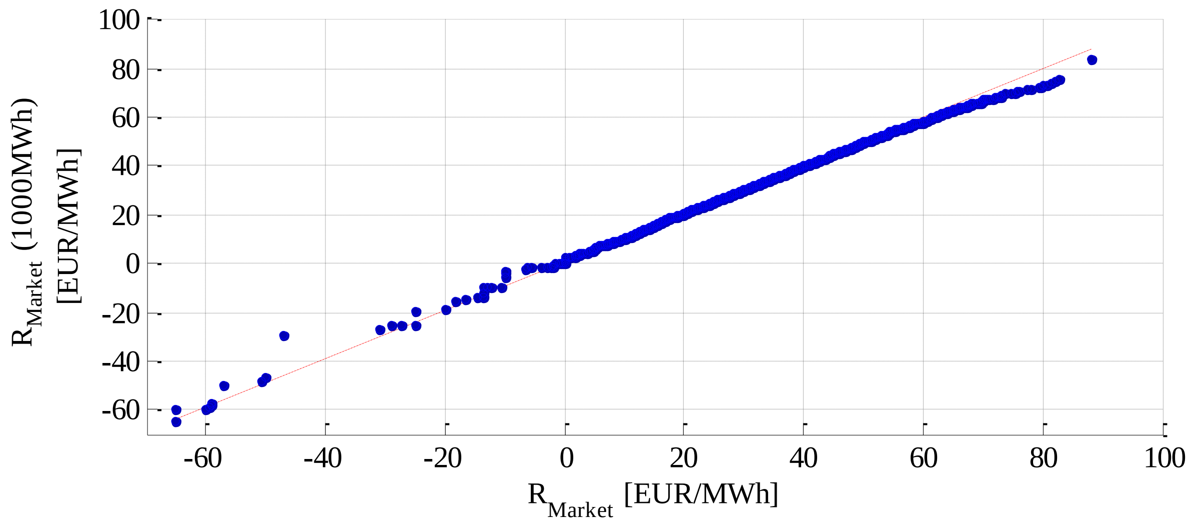

Figure 5.33: Change of market prices

The chronological relationship of the price changes is shown by Figure 5.34. The most significant price increases from arbitrage operations can be expected during the early afternoon. In addition, prices during the night, when the storage device is typically charged, can also be expected to rise, despite at more modest levels. Contrary, the supply of energy from storage frequently leads to price reductions both in the evening hours as well as in the early morning. Overall, price decreases are more pronounced than price increases.

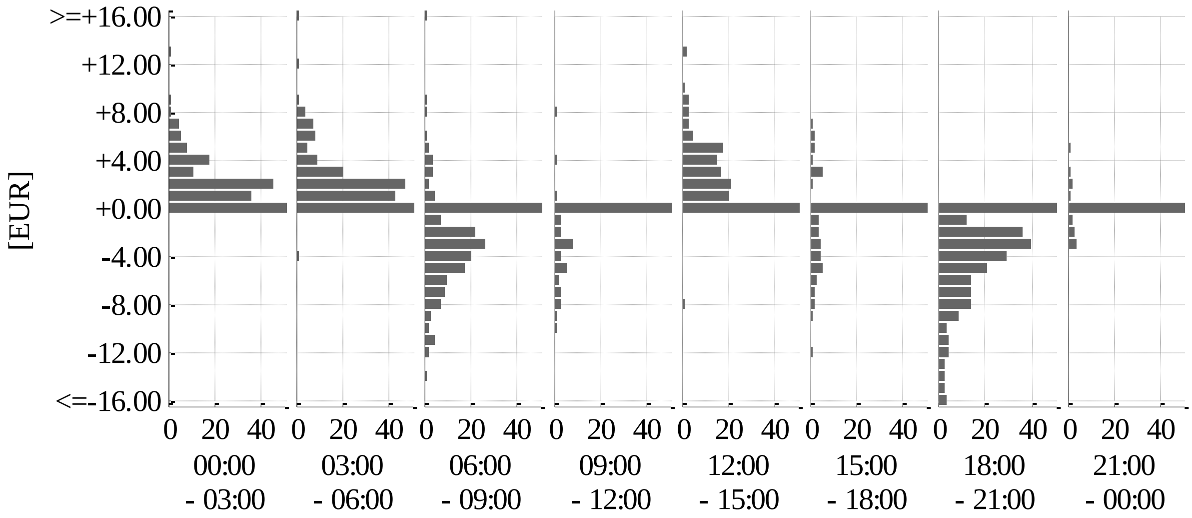

Figure 5.34: Change of market price along the day

Last, Figure 5.35 shows the relation between market prices and price sensitivity. As previously mentioned, no relationship exists. In addition, the figure also highlights the data points where charge / discharged operations from a storage device pursuing arbitrage under an optimal dispatch would have occurred. While the dispatch algorithm operates the storage device at the local minimum / maximum price, apparently these do not have a higher sensitivity towards demand or supply changes.

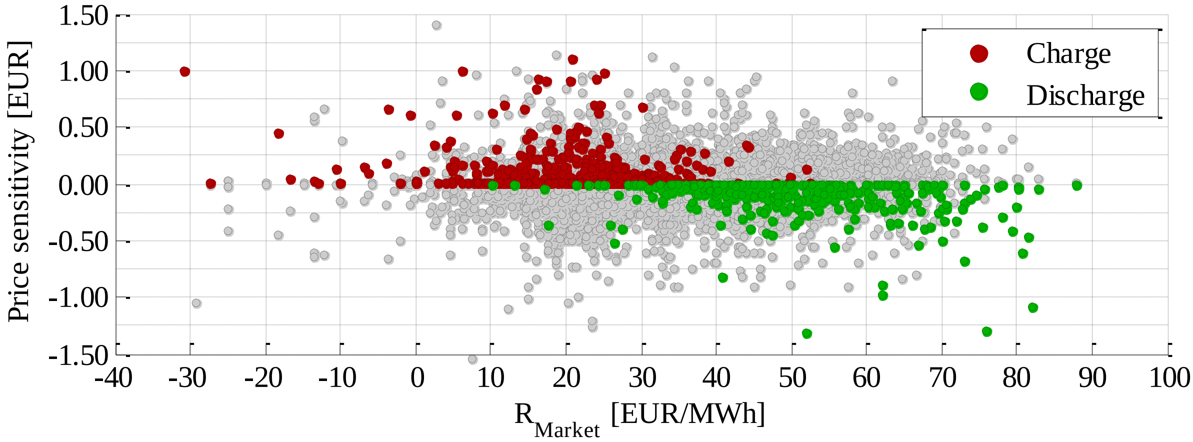

Figure 5.35: Relation of price sensitivity and arbitrage operations

Overall it can be concluded that arbitrage operations reduce the price range and therefore the volatility of prices. In addition, they induce a slight decrease of market prices.

5.4 Consequences and Feedback Reactions

Last, the consequences from the induced load and market price changes on the initial business cases will be discussed.

The consequences from time shifting on electricity markets are of an indirect nature, as private consumers typically do not directly participate in the market. Furthermore, due to individual consumption pattern and generation capacities, there will be a smoothing effect on the impact. Contrary, arbitrage operations have immediate consequences on market prices and other market agents. As charging and discharging is driven by market prices, the actions of agents are closely aligned.

5.4.1 Time Shifting

As shown in Section 5.3.2, storage dispatched for time shifting results in a slight reduction of market prices due to both lower demand from the grid as well as feed-in of excess energy. However, despite the decreasing impact on wholesale market prices, it is unlikely to have a major effect on retail rates. First, the wholesale price is responsible for less than one quarter of the retail rates [197]. Second, retailers would likely demand a compensation for the increased uncertainty and higher volatility of electricity demand, which significantly increases the complexity and difficulty of their hedging operations. Hence, the impact of market price changes on the viability of the time shifting business case is limited.

Compared to the potential influence from time shifting on market price, the impact on the grid infrastructure, required generation capacities as well as the power balance has more far reaching consequences. Table 5.5 and Table 5.6 summarize the power exchange with the grid under the three previously discussed implementation cases and the respective reference cases for the winter and summer period (see Section 5.2.1). While the absolute numbers are subject to the previously specified assumptions, the comparison does show the general impact of each installation.

In each case, the installation of a storage device decreases the total amount of energy taken from the grid, as previously imported energy is substituted by locally generated energy. During the winter the effect is less pronounced for configurations with only a photovoltaic system due to the lower solar yields. In the case of refitting an existing photovoltaic installation with a storage system, the feed-in of energy is also reduced, as some energy is shifted in time and hence consumed locally instead of delivered to the grid. In the case of new installations with no previous local generation, there is now a significant feed-in of energy especially during the summer months.

	$\sum P_{Grid}^{Import}$ [kWh]	Max [W]	$\sum P_{Grid}^{Export}$ [kWh]	Max [W]
All energy from the grid	284.1	268	-	-
New PV + storage	176.2	268	-24.9	-611
New PV + CHP +storage	3.6	124	-82.3	-700
Agent with PV system	205.4	268	-57.2	-611
Re-fitting of storage	176.2	268	-24.9	-611

Table 5.5: Power exchange with the grid (winter)

	$\sum P_{Grid}^{Import}$ [kWh]	Max [W]	$\sum P_{Grid}^{Export}$ [kWh]	Max [W]
All energy from the grid	211.1	182	-	-
New PV + storage	17.9	145	-150.1	-644
New PV + CHP + storage	2.9	111	-201.0	-683
Agent with PV system	89.7	149	-229.7	-652
Re-fitting of storage	17.9	145	-150.1	-644

Table 5.6: Power exchange with the grid (summer)

Besides the total energy amounts, the tables also show the maximum power flows and hence the required capacity for the grid interconnection. While the amount of energy taken from the grid is reduced significantly, time shifting nonetheless relies on the grid connection to cover demand peaks as well as a backup-source, if local generation is not sufficient to satisfy demand. As shown by the column 'Max' in Table 5.5 and Table 5.6, the required capacity for the grid connection is only slightly reduced. However, as overall significantly less energy is taken from the grid, the utilization of the interconnection is substantially reduced.

Considering the feed-in of energy, the capacity of the required grid connection increases when previously no local generation resource was present, as the maximum feed-in power exceeds the maximum demand. The grid utilization is therefore reduced even further, as the average usage of the connection is lower. Re-fitting an existing photovoltaic installation with a storage device does not reduce the required grid capacity.

The consequences from these developments are manifold:

- With decreasing cost for distributed generation technologies and storage devices and hence improving economics for such installations, more consumers will turn to 'prosumers'. As a consequence, more grid capacity will be required in residential areas to accommodate the simultaneous feed-in of surplus PV generation, resulting in higher infrastructure cost. The impact can be reduced by further decreasing the feed-in limit from the current limitation of 70% to lower values and therefore enforce storage operators to a more grid-beneficial behaviour. In addition, differentiated tariff schemes can incentivize agents to accommodate their charging and feed-in to more suitable times as a way to reduce the grid capacity requirements.
- In environments, where energy consumption is subject to high taxes and fees, there will be a significant financial impact on the recipient of these payments. Due to the significantly lower amounts of energy taken from the grid, the related income will be reduced substantially. However, infrastructure requirements might even increase in order to accommodate the feed-in of surplus generation from photovoltaic installations. Policy makers must therefore find a fair and sustainable tariff structure to redistribute the network related costs that correspond to regulated terms in most countries. A shift to capacity related tariff terms to pay grid costs does not appear very promising, as storage can simultaneously be used to minimize the required grid connection capacity (see Section 3.6). As a result, again consumers without a storage device would be allocated the majority of grid cost. While the introduction of a capacity payment for the feed-in of surplus local generation might reduce this funding gap, this step would likely contradict other objectives, such as environmental goals. However, it would set the right financial incentives for local generators and storage owners to adapt their charging and feed-in strategy to a more grid-beneficial strategy. Alternatively, policy makers and regulators could consider a fixed annual fee for the grid interconnection, and reduce the energy related taxes and

fees. However, with further decreasing storage cost, consumers might choose to go completely off-grid and rely only on local generation resources and storage to satisfy their demand, leaving a huge funding gap for the transition period.

- Operators of power plants should invest into flexibility. Periods with low solar yields will affect all storage operators in a similar fashion, resulting in a simultaneous grid demand which is usually served by local generation.
- In the past, grid operators were faced with the challenge to forecast electric load and – increasingly over the last years – the contribution of distributed intermittent generation. A wide-scale introduction of storage devices for time shifting will further increase the difficulty to accurately predict demand. However, overall, as shown in the previous analysis, storage dispatched for time shifting should have a balancing effect on the power exchange of individual consumers with the grid. To reduce the forecasting complexity, grid-connected storage operators could be required to communicate their expected load and grid injection forecast to give the grid operator more confidence about future demand and energy fed to the grid. Grid-beneficial behaviour could then be rewarded by financial incentives, and significant deviations from the forecast would be penalized.

5.4.2 Arbitrage

Overall, storage devices dispatched for arbitrage operations steady the supply and demand of electricity (see Section 5.2.2). Their charging operations typically increase the demand for baseload, whereas the discharging operations oftentimes occur during periods with high demand and hence they reduce the required peak-generation capacity. Furthermore, it was shown that storage operations reduce the observed price ranges (see Section 5.3.3). This effect has a potentially adverse impact on the underlying business case on the long term.

In order to analyse the reverse feedback from arbitrage operations on its own business case, first the optimal dispatch according to Section 3.4.2 was identified. Following, the impact on the supply and demand balance was determined. Based thereupon, the resulting market price was estimated. Last, the resulting revenues were calculated, considering the altered market price. Hence, it was assumed that all agents expect the same market price, do not consider their impact on market prices and simultaneously pursue the same operation.

Figure 5.36 shows the resulting degradation in revenues depending on the aggregated installed capacity[4]. While the impact on revenues from the initial agents pursuing arbitrage is limited, the influence increases significantly with the installed capacity. For an aggregated installed capacity of 500 MWh, revenues would decline by 15.5%. Doubling the installed capacity to 1 000 MWh would reduce revenues by a total of 28.8%. Hence, arbitrage operations have a significant negative impact on the revenues and therefore on the profitability of their own business case.

[4] Based on the previously discussed aggregated demand and supply curves. Assuming storage devices with a power-to-energy ratio of 1, and a minimum revenue threshold for the optimal dispatch of 15.60 EUR / MWh.

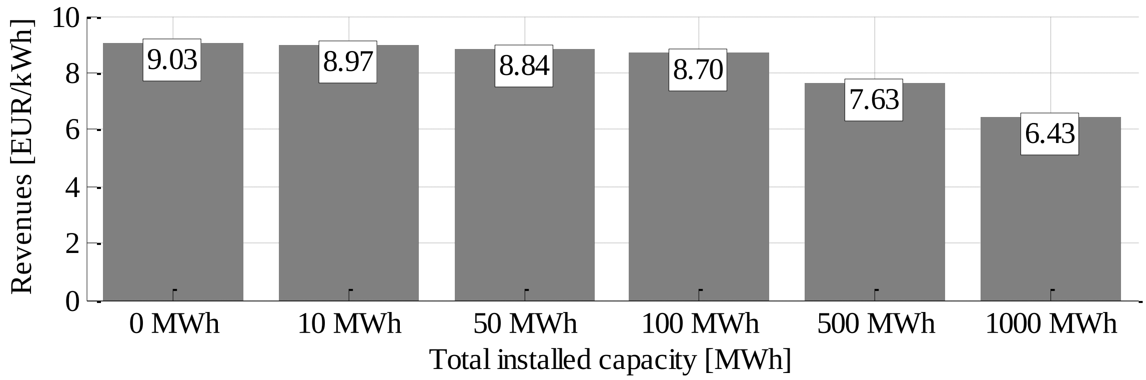

Figure 5.36: Revenue degradation for arbitrage operations with increasing installed capacity

However, the described approach is static and likely overestimates the negative feedback and consequences on the business case, as it assumes that all agents act on the same price signals. A more complete approach should also take the reaction of agents to the potentially changing market prices into account. If some agents would have anticipated the actions of other agents and correctly predicted their impact on market prices, they would be able to adjust their storage operation by incorporating the expected price changes in their dispatch problem. This would reduce the drop in revenues significantly.

Figure 5.37 compares the case for a total installed capacity of 1 000 MWh. If all agents follow the same price signals and do not consider their impact on market prices, revenues would fall by 28.8%, as previously identified. Contrary, if half of the agents would correctly anticipate the actions and the impact of the other agents, the reduction in revenues would be significantly reduced. In that case, the drop in revenue would only amount to 21.1%.

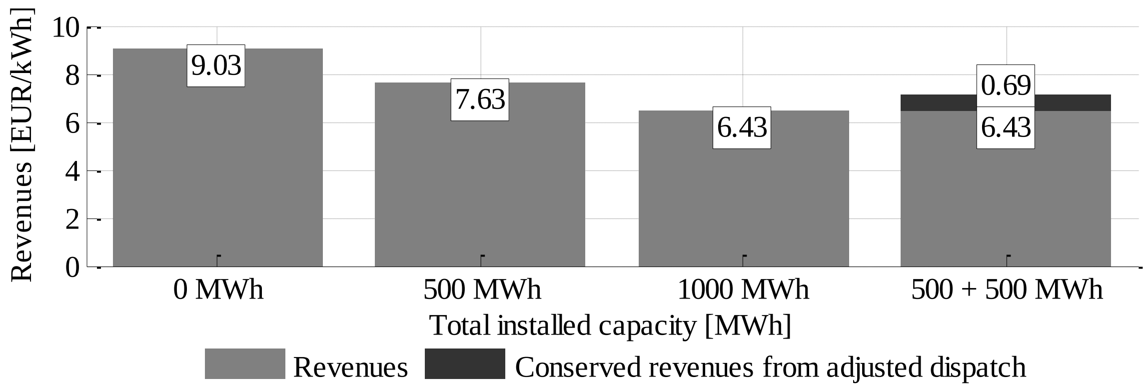

Figure 5.37: Revenue conservation from a dispatch adjusted to the new market prices

Hence, implying that agents are at least partially able to estimate the actions of other market participants as well as the impact of their actions on market prices allows them to take measures to preserve some of the revenues by considering the estimated impact in their dispatch.

Based upon the previous approach, a search routine can be devised to estimate the market potential, before the entrance of additional market agents deteriorates the business case and market conditions to a point where revenues are no longer sufficient. Algorithm 3 provides a high-level overview of the search process to identify the market potential based upon a minimum revenue requirement.

Algorithm 3: Search routine to determine the market potential for arbitrage

1. Determine the optimal dispatch for the first market agent
2. Estimate the impact on the supply and demand balance as well as the expected market prices
3. Based on the expected market prices, determine the optimal dispatch for an additional market agent
4. Estimate the additional impact on the supply and demand balance and based thereupon the expected future market prices
5. Repeat steps 3-4 until the realized revenues fall short of a pre-defined minimum revenue threshold, such as the annual depreciation cost of a typical storage system

Concluding, it was shown that arbitrage operations erode their own business case by reducing peak prices and increasing valley prices. While the impact is limited for small amounts of installed capacity, it becomes a substantial thread once more capacity is installed. This reverse feedback should be considered in the financial evaluation by first-movers, as the amount of available revenues deteriorates once further agents enter the market. However, a linear approach likely overestimates the decrease in the revenue potential, as agents will likely adjust their dispatch to consider the action of further market agents. Therefore, a search routine considering the reaction of additional market agents was presented which allows estimating the market potential for arbitrage.

Chapter 6

6 Case Study

Abstract

Sections 6.1 - 6.4 present four case studies, where the storage dispatch models introduced in Chapter 3 are implemented as well as the evaluation methods discussed in Chapter 4 are applied. For each case study, initially the required data will be presented as well as the assumptions explained. Following, it will be discussed how the presented models can be implemented. Thereafter, the dispatch will be evaluated from a financial perspective and results discussed. An additional section will analyse specific aspects beyond the financial evaluation. Each section concludes with a discussion of the results. The objective of these case studies is not to provide a definite answer to the question whether storage is valid today, as rapidly decreasing investment cost will require a reevaluation shortly. Instead, this chapter intents to present the application of the presented frameworks and provide general insights into the validity of storage and its drivers. Furthermore, Section 6.5 will look at the impact of storage deployed for time shifting on the grid. Based on a forecast of storage installations, the change in energy demand seen by the grid is analysed. In addition, the case study will look at the impact on affected entities from a financial perspective.

6.1 Time Shifting of Energy

The first case study is based on the model presented in Section 3.3, considering the economics of storage for time shifting of energy in a consumer setting. The case study will consider a theoretical, multi-family house assumed to be located in Germany. The building is assumed to be well insulated with low heating demand. Even though there will be many different consumers in such a house, they are considered as one entity, with one interconnection to the grid. Residential retail consumers were chosen in this case study as they currently have the highest tariffs to pay and hence will most likely be the first ones for which storage breaks even. A multi-family house is selected as several system components display economies of scale and therefore very small-scale systems have very high specific cost. In addition, the load profile becomes smoother as compared to a single-family house.

6.1.1 Data and Assumptions

The simulation horizon will be one year to ensure that all seasons are included. All historical data will be scaled to average values. While in reality individual years will deviate from the obtained results, the outcome of the simulation will therefore represent the result that can be expected in an average year. The duration of each time step in the simulation will be 15 minutes. The discount rate is assumed to be 5%.

Parameter	Value
Δt	0.25 (15 minutes)
T	35040 (1 year)
r_{Equity}	5%

Table 6.1: Simulation parameters

In the following, the required demand and generation time series will be presented, both for the thermal as well as for the electric system. In addition, the system components together with their technical characteristics and their cost will be discussed. Last, the available electricity tariffs will be introduced.

Demand and Generation Time Series

The assumed electricity consumption is based on [193], compiled by the Association of German Engineers. It provides realistic load profiles of individual single- and multi-family houses, differentiating the demand between weekdays (working days and Sundays), between seasons (summer, winter, transition period) and between days with mostly clear or cloudy sky. Furthermore, the impact of different climatic zones in Germany is accounted for. The profile is normalized and can be easily scaled to match the forecasted annual demand, which is assumed to be 150,000 kWh / year. The data for multi-family houses is available in 15-minute resolution.

Figure 6.1 shows the distribution of demand along a day over the year as boxplot. During the nighttime, demand is subdued and very steady. A first peak exists during the morning hours, followed by a slightly reduced plateau during midday and early afternoon. Consumption increases again during the later afternoon and remains elevated during the evening hours. It decreases again in the late evening. Along the year, electricity consumption is relatively constant, with slightly higher demand during the winter months as compared to the summer time.

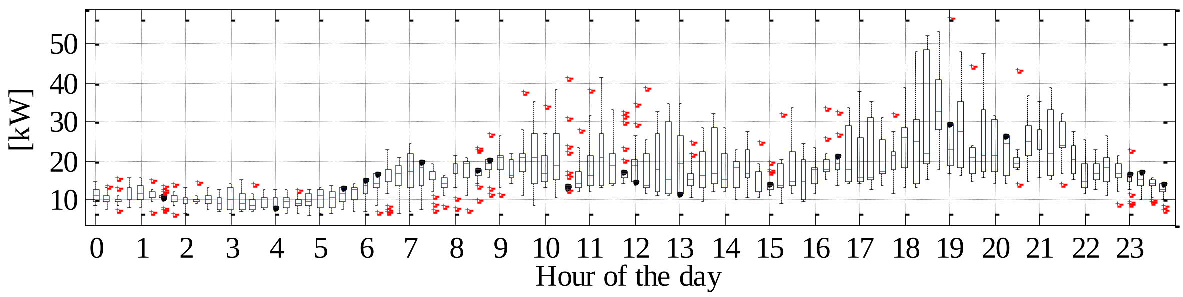

Figure 6.1: Boxplot of daily electricity demand

The resulting load duration curve is displayed in Figure 6.2. Demand exceeded 50 kW during 181 15-minute periods (45 hours in total) and was more than 40 kW during 589 periods (147 hours in total). It remained below 30 kW for more than 93% of the time. Furthermore, demand was below 10 kW during about 1 000 hours. The majority of time (62%), demand was between 10 kW and 20 kW.

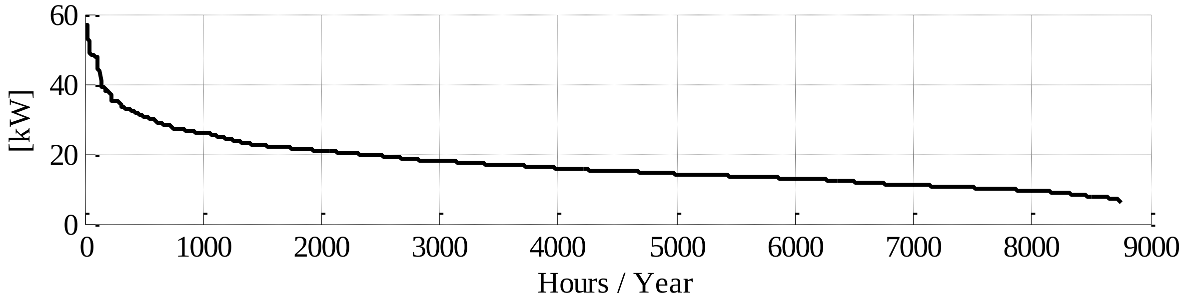

Figure 6.2: Electric load duration curve

Besides the load profile for electricity, [193] also provides data for thermal demand. The data is organized in the same way as described above. The overall annual heat demand of the multi-family house is assumed to be 220 MWh, both for heating and hot water supply.

Figure 6.3 shows a boxplot of the evolution of heat demand along the day. Overall, the demand is steadier than for electricity, with a lower daily variation between minimum and maximum demand.

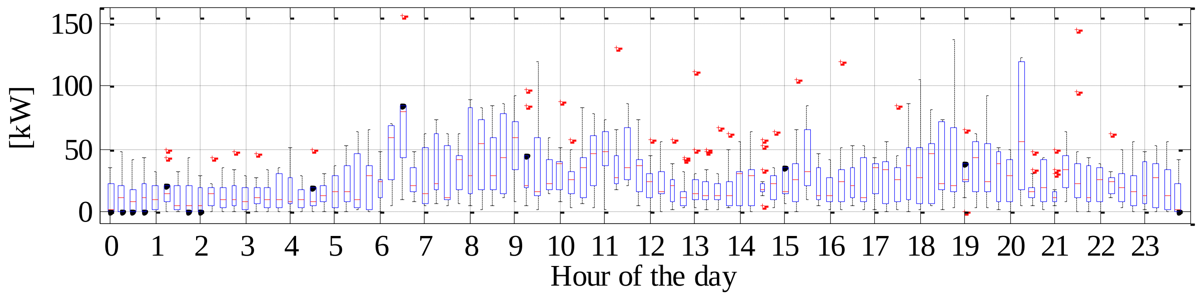

Figure 6.3: Boxplot of daily heat demand

The accompanying thermal load duration curve is shown in Figure 6.4. Whereas there is always some demand for electricity, demand for heat during several hours every year is zero.

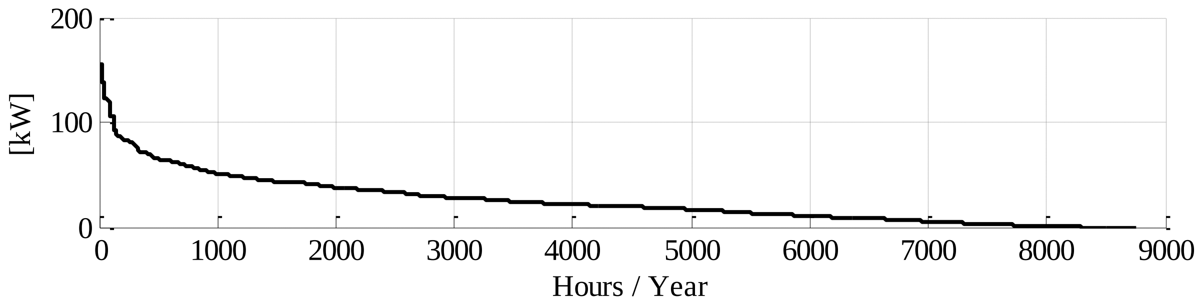

Figure 6.4: Thermal load duration curve

Last, Figure 6.5 shows the distribution of monthly heat demand. Heating is required mostly during the winter months, but also at a reduced rate during spring and autumn. Demand during summer months comes primarily from hot water consumption.

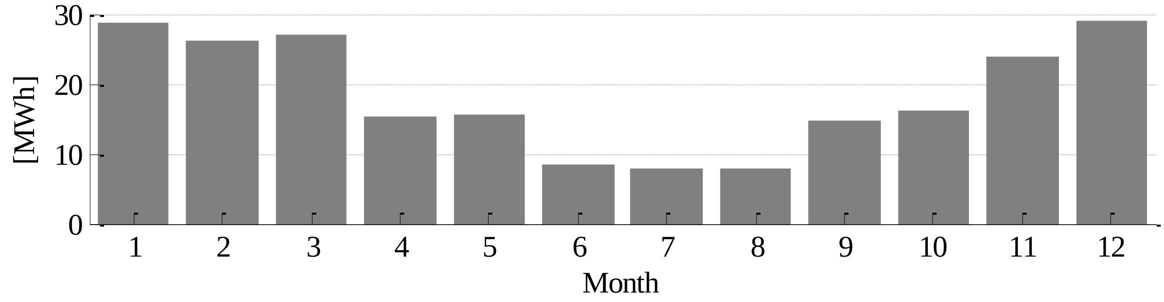

Figure 6.5: Monthly heat demand

Historical 15-minute solar radiation data for Berlin (Germany) for the year 2005 [198] was used to estimate both photovoltaic generation $P_{PV}(t)$ as well as solar thermal generation $H_{ST}(t)$.

For the photovoltaic generation, the radiation data was scaled to an annual value of 950 kWh, which corresponds to the average yield that can be expected according to the Joint Research Center of the European Commission [192] for an installation with 1 kW capacity. Figure 6.6 shows the resulting monthly distribution of photovoltaic generation. The significant difference in generation between the months is obvious: during sunny months, monthly yields are about 120 kWh/kW. Contrary, generation falls as low as 20 kWh/kW per month during winter time.

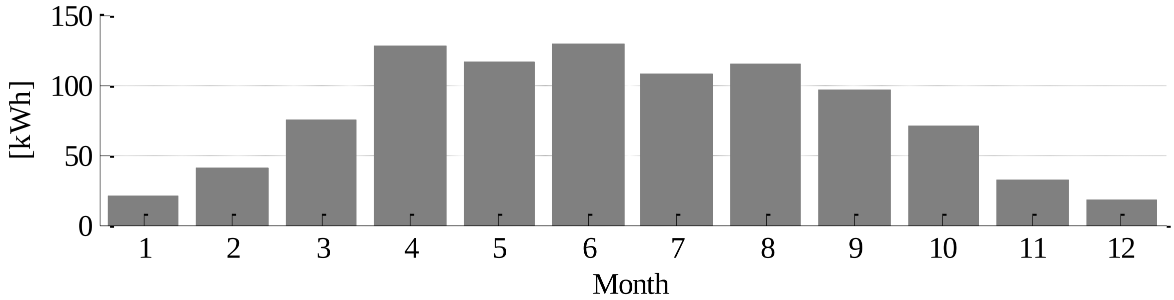

Figure 6.6: Monthly distribution of generation of a 1 kW photovoltaic installation

Figure 6.7 displays the generation along the year. Not only are the solar gains higher during summer time, but also available during more hours along the day. However, it is also obvious that generation varies not only between seasons, but that there is also a high variability from day to day and even from hour to hour.

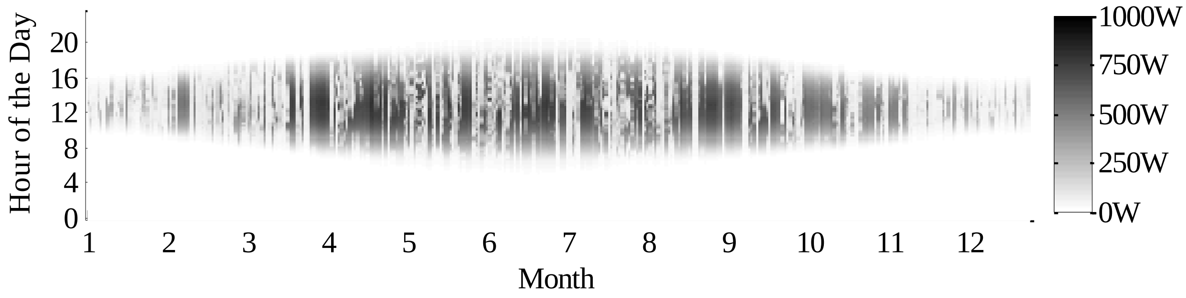

Figure 6.7: Photovoltaic generation along the year of a 1 kW installation

The generation data from a solar thermal installation was estimated analogous, with an expected annual yield of 1 000 kWh/kW. Hence, the generation pattern of photovoltaic panels and solar thermal installations are identical on a temporal scale.

Last, in order to determine the coefficient of performance for the heat pump, information about the outside temperature is required. [199] provides 30-minute measurements from the year 2005 for Berlin, which were interpolated to the required 15-minute interval. Figure 6.8 shows the resulting temperature time series.

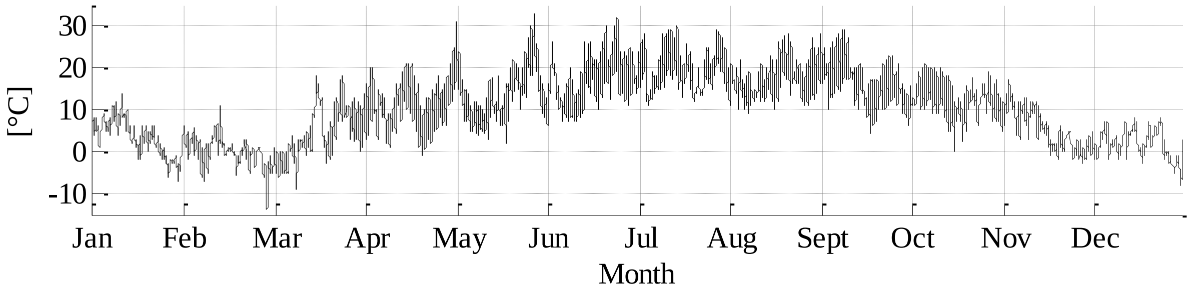

Figure 6.8: Temperature along the year

System Components

For the electric storage, lithium-ion batteries are considered. The technology has reached technical maturity for widespread deployment in households and is commercially available as preconfigured system.

Lithium-ion batteries can typically be discharged down to 25% ($\delta_{Storage}$ = *0.25*) of their capacity. Besides the maximum depth of discharge, the maximum charge / discharge rate $P_{Storage}^{Capacity}$ is also restricted. It will be assumed that the power is limited to 50% of the capacity and that the limitation is linear, that is independent of the current state of charge. Charge- and discharge efficiencies $\eta_{Storage}^{In}$ and $\eta_{Storage}^{Out}$ are assumed to be 95% each, resulting in an overall efficiency of 90.25%. The expected cycle lifetime is assumed to be 5 000 cycles and the maximum calendric lifetime 15 years.

The installation cost for the storage system shows a scale effect due to the cost for planning and installation, battery management system as well as inverter. A cost of 2 000 EUR plus 600 EUR for each installed kWh of capacity was assumed. Neither annual fixed cost nor variable costs were considered. Table 6.2 provides an overview over the relevant parameters of the storage device.

Parameter	Value
$C_{Storage}^{Invest}$	$2.000 + 0.6\ EUR \times E_{Storage}^{Capacity}$
$C_{Storage}^{Fixed}$	*0 EUR*
$C_{Storage}^{Variable}$	*0 EUR / Wh*
$E_{Storage}^{Capacity}$	*up to 100 000 Wh*
$P_{Storage}^{Capacity}$	$0.5 \times E_{Storage}^{Capacity}$
$\eta_{Storage}^{In}$	*95%*
$\eta_{Storage}^{Out}$	*95%*
$\delta_{Storage}$	*25%*
$L_{Storage}^{Calendric}$	*15 a*
$L_{Storage}^{Cycle}$	*5 000*

Table 6.2: Parameters of the storage device

The assumed thermal storage system stores thermal energy as hot water in a well-insulated container. The hot water can then be released and used at a later time when there is demand. In order to easily integrate the thermal storage into the mathematical formulation of the problem, its capacity in liters will be converted to Wh by assuming a maximum temperature difference of 30°K. Given the heat capacity of water of 1.163 Wh/kg*K, the storage capacity equals about 35 Wh/L.

The capacity $H_{ThStorage}^{Capacity}$ of the integrated heat exchanger is assumed to be half the storage capacity, that is it takes two hours to fully charge or discharge the thermal storage. Contrary to the electrical storage system, the thermal system can be fully discharged. Furthermore, as no conversion process is involved, efficiency losses are assumed to be 0%. However, the system suffers from self-discharge $\phi_{ThStorage}$. These decrease with scale due to the relative decrease of the surface area in relation to the total stored volume. A logarithmic relation between the hourly self-discharge and the capacity was assumed. For a thermal storage system with a capacity of 20 000 Wh, hourly loss was assumed to be about 96 Wh ($\phi_{ThStorage} =$ 0.48%), whereas for a thermal storage system with 40 000 Wh the loss would amount to 123 Wh ($\phi_{ThStorage} =$ 0.31%).

As bigger storage capacity is usually achieved by arranging several thermal storages in parallel, only little economies of scale exist. In addition to 700 EUR for installation, capacity related cost is assumed to be 0.05 EUR / Wh. Neither fixed nor variable cost exist. Lifetime is assumed to be 25 years. The relevant characteristics of the thermal storage device are summarized in Table 6.3.

Parameter	**Value**
$C_{ThStorage}^{Invest}$	$700EUR + 0.05EUR \times E_{Storage}^{Capacity}$
$C_{ThStorage}^{Fixed}$	*0 EUR*
$C_{ThStorage}^{Variable}$	*0 EUR*
$E_{ThStorage}^{Capacity}$	*up to 100 000 Wh*
$H_{ThStorage}^{Capacity}$	$0.5 \times E_{ThStorage}^{Capacity}$
$\eta_{ThStorage}^{In}$	*100%*
$\eta_{ThStorage}^{Out}$	*100%*
$\phi_{ThStorage}$	$\frac{38 \times LN\left(E_{ThStorage}^{Capacity}\right) - 280}{E_{ThStorage}^{Capacity}}$
$\delta_{ThStorage}$	*0%*
$L_{ThStorage}^{Calendric}$	*25 a*

Table 6.3: Parameters of the thermal storage device

Photovoltaic systems convert solar energy into electricity. They can oftentimes be retrofitted on existing buildings, have no sound or CO_2 emissions and are virtually maintenance free. Besides, their popularity as distributed generation technology was strongly supported by the substantial price reductions over the last few years as well as attractive feed-in tariffs. However, photovoltaic systems are non-dispatchable. Therefore, declining feed-in tariffs make the application of storage worth a consideration.

Photovoltaic systems have very limited economies of scale, as solar panels and installation cost more or less increase linearly with size. Typically, only the planning, the inverter and required communication technology benefit from small scale effects. Therefore, investment cost is assumed to increase linearly with the installed capacity. Fixed cost reflects expenses mainly for periodic maintenance and insurance. There are no variable costs. Lifetime of the panels is assumed to be 20 years. Table 6.4 contains a summary of the relevant parameters.

Parameter	Value
C_{CHP}^{Invest}	$1.35\ EUR \times P_{PV}^{Capacity}$
C_{PV}^{Fixed}	$100\ {EUR}/{a} + 0.025\ {EUR}/{a} \times P_{PV}^{Capacity}$
$C_{PV}^{Variable}$	*0 EUR*
$P_{PV}^{Capacity}$	*up to 50 000 W*
$L_{PV}^{Calendric}$	*20 years*

Table 6.4: Parameters of the photovoltaic installation

Solar thermal installations provide heat from solar radiation and are therefore the counterpart to photovoltaic installations in the thermal system. They are non-dispatchable, as their generation depends on the solar radiation. The performance for solar thermal panels is typically given in kWh/m². Based on [200], the power of the system was determined as 1 000 W per 1.6 m² of panel surface and the yield estimated with 1 000 kWh/kW.

Investment cost for solar thermal installations are determined by the cost for the panels. Hence, installations have low economies of scale, benefitting only from a shared controller and pump as well as common pipes. After the initial installation, they require very little maintenance. Fixed cost reflect expenses for periodic maintenance and insurance. Variable cost stem from the required electricity for the circulation pumps. However, these are minimal and are as a simplification therefore also considered in the fixed, annual cost. Lifetime expectation is 20 years. Table 6.5 provides all relevant parameters.

Parameter	Value
C_{ST}^{Invest}	$1500\,EUR + {H_{ST}^{Capacity}}/{1000} \times 450\,EUR$
C_{ST}^{Fixed}	${H_{ST}^{Capacity}}/{1000} \times 25\ {EUR}/{a}$
$C_{ST}^{Variable}$	*0 EUR / Wh*
$H_{ST}^{Capacity}$	*up to 100 000 W*
$L_{ST}^{Calendric}$	*20a*

Table 6.5: Parameters of the solar-thermal installation

By using the waste heat from the power generation for the thermal system, a cogeneration unit generates simultaneously both heat and power. Thereby, almost all the primary energy can be used. For this case study, it is assumed that the ratio of power- to heat-output is constant at the ratio of 2.2. Furthermore, it is assumed that the power output is variable from 40% - 100% of its nominal capacity.

Initial investment cost depends mainly on the chosen capacity of the cogeneration plant. Fixed annual costs are substantial as periodic maintenance is required. It is therefore assumed that a maintenance contract is implemented, covering all potential repairs. Variable costs are dominated by the cost for the fuel. The calendric lifetime of the system is limited to 12 years.

Under certain conditions, CHP installations are entitled to an incentive payment, which is paid in addition to a feed-in tariff (which will be presented in the following section) [201]. For electricity fed into the grid from a cogeneration unit with an electric capacity of up to 50 kW, the operator receives in addition to the feed-in tariff 0.08 EUR / kWh. For locally consumed electricity, the incentive payment is reduced to 0.04 EUR / kWh. However, the incentive is paid only for the first 60 000 hours of operation. For capacities exceeding 50 kW, both the compensation amount as well as the incentive period is reduced.

This incentive payment has not been considered in the formulation of the problem, as it is specific to the current legislation as well as non-linear. Furthermore, the results from the simulation horizon can no longer be scaled to the complete evaluation period, as the incentive payment is only paid for the first 60 000 hours of operation. However, in order to reflect reality, it will be considered in the subsequent calculation of the cash flows. Therefore, the expected total incentive payments over the lifetime of the CHP unit based on the dispatch of the first year will be deducted from the initial investment cost.

Based on the obtained dispatch over the simulation horizon *T*, equation (6.1) provides an estimate of the total incentive payments for a cogeneration unit with a capacity of less than 50 kW over the lifetime of the system.

$$C_{CHP}^{Benefit} = -60\,000 \times P_{CHP}^{Capacity} \times \left(\frac{\sum_{t=1}^{T} - P_{Grid}^{ExCHP}(t)}{\sum_{t=1}^{T} P_{CHP}(t)} \times 0.08 \Big/ 1\,000 + \left(1 - \frac{\sum_{t=1}^{T} - P_{Grid}^{ExCHP}(t)}{\sum_{t=1}^{T} P_{CHP}(t)} \right) \times 0.04 \Big/ 1\,000 \right) \quad \textbf{(6.1)}$$

However, as the incentive would be paid over the operating years and not as a lump-sum at the beginning, the discounted sum should be considered for the evaluation. Equation (6.2) provides an estimate for the duration of the incentive payments in years, based on the obtained dispatch of the simulation period.

$$T_{CHP}^{Benefit} = \left(\frac{60\,000 \times P_{CHP}^{Capacity}}{\Delta t \times \sum_{t=1}^{T} P_{CHP}(t) \times T^{years}} \right) \quad \textbf{(6.2)}$$

Finally, as shown in Table 6.6, the investment cost C_{CHP}^{Invest} considered in the evaluation is reduced by the discounted sum of the incentive payments. To simplify the calculation, the complete lump sum $C_{CHP}^{Benefit}$ was discounted to half of the expected payment duration.

Parameter	**Value**
C_{CHP}^{Invest}	$10\,000 EUR \times \left(P_{CHP}^{Capacity} \Big/ 1\,000 \right)^{0.5} - C_{CHP}^{Benefit} \times \left(1 - r_{equity}\right)^{0.5 \times T_{CHP}^{Benefit}}$
C_{CHP}^{Fixed}	$300 EUR \times \left(P_{CHP}^{Capacity} \Big/ 1\,000 \right)^{0.85}$
$C_{CHP}^{Variable}$	*0.00005 EUR/Wh*
$P_{CHP}^{Capacity}$	*up to 50 000 W*
$P_{CHP}^{CapacityMin}$	$0.4 \times P_{CHP}^{Capacity}$
$H_{CHP}^{Capacity}$	$2.2 \times P_{CHP}^{Capacity}$
$L_{CHP}^{Calendric}$	*12 a*

Table 6.6: Associated parameters of the cogeneration installation

Heat pumps transfer thermal energy from a source with a low temperature to a system with a higher temperature. Generally, heat pumps require electric energy for their operation. However, the lower the temperature from the heat source becomes, the lower the heat output per unit of electricity becomes. This relationship between heat output and temperature is described by the coefficient of performance (*CoP*), which is described by a piecewise linear relationship and shown in Figure 6.9 along with the distribution of the outdoor temperature.

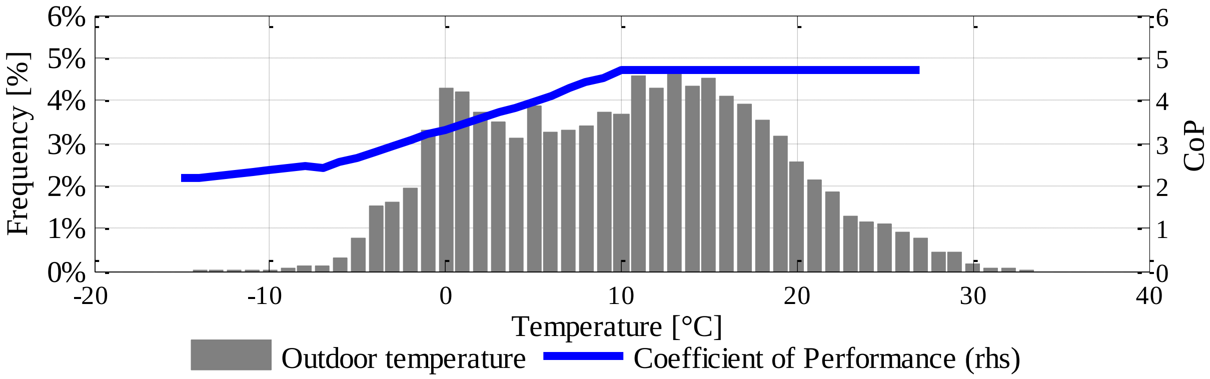

Figure 6.9: Relationship between temperature and coefficient of performance of a heat pump

In this case study, only ambient air as heat source is considered. Heat pumps using the ground as heat reservoir have overall a better performance, however the initial investment is also significant higher. Investment cost of an air-based system is dominated by the heat pump, with little overhead for pipes and installation. Fixed costs are constituted by periodic maintenance and cleaning of the outdoor unit. Besides the demand for electricity $P_{HP}(t)$, there are no further variable costs. All relevant parameters for the installation and operation of a heat pump are shown in Table 6.7.

Parameter	**Value**
C_{HP}^{Invest}	$5000 EUR + P_{HP}^{Capacity} / 1000 \times 1500 EUR$
C_{HP}^{Fixed}	$P_{HP}^{Capacity} / 1000 \times 70 EUR$
$C_{HP}^{Variable}$	*0 EUR / Wh*
$P_{HP}^{Capacity}$	*up to 25 000 W*
$L_{HP}^{Calendric}$	*18 a*

Table 6.7: Parameters of the heat pump

A gas boiler provides heat by burning natural gas. In small-scale systems, it is oftentimes the single source of heat. In larger systems, such as the one analysed in this case, gas boilers are oftentimes installed in parallel as both a backup system as well as to satisfy peak demand, as it would not be economic to dimension the primary system such as a cogeneration unit for peak demand.

Fixed cost for gas boilers are – compared to the other systems for heat provision – comparatively inexpensive. Little maintenance is required. Variable cost is determined by the cost of natural gas. The relevant parameters of a gas boiler are provided in Table 6.8.

Parameter	**Value**
C_{GB}^{Invest}	$4000EUR + H_{GB}^{Capacity} / 1000 \times 50EUR$
C_{GB}^{Fixed}	*300 EUR / a*
$C_{GB}^{Variable}$	*0.00005 EUR / Wh*
$H_{GB}^{Capacity}$	*up to 100 000 W*
$L_{GB}^{Calendric}$	*15 a*

Table 6.8: Parameters of a gas boiler

The search space for the optimum system configuration was restricted to the following maximum capacities (see Table 6.9), partly due to practical reasons (available roof space for solar-thermal and photovoltaic installations) as well as to provide a restricted search space for the Simulated Annealing process to speed up the search. If the obtained optimum capacities are within proximity of the defined upper borders, the constraints will be further relaxed.

$0 \le P_{PV}^{Capacity} \le 50\,000$
$0 \le P_{ST}^{Capacity} \le 50\,000$
$0 \le P_{CHP}^{Capacity} \le 50\,000$
$0 \le P_{HP}^{Capacity} \le 200\,000$
$0 \le P_{GB}^{Capacity} \le 500\,000$
$0 \le E_{Storage}^{Capacity} \le 200\,000$
$0 \le E_{ThStorage}^{Capacity} \le 500\,000$

Table 6.9: System capacity constraints

Electricity Tariffs

Besides a regular flat tariff, two time-based pricing schemes will be considered. Generally, these tariffs are designed to motivate consumers to shift their demand to hours when overall load is lower and – due to the merit order effect – electricity generation is cheaper. Therefore, prices are differentiated according to the consumption time. However, in order to be cost effective to consumers, this requires a behavioral change of consumption patterns. Alternatively, a storage system can be charged during these low price periods and satisfy the demand at the regular hours. If the price differentials exceed the allocated cost of a storage system, the application of storage can be economically beneficial. Furthermore, it might impact the value proposition of installing additional system components like a PV or CHP system.

Time-of-use tariffs divide the day into two or more blocks. For each period, a different tariff applies, which is predetermined and static.

Real-time pricing links the consumption tariff to the wholesale market. Prices therefore are no longer static but evolve dynamically, depending on the prices of the day-ahead market. The applicable rate for each interval is set and communicated by the retailer once the day-ahead market is cleared. Compared to a time-of-use tariff, discounted periods are therefore not necessarily related to the time of the day, but related to market prices. Due to its variable nature, this tariff scheme is considered as one of the possible implementations of dynamic pricing or dynamic tariffs.

For this case study, the availability of the following tariffs is assumed:

- Tariff $R_{flat}^{Import}(t)$: flat tariff with an identical consumption price at all times
- Tariff $R_{TOU}^{Import}(t)$: time of use tariff, which offers a reduced rate during the night (22pm to 6am)
- Tariff $R_{RTP}^{Import}(t)$: real-time pricing tariff, which is linked to market prices, but still considers all network fees and taxes.

As real-time pricing tariffs do not yet exist in the German marketplace, $R_{RTP}^{Import}(t)$ is fictional. It is constituted by the fixed prices components, which are not controlled by the retailer (such as network charges, fees and taxes), and the market prices [197]. For the simulation, market prices of 2015 have been considered.

The assumed tariffs are shown in Table 6.10.

Parameter	Value
$R_{flat}^{Import}(t)$	*0.27 EUR / kWh*
$R_{TOU}^{Import}(t)$	*Hours 22-06: 0.249 EUR / kWh* *otherwise 0.289 EUR / kWh*
$R_{RTP}^{Import}(t)$	*R(t) + 0.215 EUR / kWh*

Table 6.10: Electricity tariff parameters

Figure 6.10 shows a comparison of the three tariff schemes over some exemplary days.

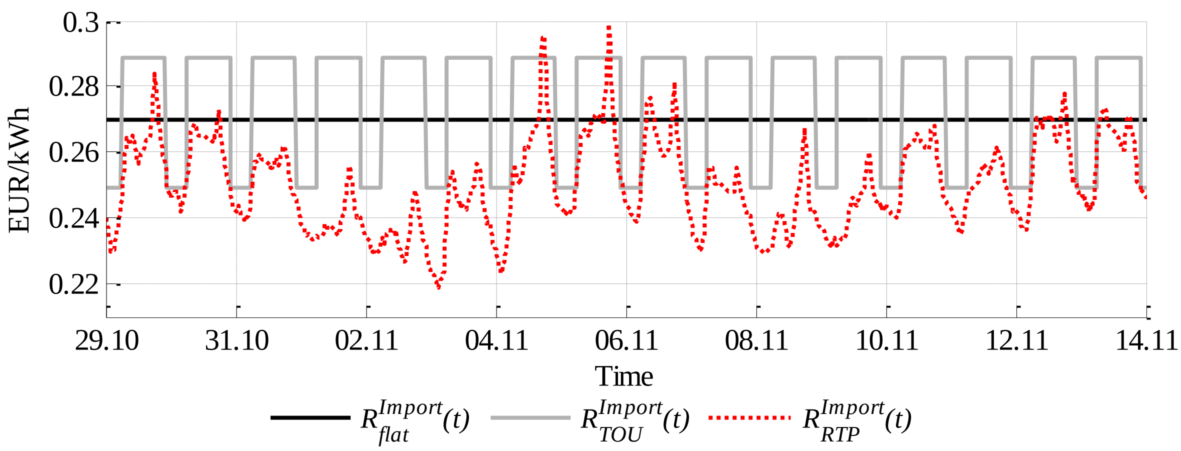

Figure 6.10: Evolution of tariffs over several exemplary days

Feed-in of electricity generated by a photovoltaic installation is rewarded according to the German renewable energy act [126] with 0.12 EUR / kWh. The regulation requires a limitation of the maximum feed-in power $P_{PV}^{max\ feed-in}$ to 70% of the installed capacity.

Electricity generated and fed into the grid from cogeneration units is regulated by the Combined Heat and Power Act [201] and is currently compensated at the average baseload price of the European Energy Exchange during the previous quarter (assumed to be 0.035 EUR / kWh).

Table 6.11 summarizes the parameter for the feed-in of electricity. Additional fees and taxes, which might be applicable when operating a distributed generation resource, will be neglected.

Parameter	Value
$P_{PV}^{max\ feed-in}$	$70\% \times P_{PV}^{Capacity}$
$R_{PV}^{Export}(t)$	$0.12\ EUR\ /\ kWh$
$R_{CHP}^{Export}(t)$	$0.035\ EUR\ /\ kWh$

Table 6.11: Feed-in tariffs

6.1.2 Model Implementation

Mixed Integer Program

The implementation of the model described in Section 3.3.4 becomes computational very challenging for longer time horizons. Figure 6.11 shows the computation time to solve the mixed integer program for different time horizons on the right-hand scale. It is obvious, that the relation between the optimization period and the total computation time is not linear, but that the computational burden increases with the time period. In addition, the figure also shows the computation time per considered time step, which is not constant but increases with longer optimization periods.

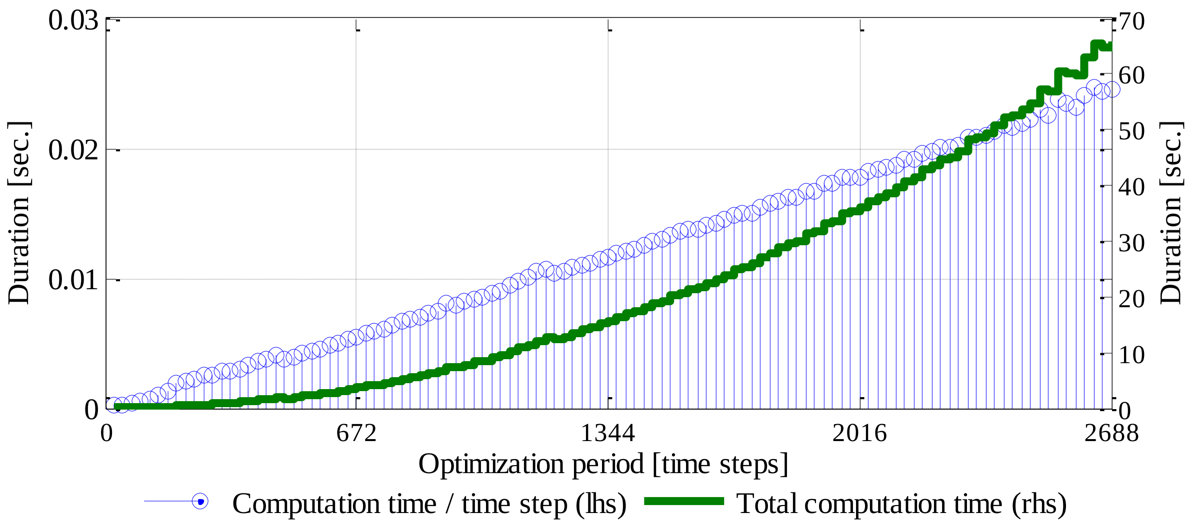

Figure 6.11: Computation time for the mixed integer program

A linear regression (correlation coefficient: 0.9993) shows that the computation time for each time step increases by 9.15×10^{-6} seconds for each additional time step considered. Given the period of this case study (1 year with 15-minute intervals), the optimization period extends to 35 040 time steps. The theoretical computation time would therefore amount to 0.32 seconds per considered time step, or to a total of 187 minutes per optimization. In order to determine the optimal system configuration, an optimal dispatch has to be calculated for each iteration of the Simulated Annealing search algorithm. Hence, this is obviously not a practical approach.

In order to decrease the complexity, the required time and the resulting hardware requirements, the problem will be split into several, smaller problems. Figure 6.12 shows the approach exemplary. However, simply breaking the problem into smaller serial sub-problems yields a less optimal dispatch. As each time period is considered on its own, energy flows between the periods are not optimized nor are any subsequent operations considered.

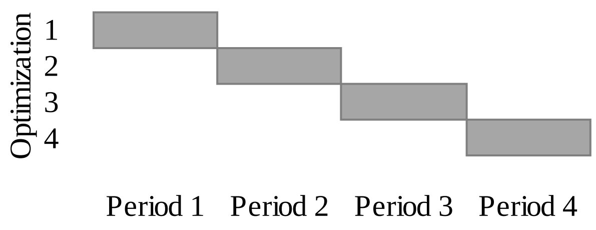

Figure 6.12: Simple implementation approach

The joint dispatch along the entire horizon might therefore deviate from the optimal dispatch solution obtained with a single run that optimizes on all data at once. As energy left over in the storage device would have no value, the storage device will typically be fully discharged at the end of each considered period. Contrary, if the algorithm considers the full evaluation timeframe, it might be worthwhile to carry over energy on the end of each considered time period.

Therefore, data of the next optimization period will be taken into account. By including the subsequent period partially into the current optimization problem, the algorithm can look into the future and consider energy demand and generation beyond the current period. Using overlapping data, the error should be reduced at the computational cost of calculating the dispatch twice on that data. Figure 6.13 shows the approach exemplary. In the following, the period considered for the dispatch will be called 'horizon', whereas the overlapping period will be called 'forecast'.

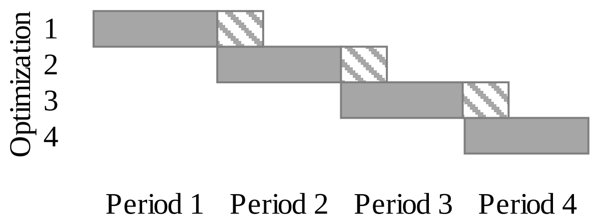

Figure 6.13: Enhanced implementation approach

In order to determine the magnitude of the committed error (the difference in operational revenues) and find a good balance between error and computational time, the approach will be tested against some historical data. Figure 6.14 shows the resulting shortfall in revenues depending on different optimization horizon and forecast periods versus the reference case, which optimized on all data at once. It is clearly visible that the missed revenue decreases both with longer optimization horizons and longer forecast period, leading to the optimal result where all data is optimized in a single run. However, it also becomes apparent that the percentage error becomes neglect able, when the optimization windows are chosen large enough. Hence, the approach of breaking the problem into smaller, easier to solve sub-problems appears viable.

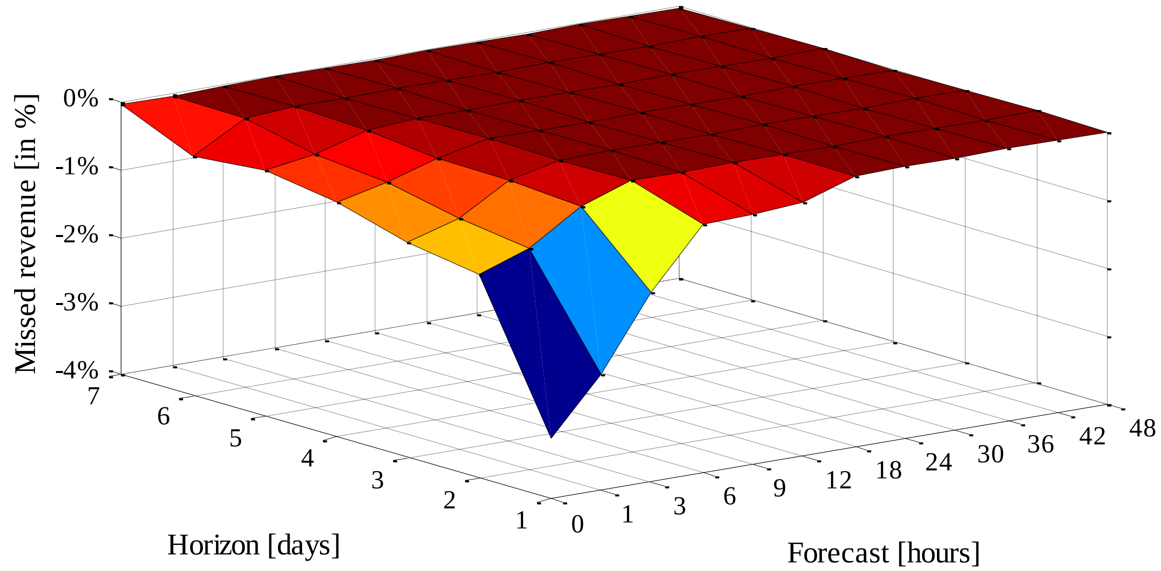

Figure 6.14: Missed revenue depending on the optimization horizon and forecast period

The magnitude of available improvements shown in Figure 6.14 differed significantly between different system configurations. However, the pattern was consistent. Generally, the potential improvements versus the reference case increased with the available storage capacity, as the algorithm has more flexibility to shift energy in time. Below a certain threshold, almost no improvements could be identified as the storage would be frequently depleted well before midnight and hence optimizing one day at a time would be sufficient.

Figure 6.15 shows the associated computation times, where optimizing a single day at a time is taken as a reference point. As expected, the more data is considered in each individual optimization, the more complex the problem becomes and the longer the computation takes. This is in line with the results determined initially in this section – see Figure 6.11 – that the computation time increases significantly with the length of each optimization period.

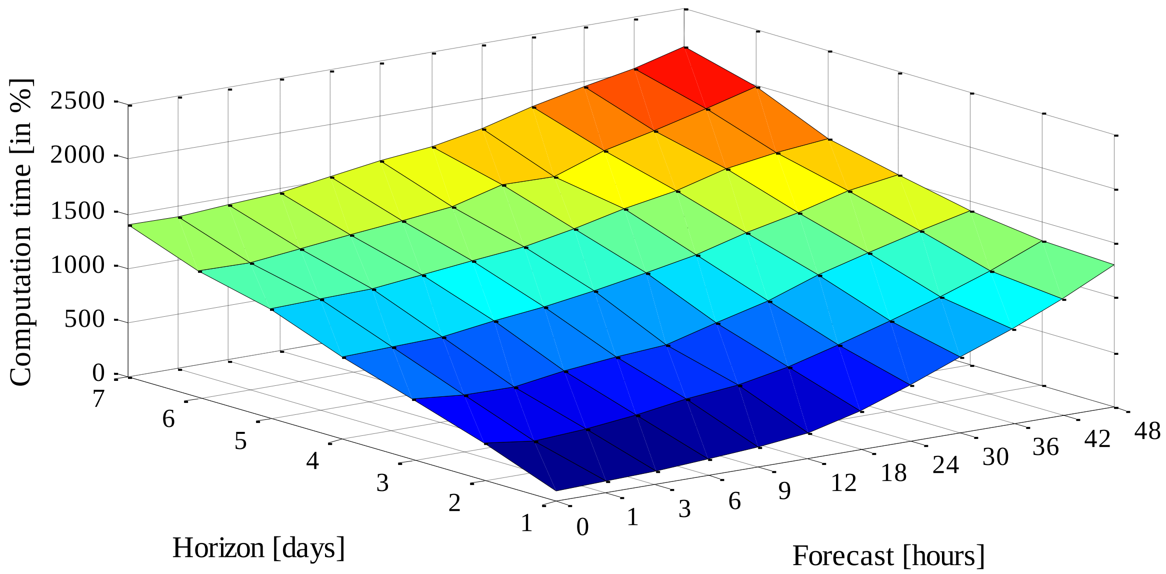

Figure 6.15: Computational cost depending on the optimization horizon and forecast period

Looking at the shortfall in revenues (Figure 6.14) and the associated computation time (Figure 6.15), considering a daily optimization horizon with a forecast period of six offers a good compromise between minimizing the missed revenues and the computation time. While further improvements are possible, their realization become computational very challenging and - given their marginal revenue contribution - hard to justify. Implicitly, it is therefore assumed that electric storage will only be used to shift energy from day to day, as longer transfer periods would require more foresight.

As the overall optimization is too complex to solve, this section presented an approach on how the problem can be simplified. It was analyzed how both the introduced error as well as the computational time can be minimized. Optimizing one day at a time and considering the first six hours of the following day presents a good compromise, as it comes close to the assumed optimum while only slightly increasing the computational time. The major disadvantage is that additional metrics like slack variables are only available for each optimized window, but not for the overall period. However, they can be obtained using sensitivity analysis.

Simulated Annealing

To identify the optimum parameters for the Simulated Annealing search process, which minimize the search time before a sufficiently good solution is found, the parameters were changed once at a time and the search routine rerun. The test was run on an arbitrarily chosen week of data, with the objective to identify the cost-minimizing system configuration. The following parameters of the simulated Annealing algorithm have been compared:

1) Reference case
   - Starting temperature: such that a decline in the objective function by 50 EUR is accepted with 60% probability
   - Stopping condition: temperature ≤ 0.01°C
   - Cooling process: temperature is reduced by 5% for each step
   - Neighborhood search: the process can jump by a maximum of $1/\sqrt{n}$ of the possible parameter range away from the current location, where n is the number of iterations completed so far
2) Decreased starting temperature
   - Starting temperature is reduced such that only a decline by 5 EUR is accepted with 60% probability;

   ➔ The process will spend less time initially to jump within the search space
3) Increased starting temperature
   - A decline by 500 EUR is accepted with 60% probability;

   ➔ The search space is more exhaustively analyzed for interesting areas.
4) Increased stopping temperature
   - Stopping condition: temperature ≤ 0.1°C;

   ➔ The most interesting area of the search space will not be explored that thoroughly and the local optimum might not be identified.

5) Decreased stopping temperature

   ▪ Stopping condition: temperature ≤ 0.001°C

   ➔ More extensive search to identify the local optimum

6) Modified neighborhood search

   ▪ The jump distance away from the current location is modified to: $\sqrt{Temperature} / Starting\ Temperature$

In addition, a further option with a slower cooling process (decrease of the temperature by only 1% for each iteration) was tested. The modification should result in a more exhaustive search, both initially to identify interesting search spaces as well as locally at the end. However, due to significantly longer run times and no substantial improvements on the outcome, it was immediately rejected.

Figure 6.16 compares the results of the remaining six parameter sets in terms of obtained results, total search time as well as search time until the best solution was identified.

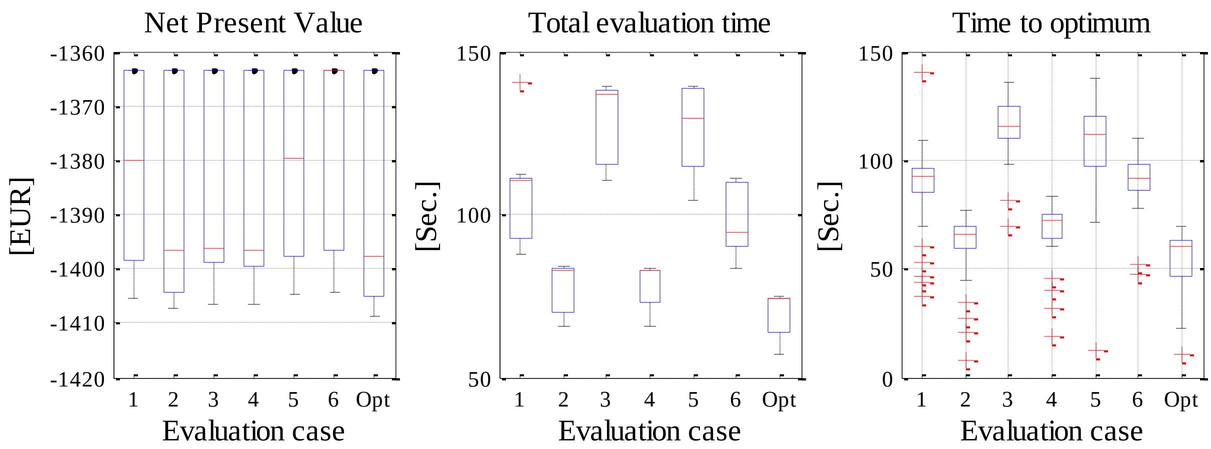

Figure 6.16: Comparison of parameters for the simulated annealing process

The mean of the obtained results differs by less than 10 EUR between the different parameter sets, with all identifying the overall best case (-1 363.50 EUR) in at least one run and even in the worst case not deviating by more than 3.2% from it. While the obtained results are very comparable, the total evaluation time differs widely. Case 3 (increased starting temperature) and 5 (decreased stopping temperature) have significantly longer search times, which however does not contribute to improve the results. Moving the parameters in the opposite direction (Case 2, decreased starting temperature and Case 4, increased stopping temperature) does not adversely affect the outcome, but significantly reduces search time. Cases 3 and 5 also take a longer time before identifying the optimum result. In the case of parameter set 3 this is likely due to the algorithm spending a long time identifying interesting search areas before moving towards the local optimum. In the case of set 5 the algorithm likely spends too much time trying to find a parameter set with only marginal improvements.

Based on the above findings, the following parameters of the proposed reference case will be modified for the deployment of the Simulated Annealing search routine:

- Lower start temperature: even a decreased starting temperature allows a sufficient random evaluation in the beginning to identify interesting search areas. However, the temperature is linked to a specific EUR amount, which should be chosen in relation to the expected value of the objective function;

- Increased stopping temperature: as the objective function converges quickly enough, the stopping temperature can be increased without compromising the final result. Local optima are still determined with sufficient accuracy.

The results of this parameter set analysis is shown in Figure 6.16 as case ‘Opt’. Its accuracy in identifying the optimum is as good as in the other cases, but requires shorter evaluation time – both to finish as well as to identify the local optimum.

6.1.3 Evaluation

Based on the data and assumptions presented in 6.1.1 and the parameters of the search process defined in 6.1.2, the optimum system configuration was determined. Therefore, following the approach described in Section 3.3.5, the optimum dispatch was repeatedly determined for different system configurations, which were chosen by the Simulated Annealing search.

The evolution of the search process is shown in Figure 6.17. Initially, a wide range of different configurations was tested by the Simulated Annealing approach in order to identify attractive neighbourhoods, resulting in widely different outcomes. Over time and with a decreasing temperature of the annealing process, the analysed configurations became more similar and the process was trying to identify the optimum solution. As obvious from the dispersion of the current search points, the process spent roughly 50 iterations to determine the most interesting neighbourhood, followed by the more local search to identify the optimum. The search converged to a net present value of EUR -29 800, which reflects – according to equations (3.14) - (3.16) and (3.20) - the value of all cash flows from operation, the energy exchange with the grid as well as the attributable depreciation charges over the simulated time horizon of one year.

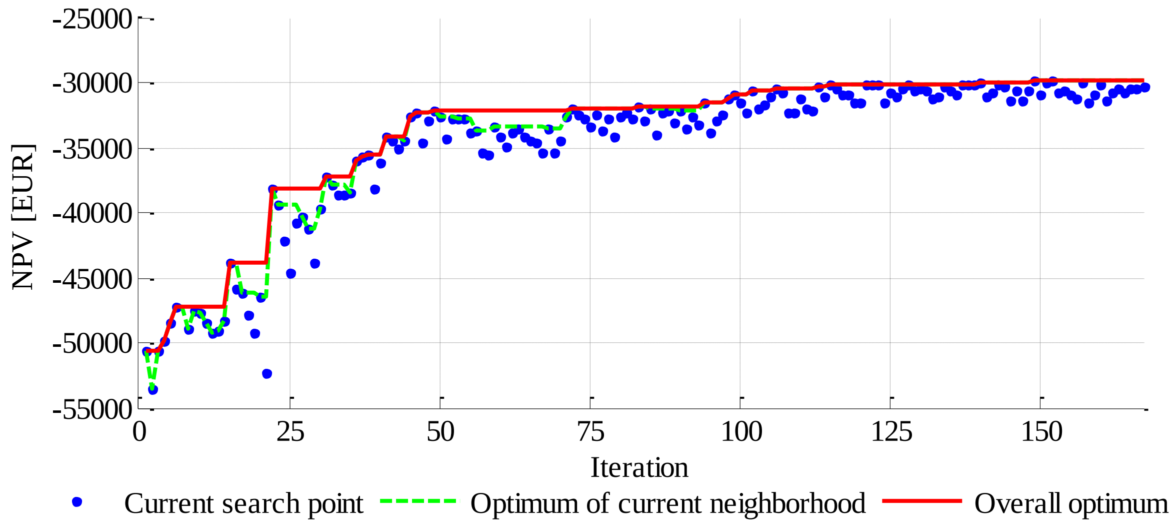

Figure 6.17: Evolution of the Simulated Annealing search process

Figure 6.18 shows the search space of the system capacities. Each line presents a system configuration which was tested during the search process, with the color reflecting the financial outcome of the particular configuration. Even though the Simulated Annealing search routine did not investigate every possible combination, it is obvious that a wide range of potential configurations were tested. Initially, the considered system configurations had been very different. However, over time the search routine focused on the most promising neighborhood to evaluate similar alterations of the most attractive configuration in order to determine the optimum system capacities.

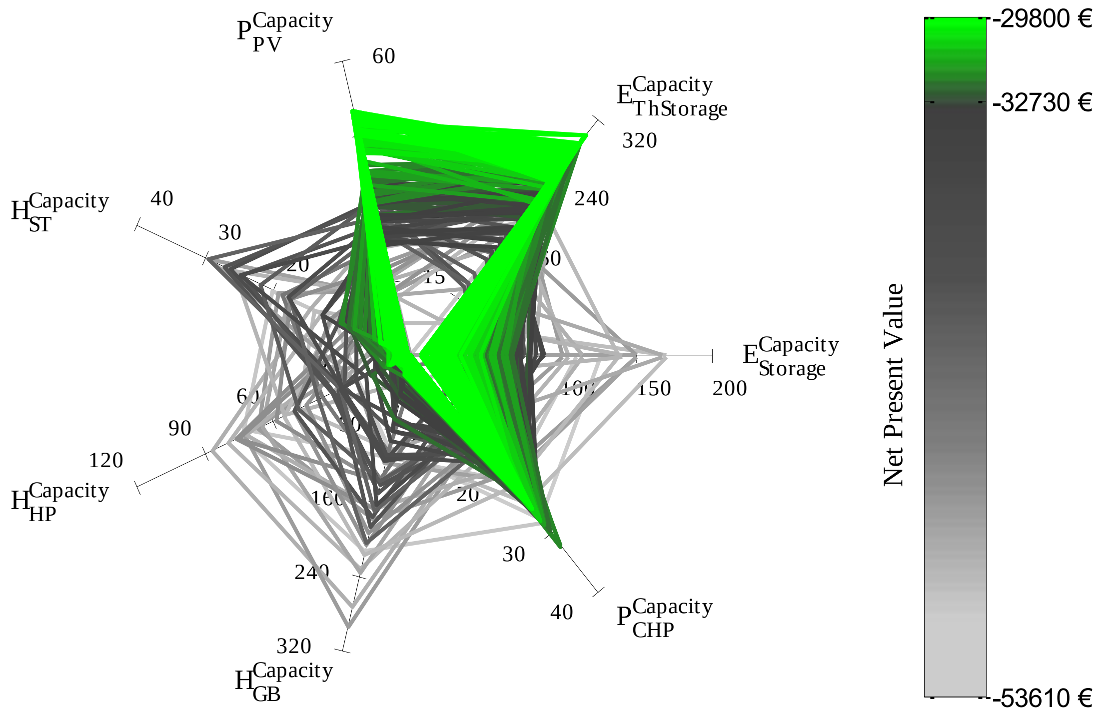

Figure 6.18: Capacities (in kW / kWh) of analyzed system configurations

6.1.4 Results

The identified optimum system configuration has the following system capacities:

- cogeneration unit with an electric / thermal capacity of 20.9 kW / 46.0 kW
- photovoltaic system with a capacity of 50.0 kW, which is equivalent to the upper boundary
- and a thermal storage with a capacity of 225.0 kWh

Hence, even though a wide range of capacities for the electric storage device have been considered by the Simulated Annealing process in the search (see Figure 6.18), the NPV maximizing configuration under the taken assumptions is to disregard electric storage. In order to determine the value proposition of electric storage, two further system configurations were considered in addition to the optimum system.

First, as discussed in Section 3.3.6, a reference case was established where all heat demand is satisfied by a gas boiler and all electricity is taken from the grid. Therefore, the Simulated Annealing search process was run again, restricting all system capacities to zero except for a gas boiler and thermal storage, which are required to satisfy heat demand. The most cost-effective system configuration under this limitation was a gas boiler with a capacity of 46.0 kW and a thermal storage system with a capacity of 225.0 kWh. The heat generating and storage capacities are therefore analogous to the case of the optimal system configuration. Second, the previously identified optimal system configuration was complemented with an electric storage device with a capacity of 50 kWh.

Table 6.12 shows the capacities of the three considered configurations in comparison.

	Reference case	Optimal configuration	Optimal configuration + el. storage
$E_{Storage}^{Capacity}$	-	-	50.0 kWh
$E_{ThStorage}^{Capacity}$	225.0 kWh	225.0 kWh	225.0 kWh
$P_{PV}^{Capacity}$	-	50.0 kW	50.0 kW
$P_{CHP}^{Capacity}\left(H_{CHP}^{Capacity}\right)$	-	20.9 kW (46.0 kW)	20.9 kW (46.0 kW)
$H_{ST}^{Capacity}$	-	-	-
$H_{GB}^{Capacity}$	46.0 kW	-	-
$H_{HP}^{Capacity}$	-	-	-

Table 6.12: Considered system capacities

The initial investment cost for the reference case amounts to 18 250 EUR. For the optimum system configuration, the required total investment amount increases to 125 167 EUR. Further extending this configuration by storage, the investment amount increases by 32 000 EUR to a total of 157 167 EUR. Figure 6.19 shows the breakdown of the total investment cost to the individual system components for all three analyzed cases.

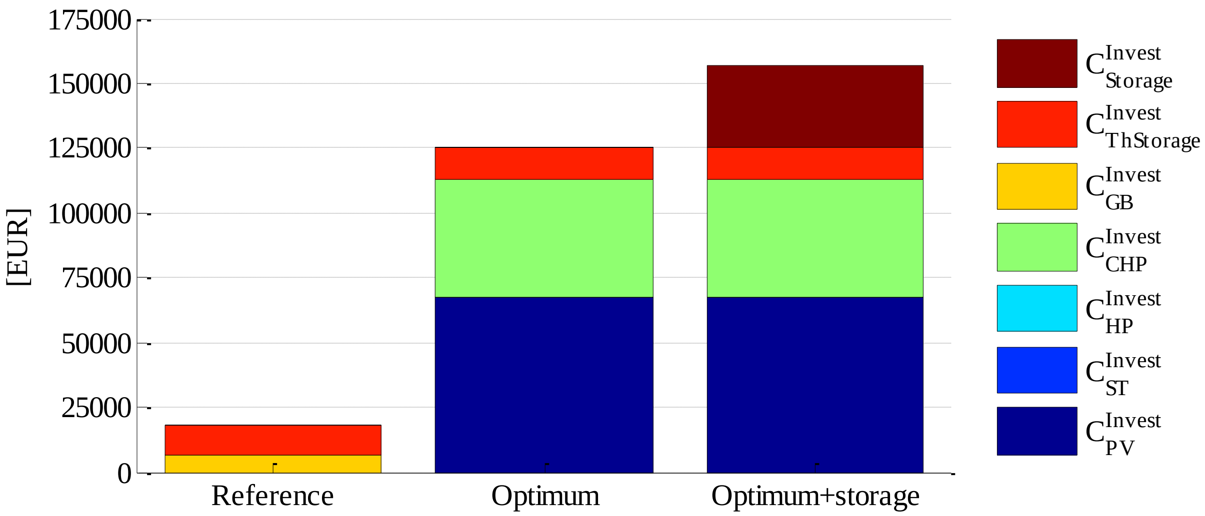

Figure 6.19: Breakdown of investment cost

As discussed in 3.3.6, due to the diverging lifetime of the individual system components to the evaluation horizon of one year, the net present value considers the initial investment cost proportionally according to the individual component lifetimes. The NPV therefore reflects the total of operating cost, exchange with the grid as well as the attributable investment cost.

The net present values for the three considered system configurations are shown in Table 6.13. Baseline for the further evaluation is the result of the reference case, with a net present value of -51 506. The more complex system configuration with a cogeneration unit and a photovoltaic system results in an NPV of -29 800 EUR. Adding a storage device to the system decreases the annual NPV by 591 EUR to -30 391 EUR.

	Reference case	Optimal configuration	Optimal configuration + el. storage
NPV	-51 506 EUR	-29 800 EUR	-30 391 EUR

Table 6.13: Net present value of the considered system configurations

These numbers show that there is significant potential to reduce cost / increase the NPV by investing in a more sophisticated energy supply concept at the cost of a high initial investment. In order to determine the reason for these significant differences, both power and heat flows will be analysed in the following. In Table 6.14, the power flows for all three configurations are compared.

Under the optimal system configuration, the cogeneration unit would generate 101 626 kWh of electricity. The unit would be operating almost constantly along the year (6 722 hours), even though mostly (4 302 hours) only at partial load. Given the presence of an electric storage device, the cogeneration unit would operate for slightly less hours (6 552 hours). However, total electric output is almost unchanged with 101 574 kWh, as the unit was operating at partial load for less hours (4 119 hours). However, given the presence of a storage device, the most significant difference is the substantial lower feed-in of energy from the cogeneration unit: 7 137 kWh versus only 969 kWh.

Even though the power generation of the photovoltaic panels is independent of the presence of a storage device, without a controllable load the output might be downregulated for several hours in order to not violate the feed-in limit. However, as sun irradiance for the chosen location is not very strong, even without any load the annual downregulated energy would amount to only 182 kWh for the chosen PV installation, equivalent to about 0.4% of annual generation. Therefore, even for the installation without a storage device, no energy is lost as sufficient demand is available during peak PV generation times. However, the amount of exported energy from photovoltaic generation was reduced under the presence of the storage system by about 30%, indicating that it is more beneficial to consume the energy locally than to feed it into the grid.

In total, the storage device was charged with 13 495 kWh. 12 179 kWh were provided again for local consumption, resulting in 1 766 kWh of efficiency losses. Summing up all power flows, the storage system completed a total of 342 cycles, equivalent to about one cycle per day.

In the reference case, with no local generation resource present, all energy (150 000 kWh) is taken from the grid. Given the PV system and the cogeneration unit, demand from the grid is reduced to 24 860 kWh. Under the presence of the storage device, energy taken from the grid is further reduced to 15 161 kWh.

Last, Table 6.14 shows the self-consumption (*SC*, according to equation (3.67)), self-sufficiency (*SS*, equation (3.68)) as well as the load-factor (*LF*, equation (3.69)) across all three configurations. Without local generation resources, self-sufficiency in the reference case is zero. Under the optimal system configuration, 83.9% of generated energy is consumed locally, resulting in a self-sufficiency of 83.4%. With a storage installation, even more of the energy can be consumed locally (91.3%), resulting also in a higher self-sufficiency (90.0%). According to the load-factor, the utilization of the grid interconnection decreases significantly, when local generation resources are present.

	Reference case	Optimal configuration	Optimal configuration + el. storage
$\sum P_{CHP}$	-	101 626 kWh	101 574 kWh
$\sum P_{Grid}^{Export\,CHP}$	-	7 137 kWh	969 kWh
$\sum P_{PV}$	-	47 500 kWh	47 500 kWh
$\sum P_{Grid}^{Export\,PV}$	-	16 849 kWh	11 951 kWh
$\sum P_{Storage}^{In} / \sum P_{Storage}^{Out}$	-	-	13 495 / 12 179 kWh
$\sum P_{Grid}^{Import}$	150 000 kWh	24 860 kWh	15 161 kWh
SC	-	83.9%	91.3%
SS	0%	83.4%	90.0%
LF	3.3	14.0	30.1

Table 6.14: Comparison of power flows as well as classification numbers

Table 6.15 compares the heat generation between the three system configurations. Under the reference case, all heat is generated by the gas boiler. The thermal storage is cycled in total 220 times and experienced 434 kWh in losses from self-discharge. It is only utilized during these periods, when heat supply from the gas boiler would otherwise not be sufficient.

For the optimal system configuration, all heat comes from the cogeneration unit. The thermal storage is utilized significantly more often, with 303 cycles in total. Consequently, thermal losses also increase significantly to 3 299 kWh. The thermal storage is not only charged to cover peak thermal demand, but also during times when the cogeneration unit is dispatched to cover power demand and no or little thermal demand exists.

In the third case, which also considers the electrical storage, the thermal storage was dispatched even more frequently with 326 cycles. However, losses from self-discharge decreased slightly to 3 185 kWh, indicating that thermal storage cycles were shorter.

As neither a solar thermal system nor a heat pump were considered, their contribution is consequently zero across all three configurations.

	Reference case	Optimal configuration	Optimal configuration + el. storage
$\sum H_{GB}$	220 434 kWh	-	-
$\sum H_{HP}$	-	-	-
$\sum H_{CHP}$	-	223 299 kWh	223 185 kWh
$\sum H_{ST}$	-	-	-
$\sum H_{Storage}^{In} / \sum H_{Storage}^{Out}$	49 711 / 49 277 kWh	69 753 / 66 454 kWh	74 949 / 71 764 kWh

Table 6.15: Comparison of heat generation

In order to get a more detailed insight into the composition of the net present value, Figure 6.20 shows a breakdown of the NPV for the three considered system configurations. The depreciation charge reflects the attributable investment cost for the evaluation horizon. The power related cost summarizes the operating cost for the cogeneration unit, the cost for the energy taken from the grid and also the revenue for the feed-in of energy. Cost for the provision of heat result from the operating cost of the gas boiler as well as the operating cost of the cogeneration unit, which are attributable for the heat generation.

For the reference case, the attributable depreciation charge for the one-year evaluation horizon as reflected in the net present value amount to only 898 EUR. The largest part (39 532 EUR) is due to the energy taken from the grid. Operating cost for the heat provision is 11 077 EUR.

The distribution between cost items looks significantly different for the optimal system configuration. Due to the much higher investment cost, depreciation charges are significantly larger with 4 403 EUR. However, variable cost decrease substantially. Net cost for electricity amount to only 14 474 EUR. Heat related cost sink marginally to 10 924 EUR, as all fixed costs of the cogeneration unit are charged to the electricity generation and hence thermal generation has only variable cost.

Last, by including a storage device, depreciation charges increase further to 6 776 EUR, at the benefit of reduced electricity cost (12 697 EUR). However, this breakdown also shows the reason for the reduced NPV if a storage device is included in the system configuration: in this case, the depreciation charge increases by 2 373 EUR, due to the depreciation charges of the storage device (2 188 EUR)[5] as well as the reduced benefit payments for the operation of the cogeneration unit (185 EUR; see the related discussion of the benefits in Section 6.1.1), as less energy was fed into the grid. The benefit of using a storage device was a reduction in the variable cost of 1 783 EUR, hence leaving a value gap of 591 EUR.

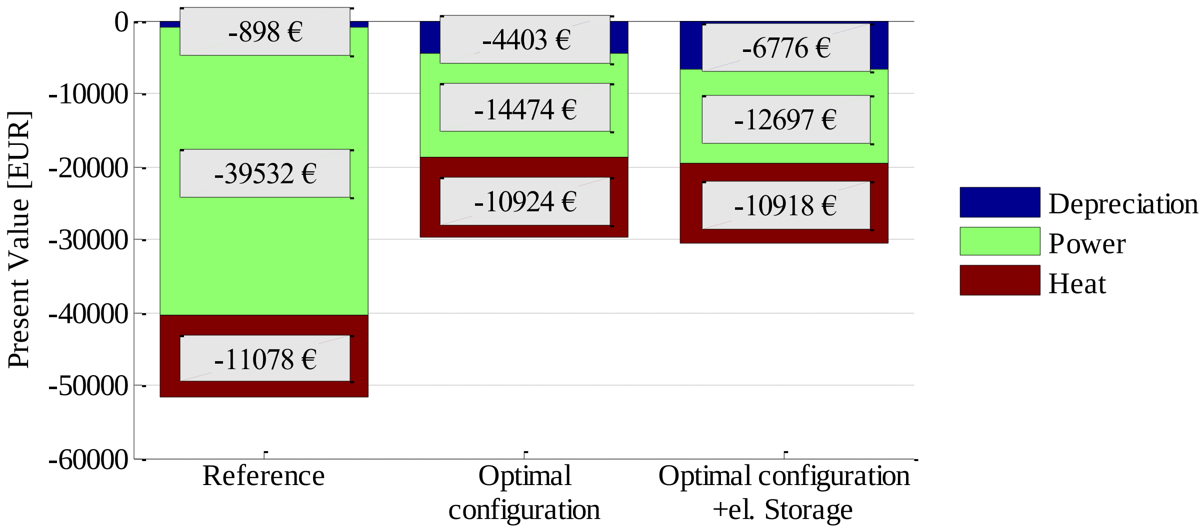

Figure 6.20: Net present value breakdown of the considered system configurations

A further breakdown of the NPV to the contribution of the individual system components is shown in Figure 6.21 for the configuration with an electrical storage system. The major driver is the operation of the cogeneration unit, both its variable cost for the heat and power production, as well as the annual fixed cost.

[5] The storage system realized 342 cycles over the one-year simulation horizon. The lifetime is therefore limited by its assumed cyclic lifetime (5 000 cycles) and not by its calendric lifetime (15 years).

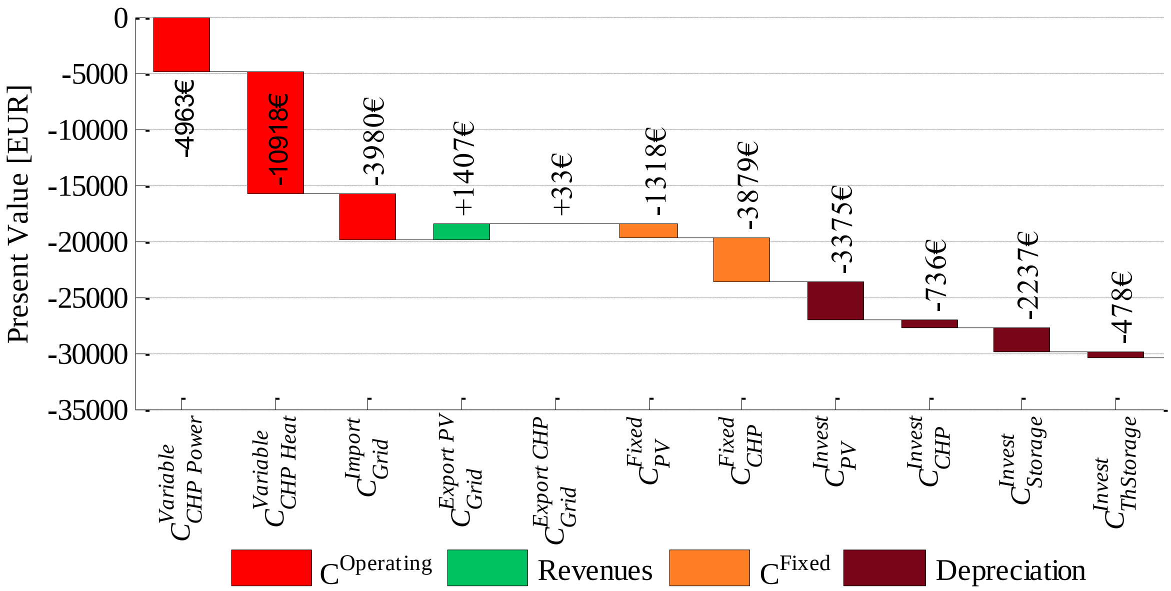

Figure 6.21: Net Present value breakdown of the configuration with a storage system

Last, Figure 6.22 shows the difference in present value between the optimal system configuration and the configuration with a storage installation. With a storage device present, less energy is taken from the grid. Consequently, the related cost C_{Grid}^{Import} is reduced. However, also less energy is being fed into the grid, resulting in lower compensation payments $C_{Grid}^{Export\,PV}$ and $C_{Grid}^{Export\,CHP}$. Furthermore, as mentioned previously, less incentive payments for the operation of the cogeneration unit can be claimed as less energy is fed-in, further decreasing the value contribution of the storage device. Last, when considering the depreciation charge for the storage device, the NPV turns negative.

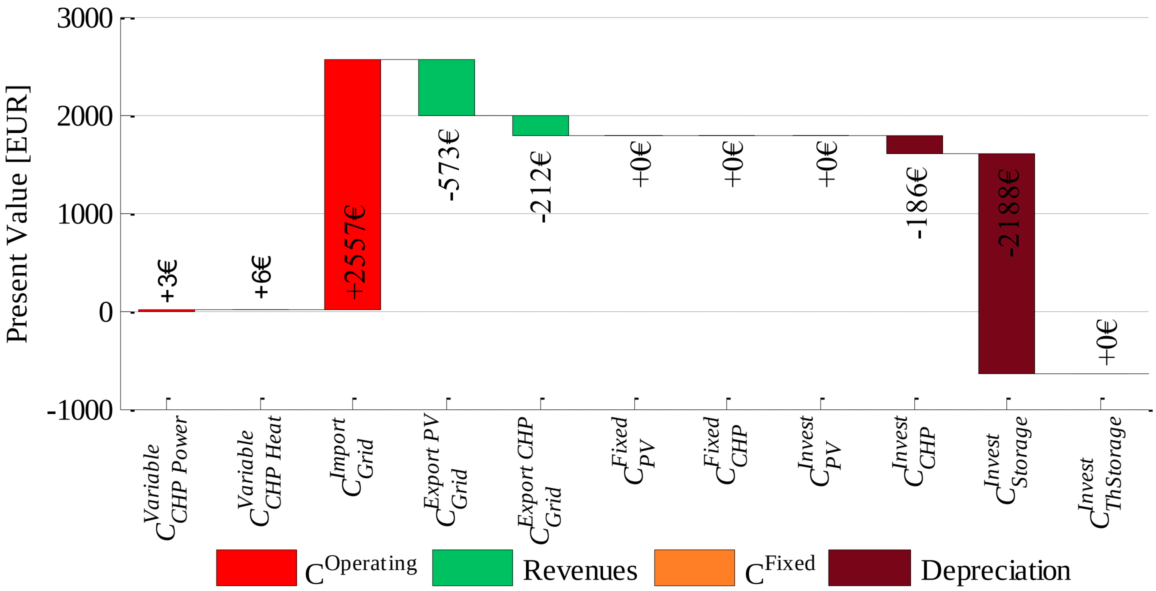

Figure 6.22: Changes in net present value due to a storage installation

In the following, the energy flows of the system configuration with a storage system present will be analysed in more detail. Figure 6.23 depicts the heat flows of the optimal system configuration with an electric storage device. Accordingly, about one third of the generated heat is stored intermittently, before it is taken again from the storage system to satisfy demand.

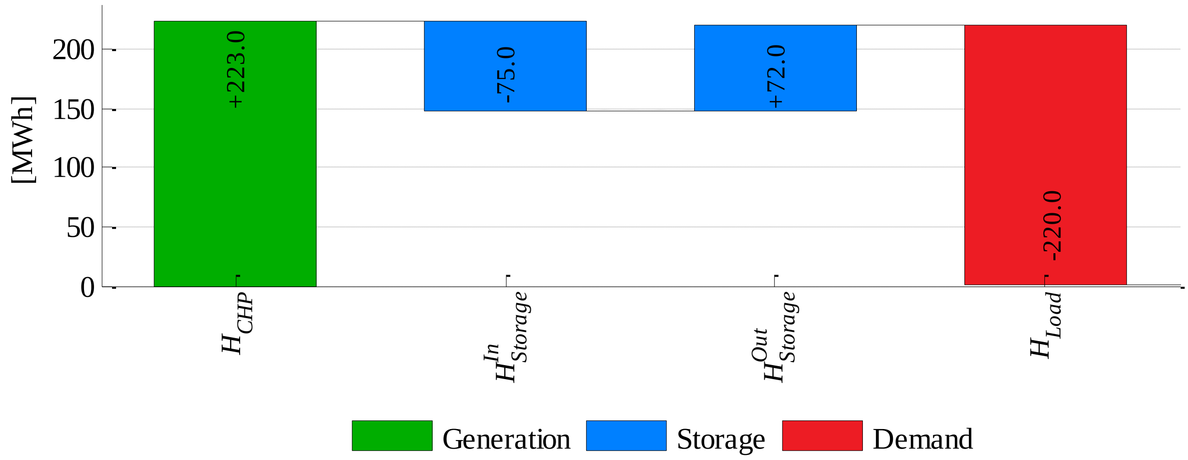

Figure 6.23: Energy flows of the heat system

The flows of the electric system are shown in Figure 6.24. Generation from the cogeneration unit covers about two thirds of the power demand, and generation from the photovoltaic system about the remaining one third. About 10% of the locally generated energy is shifted in time by the electric storage device. However, as there is still a temporal mismatch between local generation and demand despite the usage of the storage device, the remaining surplus / shortfall in energy is exchanged with the grid.

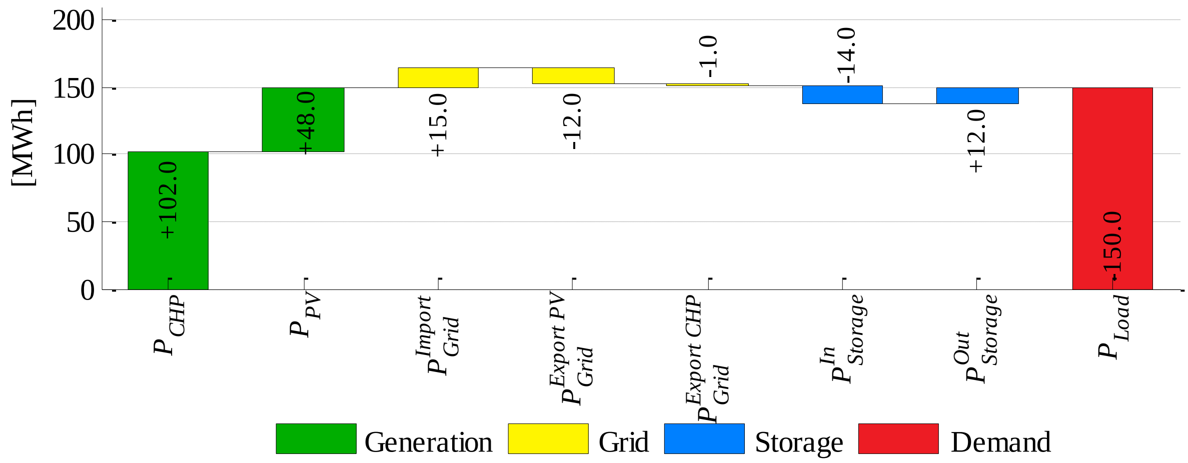

Figure 6.24: Energy flows of the electric system

Figure 6.25 shows the power output of the cogeneration unit under the optimal dispatch along the year. During the winter, the cogeneration unit is almost constantly operating, albeit at a slightly lower output level during the night and around noon. During spring and the summer, the cogeneration unit is only selectively dispatched during those times, when no photovoltaic generation is available and the electricity demand is high, mostly during the evening. Thermal demand during the day resulting from hot water usage is then satisfied by discharging the thermal storage.

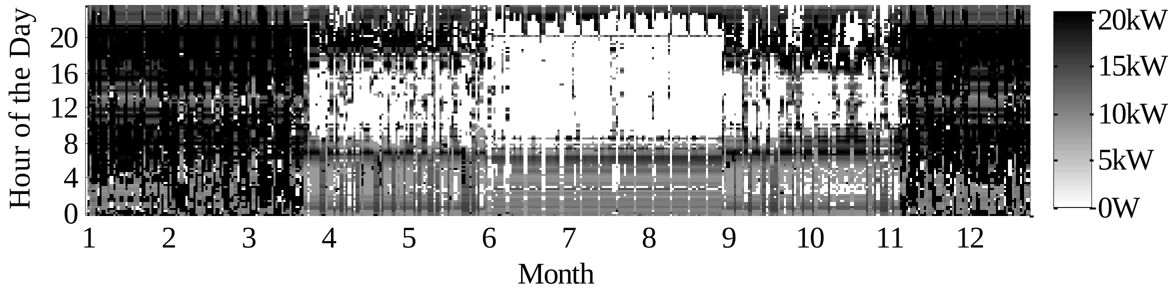

Figure 6.25: Power generation by the cogeneration unit along the year

The value of a cogeneration unit which can modulate becomes obvious when looking at the duration curve shown in Figure 6.26. The unit was operating for a total of 6 552 hours during the simulated year. However, only 2 433 hours were at full output. Contrary, the unit was dispatched for 4 119 hours at partial-load, thereof 288 hours at the minimum load level. Without the ability to modulate either significantly more storage would be required or the unit would be dispatched for less hours. In the second case, an additional gas boiler would be required. Furthermore, less electricity demand could be satisfied from local resources. Hence, cost for energy taken from the grid would increase.

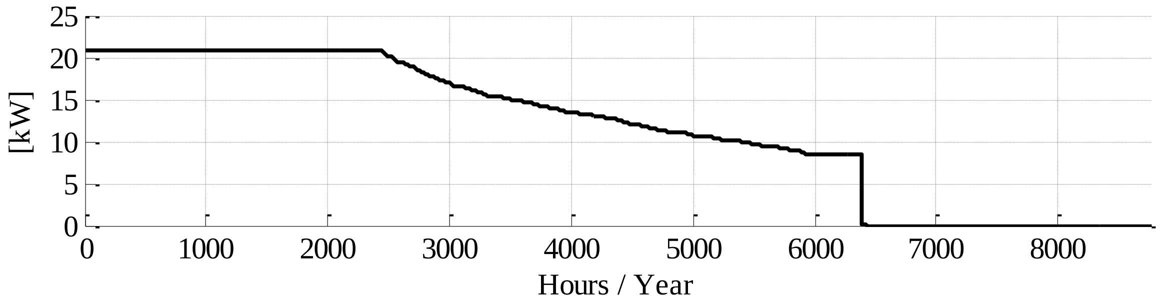

Figure 6.26: Duration curve of the cogeneration unit

Figure 6.27 shows the state of charge of the thermal storage device. The relation to Figure 6.25, which showed the generation of the cogeneration unit, is clearly visible. Most of the heat demand is directly satisfied from the cogeneration unit during the cold period of the year. Consequently, the thermal storage remains at very low charge levels most of the time, being utilized only to cover peak demand as otherwise the cogeneration unit would not be able to satisfy demand. Contrary, during the period with higher solar radiation intensity, the thermal storage device is utilized more frequently. Typically, the cogeneration unit is dispatched during the night to satisfy electric demand. Consequently, the thermal storage is slowly charged, only to be discharged again during the day to satisfy thermal demand while electric demand is satisfied from the photovoltaic generation.

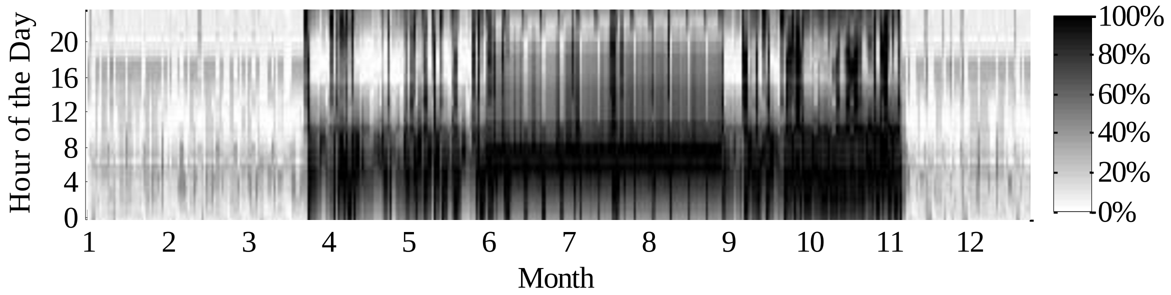

Figure 6.27: State of charge of the thermal storage device

Figure 6.28 shows the power flows of the electric storage device. Analogous to the pattern of the thermal storage system, the difference in dispatch patterns along the year is also clearly visible for the electric storage. Generally, the storage system is more frequently utilized during the winter period.

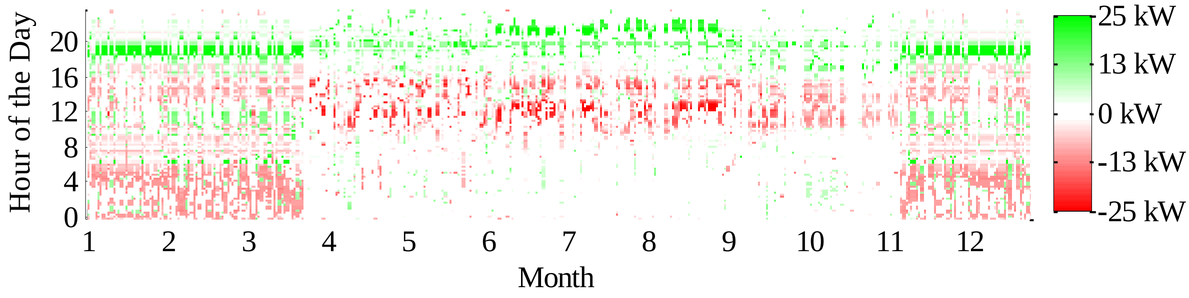

Figure 6.28: Charge / discharge flows of the storage device

The resulting state of charge is shown in Figure 6.29. During the period with low sun intensity, the storage device would be typically fully charged during the night in order to satisfy peak electric demand of the following evening. During the day, the storage device remains idle fully charged. When sufficient solar generation is available, typically the storage device will only be charged during the afternoon in order to cover peak demand during the evening hours. Hence, for most of the day, it remains at a discharged state.

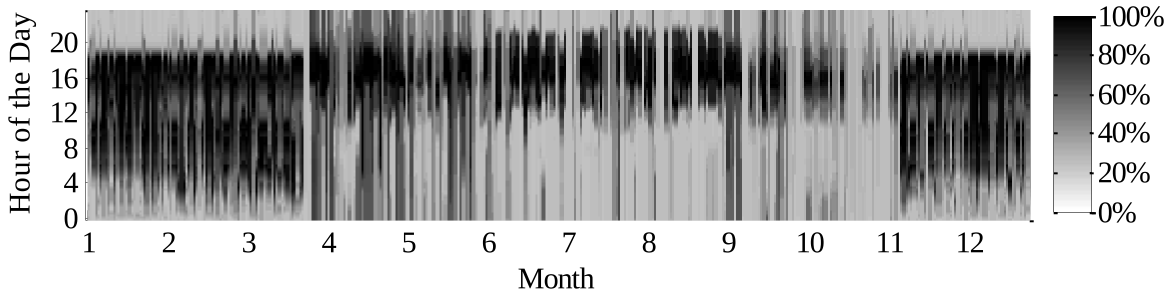

Figure 6.29: State of charge of the electric storage device

The associated duration curve of the electric storage device is shown in Figure 6.30. With 582 hours, the storage device spent a significant portion of the time completely discharged. Contrary, only during 80 hours, it was fully charged. For more than 2 000 hours, the state of charged reached at least 80%.

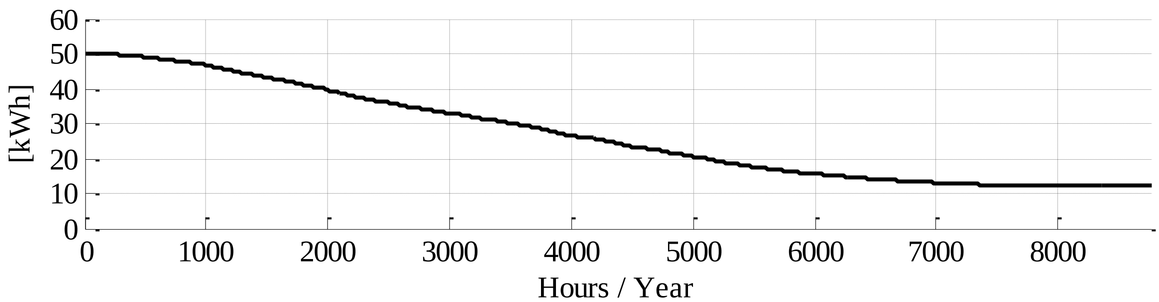

Figure 6.30: Duration curve of the electric storage device

The resulting exchange with the grid is shown in Figure 6.31. During periods with high heat demand, almost all electric demand is satisfied by the cogeneration unit and energy is only taken from the grid to satisfy peak demand during the evenings. During the summer period, when the electric demand is mostly satisfied from the intermittent photovoltaic system and heat demand is low, energy is taken from the grid more frequently. However, again, most of the import is during the evening hours.

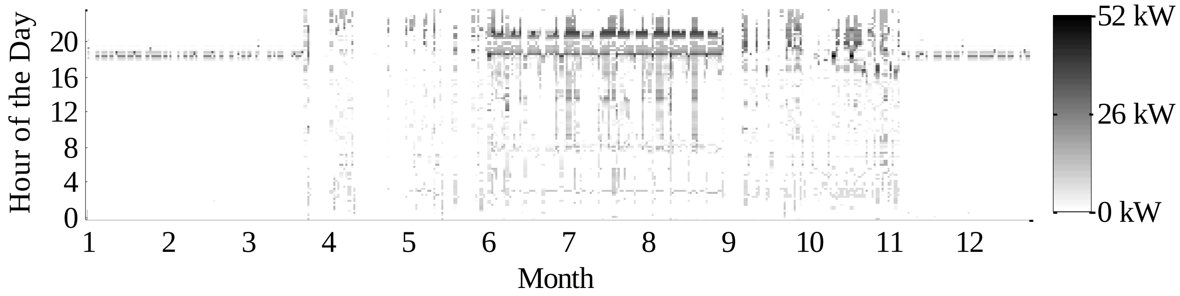

Figure 6.31: Energy taken from the grid

Last in this analysis, Figure 6.32 shows the feed-in of energy from the photovoltaic system, amounting to 11 951 kWh in total. Most of the feed-in occurs during the spring, when the photovoltaic system already generates significant yields but heat demand is still high. In that case, the cogeneration unit will be dispatched frequently. The simultaneous generated power from the cogeneration unit is preferentially consumed locally, as it is more beneficial to feed-in PV generated power under the assumed tariff structure. The feed-in from the cogeneration unit amounted to only 969 kWh and is therefore not considered.

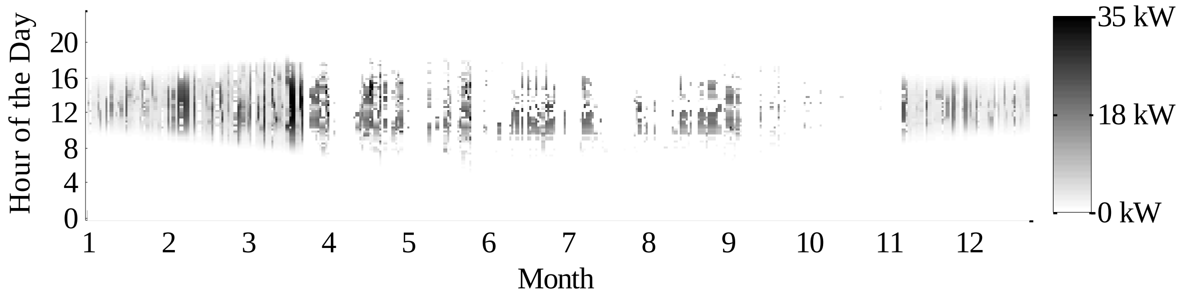

Figure 6.32: Feed-in of energy from the photovoltaic system

6.1.5 Analysis

Based on the above results, this section will provide some additional insights into the economics and usage of storage for time shifting:

- So far, the dispatch was based on a mixed integer program, which implicitly assumes perfect foresight of future generation and demand. In order to determine the value of having perfect foresight, the obtained results will be compared to the results from the operation schedule presented in Section 3.3.3, which operates on only presently available information.
- Dispatching electrical storage for time shifting strongly influences the electricity demand seen by the grid. A comparison to the optimal configuration will highlight the impact.
- A subsidy program for the installation of storage with photovoltaic systems is available in Germany. A short analysis will determine whether its benefits outweigh the associated restrictions and limitations.
- The benefit of different tariff structures in combination with a storage device is analysed.
- To get a better understanding for the major value drivers of storage, a sensitivity analysis will be conducted.

- Furthermore, a scenario analysis will be conducted to understand the economics of the analysed system configurations in different framework evolutions.
- Last, the decision making concept presented in 4.7.1 is applied to the results from the scenario analysis.

Perfect Foresight

In order to determine the value of perfect foresight, the dispatch of the mixed integer program will be compared to the dispatch from the simple operation schedule presented in Section 3.3.3. The first has perfect knowledge about the future, and hence will operate all system components in such a way that the cost is minimized. Contrary, the second is driven by heat demand and operates on several simple 'if-then' rules, with no knowledge about the future.

For the comparison, the same optimal system configuration with an electric storage device as previously will be assumed. However, as the ordinary operation schedule has no knowledge about future demand, there would be frequent periods with insufficient heat supply due to depleted thermal storage and insufficient CHP capacity. Therefore, an additional gas boiler with a capacity of 90 kW is required, which results in an additional investment requirement of 8 500 EUR. As a consequence, the annual depreciation cost increases by 567 EUR.

Figure 6.33 shows the resulting energy flows of the heat system. While the addition of the gas boiler was required to ensure that peak heat demand is matched, total heat output of it amounts to only about 1 MWh. Total heat generation from the cogeneration unit also increases by about 10 MWh, which is lost from self-discharges by the more frequently used thermal storage device.

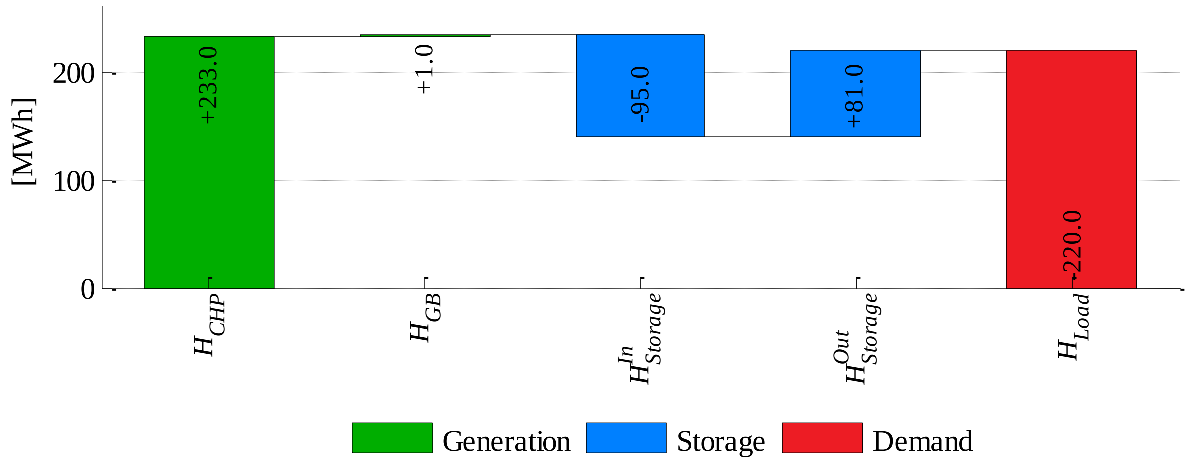

Figure 6.33: Energy flows of the heat system

While the heat flows still look comparable to the previous optimal dispatch, power flows (shown in Figure 6.34) look very different. The power generation increases slightly in line with the heat generation from the photovoltaic unit, photovoltaic generation remains identical. However, energy taken from the grid increases significantly, from about 15 MWh to 34 MWh. Energy fed into the grid from the photovoltaic system doubles, whereas cogeneration feed-in increases from about 1 MWh to 11 MWh. Usage of the electric storage device also increases significantly, from 342 cycles to 501 cycles.

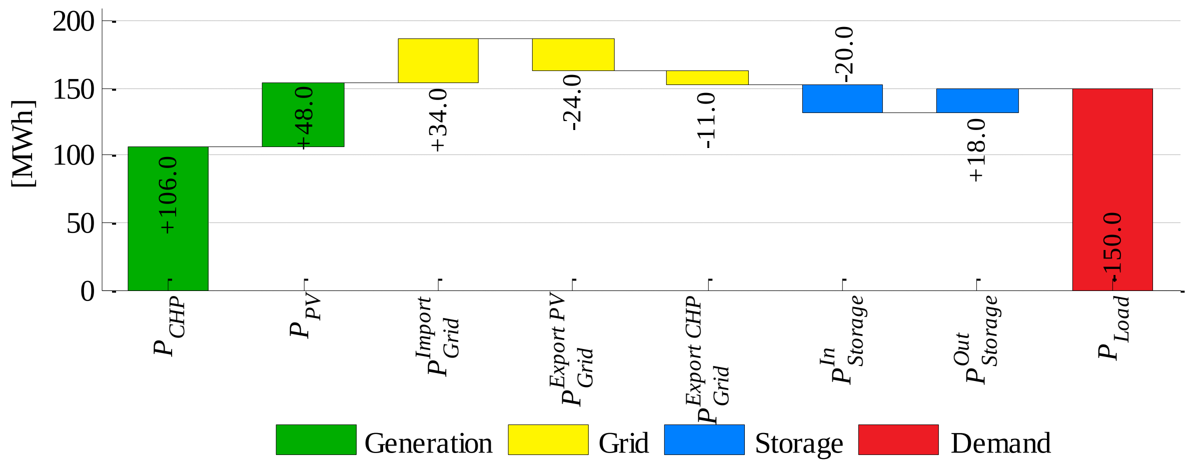

Figure 6.34: Energy flows of the power system

The net present value for the operation of one year without perfect foresight is -35 753 EUR. Compared to the case with optimal foresight (NPV of -30 391 EUR), the value of optimal foresight is hence 5 362 EUR.

Figure 6.35 shows the difference in cost between the two dispatches. The major reason for the strong decline in NPV is the increase of the energy taken from the grid. Furthermore, the strong increase in the usage of the electric storage device increase the depreciation charges, as the expected lifetime is significantly reduced due to its cycle limitation. Furthermore, the variable cost of the cogeneration unit increased due to its higher output. In addition, the fixed and depreciation charges of the gas burner further worsen the result. Contrary, the higher feed-in of power from the photovoltaic system and the cogeneration unit contribute positively. In addition, the benefit payments for the cogeneration unit also increase due to the higher amount of energy fed-in.

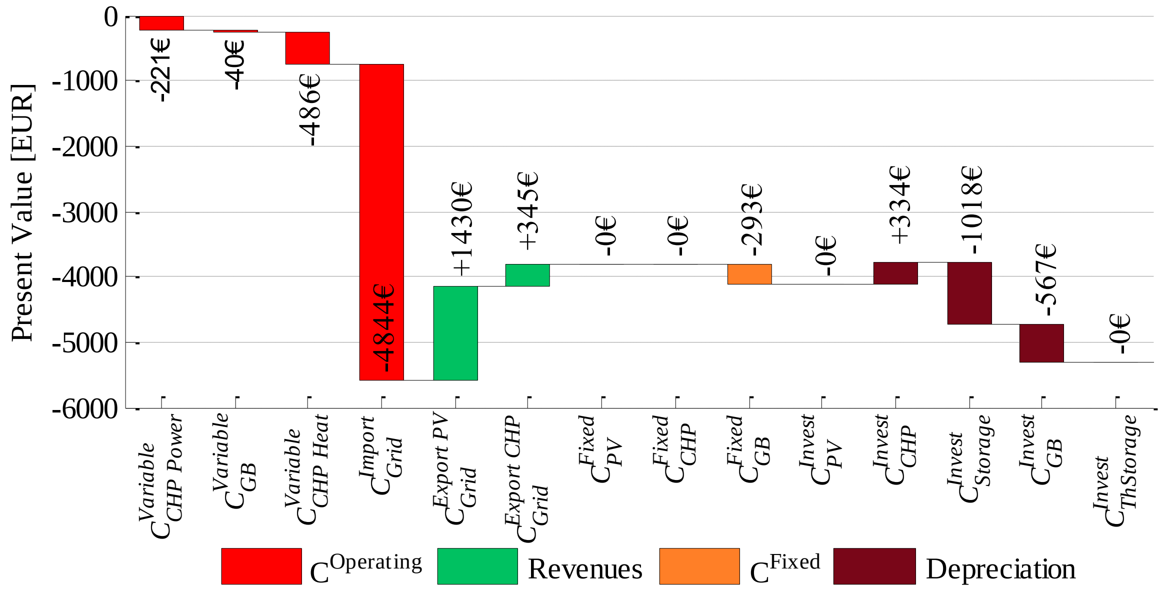

Figure 6.35: Breakdown of changes in value without perfect foresight

Exchange with the Grid

This section looks at the impact of utilizing local generation resources and storage on the power exchange with the grid. This has wide-reaching consequences for a range of stakeholders beyond the financial implications for the owner.

Figure 6.36 compares the power exchange with the grid under the different system configurations. Under the reference case, all energy is taken from the grid. With local generation resources present, the annual consumption is reduced to less than 25 MWh. If the consumer also utilizes a storage device, demand further drops to 15 MWh. With local generation resources present, the grid is as much utilized for feed-in of energy as it is for consumption. Even under the ordinary dispatch, which does not utilize future information, energy taken from the grid is significantly reduced.

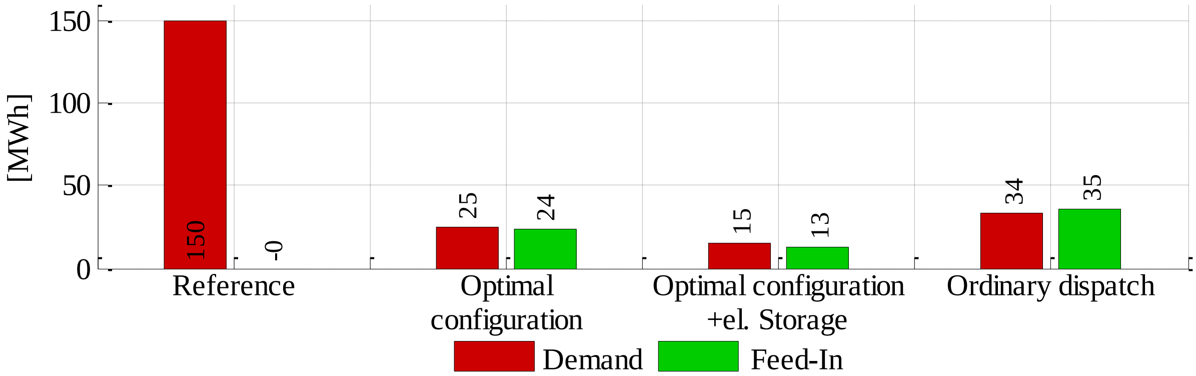

Figure 6.36: Power exchange with the grid

In Figure 6.37, the distribution of power flows under the different implementations is compared. While the amount of energy taken from the grid is reduced by up to 90%, the peak demand is only slightly reduced across the different system configurations. The capacity for feed-in is in line with the required demand capacity.

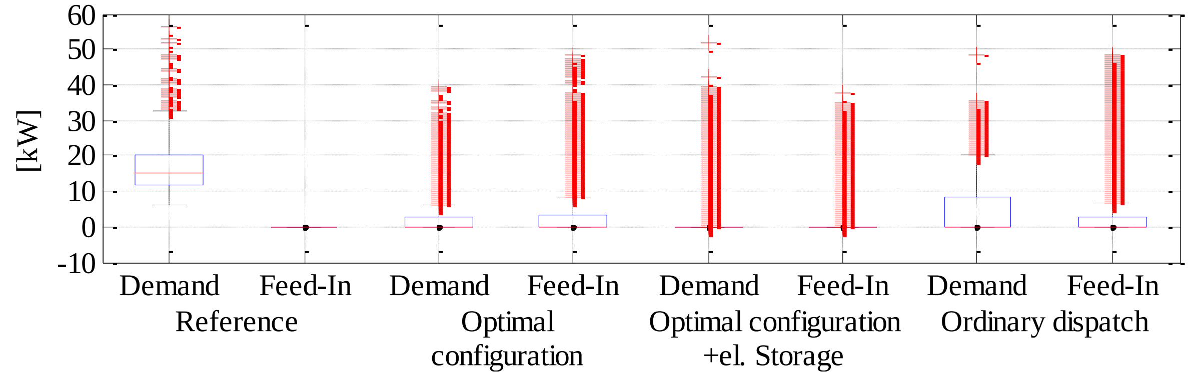

Figure 6.37: Distribution of electricity demand and feed-in

As shown for example in Figure 6.28, the dispatch of the storage device underlies strong seasonal influence due to the heat-related generation of the cogeneration unit and the intermittent photovoltaic generation. In the following, therefore, the impact will be analyzed once for the case with high contribution from the cogeneration unit and once with high photovoltaic generation. Therefore, the months of January and July were considered in Figure 6.38 and Figure 6.39.

The first row in Figure 6.38 shows the average daily load seen by the grid for the month of January. With local generation resources present – in this case mainly the generation from the cogeneration unit – the demand seen by the grid is reduced to zero during the night. During the day, very little energy is taken from the grid in the morning with the main peak during the evening hours, even though at reduced levels as compared to the reference case. With a storage device present, the demand during the morning hours is reduced to zero. While the capacity of the storage device is not sufficient to completely eliminate the demand during the evening, its amount and level is also significantly reduced. Under the ordinary dispatch, the local generation resources and the storage device are not as efficiently dispatched as shown previously. Nonetheless, demand levels from the grid are down to about the same level as under the optimal configuration.

The change in energy demand of the respective system configuration versus the reference case is shown in the second row. Under the optimal configuration, a downward shift of up to 20.9 kW (the capacity of the cogeneration unit) can be identified. With the presence of the storage device and sufficient energy available, a further reduction by up to 25 kW (power capacity of the storage device) can be observed. The later effect is also clearly visible in row three, which compares the energy exchange under the presence of a storage device to the optimal dispatch without storage.

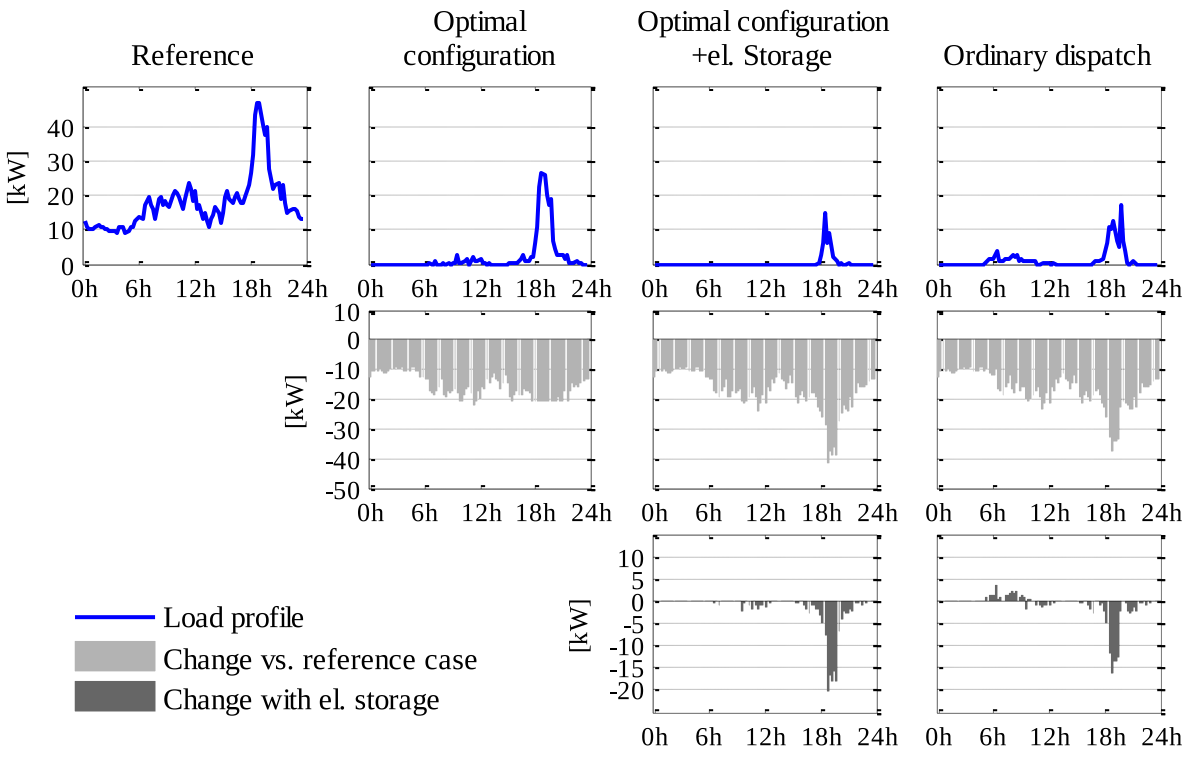

Figure 6.38: Change in demand seen by the grid during winter

Figure 6.39 is structured in an analogous way to Figure 6.38. Contrary to the winter month, however, electricity demand seen by the grid during the summer is generally more elevated as there is less demand for heat and hence the cogeneration unit is dispatched less frequently. While the generation from the photovoltaic system significantly reduces demand during the day, its contribution during the evening and nighttime is zero. The overall reduction in demand versus the reference case – as shown in the second row – is therefore less pronounced than in the winter.

The addition of the storage device reduces demand seen by the grid during the night. However, demand during the evening hours increases versus the optimal dispatch without storage, as the cogeneration unit is preferentially run during the night. Thereby, losses from the self-discharge of the thermal storage device are minimized, making it the most cost-effective dispatch.

Contrary to the first case, where the ordinary dispatch was similar to the optimal dispatch from the mixed integer program, significant differences in the energy exchange with the grid can be observed during the summer month. Under the ordinary dispatch, both storage as well as cogeneration unit are providing energy during the evening, reducing the demand from the grid to zero. However, power demand from the grid during the night is almost identical to the reference case as the fully charged thermal storage device from the previous evening is discharged to satisfy any heat demand during the night.

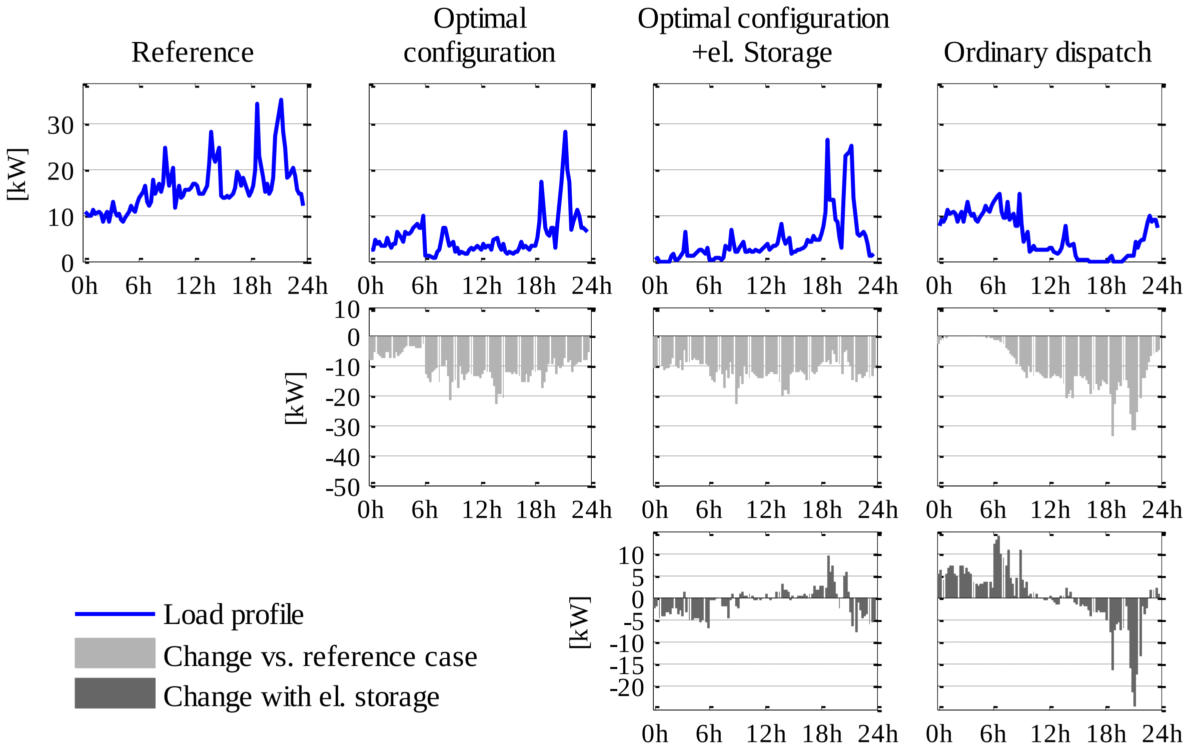

Figure 6.39: Change in demand seen by the grid during summer

German Subsidy Program

As already mentioned in the literature review (see Section 2.3.10), the German development bank *Kreditanstalt für Wiederaufbau* offers a subsidy program for combined photovoltaic and storage installations. Under the program, the applicant does not only receive access to cheap financing, but also a grant for the storage system. The amount of the grant depends on the date of the application and is decreasing over time. In this case, it is assumed that the grant covers 20% of the storage investment cost $C_{Storage}^{Invest}$. While in reality the program is targeted towards single family houses and the capacity of the associated photovoltaic system cannot exceed 30 kW, this constraint is not considered in this case, as the general benefit will be analyzed.

One of the major requirements, which directly influences the operation of the installed system, is the reduction of the photovoltaic feed-in limit to 50% of the installed capacity. Usually, photovoltaic systems can feed-in up to 70% of their installed capacity. All other requirements do not directly impact operations or the storage dispatch and are therefore not further considered.

Figure 6.40 shows the generation from the photovoltaic system as well as the resulting feed-in from the optimal dispatch under the presence of a storage device. Furthermore, the 70% limit is shown as well. Apparently, the storage device was dispatched in such a way that it absorbs any power which would otherwise violate the limitation. Hence, no power was lost. When considering the grant, the feed-in limit would be lowered to 50%. Under the current dispatch, this would amount to 214 kWh, which could not be fed-in. Hence, accepting the grant and implementing the 50% regulation without altering the dispatch would result only in 25 EUR of lost revenues.

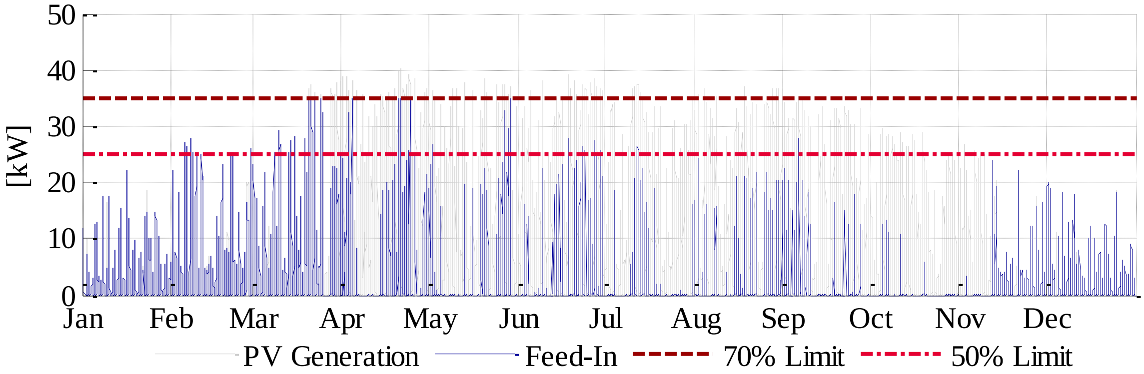

Figure 6.40: PV generation and feed-in under the optimal dispatch with a storage device

Re-dispatching the storage device however shows, that the limit of 50% can be incorporated without losing energy and minimal consequences for the further dispatch. The resulting feed-in is shown in Figure 6.41.

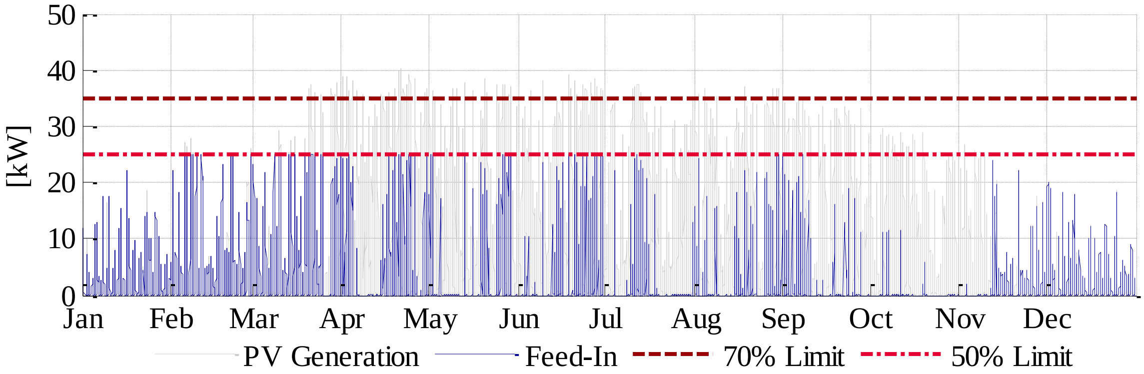

Figure 6.41: PV generation and feed-in considering the 50% limitation

After demonstrating that the technical requirements can be incorporated without losing energy, the primary concern is the financial evaluation. Considering the grant of 20%, the investment cost of the storage device decreases from 32 000 EUR to 25 600 EUR. Taking the slightly changed dispatch into account, the NPV improves by 418 EUR to -29 973 EUR. Therefore, while the grant is still not sufficient to make storage financially viable, it reduces the value gap to only 173 EUR regarding the NPV that was obtained for the optimal configuration (-29 800 EUR).

Tariff Structures

Besides the so far implemented flat tariff $R^{Import}_{flat}(t)$, in Section 6.1.1 two additional electricity tariffs were discussed: a time of use tariff $R^{Import}_{TOU}(t)$ as well as a real-time pricing tariff $R^{Import}_{RTP}(t)$. In the following, their benefit will be analyzed.

Table 6.16 compares the cost for the energy taken from the grid for the different system configurations / dispatches. Therefore, for each configuration and tariffs scheme, the optimal dispatch was determined. The real-time pricing tariff therefore appears attractive in all cases. Contrary, the dual tariff is only beneficial versus the flat tariff in those cases in which a storage device is present. While the potential savings are significant for the reference case, the benefit is comparatively small when looking at the more complex system configurations due to the lower amount of energy taken from the grid.

	Reference case	Optimal configuration	Optimal configuration + el. storage	Ordinary dispatch
$R_{flat}^{Import}(t)$	-39 532 EUR	-6 538 EUR	-3 980 EUR	-4 029 EUR
$R_{TOU}^{Import}(t)$	-41 029 EUR	-6 568 EUR	-3 818 EUR	-3 831 EUR
$R_{RTP}^{Import}(t)$	-36 547 EUR	-6 004 EUR	-3 565 EUR	-3 577 EUR

Table 6.16: Cost for electricity import under different tariff schemes

When looking at the resulting net present value (Table 6.17), the savings in electricity cost under the dual tariff are at the cost of an otherwise more expensive dispatch. Therefore, the dual tariff is more expensive in every case. Contrary, the real-time tariff enables savings under every configuration.

	Reference case	Optimal configuration	Optimal configuration + el. storage	Ordinary dispatch
$R_{flat}^{Import}(t)$	-51 506 EUR	-29 800 EUR	-30 391 EUR	-31 232 EUR
$R_{TOU}^{Import}(t)$	-53 004 EUR	-29 822 EUR	-30 589 EUR	-31 434 EUR
$R_{RTP}^{Import}(t)$	-48 521 EUR	-29 255 EUR	-30 134 EUR	-30 893 EUR

Table 6.17: Net present value under different tariff schemes

Hence, under the taken assumptions, in no case it is beneficial to adopt the dual tariff which offered a reduced consumption rate during the night at the cost of a slightly increased rate during the day. The real-time pricing appears attractive, however the assumed tariff is hypothetical and currently not available in reality. Overall, the impact of different tariff schemes on the business case of time shifting appears limited as overall it is more beneficial to reduce grid electricity demand than to shift it to other, relatively cheaper periods.

Sensitivity Analysis

As a last step, a sensitivity analysis - based on the approach described in Section 4.3 - is conducted in order to establish the extent of the impact of several parameters.

Figure 6.42 shows the change in net present value when a single parameter is changed and the new optimum dispatch is determined. The steeper the slope of a line, the more impact the parameter has on the economic result. While some parameters have a linear relationship with the net present value, for other parameters the relationship is more complex.

The following parameters have been considered:

- Investment cost of the storage device $C_{Storage}^{Invest}$. While the analysis of the German subsidy program has shown that a grant of 20% is not sufficient to make storage economic viable, the sensitivity analysis shows that cost reductions of about 25% would be sufficient to bring the NPV to the same level as the optimal system configuration without a storage device.
- The capacity $E_{Storage}^{Capacity}$ of the storage device. As storage is currently not economic viable, a reduction would consequently increase the overall net present value. However, interestingly, small reductions in capacity would actually decrease the overall value, as the cost function of the storage device is not linear.

- The ability of the cogeneration unit to modulate its output ($P_{CHP}^{CapacityMin}$). While a lower minimum output (hence, a more flexible cogeneration unit) only marginally increases the NPV, an increase in the minimum output level by more than 50% (hence, a cogeneration unit with a minimum power output of more than 60% of rated power) would reduce the value significantly.
- Power rating ($P_{Storage}^{Capacity}$) of the storage device. The analysis shows that as long as the rating is not reduced to very low levels, the impact on the value is insignificant.
- Due to the low feed-in of CHP-generated power, the associated feed-in tariff R_{CHP}^{Export} is more or less irrelevant for the financial evaluation.
- Contrary, higher feed-in tariffs for power generated by the photovoltaic system (R_{PV}^{Export}) would increase the profitability. However, the relation is linear for the analyzed range as even under a 100% increase, it is still more beneficial to consume PV generation locally. Hence, the amount of feed-in energy would not increase, only its remuneration.
- Last, increasing electricity cost from rising tariffs (R_{flat}^{Import}) would reduce the net present value in a linear fashion, as already under current prices electricity import was minimized as far as possible.

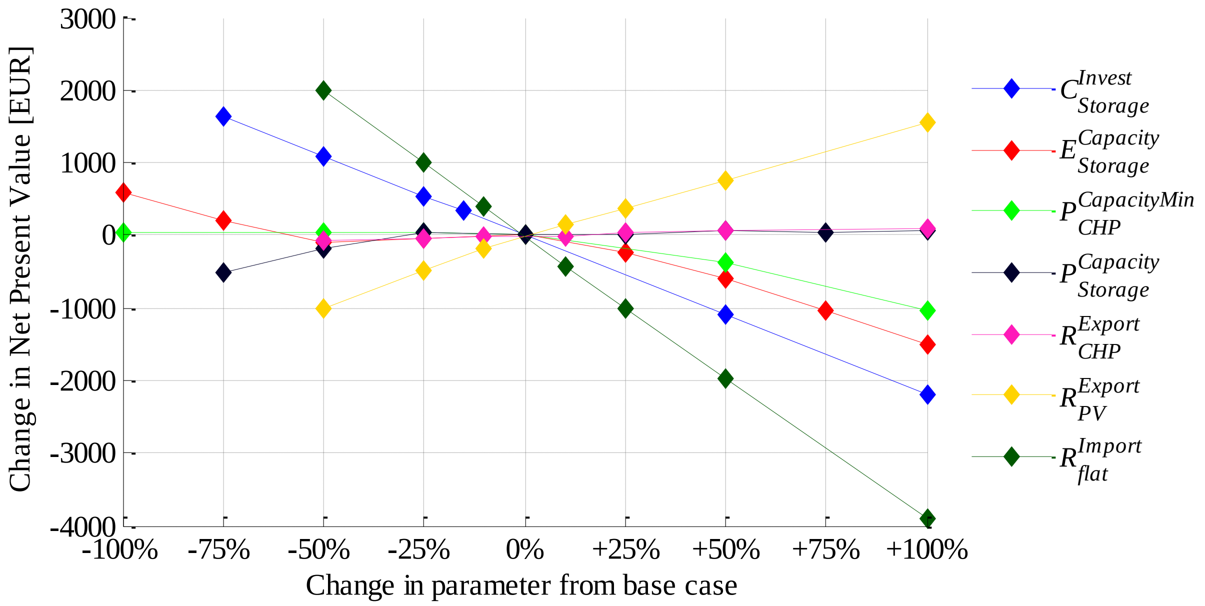

Figure 6.42: Sensitivity plot of the optimal system configuration with energy storage

Scenario Analysis

Based on the concept presented in Section 4.4, the three discussed system configurations will be evaluated under the discussed scenarios (Section 4.4.2) to understand their economics in a wide array of potential future worlds. As the business case is not affected by wholesale prices, price volatility and compensation for ancillary services, only consumption and feed-in tariffs will be considered.

Table 6.18 shows the assumed evolution under the presented scenarios.

	Consumption tariff	Feed-in tariffs
Baseline	-	-20%
Scenario 1: strong increase in distributed generation	+35%	-50%
Scenario 2: strong increase in renewable generation	+25%	+20%
Scenario 3: return to old paradigm	-	-80%
Scenario 4: increased demand from electric vehicles	-10%	-25%

Table 6.18: Comparison of assumed parameters under the different scenarios

For every system configuration and each scenario, the optimum dispatch was determined. Figure 6.43 shows the resulting net present values. The reference system configuration is the least preferential in every case. The installation of a storage device is economic preferential only if consumption tariffs increase significantly, accompanied by a substantial decrease in feed-in tariffs (Scenario 1). In all other cases, the installation of the optimum system configuration would have been the best choice.

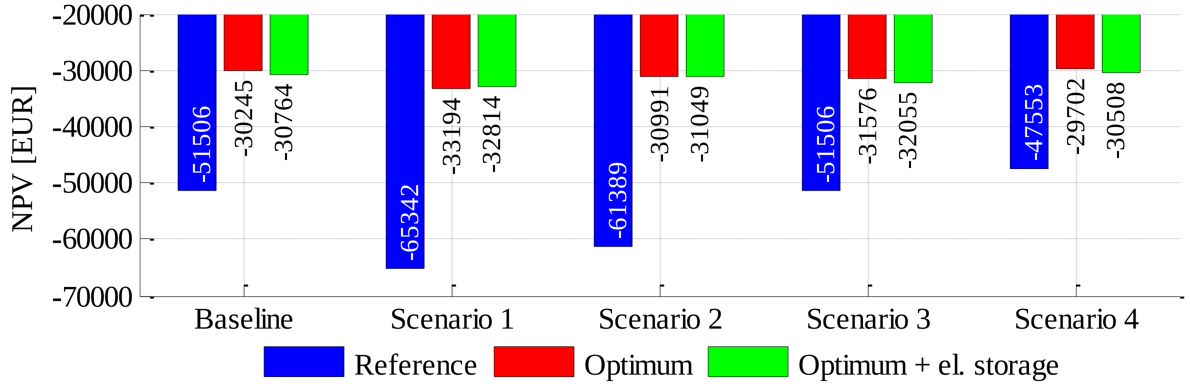

Figure 6.43: Net present value of the three system configurations under different scenarios

A more complete analysis would not only consider an intermediary or final state of a parameter, but also their evolution over time. However, this would require a more complete definition of the scenarios. In addition, this would raise again previously discussed issues such as the requirement of sufficient simulation data as well as the handling of differing lifetimes of system components.

Decision Making

Last, the decision making approach described in 4.7.1 will be applied to the results from the previous Section. Table 6.19 compares the expected NPV as well as the variability of outcomes across the three analyzed system configurations. Accordingly, the optimum system configuration shows also under the assumed scenarios the best expected outcome. However, the results are further spread apart as indicated by the standard deviation as compared to a system with a storage device, which shows overall a slightly worse expected outcome but lower variability of results.

	$\overline{NPV}$	σ
Reference case	-55 460	7 527
Optimal configuration	-31 142	1 351
Optimal configuration + el. storage	-31 438	967

Table 6.19: Expected NPV and result variability of the three system configurations

Following, the ideal system configuration according to the decision maker’s preference towards profitability, losses and risk can be selected. Table 6.20 shows the ranking of the alternative for all four discussed investment criterion (Section 4.7.1). If the primary objective of the decision maker is the maximization of profits, he should install the optimum system configuration. However, if the decision maker is more concerned about his potential loss, minimizing his regret or avoiding variability, the recommended alternative is to install a storage device as well.

	Reference case	**Optimal configuration**	**Optimal configuration + el. storage**
Maximization of the expected result	(3)	(1)	(2)
Minimization of potential losses	(3)	(2)	(1)
Minimization of regret felt by the decision maker	(3)	(2)	(1)
Avoiding variability	(3)	(2)	(1)

Table 6.20: Ranking of alternatives depending on the decision making objectives

Hence, while storage cannot yet compete on a cost basis, it offers additional benefits such as a lower variability of outcomes. However, these advantages are only taken into account when uncertainty is considered in the evaluation process.

6.1.6 Conclusion

In this case study, the value of storage for time shifting of energy in a consumer context (a multi-family house located in Germany) has been analysed. Therefore, a synthetic time-series for electric and heat demand as well as historical series for temperature and solar radiation with a spatial resolution of 15-minutes were considered. In order to determine the system configuration which maximizes NPV, a simulated annealing search process was designed and implemented. To identify the optimum dispatch for each tried configuration, a mixed integer program was employed. All values were simulated and considered in the financial evaluation for one year to negotiate the problem of differing lifetimes of the various system components.

If all heat demand is satisfied from a traditional gas boiler and all electric energy is taken from the grid, annual cost amount to 51 506 EUR. The cost minimizing solution is to invest in the maximum PV capacity, that can be fitted on the available space, and a cogeneration unit. In addition, in order to cover peak heat demand and to avoid the installation of a gas boiler, a thermal storage device should be installed. Besides matching peak heat demand, the thermal storage also helps to run the cogeneration unit during those times when electricity is required but heat demand is low. By means of the PV system, the cogeneration unit and the thermal storage, the annual cost (including depreciation charges) can be reduced to only 29 800 EUR. Adding an electric storage device to the system increases total cost including depreciation charges to 30 391 EUR. While the storage system was found to be beneficial as electricity imports could be further reduced, the associated cost from the depreciation still outweigh the value added. Solar-thermal systems as well as heat pumps were excluded by the search routine, as they did not add value.

Breaking the overall cost down and comparing their contribution across the three different settings shows that the cost associated with the provision of heat can only be reduced marginally. Contrary, significant savings are available by reducing the amount of energy taken from the electric grid and generating the major part of the electric consumption locally. The required photovoltaic system and the cogeneration unit however require high initial investments. A calendric break-down shows that the dispatch of the electric storage varies significantly along the year, depending on the availability of intermittent solar generation and the heat demand. Furthermore, especially during the summer time, there is a high number of hours when the storage device remains idle. Hence, for a real implementation, a sophisticated control strategy considering both local heat and power balance is required.

In the following analysis it was found that the difference in value between a simple, heat-demand driven strategy and a dispatch based on perfect foresight is 5 362 EUR. While integrating local generation resources reduces the energy taken from the grid substantially, the required grid connection capacity remains more or less unchanged as consumers still rely on the grid to cover demand during times with little local generation as well as to feed-in excess generation. An analysis of the impact of different tariff schemes showed, that a real-time pricing scheme could be beneficial to consumers. However, overall it was found to be more valuable to focus on reducing grid demand. A sensitivity analysis showed – among others – that cost reduction of about 25% are required to bring storage devices to the break-even point, slightly more than offered by a German subsidy program. Last, a scenario analysis and the presented decision making process were applied, highlighting that storage can be beneficial already today when considering uncertainty.

The key findings of this case study can be summarized as follows:

First, there is a significant potential for residential consumers to lower their energy cost by investing in more sophisticated energy system with local electricity generation from cogeneration units and photovoltaic systems. However, determining the value maximizing system configuration is not a trivial task and requires detailed knowledge about consumption patterns.

Second, storage systems can add value by further aligning electric local generation and demand. However, they require additional price reductions of about 25% to become economic viable. Furthermore, a sophisticated control strategy is required to determine the optimal dispatch. Taking additional considerations (such as uncertainty about future price developments) into account, storage can already be economic attractive at today's price level.

Third, most of the cost savings result from a reduced electricity grid demand. However, not only is this a threat to electricity generators due to the reduced demand, but also to public funds due to significantly reduced tax and fee income. Furthermore, as the required connection capacity and hence the infrastructure cost remain almost unchanged, charged fees might not be sufficient to cover cost. Policy makers as well as regulators will therefore have to take proactive steps to safeguard the financial framework of the future electric system.

6.2 Arbitrage of Electricity Prices

Based on the results from Section 3.4, an implementation of a storage system for pursuing arbitrage is discussed in this case study. The storage system is assumed to participate in the German spot market auction for electricity. This case study intends to clarify if there is sufficient revenue potential to justify a storage investment for pursuing arbitrage.

6.2.1 Data and Assumptions

Market Prices

Electricity is commonly traded in the day-ahead auction. A review about the operation of the auction for the German spot market is given in the literature review (Section 2.2.2). For this case study, historical data from the years 2011-2015 [189] for the hourly day-ahead contract will be considered. In addition, by the end of 2014, 15-minute contracts have been introduced, which will be considered for the year 2015.

Figure 6.44 displays the development of market prices for the 1-hour contract over the last five years. Accordingly, most prices are within a narrow range of values. However, significant deviations occur to both up- and downside at times.

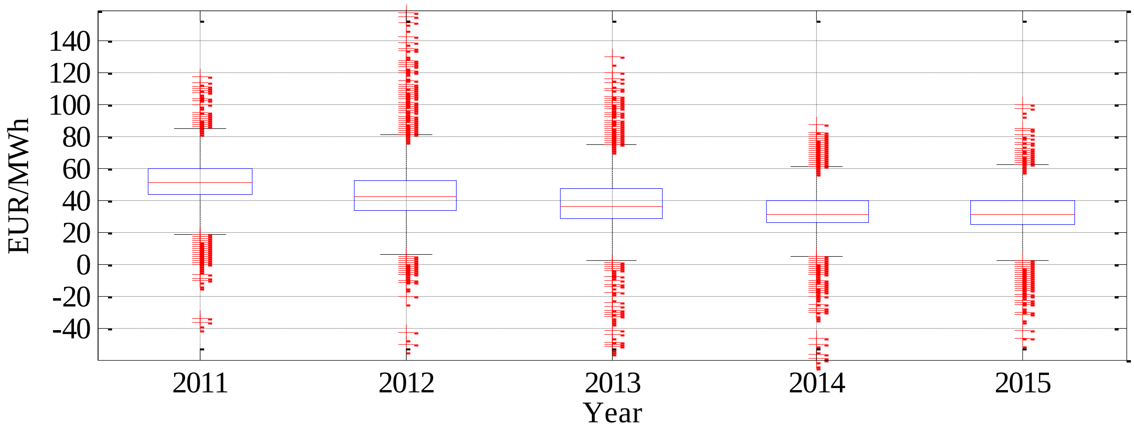

Figure 6.44: Boxplot of historical prices for the 1-hour day-ahead auction

The average price level has significantly decreased over the last five years, from 51.12 EUR / MWh in 2011 down to 31.63 EUR / MWh in 2015 (see Table 6.21). At the same time, volatility (measured as the standard deviation of prices) remained almost constant. Simultaneos with the decrease in prices, also the average daily maximum price as well as the average daily minimum price have decreased.

The number of hours with negative prices has slightly increased over the years, from 15 hours in 2011 up to 126 hours in 2015. The lowest traded price over the five years was -221.99 EUR / MWh (25 Dec 2012 at 02:00), and the highest traded price was 210.00 EUR / MWh (08 Feb 2012 18:00).

Looking at the price history of 15-minute contracts, a much higher spread between the average daily minimum and maximum price is obvious. In addition, significant more periods with negative prices occurred.

Year	**2011**	**2012**	**2013**	**2014**	**2015**	**2015**
Contract	1 h	1 h	1 h	1 h	1 h	15 min
Mean price	51.12	42.60	37.78	32.76	31.63	31.66
Standard deviation	13.60	18.69	16.46	12.78	12.67	14.94
Ø daily minimum price	32.86	24.01	20.30	18.80	18.10	3.86
Ø daily maximum price	67.92	63.16	58.61	48.83	47.32	59.83
Periods with negative prices	15 h	56 h	64 h	64 h	126 h	737 (184 h)

Table 6.21: Market price statistics (year 2011-2015)

Figure 6.45 shows the spread between daily minimum and maximum prices for the 1-hour auctions over the years 2011-2015. On average, the spread was 34.36 EUR with a standard deviation of 16.72. Despite declining average prices, the distribution of the spread between daily minimun and maximum price shows a very similar pattern across the individual years with only a slight reduction in price ranges.

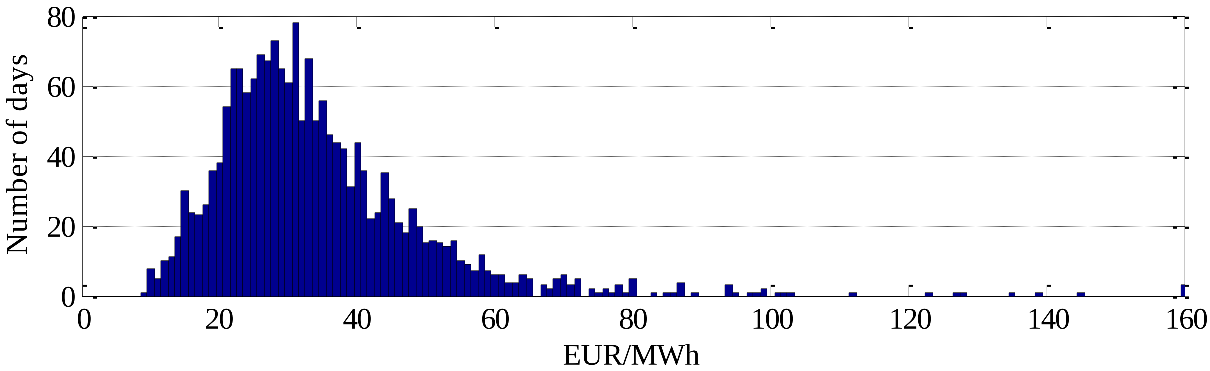

Figure 6.45: Difference between daily minimum and maximum price for 1-hour contracts (2011-2015)

Looking at the recently introduced 15-minute contracts, the distribution of price spreads is significantly shifted to the right (see Figure 6.46), reflecting a higher volatility of prices and hence more extreme minimum and maximum prices over the course of a day. Average daily spread was 55.98 EUR with a standard deviation of 34.46.

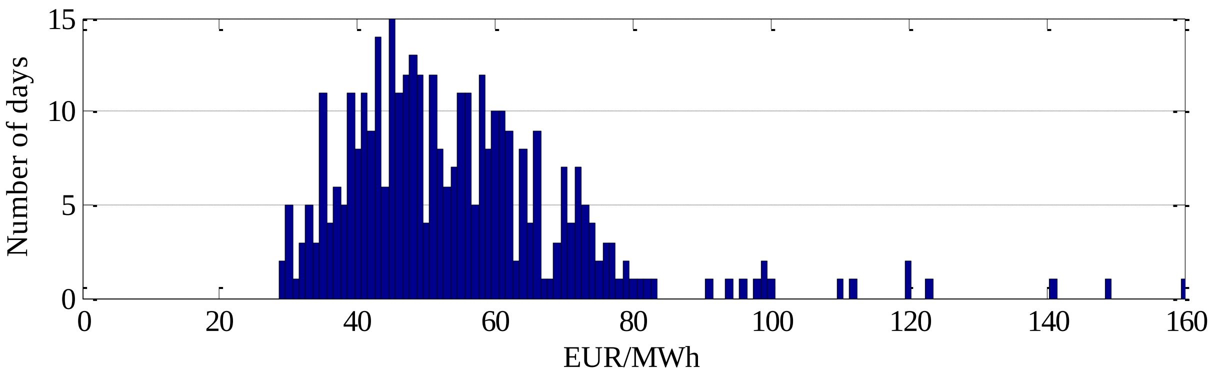

Figure 6.46: Difference between daily minimum and maximum price for 15-minute contracts (2015)

Arbitrage benefits from a wide price range, so that the storage system can be charged during periods with low prices and discharged during peak-price periods. Given the higher price variability, there is a strong case for pursuing arbitrage on the 15-minute contracts as compared to the hourly contracts.

Figure 6.47 provides an insight about the price evolution along the day and year. During the first hours of the day, prices are typically depressed. A first price peak occurs around 09:00, followed by slightly reduced prices during midday and the early afternoon. A second peak can be identified in the evening hours. In addition, a weekly cycle is visible. While the extent of price peaks has diminished from 2011 onwards, no change to the overall pattern is recognizable.

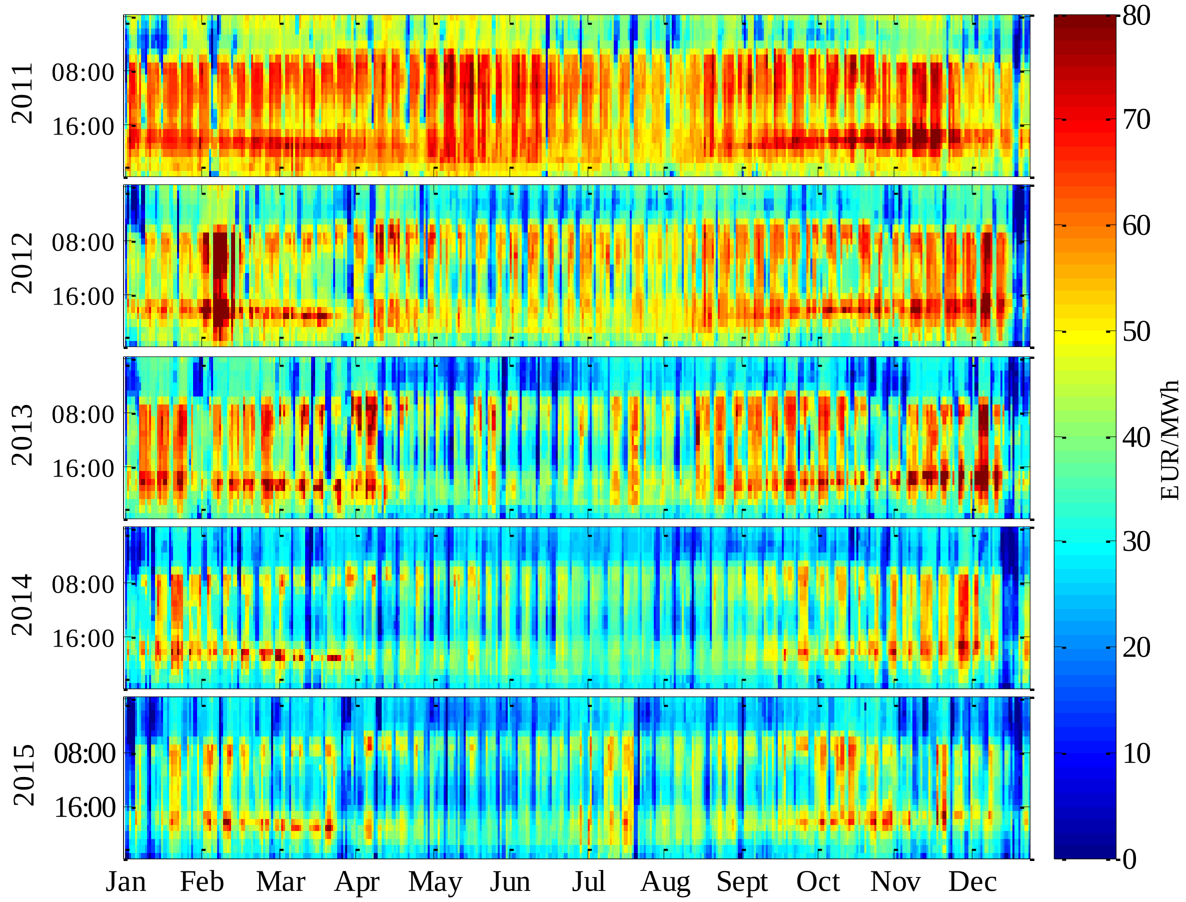

Figure 6.47: Market prices over five years for the day-ahead hourly auction

Figure 6.48 shows that the same pattern persists for the 15-minute contracts.

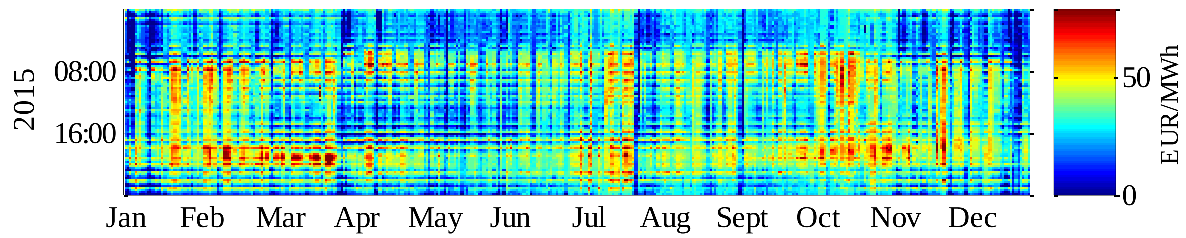

Figure 6.48: Historic market prices of the 15-minute day-ahead auction

The occurrence of the minimum and maximum prices along the day over the individual years has remained more or less unchanged. Figure 6.49 shows that the minimum price typically occurs during the night. Contrary, the maximum price of a day typically occurs either in the morning or in the evening hours.

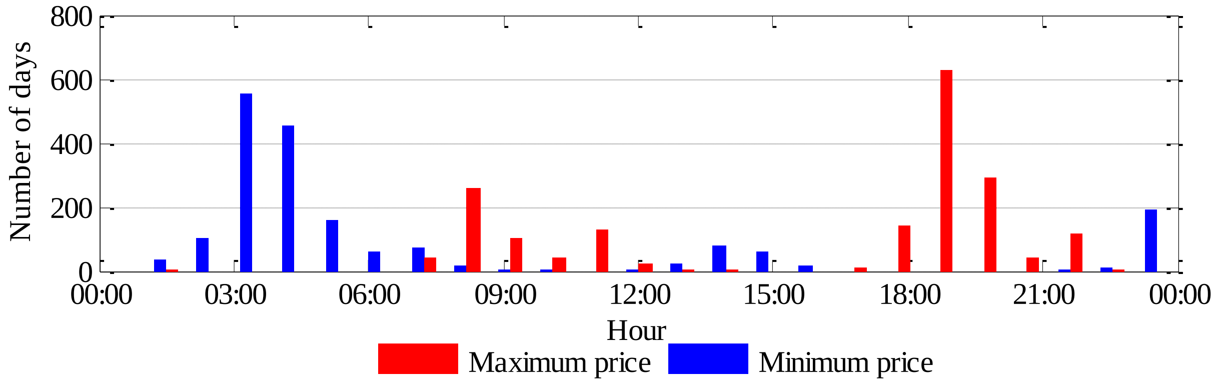

Figure 6.49: Occurrence of maximum / minimum price during a day (2011-2015)

Over the course of a day, it should therefore be possible to cycle a storage device at least once, by charging it during the night and discharging it during the following evening. Additionally, it might be possible to discharge the storage device already during the morning peak, charge it again during the afternoon hours and sell the energy in the evening.

Storage System

In the case study, two storage systems will be considered. First, a lithium-ion system will be implemented, which has a high power to energy rating and a high efficiency. Second, a vanadium redox flow battery with a lower efficiency and lower power rating will be considered. While the lithium-ion battery should be able to benefit more from short peaks in prices, the flow battery has a better life expectation and lower cost.

The lithium-ion system is assumed to have a power rating ($P_{Storage}^{Capacity}$) of 1 MW. The overall efficiency $\eta_{Storage}$ is assumed to be 90%, resulting in individual charge- and discharge efficiency of 94.87% each. The discharge should not exceed 80% of capacity ($\delta_{Storage} = 0.2$). The nominal storage capacity is chosen at 1.25 MWh ($E_{Storage}^{Capacity}$), allowing to charge the storage system with 1 MW for one hour, followed by a discharge of 0.9 MW for one hour without injuring technical limits. The expected cycle lifetime ($L_{Storage}^{Cycle}$) is assumed to be 4 500 cycles, the maximum calendric lifetime ($L_{Storage}^{Calendric}$) 15 years [114].

In their review of storage cost, Zakeri and Syri [114] determined the average cost for various storage systems. For lithium-ion systems, they found power related cost of 463 EUR / kW, and energy related cost of 795 EUR per kWh deliverable energy. Hence, for the above assumed installation the total cost would amount to about 1 250 000 EUR. This cost estimate is in line with a number of recent actual installations or current investment proposals (see Section 2.3.10). Annual fixed costs are assumed to be 10 000 EUR.

The flow battery is assumed to have the same effective energy capacity, but with only 250 kW ($P_{Storage}^{Capacity}$) a much lower power rating. As the battery can be completely discharged ($\delta_{Storage} = 0$), the effective capacity equals the nominal capacity ($E_{Storage}^{Capacity}$). The roundtrip efficiency is assumed to be 75%. Furthermore, the system is assumed to have a maximum lifetime of 13 000 cycles and 15 years [114] .

According to [114], power related costs are slightly higher than for lithium-ion systems with 490 EUR / kW. However, the energy related cost is significantly lower with only 467 EUR / kWh. Total cost for the installation are assumed to be 600 000 EUR. Analogous to the lithium-ion system, the fixed annual cost is assumed to be 10 000 EUR.

Parameter	Lithium-ion battery	Vanadium redox flow battery
$C_{Storage}^{Invest}$	*1 250 000 EUR*	*600 000 EUR*
$C_{Storage}^{Fixed}$	*10 000 EUR*	*10 000 EUR*
$E_{Storage}^{Capacity}$	*1.25 MWh*	*1.00 MWh*
$P_{Storage}^{Capacity}$	*1.00 MW*	*0.25 MW*
$\eta_{Storage}^{In}$	*94.87%*	*86.60%*
$\eta_{Storage}^{Out}$	*94.87%*	*86.60%*
$\delta_{Storage}$	*20%*	*0%*
$L^{Calendric}$	*15 a*	*15 a*
L^{Cycle}	*4 500*	*13 000*

Table 6.22: Parameters of the storage systems for pursuing arbitrage

The levelized cost of the storage systems (*LCOS*) amount to 277.78 EUR for the lithium-ion battery and to 46.15 EUR for the vanadium redox flow battery. Looking at the distribution of the daily price spreads (Figure 6.45 and Figure 6.46), it therefore appears unlikely that there will be sufficient opportunities for the lithium-ion system where the potential profit exceeds the attributable cost. The vanadium redox flow battery appears more promising, with daily spreads in the 15 minute market exceeding the levelized cost about every other day. However, this simple analysis neglects efficiency losses, which must be overcome by realized profits, as well as the fact that the considered spread referes to hourly / 15-minute intervals, whereas the batteries require 1 hour / 4 hours to be fully charged.

6.2.2 Model Implementation

Mixed Integer Programming

Even though the problem of finding the optimal dispatch for pursuing arbitrage is less complex than for time shifting of energy due to the lower number of variables and constraints, the required computational effort and especially the resulting memory requirement for the mixed integer program is still considerable (see Figure 3.4). Therefore, following the approach discussed under Section 6.1.2, the overall optimization problem is again broken into several smaller time windows, potentially overlapping each other.

The resulting improvement versus optimizing each day on its own is shown in Figure 6.50, rerunning the optimization on 12 month of historical data[6] with different optimization windows and different forecast periods. The improvements found were rather modest (up to 0.5%), much lower than in the case of time shifting of energy (see Section 6.1.2). Apparently, the majority of arbitrage profits is obtained within one day, and little benefits can be taken from forecasts beyond the 24 hours of a day. This observation becomes more pronounced the higher the power-to-energy ratio of the storage device is. Contrary, for lower power-to-energy ratios, the forecast period should be extended further into the future.

[6] 1st January 2014 – 31st December 2014 for the German Market. The power rating of the storage device was ¼ of its energy capacity, a hurdle rate was not considered for the dispatch.

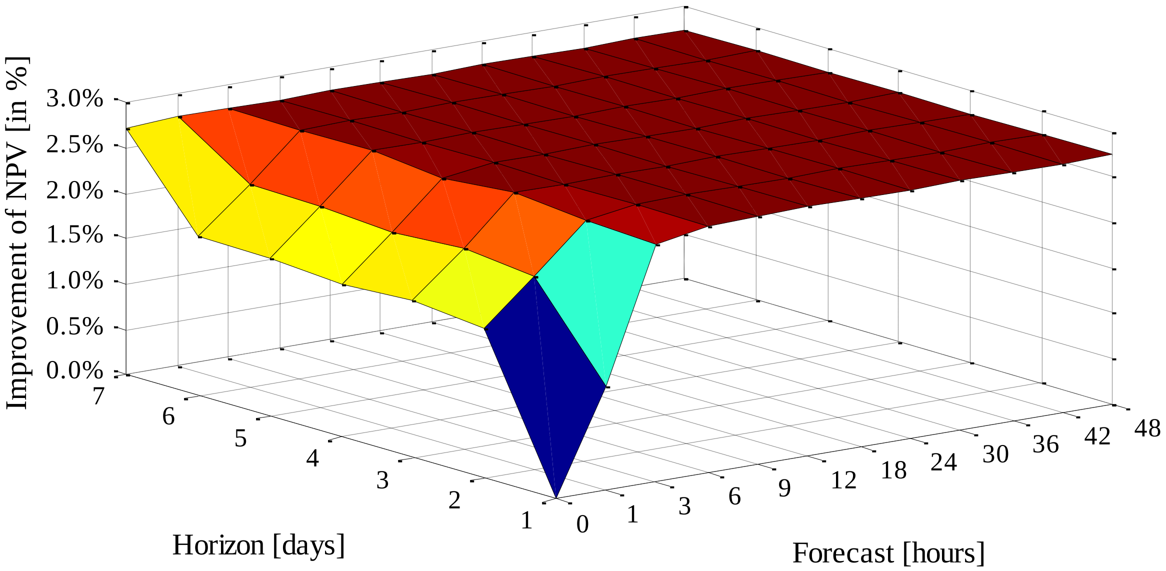

Figure 6.50: NPV improvement for different implementations of the optimization problem

The improvement can easily be achieved by extending the optimization period for a few hours beyond the actual dispatch period and therefore allowing the algorithm to look into the future. Considering the computational time in relation to the gained improvements (see Figure 6.51), the optimal approach is to consider three days at once with an overlapping period of three hours. However, in order to closely resemble the daily auction of the spot market and in order to err at the right side, one day at a time with 12 hours of the next day will be used for the following calculations. While slightly larger improvements can be found by looking further into the future, the additional computational cost does not justify the marginal improvements.

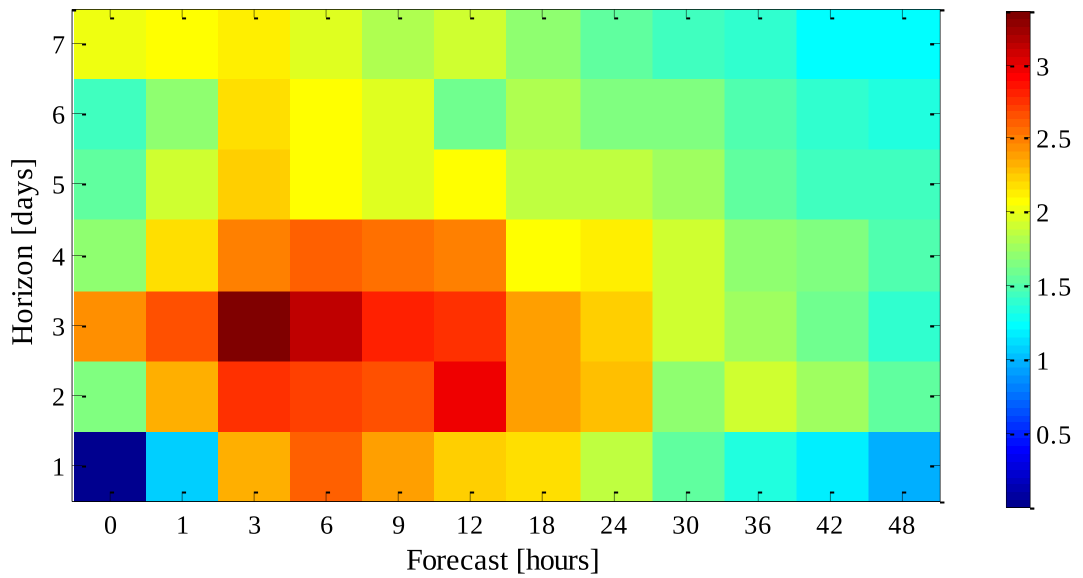

Figure 6.51: Trade-off between improvement and computational cost

Search Process for the Optimum Hurdle Rate

The implementation of the search routine, which spans the mixed integer program, is straightforward. Exemplary, Figure 6.52 shows the search process. During the first iteration, the search space starting from a hurdle rate of 0 EUR/MWh is traversed in big steps. The search is interrupted once a decline in the net present value was detected. Following, in the second iteration, the potential space is searched in smaller steps, again until the net present value declines. After the third iteration, the termination criterion was fulfilled and hence the search was terminated.

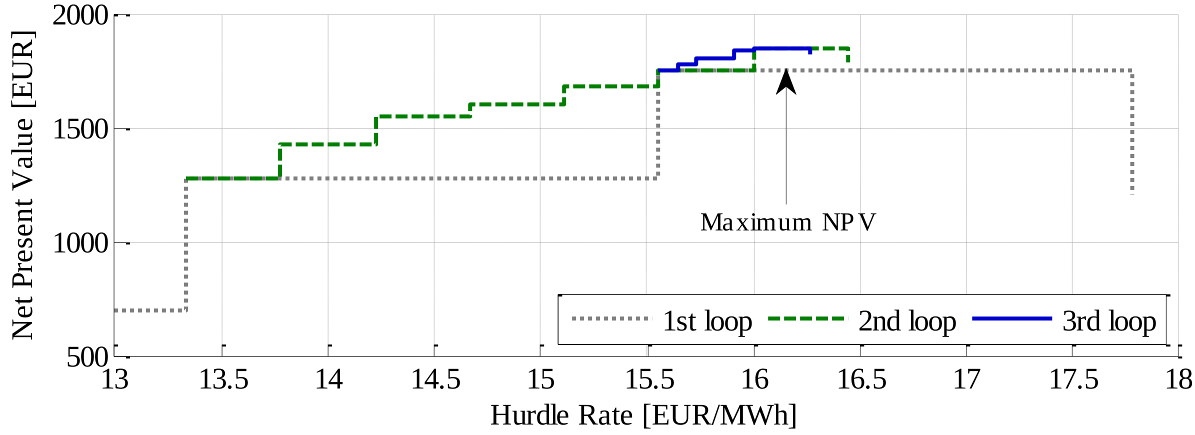

Figure 6.52: Demonstration of the search process for the NPV maximizing hurdle rate

In order to determine the optimum number of search points within each iterative search space (parameter *n* in Algorithm 2), the search routine was rerun for a range of numbers and the resulting number of required cycles was recorded. Figure 6.53 shows the absolute number of required searches before the termination criterion was fulfilled. If a small number of search points is chosen, each search space is traversed in rather big steps. However, a higher number of iterations are required. Contrary, when a high number of search points is chosen, it will take longer to analyze each search space, but the result will be already more precise and overall less iterations will be required.

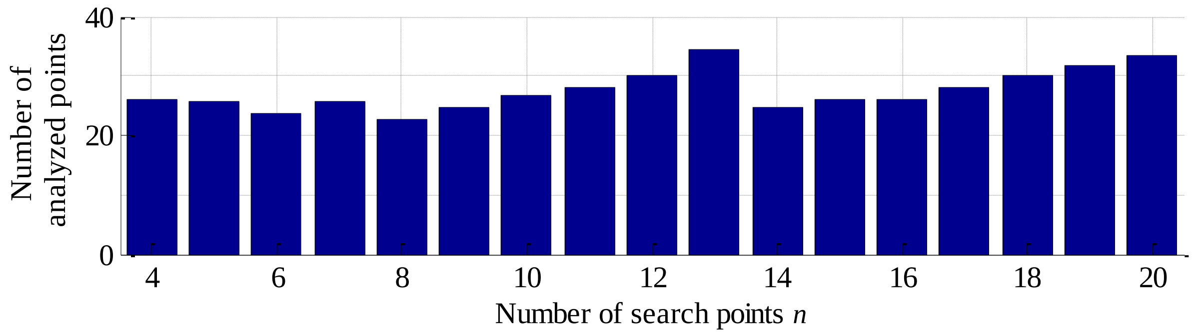

Figure 6.53: Number of required searches to identify the optimum hurdle rate

For the further analysis, the number of search points was set to eight. The initial search space is limited by 0 EUR / MWh on the lower end, and twice the levelized cost of storage as the upper end. The search routine is terminated once the remaining search space is less than 0.5 EUR / MWh.

Backward Looking Approach

Besides the dispatch assuming perfect foresight, in Section 3.4.3 also two dispatch algorithms based solely on historic data were presented.

Figure 6.54 shows for both storage systems and both dispatch approaches the cumulative revenues for the hourly contracts over the years 2011-2015 depending on the chosen parameters. Approach ‘B’ clearly dominates approach ‘A’ for both storage systems. The best results can be obtained by placing the upper / lower threshold for the dispatch about ±0.8 standard deviations away from the average price over the last 24 hours.

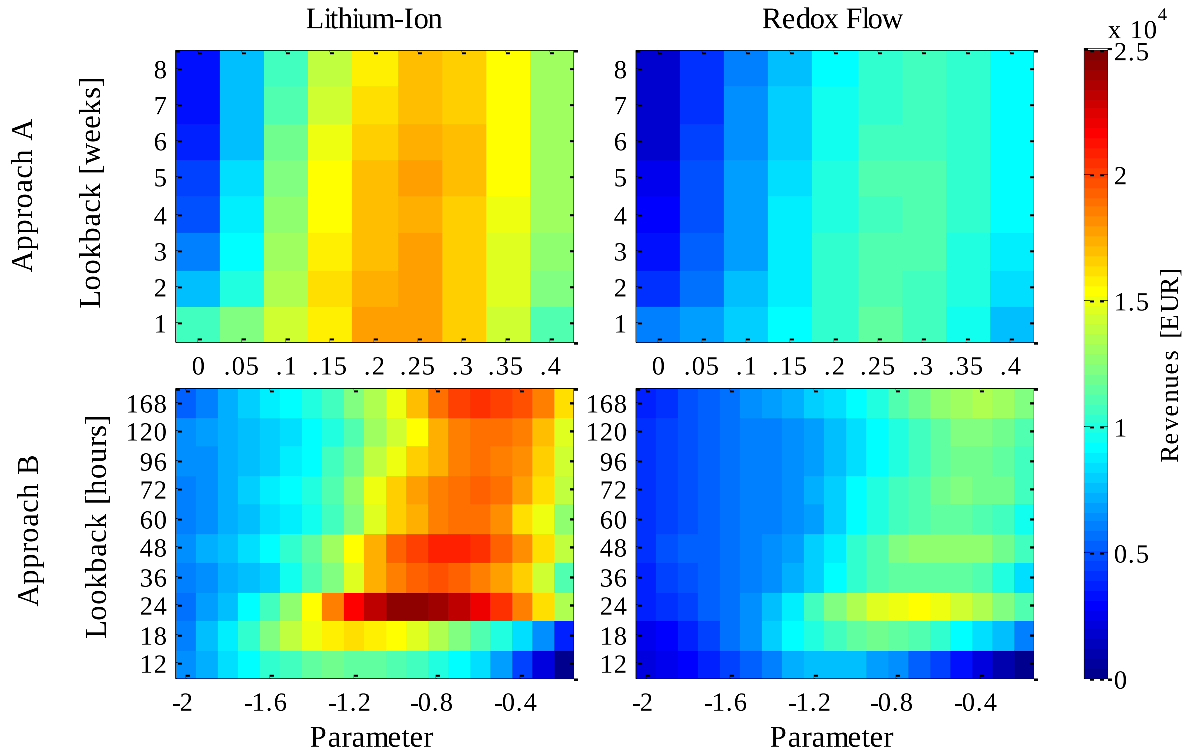

Figure 6.54: Comparison of revenues from the backward looking approaches for 1-hour contracts (2011-2015)

The same analysis was also conducted for the historical prices of the 15-minute contracts for the year 2015. Figure 6.55 shows that the difference between the lithium-ion and the redox flow system is even more pronounced. Again, approach ‘B’ delivers superior results compared to approach ‘A’. For the further analysis, a lookback period of 48 time steps (12 hours) will be considered for the 15-minute contract. The threshold for the lower- and upper boundary will be set significantly tighter than in the previous case at ± 0.5 standard deviations away from the mean.

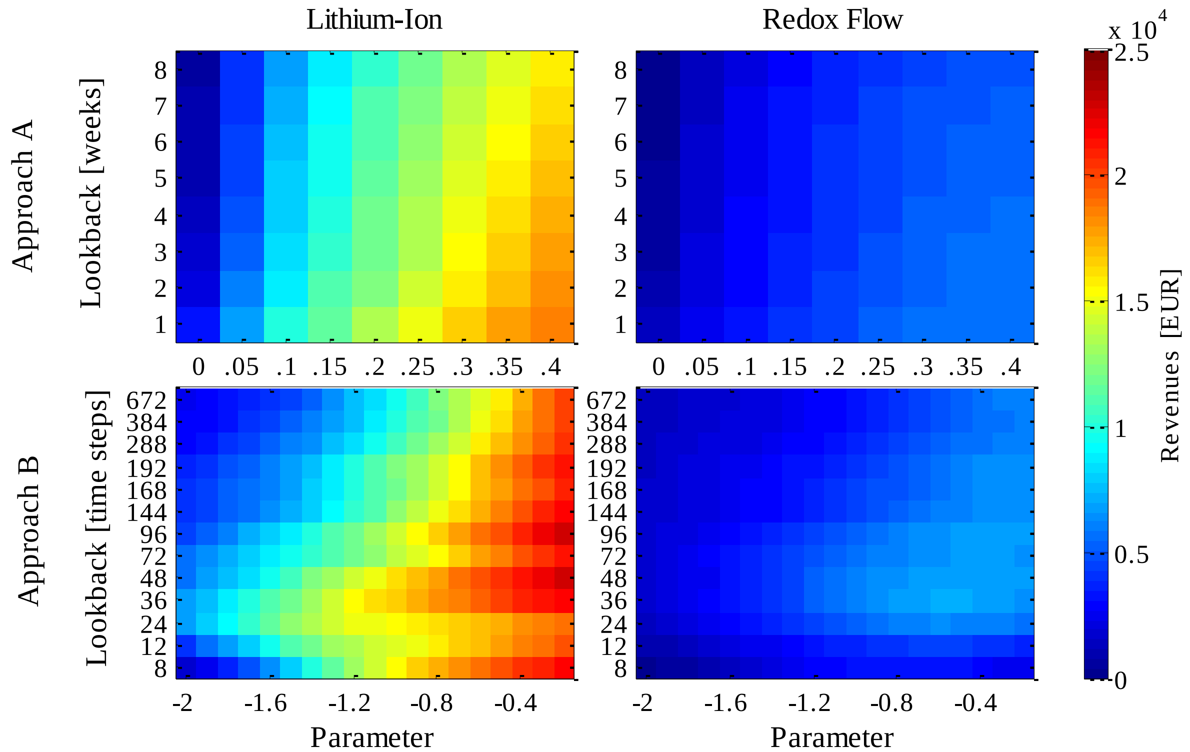

Figure 6.55: Comparison of revenues from the backward looking approaches for 15-minute contracts (2015)

6.2.3 Historic Revenue Evaluation

In this Section, historic prices will be analyzed for their revenue potential when pursuing arbitrage. As the price history shows a significant number of negative prices, the mixed integer programming approach instead of the linear programming method will be used (see Section 3.4.2).

First, investment cost of the storage systems will be neglected in the MIP for the dispatch decision. Hence, the storage system is dispatched without considering attributable depreciation cost. In a second step, the hurdle rate will be considered. In this case, the battery is only dispatched, if the revenues from that operation exceed the defined threshold. Last, the two backward looking approaches will be analyzed.

Optimal Revenues

In a first step, the investment cost has been neglected and the hurdle rate was set to zero in order to determine the maximum available revenues for both systems. These are shown in Figure 6.56. As expected, the lithium-ion system was able to realize significantly higher revenues, both due to the higher power rating as well as the higher efficiency. Considering the hourly contracts, available revenues for the lithium-ion system averaged 13 320 EUR per year for the years 2011-2015 versus only 6 426 EUR per year for the redox flow battery. Looking at the 15-minute contracts for the year 2015, the available revenues are significantly higher (43 149 EUR and 11 082 EUR).

Overall, available arbitrage revenues from the hourly day-ahead market have therefore decreased over the last few years. They remain significantly below the values identified for previous years in the existing literature (see Section 2.3.4). However, the introduction of 15-minute contracts presents an attractive alternative.

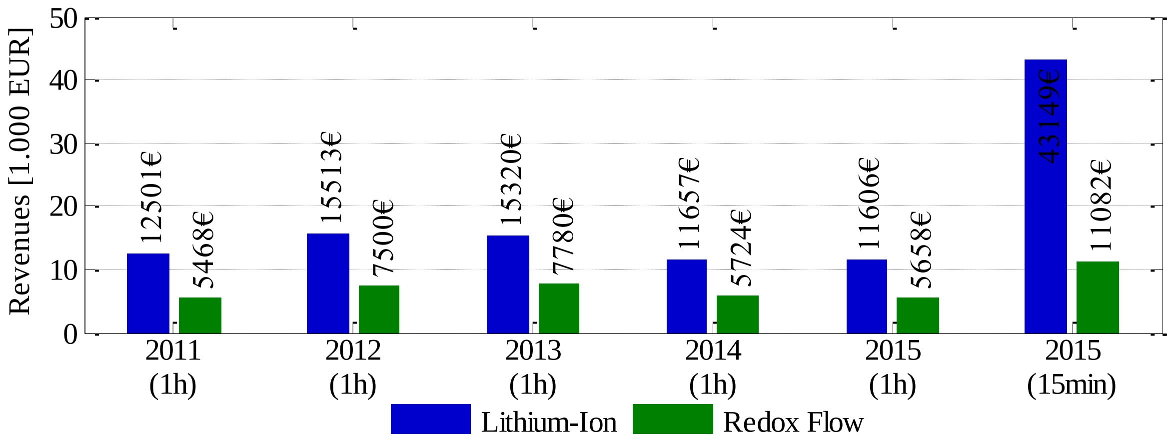

Figure 6.56: Optimal revenues from pursuing arbitrage

Figure 6.57 shows the number of equivalent charge- and discharge cycles. While the lithium-ion system completes about two charge- and discharge cycles per day on average, the redox flow battery has been charged- and discharged only 1.1 times on average per day (years 2011-2015 for the 1-hour contract). Looking at the optimal dispatch for the 15-minute contract during the year 2015, both systems have undergone a much higher number of charge- and discharge cycles. The lithium-ion battery has been cycled more than eight times per day on average, whereas the redox flow battery was charged- and discharged about twice per day on average. The amount of obtained revenues therefore is clearly linked to the number of charge- and discharge cycles.

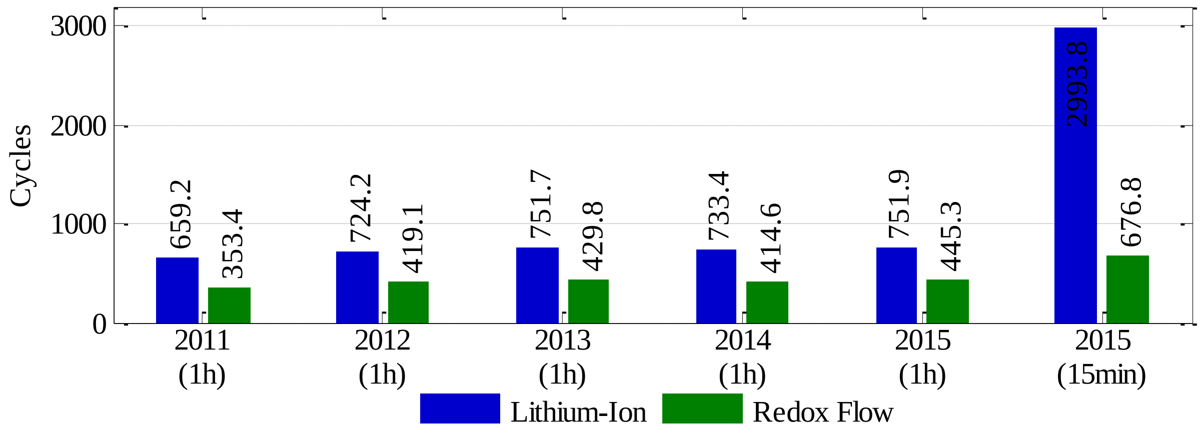

Figure 6.57: Undergone cycles for pursuing arbitrage neglecting a hurdle rate in the dispatch

Optimal Dispatch

In the previous section, the storage system was dispatched as soon as revenues exceeded efficiency losses. Now, the limited lifetime of the storage system and hence the associated depreciation charge with each operation will also be considered. Therefore, the storage device was dispatched according to the search process presented in 3.4.2 in such a way that the net present value (instead of the revenues) was maximized. Therefore, the individual hurdle rate has to be determined for every case. As the considered time-frame is only one year, the attributable investment costs were determined according to equation (3.15).

The resulting revenues are shown in Figure 6.58. While the dispatch (and hence also the revenues) for the redox flow battery remain unchanged, the value maximizing strategy for the lithium-ion battery is to focus on the most profitable operations and therefore pursue less opportunities. Consequently, the revenues decline by about 24% for the 1-hour contract and about 66% for the 15-minute contract. While the later still appears more attractive than the hourly market, the difference is significantly reduced.

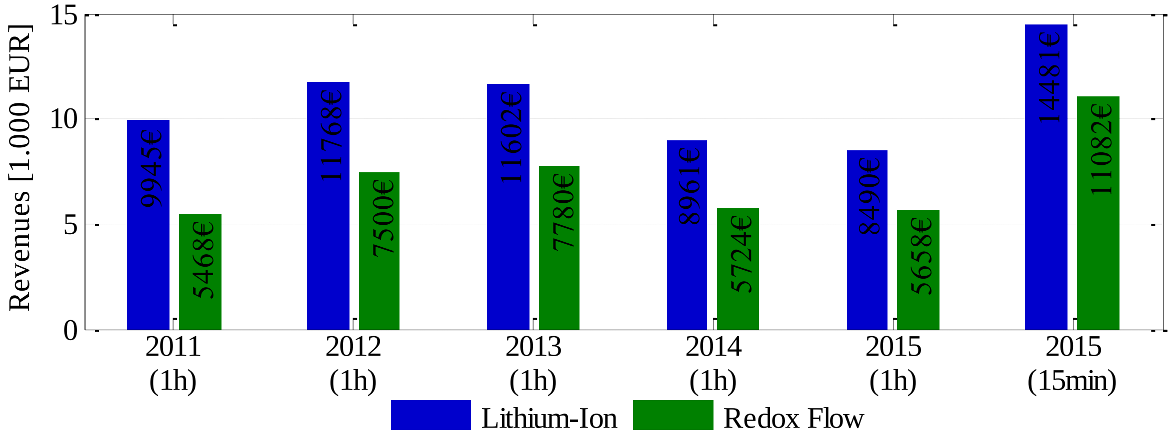

Figure 6.58: Revenues for the NPV maximizing dispatch

Figure 6.59 shows the associated number of undergone cycles. While the number is unchanged for the redox flow battery, the lithium-ion battery was operated significantly less frequent. In the hourly market, the reduction in operated cycles was about 59%, in the 15-minute market about 90%. The relation between the reduction in revenues and number of operation cycles shows that only the most profitable opportunities have been pursued.

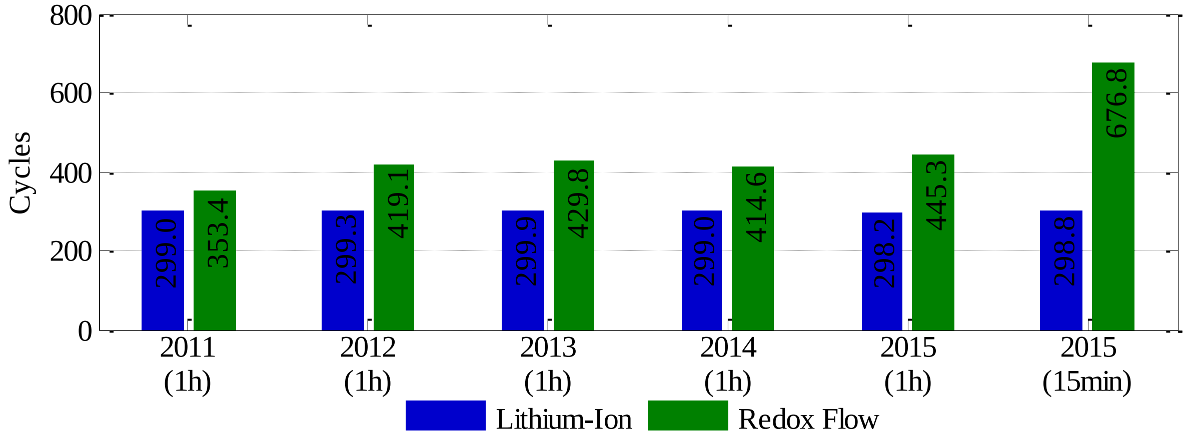

Figure 6.59: Realized cycles under the NPV maximizing dispatch

The optimal number of realized charge- and discharge cycles of the lithium-ion battery was about 300 in each case, the point of intersection between the calendric aging (assumed to be 15 years) and the aging due to frequent cycling (4 500 cycles over the lifetime).

Figure 6.60 shows the dispatch hurdle rates for the lithium-ion battery, which maximized the net present value for each individual year. These were relatively constant along the years for the hourly contracts. Maximizing the NPV over the years 2011-2015 at once, a hurdle rate of 18.40 EUR / MWh was found, close to the average of 18.70 EUR / MWh for the five individual years. For the 15-Minute contracts, the value maximizing hurdle rate was found to be significantly higher.

The NPV maximizing hurdle rate for the redox flow battery was found to be 0 EUR / MWh in all cases. Contrary to the lithium-ion battery, an operator should therefore pursue every possible opportunity.

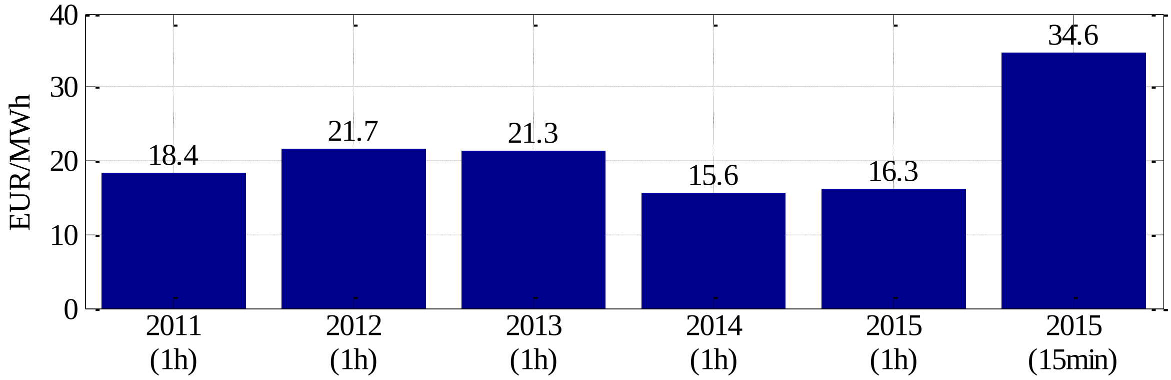

Figure 6.60: Profit maximizing hurdle rate for the lithium-ion battery

Backtest

The mixed integer program inherently assumes perfect knowledge of future prices. Contrary, the two presented backward looking approaches (see Section 3.4.3) rely only on past information to determine the storage dispatch. Figure 6.61 shows the revenues from implementing approach 'B' as discussed in the Section 'Model Implementation' (see Section 6.2.2). As expected, obtained revenues remain substantially behind the case of having perfect knowledge (as shown in Figure 6.56).

The introduction of the 15-minute contract again represents an interesting revenue opportunity. The lithium-ion battery, with a high power-to-energy ratio, was able to deliver about four times as much revenue as compared to participating in the hourly market. The results for the redox flow battery are less impressive, but still about twice as high.

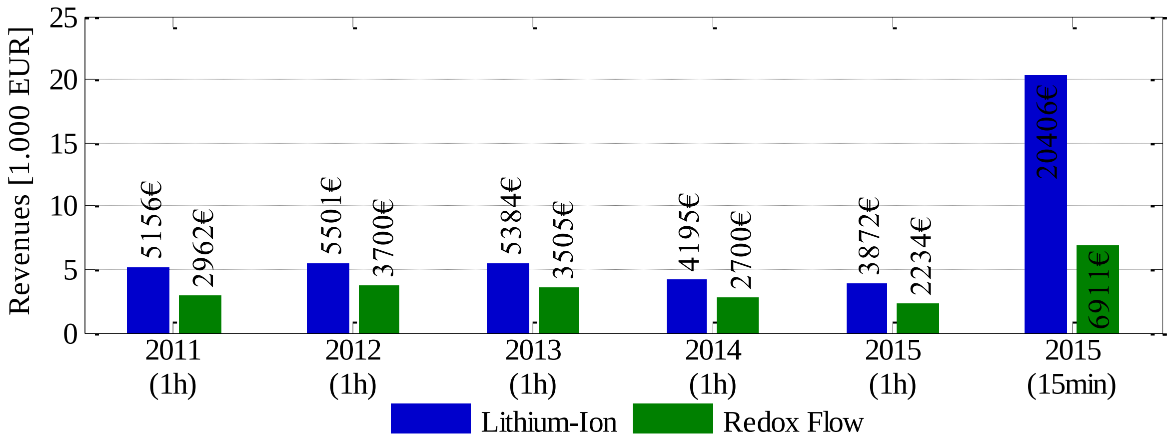

Figure 6.61: Revenues from pursuing arbitrage based on historical data (approach 'B')

The associated number of charge- and discharge operations is shown in Figure 6.62. In the hourly market, the lithium-ion battery was cycled about once a day, the redox flow battery slightly less. Hence, the lithium-ion battery is deployed significantly less than under perfect foresight (0.9 cycles per day versus 2), while the usage of the redox flow battery is only slightly reduced (0.8 cycles per day versus 1.1).

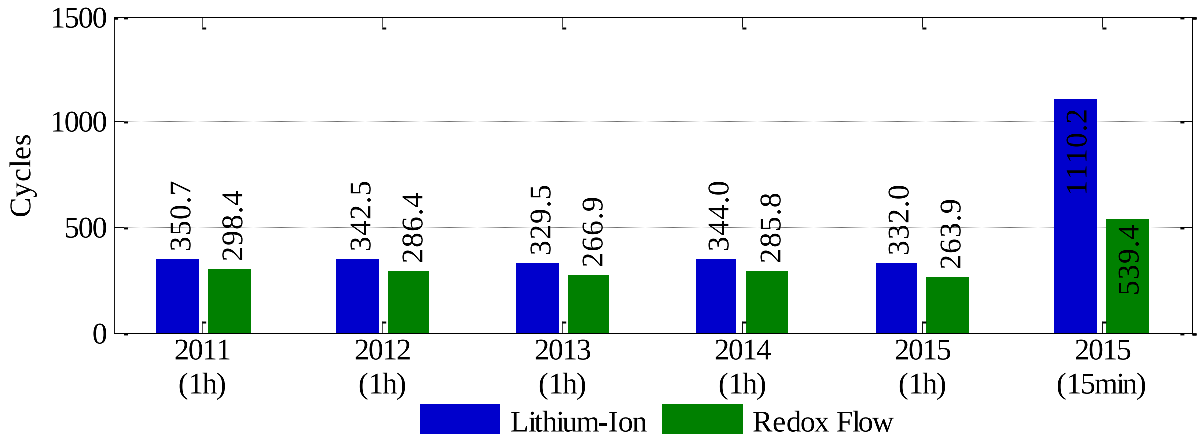

Figure 6.62: Realized cycles under the backward looking approach 'B'

A more detailed analysis of the difference and hence the value of having good forecasts is discussed in the Section 6.2.5.

6.2.4 Results

In the previous section, historical data of the years 2011-2015 for hourly contracts as well as of the year 2015 for 15-minute contracts was analyzed for its revenue potential when pursuing arbitrage. Considering the calendric lifetime of the storage system as a first valuation guidance, it appears unlikely that any of the systems can break-even. With an expected lifetime of 15 years for both systems, the required annual revenue is 93 333 EUR for the lithium-ion system and 50 000 EUR for the redox flow battery to break-even with initial investment cost as well as annual fixed cost. Average annual revenues for the hourly contracts were found to be 13 320 EUR for the lithium-ion battery and 6 426 EUR for the redox flow battery (see Figure 6.56). Looking at the undergone cycles over the same time, the lithium-ion system would have been almost at the end of its lifetime after the years 2011-2015 with 3 642 cycles out of the assumed 4 500 cycle lifetime, however significantly short of the required revenues to break-even with initial investment cost. Over the same time, the redox flow battery would have been cycled 2 083. While the recently introduced 15-minute contracts offer a substantially higher revenue potential (43 149 EUR for the lithium-ion battery, 11 082 EUR for the redox flow battery), the resulting dispatch also cycles the storage device much more frequently (2 998 and 684 cycles in one year). Hence, depreciation charges are also significantly elevated.

Instead of maximizing revenues, which results in a very high number of operation cycles and hence a short expected lifetime of the storage system, the net present value should be maximized, which takes the negative impact of frequent cycling on the expected lifetime into account. Based on the search process to identify the optimum hurdle rate and the mixed integer program to solve for the optimum operation schedule, the dispatch which maximizes the net present value was determined. Assuming that the price history will repeat itself again in the future, Figure 6.63 shows the resulting net present value for both storage systems and both markets (the hourly as well as 15-minute contracts) in comparison to the initial investment cost. With an initial investment cost of 600 000 EUR, the net present value for the redox flow battery would amount to -503 700 EUR when dispatched in the hourly market and -488 600 EUR for the 15-minute contracts. The optimum dispatch hurdle rate in each case was found to be zero, hence all opportunities have been pursued. Based on the investment cost of 1 250 000 EUR, the net present value of the lithium-ion battery would be -1 097 000 EUR for the hourly market and -1 075 300 EUR for the 15-minute market. The value maximizing hurdle rate was found to be 18.40 EUR and 27.42 EUR, respectively. Overall, the 15-minute market offered slightly higher returns.

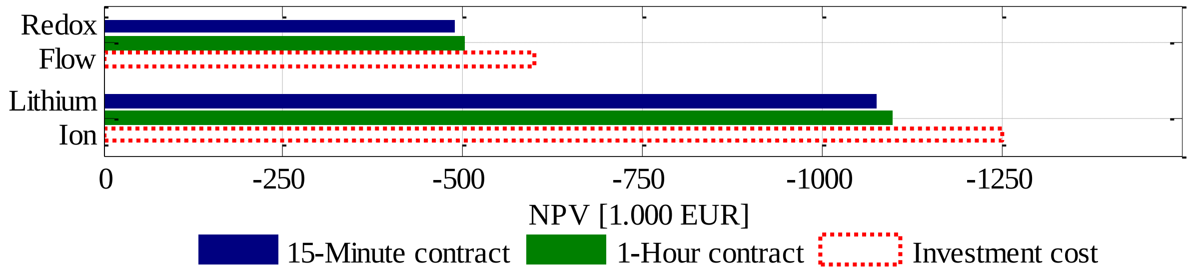

Figure 6.63: Net present value of pursuing arbitrage

Summing up, the required revenue therefore has even under perfect foresight not been achieved in any of the most recent years. Hence, it can be concluded that currently no business case exists for pursuing arbitrage in the electricity spot market.

6.2.5 Analysis

These results raise a number of questions:

- which cost reductions are required to make investments in storage for pursuing arbitrage financially attractive? (Section 'Break-Even Cost')
- to what extend can technical improvements reduce the current gap between revenues and cost? (Section 'Technical Improvements')
- which ratio of power to energy is optimal for a storage system pursuing arbitrage? (Section 'Power to Energy ratio')
- which price fluctuations are required in order to make storage participating in the spot market profitable? (Section 'Price fluctuations')
- how important is the dispatch process and the knowledge about future prices? (Section 'Perfect foresight')

Break-Even Cost

Under current cost, both lithium-ion and redox flow systems were not able to break-even when pursuing arbitrage. The break-even point refers to a net present value of zero, that is the point when revenues equal total cost considering the time-value of money. This section analyses what level of investment cost will make arbitrage operations break-even.

As the value maximizing dispatch strategy is independent of the initial investment cost and neither time-value of money, fixed annual cost nor financing cost have been considered, the break-even can be easily obtained by looking at the difference between the investment cost and the resulting net present value.

Hence, in order to break-even in the hourly market, investment cost for the lithium-ion battery would have to fall to 153 000 EUR (-87.8%). As the available revenues are slightly higher when pursuing arbitrage in the 15-minute contracts, a cost reduction to 174 700 EUR (-86%) would be sufficient. For the redox flow battery, the required cost reductions are similar. In the hourly market, the system would break-even once initial investment cost fall to 96 300 EUR (-83.9%). For participation in the 15-minute market, the battery would break-even with investment cost of 111 400 EUR (-83.4%). If the time-value of money would be considered in the evaluation, the required cost reductions would be even higher, as revenues accumulate only over time whereas the investment cost are due at the beginning.

Technical Improvements

Besides decreasing investment cost, the net present value can also be increased by improving the technical characteristics of storage systems. Improvements in the efficiency would lead to lower losses in the storage process, and hence more energy can be fed back into the grid for every unit of energy purchased and taken from the grid. Reducing the depth of discharge increases the effective energy capacity of the storage system, and hence more energy can be shifted from low to high price periods. An increase in the cycle lifetime allows the storage system to be cycled more frequently over its calendric lifetime, hence more opportunities can be pursued. Contrary, an increase in the calendric lifetime allows the dispatch process to be more selective and hence only more profitable opportunities will be pursued.

Figure 6.64 shows the increase in net present value versus the reference evaluation for individual improvements of the technical features considering the lithium-ion battery, when dispatched in the hourly market.

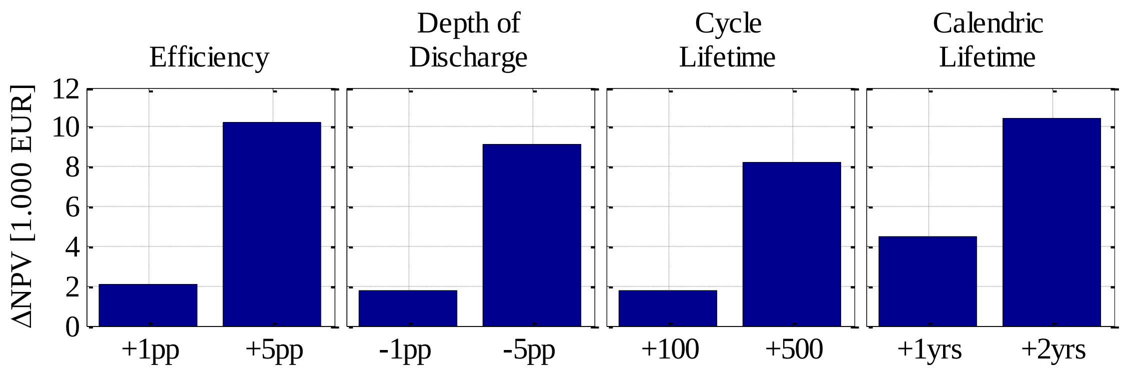

Figure 6.64: Sensitivity Analysis for the lithium-ion battery

The same analysis for the redox flow battery is shown in Figure 6.65. As the depth of discharge for these systems is already at 0%, no further improvements are possible. Furthermore, as the lifetime of the system was only limited by the calendric lifetime, improving the cycle lifetime would also have no impact.

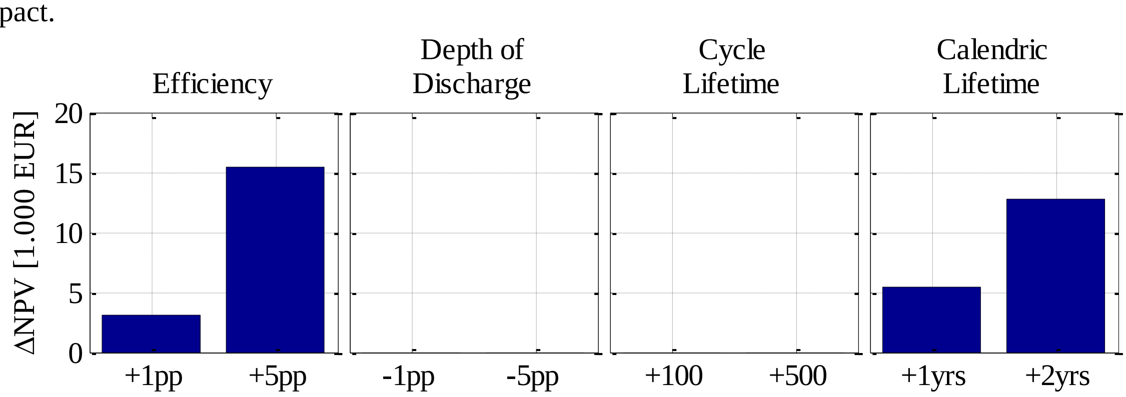

Figure 6.65: Sensitivity Analysis for the redox flow battery

Hence, redox flow batteries appear to benefit slightly more from technical advances, but they are limited to efficiency gains and longer calendric lifetimes. An evaluation, of how likely these advances can be achieved, is outside of the scope of this work. However, at current investment cost, it is obvious that technical improvements are not nearly sufficient to make arbitrage profitable and only improve the net present value insignificantly.

Power to Energy Ratio

The previous Section 6.2.3 has shown widely differing optimal revenues between the lithium-ion and the redox flow systems. These can be traced back to a significant difference in their efficiency (90% to 75%), but also to their differing power-to-energy ratios. While the lithium-ion battery could be fully charged within one hour, it takes four hours to bring the state of charge of the redox flow system back to 100%. Therefore, the redox flow system is limited to less attractive opportunities, as it needs to charge / discharge also at less advantageous prices (that is not only at the lowest / highest price level, but also at slightly higher / lower levels). Hence, for a given power capacity of a system, it can be expected that marginal revenues decline with an increase in energy capacity as also less attractive opportunities are realized.

This view is confirmed by Figure 6.66 and Figure 6.67, which show the potential available marginal revenues to an agent participating in the 1-hour / 15-minute market for an increase in the (effective) energy capacity by 1 MWh / 0.25 MWh. With an increase in energy capacity for a given power capacity, generally the marginal revenues decrease.

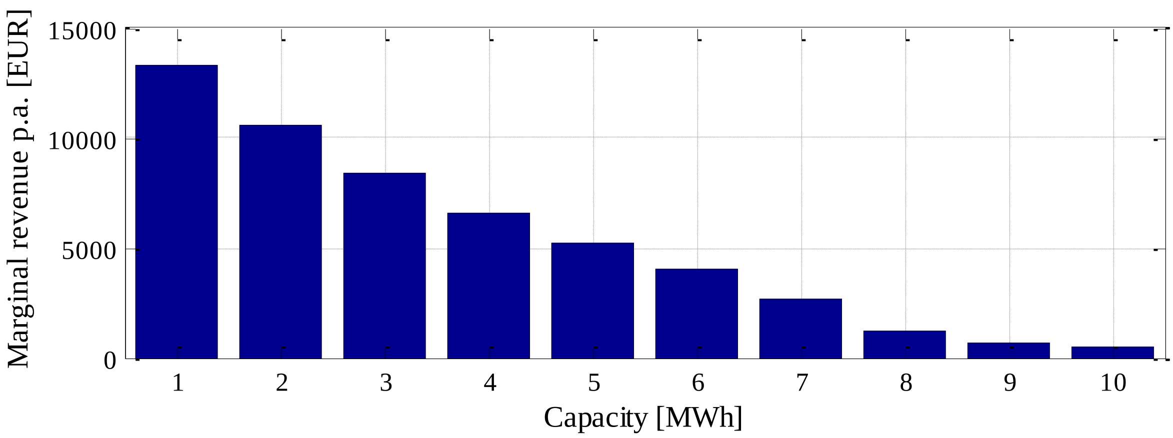

Figure 6.66: Marginal revenues for additional energy capacity (2011-2015, 1-Hour contract)

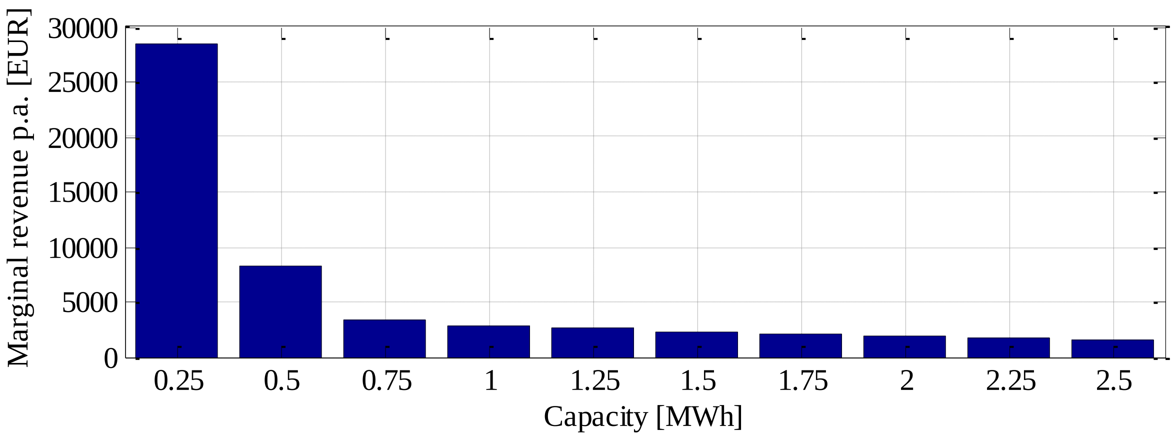

Figure 6.67: Marginal revenues for additional energy capacity (2015, 15-Minutes contract)

This effect is significantly more pronounced for the 15-minute contracts, with capacities beyond 0.5 MWh / 1 MW (a 30-minute charge / discharge interval) not adding much value. This can be traced back to the magnitude of price spreads. While the spreads between minimum and maximum prices are significantly wider for the 15-minute contracts, those extreme values only persist for short durations.

Hence, investors with an interest in pursuing arbitrage should focus on the power-rating of the system. Furthermore, the introduction of auctions for 15-minute contracts presents an interesting alternative for storage devices with a high power ratio and limited energy capacity. However, it is important to remember that this analysis assumes perfect knowledge of future prices. In reality, it would present an even more difficult challenge to identify the extreme values for 15-minute periods instead of hourly intervals.

Price Fluctuations

Arbitrage revenues are driven by the frequency and the extent of price spikes. In order to determine the required price fluctuations to bring storage to the break-even point, the market environment is amended in this section in order to provide a more favourable setting for arbitrage. Therefore, the framework developed in Section 4.5.2 is applied in order to simulate market prices, which resemble todays price patterns but display more frequent and more extensive price spikes.

First, the elaborated model was calibrated to historical hourly data for the years 2011-2015. The probability for price jumps (δ_{jump_down} and δ_{jump_up}) was found to be 0.29% each. The assumed exponential distribution for jumps was found to fit best with the mean parameter λ_{jump_up} = 17.15 and λ_{jump_down} = 37.81. Hence, jumps down showed a significantly larger magnitude than jumps up.

Following, the parameters for the jump process were modified. The resulting time series then displays the same characteristics as the historic price paths, but more frequent and more extensive jumps. Figure 6.68 shows the resulting net present value for the previously analysed lithium-ion battery for different jump probabilities and extent of price spikes.

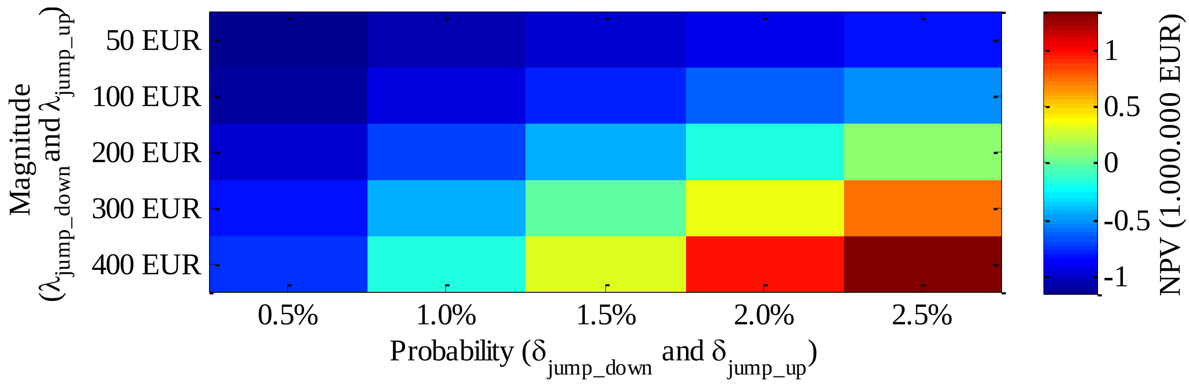

Figure 6.68: Net present value depending on magnitude and probability of price jumps

Assuming a jump probability of 1.5% each for jumps up (δ_{jump_down}) as well as for jumps down (δ_{jump_up}), the mean of the exponential distribution (λ_{jump_up} and λ_{jump_down}) must be 310 EUR in order for the storage system to break-even. Compared to the current price process, jumps would therefore occur about five times as often and about 18 times (jumps up) / eight times (jumps down) as distinctive as empirically identified.

Figure 6.69 shows exemplary a simulated price path for one year. More frequent and more extreme price jumps would also simplify the storage dispatch process: simple linked limit orders below / above an extreme point would be sufficient to capture the most extreme price spikes.

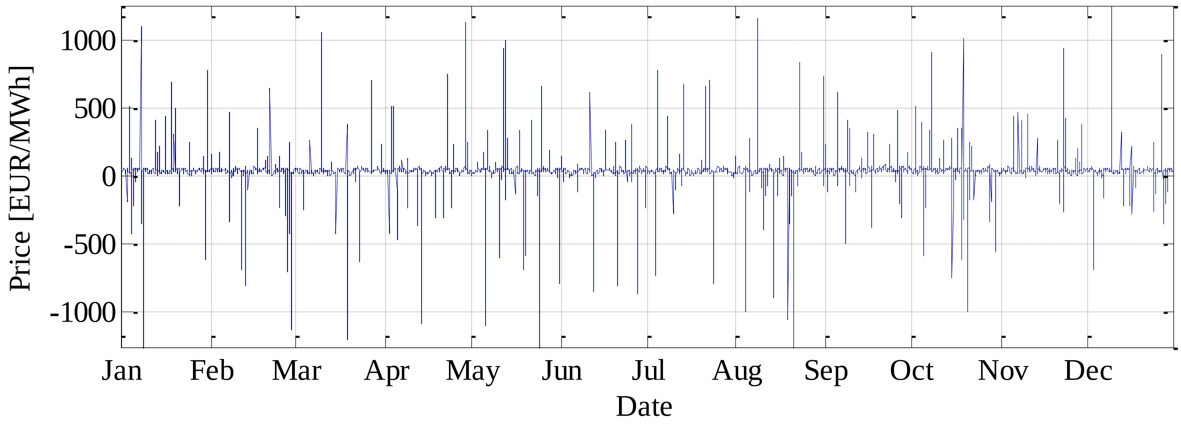

Figure 6.69: Simulated price path with more frequent and more pronounced jumps

Perfect Foresight

By comparing the revenues available from a dispatch utilizing information about future prices for its operation to a dispatch only considering available information at that time (such as historic prices), a statement about the value of forecasts can be made.

Figure 6.70 shows, how much revenues could have been extracted from the backward-looking approaches in comparison to the mixed integer program in the 1-hour market, depending on the chosen parameters. The share was significantly higher for approach 'B', which was already previously shown to generate higher revenues. In addition, the percentage of realized revenues was also significantly higher for the redox flow battery as compared to the lithium-ion battery. Nonetheless, even in the best case, the backward-looking approach was able to realize less than 50% of the revenues identified by the mixed integer program.

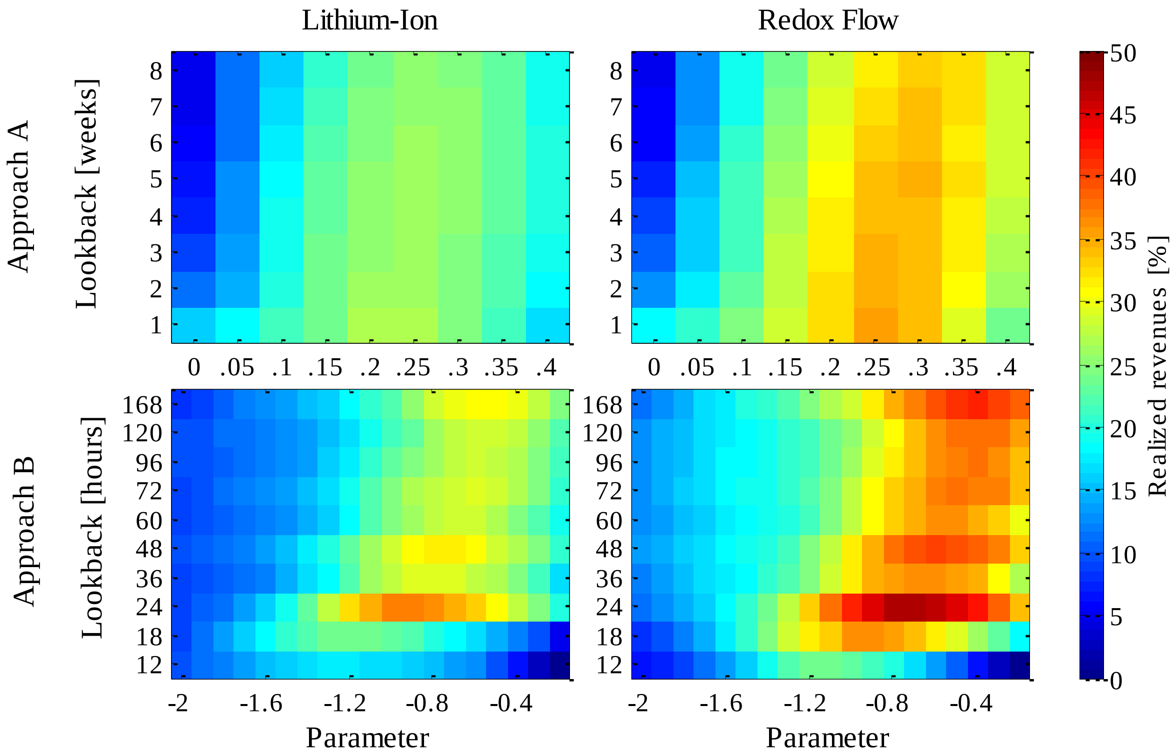

Figure 6.70: Realizable revenues in the 1-hour market by the backward-looking approaches in comparison to perfect foresight

The same statements are valid for the dispatch in the 15-Minutes market (Figure 6.71). However, the share of realizable revenues is generally higher, up to 65%.

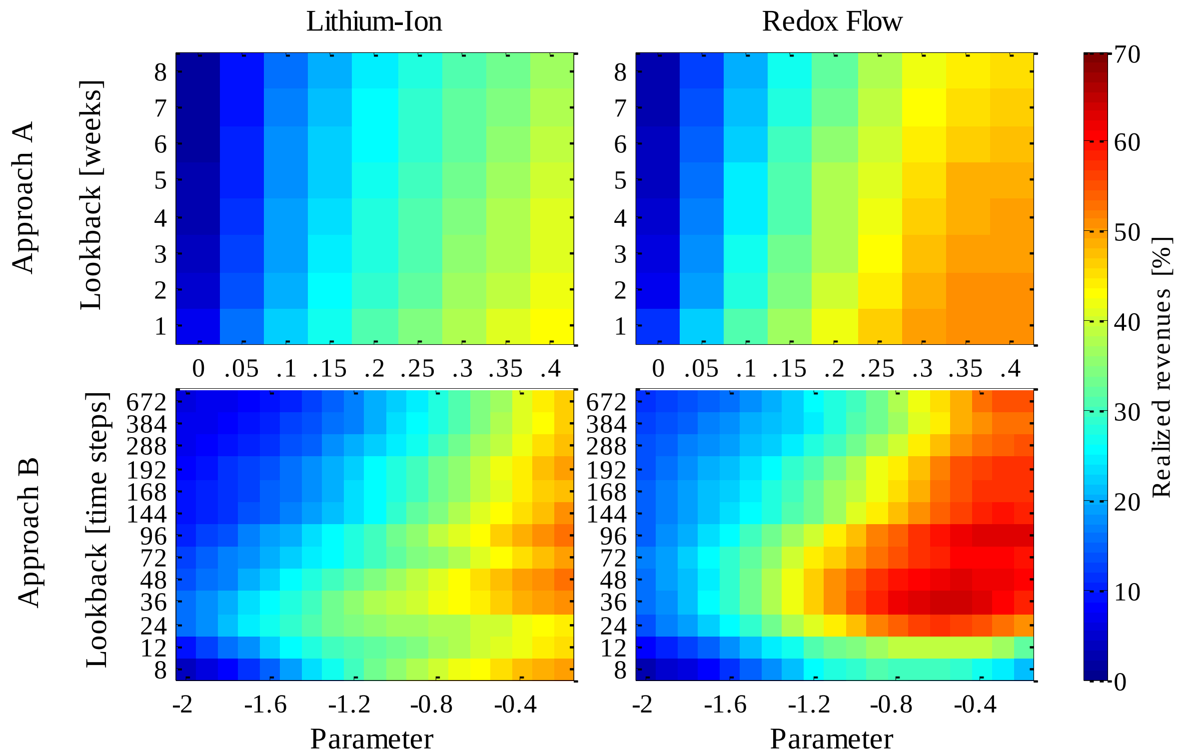

Figure 6.71: Realizable revenues in the 15-minute market by the backward-looking approaches in comparison to perfect foresight

This comparison highlights the importance of good forecasts. While the revenue gap is already substantial when assuming knowledge about future prices, it becomes even more difficult to reach the break-even without perfect foresight. The difference of realized revenues between the lithium-ion and the redox flow battery shows that the value of good forecasts is even more important for storage devices with a high power to energy ratio, as it is more difficult to predict the absolute peaks. When charging over several periods, this issue is less important. While the integer programming approach dispatches the storage system during the exact peak price periods, the backward-looking approach will oftentimes not realize the precise minimum / maximum. As peaks are oftentimes short-lived, the error is therefore greater for storage devices which require little time to fully charge / discharge.

6.2.6 Conclusion

This caste study has considered the dispatch of both a lithium-ion and a redox flow storage system for pursuing arbitrage in the German grid zone. An initial analysis of historic market prices over the years 2011-2015 for the 1-hour contracts as well as for the 15-minute contract during the year 2015 has shown that overall prices have declined slightly. However, volatility remained more or less constant. Furthermore, an average daily spread between minimum and maximum price of 34.36 EUR (1-hour contract) / 55.98 EUR (15-minute contract) was identified. An evaluation of the theoretical historic revenues showed that these are not sufficient to cover the investment cost over the lifetime of the storage device. For the lithium-ion system, annual revenues of 13 320 EUR were found. However, the dispatch would result in a very high number of operations, significantly cutting short the expected lifetime of the system. A dispatch, taking both the calendric as well as cycle lifetime into account and therefore maximizing the overall value, would result in average annual revenues of 10 153 EUR. For the redox flow system, having a much higher cycle lifetime, potential revenues amounted to 6 426 EUR per annum. The 15-minute contracts were overall found to have a slightly higher revenue potential and therefore present an attractive alternative. Revenues in the hourly market have slightly declined over the last years.

Determining the net present value of both systems it was shown that currently a significant revenue gap exists, even when neglecting fixed annual and financing cost. In order to break-even, cost reductions of about 85% for both systems are required. While technical advances would improve the economics slightly, these are not significant enough to reach profitability. However, more volatile prices would create a more favorable environment for storage systems. It was found that with current investment cost, a lithium-ion battery would require that price jumps occur five times as often with a magnitude of about 18 times (jumps up) / eight times (jumps down) of today’s price process in order to break-even.

Furthermore, the ideal power-to-energy ratio was determined. It was found that the first unit of energy capacity for a given rated power was generating the highest revenue, with decreasing returns for higher energy capacities. This effect was especially pronounced for the more volatile 15-minute contracts. However, the shorter the charging / discharging duration, the more important becomes the issue of perfect foresight. It was shown that a dispatch based on historic data was able to only obtain less than 50% (65% for the 15-minute contracts) of the revenues. Therefore, the break-even point is pushed even further away. While the presented backward-looking dispatch algorithms were of a simple nature, they highlight the importance of the issue.

Concluding, currently no opportunity exists for storage systems participating in the electricity spot market pursuing arbitrage. Both considered storage systems were not able to break-even in any of the analysed years due to their high installation cost, despite not considering fixed and financing cost as well as assuming perfect knowledge of future electricity prices.

In reality, there exist some further hurdles that have not been considered in the case study. Exemplary, energy can only be traded in multiples of 0.1 MW (see Section 2.2.2). A dispatched storage system must consider this limitation in order to avoid balancing penalties. Hence, both power as well as storage capacity cannot be as efficiently used as assumed in the case study. Furthermore, among others, no grid connection or exchange fees have been considered.

This analysis highlights several important facts:

First, in order for storage systems to break-even, significant investment cost reductions of more than 85% are required. The focus of policy makers should therefore concentrate on this aspect, instead of supporting projects which aim at improving technical characteristics of storage systems. Even for significant improvements, additional revenues remain marginal and will alone not help storage dispatched for arbitrage to become profitable in the near future.

Second, more frequent and more pronounced price spreads would create a more favourable environment for the deployment of storage. The introduction of higher shares of non-dispatched resources like wind or solar power might provoke such a development. Contrary, policy makers faced with the decision to introduce capacity markets, which would effectively limit the maximum price, could reduce the maximum price spreads and hence the available profits.

Third, even though not relevant at current investment cost, the dispatch process was shown to be of high importance. Simple backward-looking approaches were able to capture only a small fraction of total, possible revenues. If more frequent and more extreme price jumps would occur, the difficulty to forecast the exact peaks would increase even further. Hence, high-quality forecasts are of high importance. While substantial efforts have been made in the past to ensure that no information barrier exists and all market participants have access to the same information, these efforts should be continued in the future. In addition, price forecasting models must consider the further increasing share of renewables, the increasing trade with neighbouring countries as well as the potential feedback reactions from storage systems (as discussed in Chapter 5).

6.3 Provision of Ancillary Services

As indicated in the literature review (Section 2.3.10), several pilot projects have recently been installed in Germany in order to demonstrate from a technical point of view that storage can successfully provide primary reserve control. The following case study will provide additional insights from an economic perspective. Therefore, a lithium-ion battery will be evaluated according to the approach presented in Section 3.5.

6.3.1 Data and Assumptions

Historic Tender Results

For the analysis of historical results, the tenders for primary reserve control since 2012 have been considered[7] [202]. The contracted volume has slightly increased over time, from about 600 MW to almost 800 MW (see Figure 6.72), and is currently procured jointly for Germany, Netherlands, Austria and Switzerland. The joined procurement can be decoupled for several technical and regulatory reasons [203]. The required volume is determined according to the regulations of the ENTSO-E, such that two reference incidents (such as a power failure of a large power station) could be handled by available primary reserve control [40].

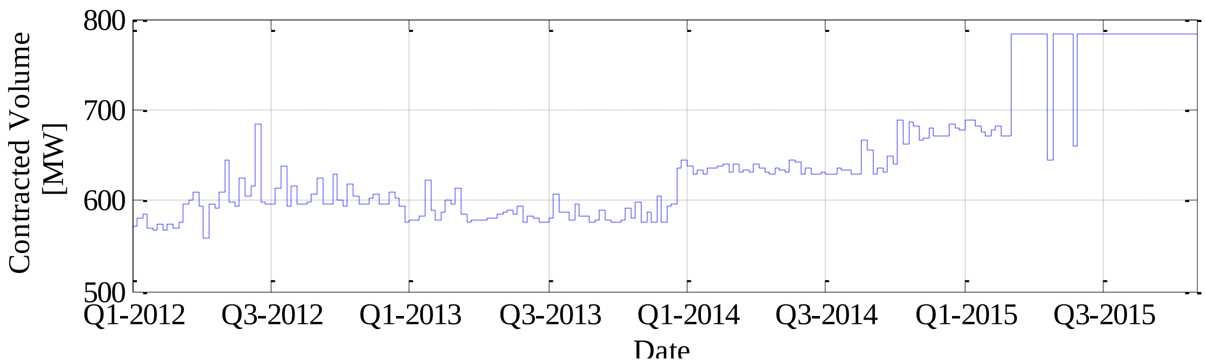

Figure 6.72: Contracted volume for Primary Reserve Control

Over the same period, the number of accepted bids for each auction has significantly increased, from about 30 bids to more than 120 bids (see Figure 6.73). Therefore, the average bid size has more than halved. However, this does not necessarily mean that more counterparties participate in the tender, as counterparties might split their total offer in several bids.

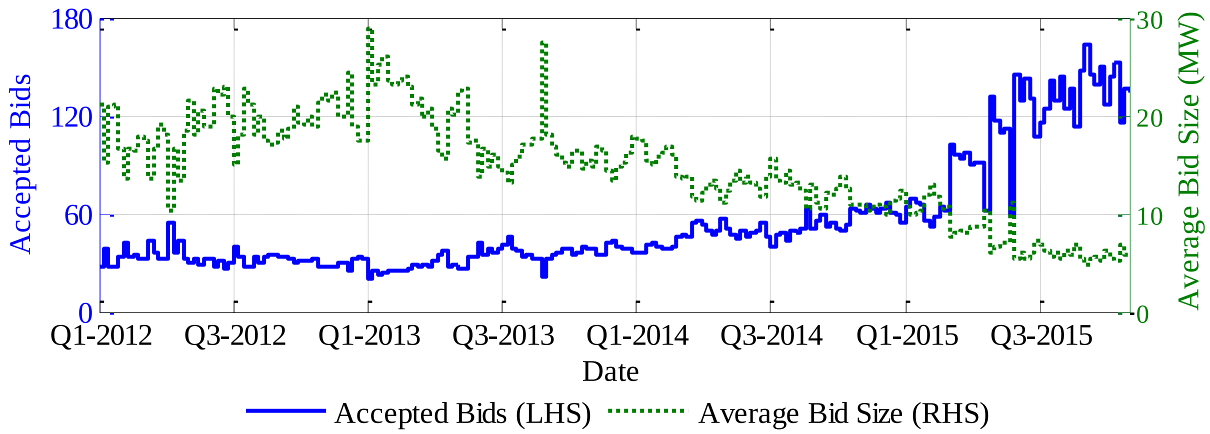

Figure 6.73: Number of accepted bids and average bid size

[7] Until 27th June 2011, the auction period was monthly and minimum bidding size was 5 MW. To have uniform conditions, only the data thereafter was considered.

Figure 6.74 shows a boxplot of the accepted bid prices of each tender. While the prices behaved very smooth for the majority of time, they show some distinctive, short-lived peaks. The spread between minimum and maximum accepted bids was within a narrow price range for most tenders. However, especially when price peaks occurred, much wider spreads between minimum and maximum accepted bid prices can be observed. Overall, prices have remained stable and no trend can be identified.

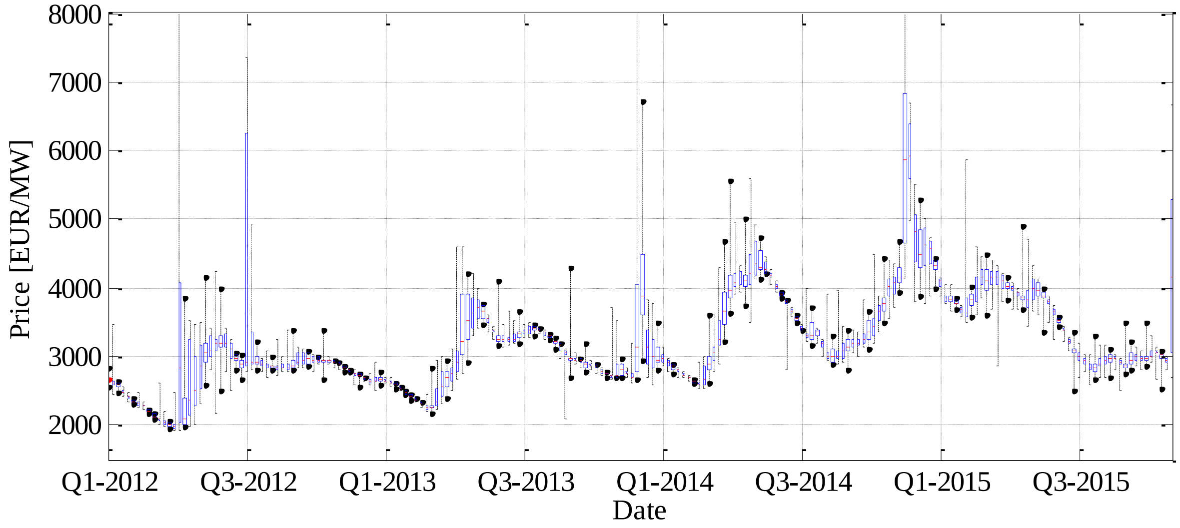

Figure 6.74: Boxplot of historic tender results

The maximum accepted bid for the one week contract period typically ranged between 2 000 EUR / MW and 5 000 EUR / MW (see Figure 6.75), which corresponds to 0,000012 – 0,00003 EUR per W and hour. Considering a storage system with 1 MW and assuming an average accepted bid of 3 000 EUR / MW, annual revenues would therefore amount to slightly more than 150 000 EUR.

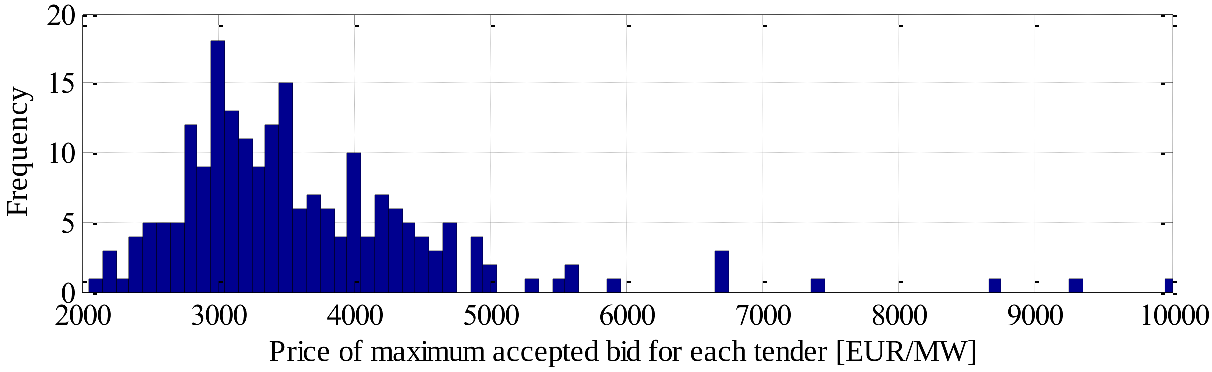

Figure 6.75: Distribution of maximum accepted bids

Figure 6.76 shows the change of the average price from week to week. Typically, the average price would not differ by more than 100 EUR from the previous week. This fact is also the reasoning for the suggested bidding strategy (see Section 3.5.2) based on historical prices.

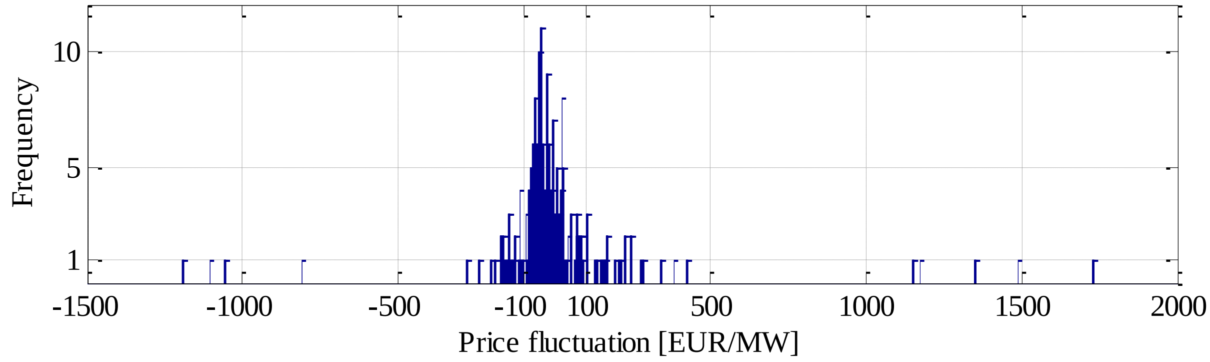

Figure 6.76: Fluctuation of average accepted bid from period to period

Last, Figure 6.77 shows the accepted bids in ascending price order for three consecutive weeks. In the week starting on the 15-Dec-2014 almost all accepted bids were at the same price. Contrary, for the following week, prices were significantly more differentiated with a much steeper bidding curve. Hence, the last MW was contracted at prices above 8 000 EUR / MW. In the third week, the lowest bid was at 5 000 EUR, significantly above the two previous weeks. Nonetheless, the complete auction was cleared at a maximum price well below the previous week.

Considering the price level as well as the steepness of the price curve, no general statement can be made about the shape of the biding curve without more detailed knowledge about the motivation and the bidding behavior of the individual operators.

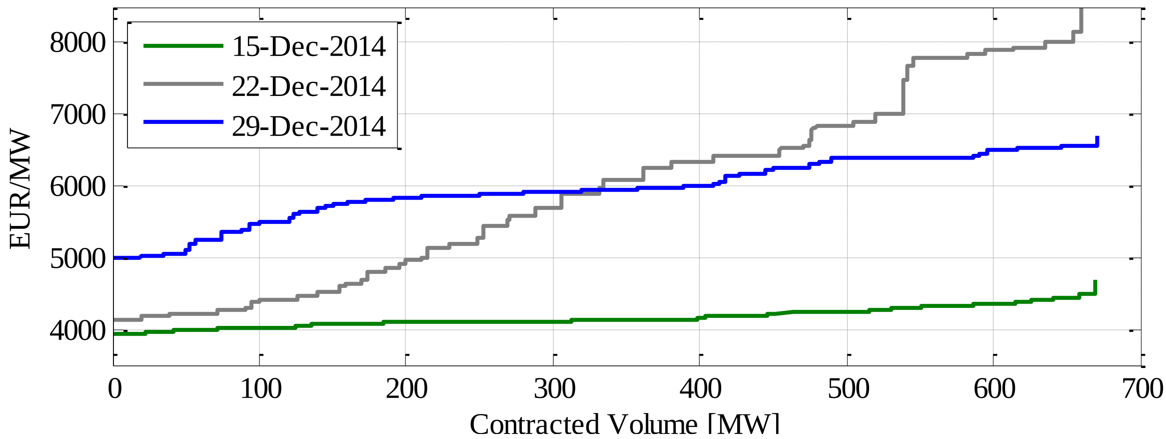

Figure 6.77: Bidding curves for three consecutive weeks

Storage System

To allow for an easy comparison, the identical lithium-ion battery as in the previous case study will be considered. These are summarized again in Table 6.23. The energy capacity is approximately in line with the technical requirements for the prequalification, as defined by equation (3.86).

Parameter	Value
$C^{Invest}_{Storage}$	*1 250 000 EUR*
$C^{Fixed}_{Storage}$	*10 000 EUR p.a.*
$E^{Capacity}_{Storage}$	*1.25 MWh*
$P^{Capacity}_{Storage}$	*1.00 MW*
$\eta^{In}_{Storage}$	*94.87%*
$\eta^{Out}_{Storage}$	*94.87%*
$\delta_{Storage}$	*20%*
$L^{Calendric}$	*15 a*
L^{Cycle}	*4 500*

Table 6.23: Parameters of the lithium-ion battery for the provision of primary reserve control

6.3.2 Model Implementation

The determination of the optimum revenue is based on the historical maximum accepted bids. As no dispatch algorithm is required, the calculation is straightforward.

The suggested backward looking approach (Section 3.5.2) is based on the distribution of accepted bids of the last tender. The bid for the current tender is then placed at a quantile of the previous week's prices. By comparing the bid with the actual results of the tender for the current week it can then be determined, if the bid would have been accepted. Figure 6.78 shows the percentage of the revenues obtained by the backward looking approach as compared to the optimum revenues, depending on the chosen quantile. In addition, the percentage of time the system would not have been dispatched is also shown. Accordingly, up to 80% of optimal revenues can be obtained by a rather simple bidding process, well above the numbers of the backward looking dispatch for arbitrage. Overall, it pays off to bid rather low and accept slightly lower revenues as compared to bid more aggressively and be not dispatched at times.

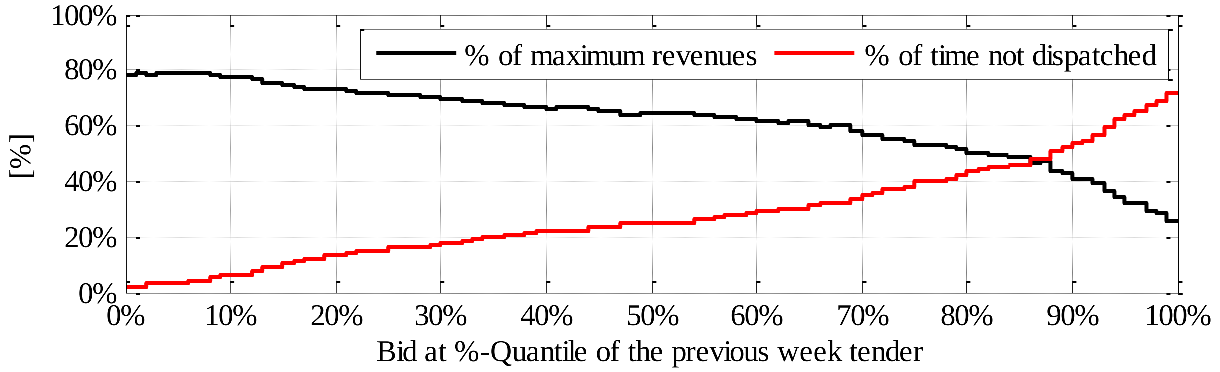

Figure 6.78: Bidding based on historical information

In the following, a bid at the 10% quantile of the previous week will therefore be assumed.

6.3.3 Historic Revenue Evaluation

This section will evaluate the revenue potential of the storage system mentioned above, considering the presented historic data.

Optimal Revenues

In a first step, it will be assumed that the storage operator had perfect knowledge of the results of the upcoming tender and hence was able to place the marginal bid, that is the bid with the highest price which was still accepted. In that case, total revenues of 769 678 EUR could have been captured over the years 2012-2015. Figure 6.79 shows the distribution between the years. The associated depreciation cost for the storage device is constant over time, as only calendric aging is considered. Over four years, depreciation charges as well as fixed cost amount to 373 333 EUR.

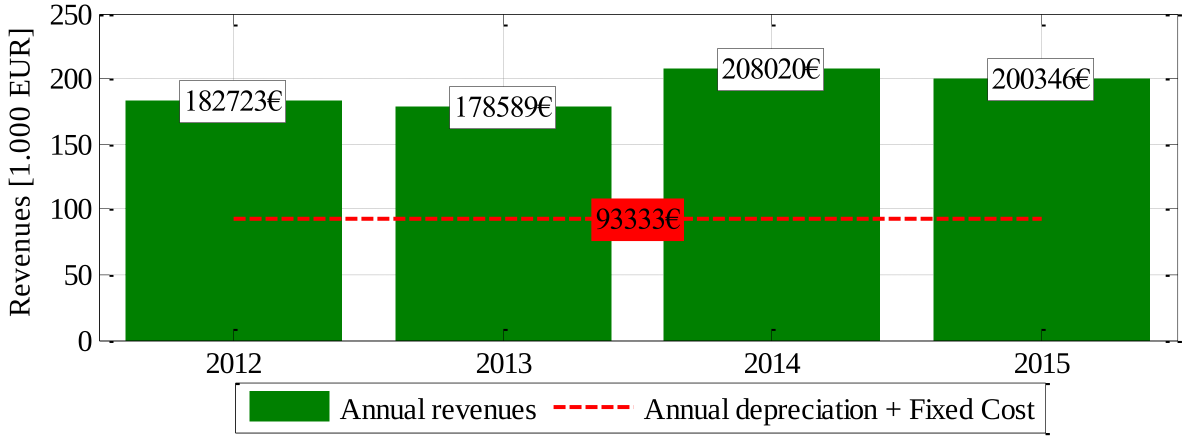

Figure 6.79: Revenues under perfect foresight for providing primary reserve control

Assuming that historic prices repeat and the storage operator has perfect foresight of the marginally accepted bid, he therefore would be able to capture revenues to the extent of more than twice the annual depreciation charges and fixed cost of the system and hence realize a significant profit.

Backtest

Relaxing the assumption of perfect foresight, the storage operator would be challenged with the task to place a bid each week. Incorporating the simple bidding process suggested, which only makes use of the distribution of the previous week and places a bid at the 10% quantile, it was already shown that up to about 80% of optimal revenues can be recovered. Total revenues in this case would have amounted to 596 142 EUR, with slightly increasing annual revenues over the years (Figure 6.80).

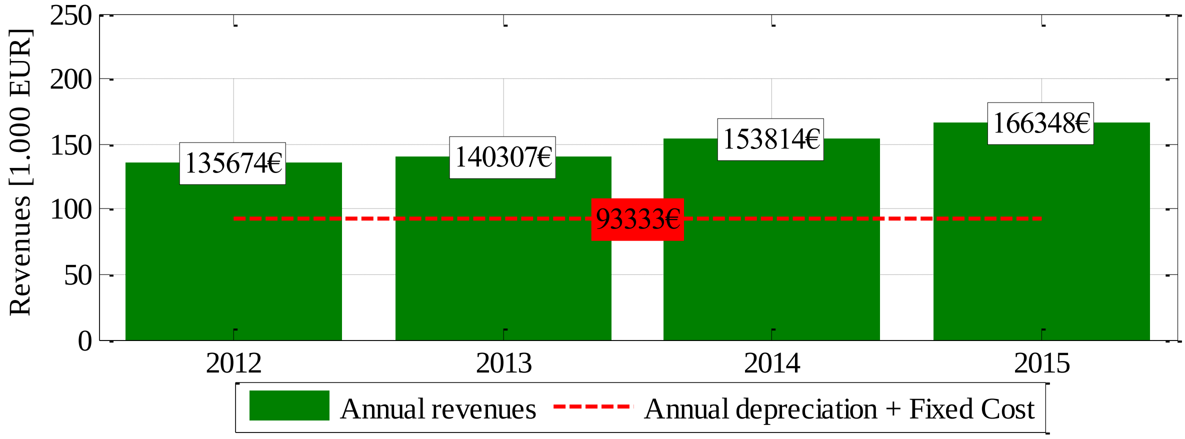

Figure 6.80: Revenues under a simple bidding process for providing primary reserve control

Hence, even when relaxing the assumption of perfect foresight and bidding in the tender based on a simple process, storage could provide primary reserve control with an attractive operating margin.

Looking at a more detailed breakdown of revenues over time (Figure 6.81), it becomes obvious how smooth revenues have developed, despite the occasional jump. However, as these jumps have exclusively occurred on the upside, they should not be of concern.

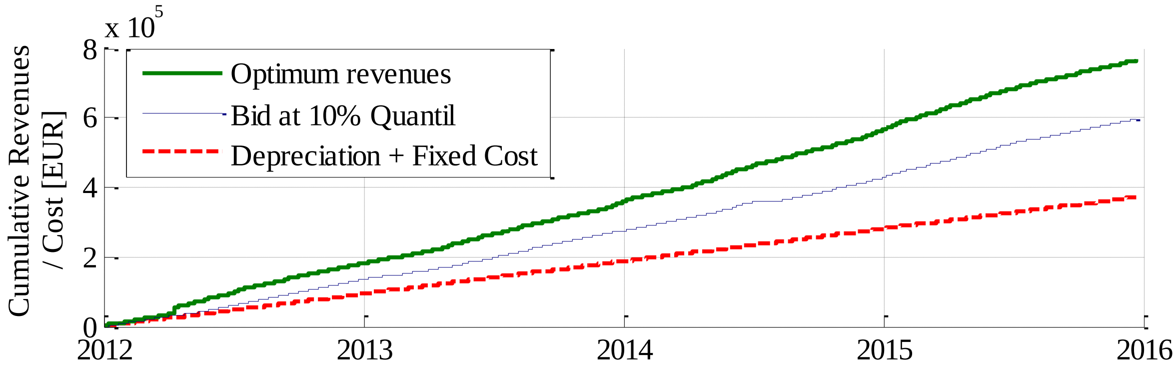

Figure 6.81: Development of cumulative revenues from 2012 - 2015

6.3.4 Results

For the following analysis, annual revenues of 150 000 EUR will be assumed as base case. This number is in line with the historic average of the backward looking bidding approach and well below the optimal revenues. The available revenues therefore clearly exceed the depreciation charges and fixed cost. However, investors must consider financing cost and also require a sufficient return on their capital.

Usually, investments will not be fully funded by the investor directly but to a large extend by a loan. In this case, it is assumed that the debt financing amounts to 70% of the investment. Hence, the loan will amount to 1 000 000 EUR, and must be repaid in 10 instalments of 100 000 EUR each. The interest is 4% on the outstanding amount. Over the first 10 years, the cash flow from operation will therefore be significantly reduced by the debt repayment. The hurdle rate for the equity financing is assumed to be 9%. Hence, the return to the company based on the equity contribution must be at least 9% in order to make the investment worthwhile. Table 6.24 summarizes the condition.

Debt	
r_{Debt}	*4.00%*
Tenor	*10 years*
Amount	*70% of C^{Invest}*
Amortization	*annually, in constant rates*
Equity	
r_{Equity}	*9%*

Table 6.24: Capital financing cost

Figure 6.82 shows the resulting cash flows. The assumed revenues are constant along the years. Over the first ten years, the loan must be repaid and hence significantly reduces the free cash flow. With an increasing amortization of the debt principal, the amount of interest due shrinks and hence cash flow to the investor increases slowly, before the loan is completely repaid at the end of year 10.

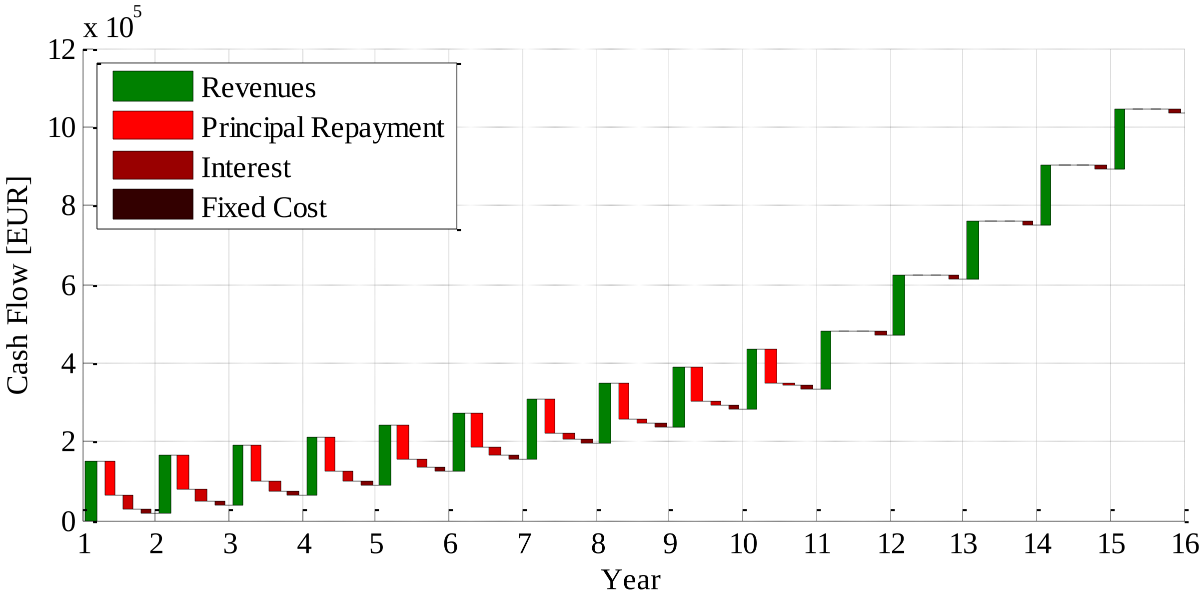

Figure 6.82: Cash flows over the storage lifetime

Based on the free cash flow to the investor, the net present value can then be calculated according to equation (3.20). Assuming a required return on the equity contribution of 9%, the NPV would amount to 52 638 EUR.

Hence, based on an annual revenue expectation of 150 000 EUR / MW, the previously presented storage system and the financing assumptions taken in this section, it would be financially attractive for an investor to invest into storage to provide primary reserve control.

6.3.5 Analysis

To better understand the influence of several factors on the overall value of the project as well as the major value drivers, a sensitivity analysis will be conducted. Furthermore, to identify the magnitude of uncertainty and risk, a Monte Carlo Simulation will be implemented.

Sensitivity Analysis

First, the financing variables (loan tenor, interest rate and required equity-ratio) were analysed. In Figure 6.83, the sensitivity towards the tenor of the loan is shown. Extending the tenor to the lifetime expectation of the storage system (15 years) would increase the net present value by about 50 000 EUR. Loan tenors of eight years or less would have insufficient free cash flows, as principal repayment in addition to interest expenses and fixed cost would exceed the assumed revenues. Hence, a loan tenor of at least nine years (everything else constant) is a critical requirement.

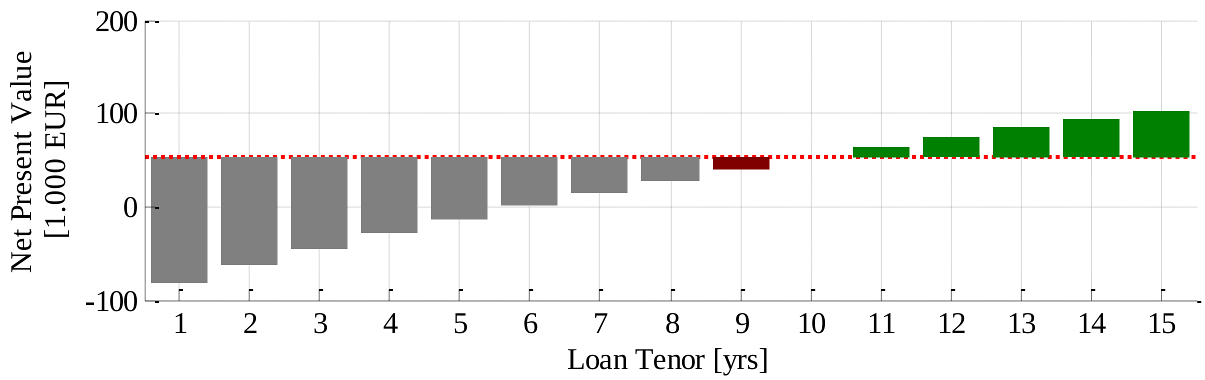

Figure 6.83: Sensitivity analysis: loan tenor

Figure 6.84 shows the sensitivity of the net present value towards the financing cost. A change of the interest rate of one percentage point would lead to a change of the net present value of about +/- 35 000 EUR. Hence, an interest rate increase of about 1.5 percentage points would decrease the net present value to zero.

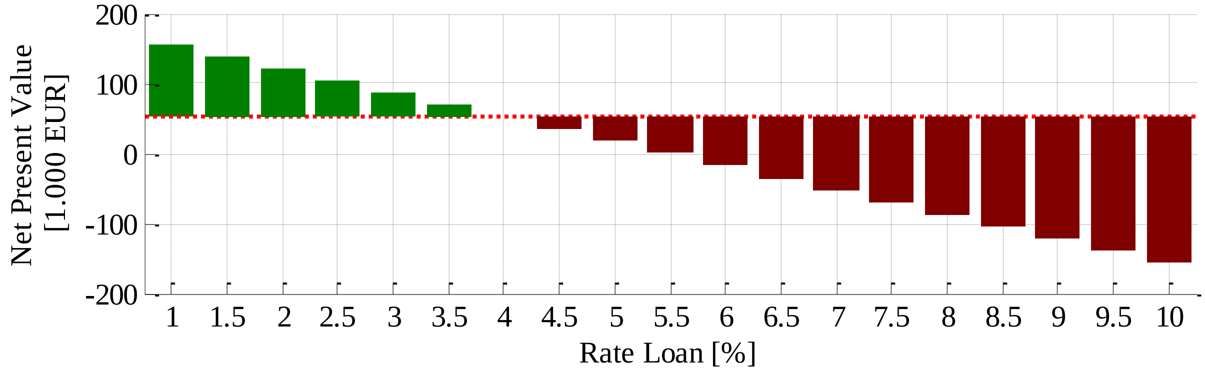

Figure 6.84: Sensitivity analysis: financing cost

Due to the difference between debt financing rate and the equity hurdle rate, the debt-equity-ratio also has an impact on the validity of the project. The lower the required equity contribution and the higher the loan, the more attractive the project becomes (Figure 6.85). Nonetheless, the project could be financed to 55% by equity and still reach a net present value of zero.

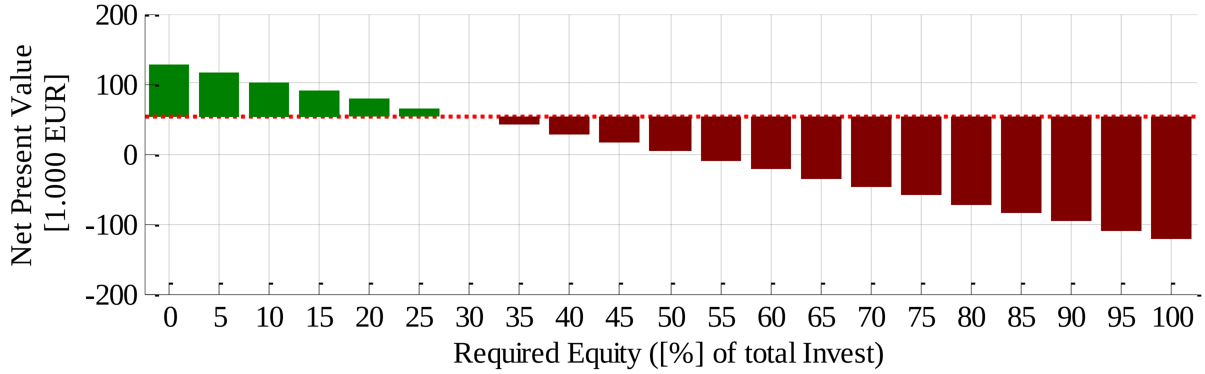

Figure 6.85: Sensitivity analysis: equity-debt-ratio

Hence, both interest rate and the equity-debt-ratio leave some flexibility. However, the tenor of the loan is a critical issue, as the revenues hardly cover the principal repayments due to the much shorter loan tenor compared to the storage lifetime. This issue is intensified by the fact that the assumed revenues are uncertain and could easily fall short during one of the years. Hence, in order to increase the financial stability of the project, investors should focus on negotiating longer loan tenors to reduce the annual principal repayment burden, even when they come with a slight increase in interest rate or a higher demanded equity contribution.

Figure 6.86 - Figure 6.88 show the sensitivities towards storage characteristics. Fixed cost (Figure 6.86) has a minor influence on the profitability and could almost double before the project would reach a negative net present value.

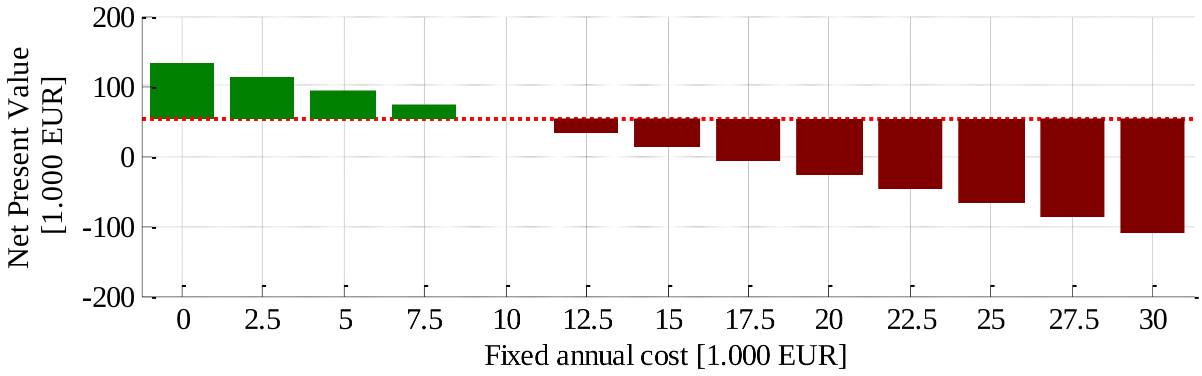

Figure 6.86: Sensitivity analysis: fixed annual cost

Contrary, both the investment cost (Figure 6.87) as well as the storage lifetime (Figure 6.88) have a strong impact on the economic validity of the project. A cost increase of only about 4.2% would already reduce the net present value to zero. Also, a reduction of the storage lifetime by two years would turn the project negative.

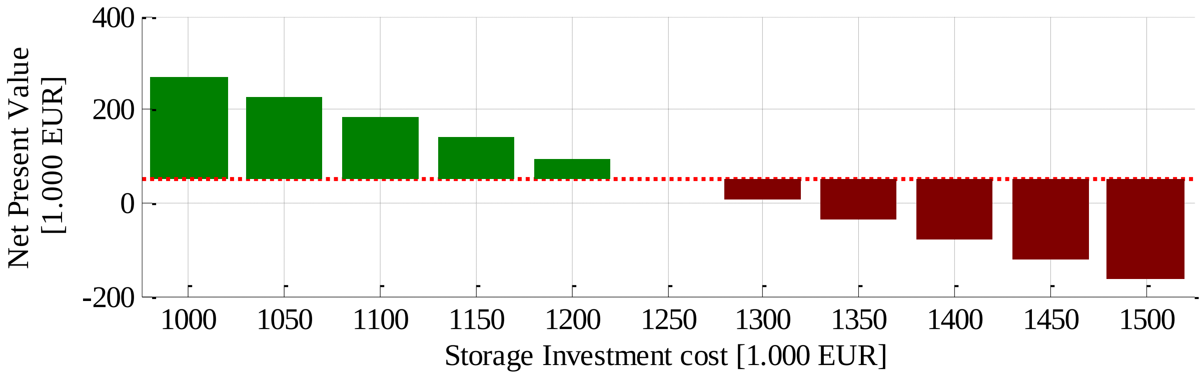

Figure 6.87: Sensitivity analysis: storage investment cost

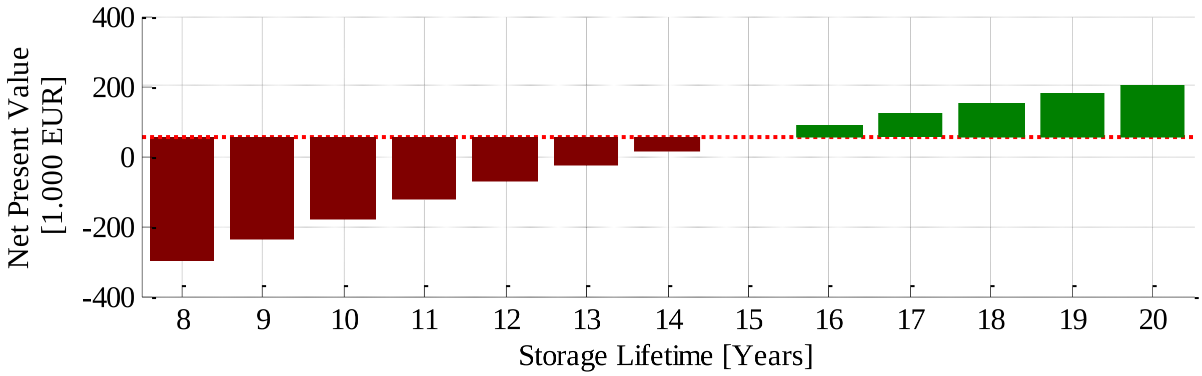

Figure 6.88: Sensitivity analysis: storage lifetime

Investment cost can contractually be fixed when the final investment decision is taken and can therefore be estimated quite accurately for the evaluation. Contrary, the storage lifetime is only revealed over the course of the project and therefore highly uncertain. However, as clearly shown in Figure 6.88, it poses a real risk to the validity of the project. Therefore, investors should prefer an established storage manufacturer with proven technology. Furthermore, investors should demand a performance guarantee for the advertised lifetime of the storage system.

Last, the sensitivity towards revenues is analysed. Figure 6.89 shows the relation between the assumed annual revenue and the resulting net present value. As expected, already slight deviations from the expected revenue result in substantial increases or reductions in net present value. So far, annual revenues of 150 000 EUR have been assumed, reflecting the revenues which could have been extracted over the years 2012-2015 with a simple bidding process. Assuming instead an optimistic case of always submitting the marginal bid, annual revenues would amount to about 190 000 EUR. In that case, Net Present value would increase to 375 066 EUR. However, on the contrary, decreasing the annual revenues by only 10 000 EUR would already turn the net present value negative.

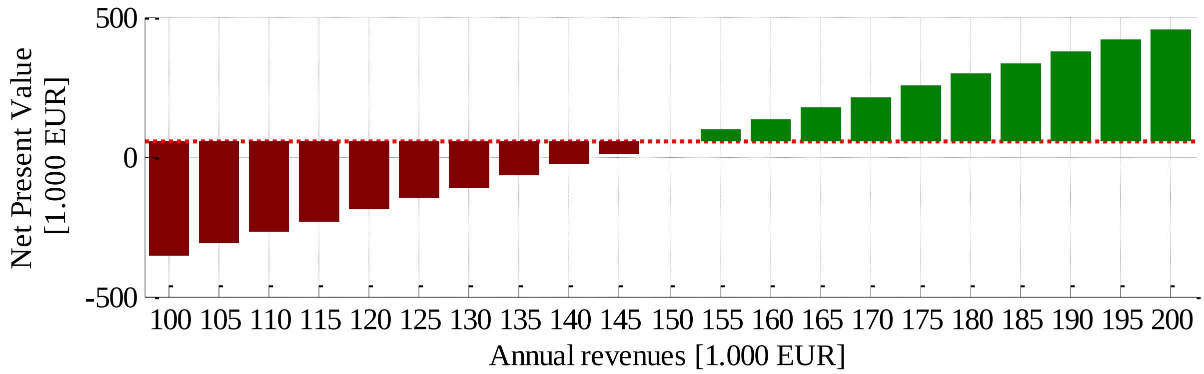

Figure 6.89: Sensitivity analysis: annual revenues

Monte Carlo Simulation

Last, a Monte Carlo simulation (see Section 4.5) is implemented to gain a better understanding about the likelihood of outcomes. It will be assumed that the investor has a firm offer for the discussed lithium-ion battery including installation and setup (Table 6.23) as well as access to funding according to the above assumptions (Table 6.24). Therefore, the major remaining uncertainty sources are the lifetime of the storage system and especially annual revenues. Fixed cost will be assumed to be certain, as they only have a minor impact due to their lower magnitude.

The lifetime of the storage system $L_{Storage}^{Calendric}$ is assumed to be uniformly distributed between 12 and 18 years, instead of the previously assumed 15 years. The annual revenues will be sampled for each year individually from the normal distribution, with a mean of 150 000 EUR and a standard deviation of 20 000 EUR. Hence, the probability of exceeding 190 000 EUR, determined as optimal revenues, amounts to 2.28% as per the cumulative distribution function of the normal distribution. Contrary, revenues will only fall short of 110 000 EUR p.a. (equivalent to about 2 100 EUR / week, about the lowest weekly revenues recorded in 2012-2015) in 2.28% of simulated years.

Taking random samples from the distributions for the revenues as well as for the storage lifetime over 100 000 runs results in the net present value distribution as shown in Figure 6.90. The mean (46 386 EUR) is slightly below the value from the previous calculation, as the positive effect from extending the lifetime is less than the negative effect from a lifetime reduction due to the time-value of money. Nonetheless, it is still significantly positive. However, in 31.68%, the net present value turned out negative, that is revenues would not be sufficient to generate the required return on equity.

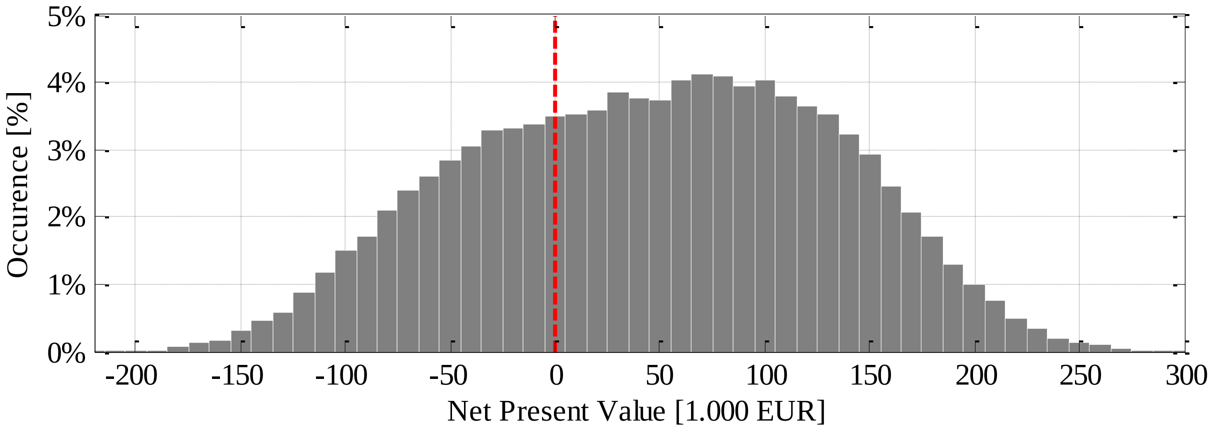

Figure 6.90: Net present value distribution of the Monte Carlo simulation for the provision of primary reserve control

However, neglecting the cost of own capital and looking only at net cash flows, the figure looks distinctively more promising. Figure 6.91 shows the distribution of cumulative cash flows over the storage lifetime.

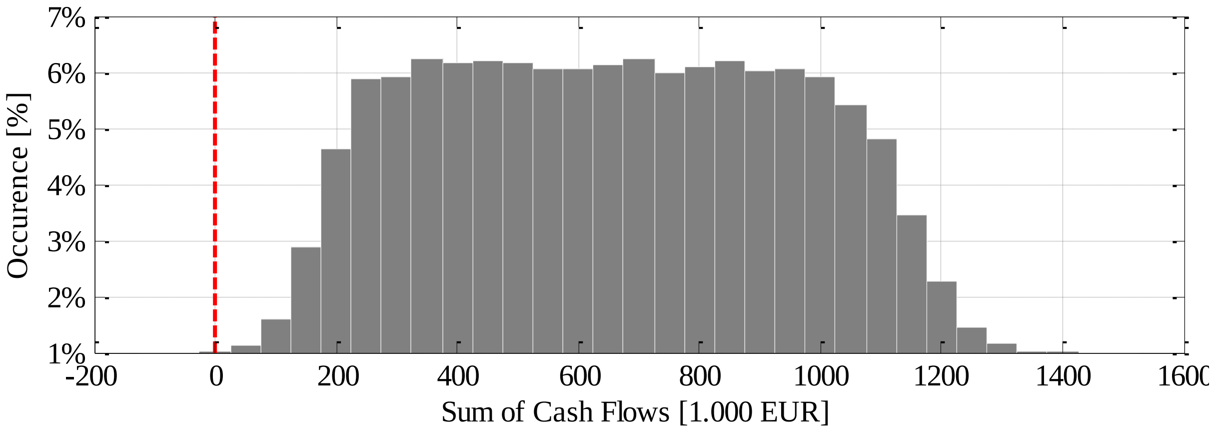

Figure 6.91: Cumulative cash flow distribution of the Monte Carlo Simulation for the provision of Primary Reserve Control

In only 0.01% of all simulations, overall cash flows were negative. However, in 22.1% of all simulations, the project had an intermittent short-fall in liquidity. This is especially problematic if the project has been realized as an individual legal entity. In that case, cash flow from the project would not have been sufficient to repay the loan. Therefore, the investor must be confident enough (despite the lack of revenues at that time) to inject additional capital to keep the entity solvent and the project alive.

This number can be significantly reduced by increasing the tenor of the loan, as thereby the annual principal repayments are reduced. By increasing the debt-tenor by one (two) year to 11 (12) years, a cash shortfall occurred only in 11% (5.7%) of all cases. For a loan-tenor of 15 years (expected storage lifetime), the short-fall occurred only in 1% of all simulations.

6.3.6 Conclusion

In this case study, the deployment of a lithium-ion battery with 1 MW for the provision of primary reserve control in the German grid zone has been considered. The weekly tender is organized as pay-as-bid auction. Over the years 2012-2015, annual average revenues were about 190 000 EUR when considering the marginal bid. A simple bidding process was able to recover 80% of revenues, about 150 000 EUR annually. As the storage system is automatically dispatched according to frequency deviation, no modelling of charge-/discharge operations was required. Despite the high investment cost for storage systems, the deployment for the provision of Primary Reserve Control appears attractive: the return on equity was found to be 10.5%. The subsidy of about 30%, which was granted to a range of recent pilot projects (see Section 2.3.10), is not necessary to reach the break-even point.

Following, a sensitivity analysis was conducted. The interest rate of the loan as well as the required equity ratio were found to be important drivers for profitability, but investors should rather focus on a long tenor for the loan. Annual fixed cost for the storage system was found to play a minor role; contrary, both investment cost as well as expected lifetime are decisive factors. While the investment cost can be contractually fixed when the investment decision is taken, storage lifetime is only revealed over time and hence remains a major source of uncertainty for the project evaluation. Last, revenues were considered. It was found that annual revenues of at least 143 470 EUR are required to reach the aspired rate of return on the equity contribution.

In addition, a Monte Carlo Simulation was run, for which distributions for both the lifetime as well as annual revenues were assumed. The simulation showed that even though the aspired rate of return is missed in about 1/3 of all cases and intermediate shortfalls in the cash flows occur, the cumulative cash flow remains positive for all simulations. In addition, the simulation showed the importance of a long loan tenor in order to guarantee sufficient liquidity for principal repayments.

The analysis highlighted two main aspects, as follows:

First, investors should demand a performance guarantee for the advertised lifetime. This significantly increases the expected value of the project and reduces the uncertainty. Furthermore, the probability (given the previous assumptions), that the project misses the aspired return rate and the net present value becomes negative, is substantially reduced. Figure 6.92 shows in comparison to Figure 6.90 the reduction of cases with a negative net present value for the project, when the lifetime of the storage device is guaranteed.

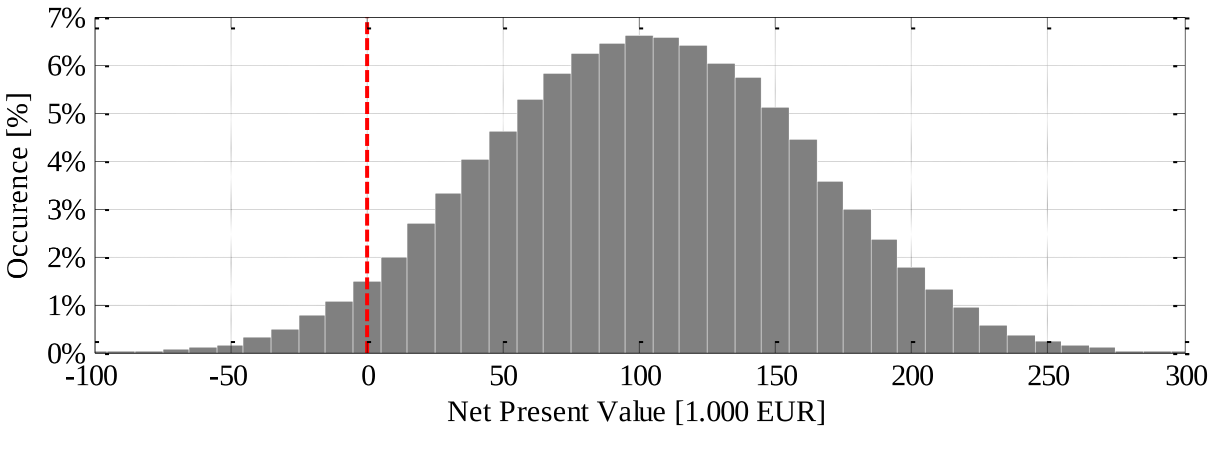

Figure 6.92: Net present value distribution of the Monte Carlo Simulation for the provision of Primary Reserve Control with a lifetime guarantee

Second, policy makers should consider providing funding through their development banks for the first projects instead of subsidies for the investment cost. It was shown that a long loan tenor is important to avoid an intermittent short-fall in liquidity and the resulting threat of insolvency, as revenues are volatile and might be lower than expectations during some years. This threat is increased as investors will most likely use separate legal entities to segregate the storage facility from their traditional business due to their novelty. On the other hand, banks will hesitate to provide the required funding and especially will prefer short loan tenors. Overall, this gap could easily be bridged by development banks until storage investments become more common. However, investments in storage for the provision of ancillary service are capital intense, and require a substantial upfront commitment by the investor for long-term revenues. It is therefore not suitable for investors who require a payback within a few years.

6.4 Co-integration of Applications

The following case study will analyze if the economic proposition of storage investments can be improved if storage is not only dispatched for a single use but for several purposes simultaneously. Based on the discussion of 3.6, the storage system is assumed to be installed in a consumer context with the primary intention to shift locally generated energy in time. In addition, the storage device will be dispatched for the provision of primary reserve control as well as for peak shaving to reduce the grid connection cost.

6.4.1 Data and Assumptions

Generally, the case study is based on the same assumptions and the same historical dataset as the case study 'Time shifting of energy' (6.1.1).

The remuneration for the provision of primary reserve control $R^{Regulation}(t)$ is assumed to be 0.00002 EUR per watt and hour, which is in line with the historic compensation (see Section 6.3.1). Furthermore, it is assumed that the compensation is fix and that agents can provide reserve control on a weekly basis, as currently required by German regulation. Last, no minimum power requirements are enforced and arbitrary capacities can be provided.

Grid connection costs are based on the observed peak demand over a 15-minute interval on a weekly basis. Each kW of required capacity is charged 1.44 EUR per week, equivalent to the annual capacity cost $C_{Grid}^{Capacity}$ of 0.075 EUR / W.

Parameter	Value
$R^{Regulation}(t)$	$0.00002\ €/(W \times h)$
$C_{Grid}^{Capacity}$	0.075 € / W

Table 6.25: Assumptions for the provision of reserve control and peak shaving

6.4.2 Model Implementation

In order to determine the optimal dispatch, the value maximizing system configuration identified in the time shifting case study (Section 6.1) combined with a storage device with 50 kWh capacity will be considered.

The optimization follows the approach presented in 6.1.2. However, in order to incorporate the assumed weekly frequency of the capacity payments, the optimization window must cover at least seven days at once. Therefore, the dispatch optimization will be done one week at a time, with an overlap of 12 hours between optimization windows.

Even though the problem formulation takes charging or discharging of energy from the provision of reserve control into account, no actual power flows will be considered in the case study due to lack of data. As foreseen by the German regulation (see Section 2.2.3), it is rather assumed that any energy absorbed or provided is again discharged or charged within the frequency dead-band. Therefore, in the implementation, there is no interference between the operations of time shifting and the provision of reserve control. The resulting numbers will be slightly sub-optimal as absorbed energy could otherwise be used to satisfy local demand.

6.4.3 Results

In order to determine the value of the storage applications, the evaluation approach presented in the discussion of the business case (Section 3.6.3) is applied.

First, the previously identified optimal system configuration (Section 6.1.3) is dispatched to establish a reference case without storage system. Due to the consideration of the grid connection cost, the NPV decreases from the previously identified figure of -29 800 EUR to -31 679 EUR.

Second, a base line for the further evaluation is established. Therefore, analogous to the case study of time shifting, a storage system with a capacity of 50 kWh is included. However, the power capacity of the storage device $P_{Storage}^{Capacity}$ is set to zero. Therefore, the investment cost of the storage device is considered in the financial evaluation, however the system cannot yet add any value. The resulting NPV is -33 813 EUR.

Following, the value for time shifting is determined by resetting the power capacity to its original parameter. In order to exclude the applications of peak shaving and the provision of reserve control, their cost / revenue contribution is only considered in the financial evaluation, but not in the objective function of the dispatch. Hence, the storage device is dispatched without knowledge about the related cost / potential revenues. In this case, the NPV increases to -32 581 EUR. As in the previously analysed case of time shifting, the value added is not yet sufficient to justify a storage investment.

Following, by considering the cost for the grid connection in the objective function, the optimal dispatch for storage simultaneously providing time shifting as well peak shaving is determined (NPV: -30 910 EUR). Analogous, the optimal dispatch for time shifting and the provision of reserve control can be obtained (NPV: -32 123 EUR). Last, the optimal dispatch for the simultaneous provision of time shifting, peak shaving and provision of reserve control is calculated. The resulting NPV is -30 536 EUR.

Table 6.26 summarizes the results. In the case of a simultaneous dispatch for time shifting and peak shaving as well as when all three applications are stacked, storage systems are clearly able to provide value beyond their depreciation charges and improve the NPV when compared to the reference case.

	Reference case	**Base line**	**Time shifting**	**Time shifting + Peak shaving**	**Time shifting + Reserve control**	**Time shifting + Peak shaving +Reserve control**
NPV	-31 679 EUR	-33 813 EUR	-32 581 EUR	-30 910 EUR	-32 123 EUR	-30 536 EUR

Table 6.26: Net present value for different dispatches

In order to determine the value added by the individual applications, their net present value is compared among each other. Comparing the NPV of a storage system dispatched for time shifting with the base case, the value added equals 1 231 EUR. If peak shaving is considered in addition, the value increases by an additional 1 671 EUR. Alternatively, dispatching the storage device simultaneously for the provision of reserve control besides time shifting increases the value only by 458 EUR. If all applications are pursued at the same time, the value increases by 3 277 EUR.

Figure 6.93 shows the value contribution of the applications in comparison. While time shifting and peak shaving significantly improve the NPV, the contribution from providing reserve control is limited. The forth bar shows that the value contribution of the individual applications are not additive. Pursuing several applications at once has implications on the operation of each individual application.

For example, when providing reserve control, the available power capacity is limited for the other applications, as the contracted power must be available at all times. However, with a gap of 84 EUR, the missed value is limited. As the value added for peak shaving and provision of reserve control is only determined in combination with time shifting, the gap might be larger in reality.

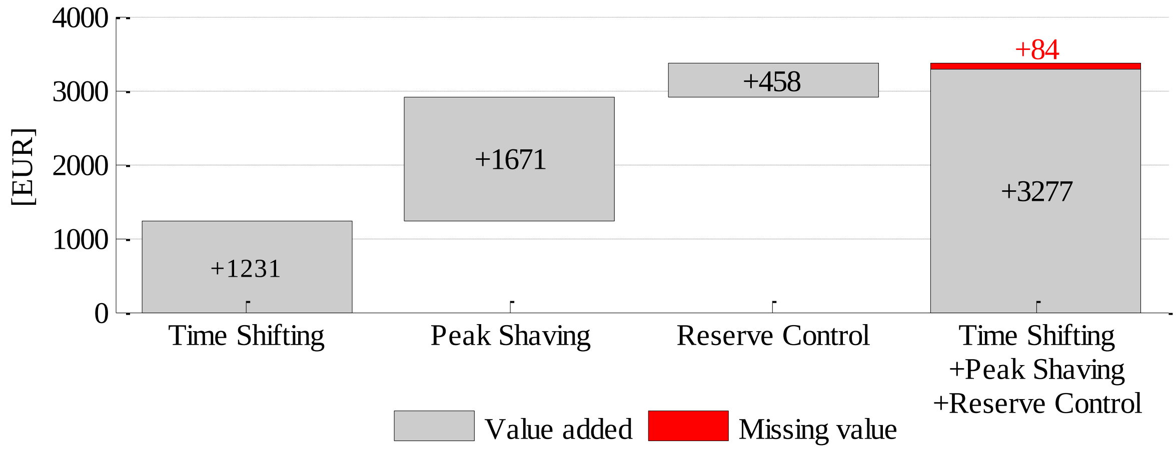

Figure 6.93: Value added by storage applications

The results of time shifting have been discussed in detail in the related case study. While the absolute figures differ slightly, the statements are transferable.

Employing a storage device for peak shaving allows reducing the required grid connection capacity. Figure 6.94 shows the reduction in grid demand, when the storage device is dispatched simultaneously for all three applications. Overall, the required capacity is rather constant along the year with about 10 kW. During spring and summer, with high intermittent contribution of the intermittent photovoltaic system, the required capacity is at times even lower. In autumn, when less photovoltaic generation is available and heat demand is not yet sufficient to constantly operate the cogeneration unit, the required grid capacity is slightly higher.

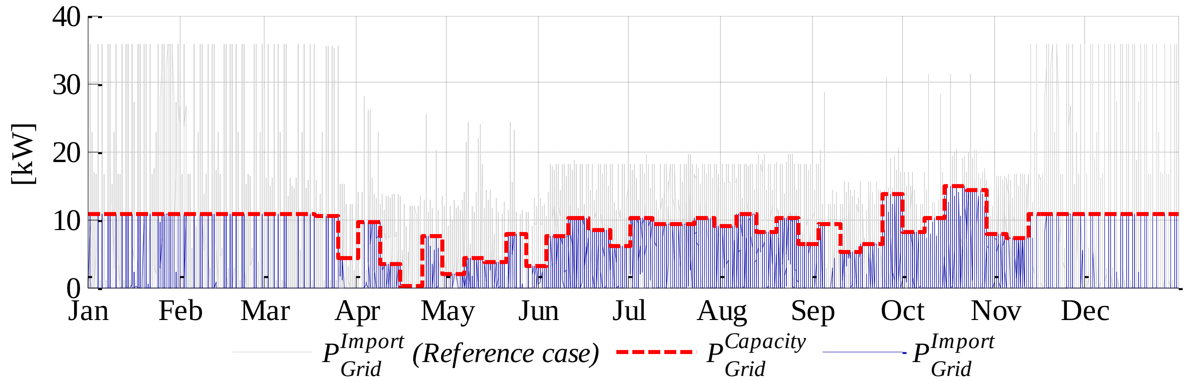

Figure 6.94: Required grid connection capacity along the year

Figure 6.95 compares the grid demand for the first week of July. Considering only the generation from the photovoltaic system, the required grid capacity is about 39 kW. This value is reduced to 19.5 kW by the cogeneration unit. However, high demand occurs very infrequently and the connection it not very well utilized. Dispatching the storage device for peak shaving reduces the required grid capacity in this particular week to 10.1 kW, about half of the previously required capacity. While the periods with low demand decrease significantly, the number of hours where grid demand is just below the limit increases significant. Overall, the connection is much better utilized.

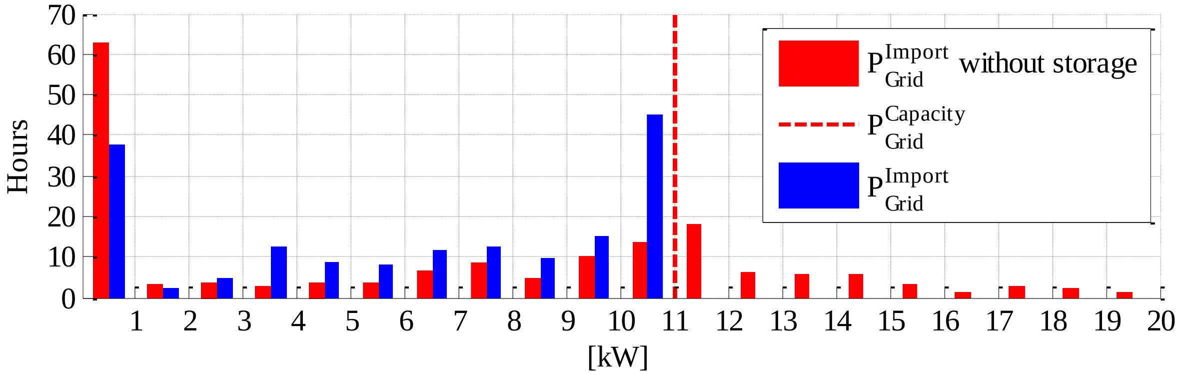

Figure 6.95: Comparison of grid demand with and without storage

Last, Figure 6.96 compares the required grid capacity when peak shaving is pursued only in combination with time shifting or also in addition to providing reserve control. During the winter, no difference is observable. Over the rest of the year, the required grid capacity is typically slightly higher when the storage system is also dispatched for the provision of reserve control. The biggest difference can be found in September and October, when the impact is up to 8.6 kW.

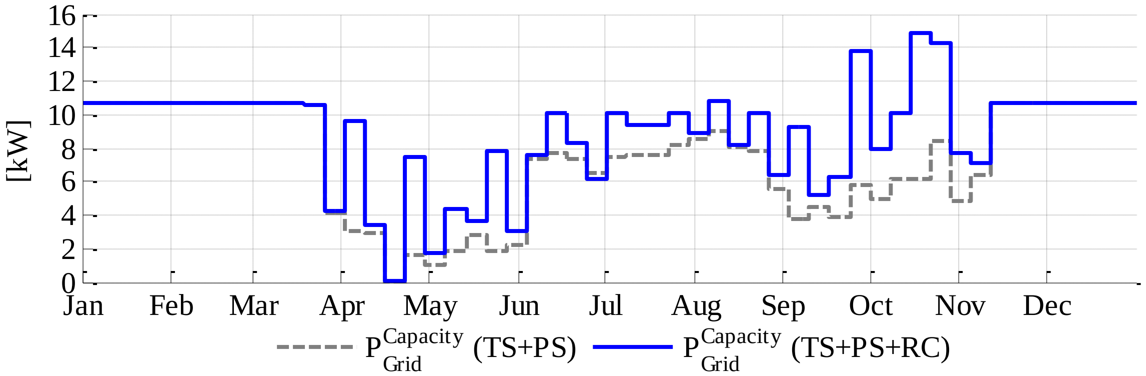

Figure 6.96: Required grid connection capacity

Figure 6.97 shows the capacity reserved for the provision of reserve control, when the storage system is dispatched for all three applications or only for time shifting and reserve control. The power capacity of the storage and hence the maximum power that can be tendered is 25 kW. However, during the winter, the storage system is barely tendered for the provision of reserve control when only providing time shifting in addition and not at all, when also peak shaving. During the rest of the year, the maximum power provided is up to 10 kW, though the storage system participates very opportunistic. Similar to the case of peak shaving, the addition of another application has only a limited impact.

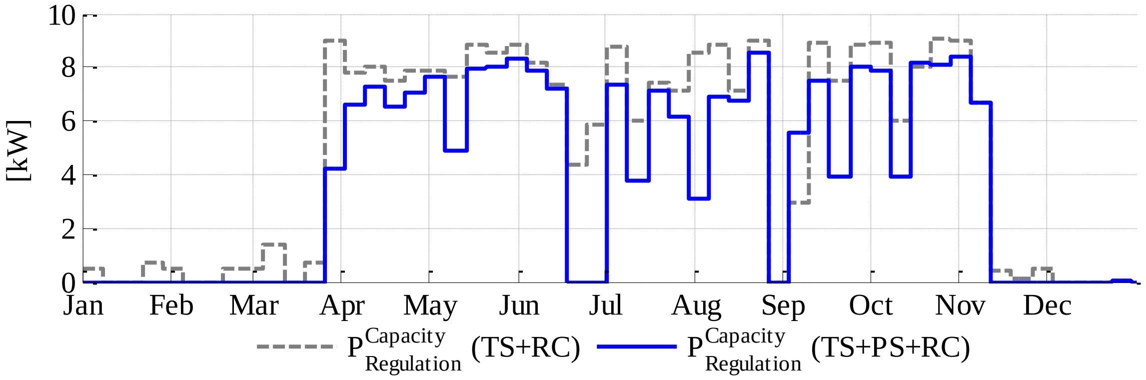

Figure 6.97: Tendered storage capacity for the provision of reserve control

Comparing the different cases to the reference case shows that storage systems dispatched for at least simultaneous time shifting and peak shaving are able to provide sufficient value to offset their associated depreciation charges. Integrating the provision of reserve control in addition further improves the investment proposal.

6.4.4 Analysis

Following the approach described in Section 4.3, a sensitivity analysis is conducted. Therefore, the parameters are varied one at a time and the new optimum dispatch is determined. Analogous to the analysis in the case study of time shifting (Section 6.1.5), Figure 6.98 shows the sensitivity of the net present value with regards to a change in the following parameters, when the storage device is simultaneously dispatched for all three applications.

- Cost for the grid connection capacity $C_{Grid}^{Capacity}$. The plot shows a linear slope, hence even for reduced connection charges it is preferential to use the same storage capacity to reduce the required connection capacity as much as possible instead of pledging more capacity towards the provision of reserve control.
- Compensation for the provision of reserve control $R^{Regulation}(t)$. Contrary to the cost for the grid capacity, at reduced compensation rates the slope becomes flat. Hence, for compensation below a certain threshold, no reserve control would be provided.
- The frequency for the provision of reserve control, that is the duration for which the tendered power must be held available. Profits increase significantly for intervals shorter or equal to 12 hours. For intervals of one or two days, almost no improvement over the weekly tender can be found.
- Last, the power capacity of the storage device $P_{Storage}^{Capacity}$. Increases of more than 25% do not add any further value, whereas decreases significantly reduce the profitability of the storage device.

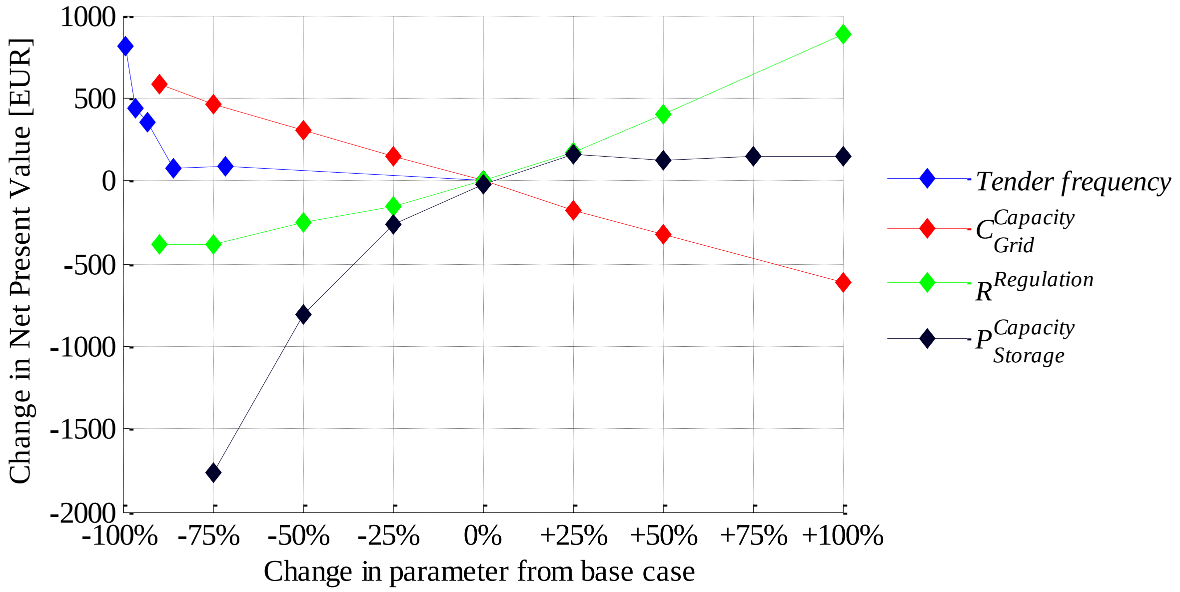

Figure 6.98: Sensitivity plot

6.4.5 Conclusions

The presented case study considered the simultaneous dispatch of storage for time shifting, the provision of reserve control and the reduction of the required grid capacity. It was shown that under the assumed cost and revenues, storage dispatched for several services in parallel does not only add value (as shown in the first case study in Section 6.1), but also overcomes its investment cost and hence increases the net present value.

Time shifting was found to add 1 231 EUR in value, peak shaving 1 671 EUR and the provision of reserve control 458 EUR. Hence, by stacking the individual applications, the value added clearly exceeded the calendric depreciation charges of the storage device of about 2 200 EUR. Furthermore, it was also shown that the considered applications can be co-integrated without a major negative impact on each other. The identified value gap due to the interference of the individual applications was found to be only 84 EUR. In addition, it was found that the dispatch of the storage device differs significantly between the seasons. While the storage device was not at all dispatched for the provision of reserve control over the winter, it regularly participated in the tender during the rest of the year.

A subsequent sensitivity analysis showed that low power ratings of a storage device might severely impact its value. Furthermore, tender periods of less than 12 hours or less for the provision of reserve control would significantly increase the value of storage.

The primary conclusions from this case study are:

First, dispatching a storage device simultaneously for several purposes can significantly enhance its value proposition up to the point that storage becomes attractive at today’s cost. The conducted analysis has shown that the combination of several applications is not a problem from a dispatch point of view. However, the applicability and availability of revenue sources is very specific to the considered context.

Second, it is up to policy makers and regulators to ensure that distributed agents can access the considered revenue sources. It was shown that participating in the ancillary service market can greatly enhance profitability, especially for short contracting tenors. However, a suitable legal framework is required. Not only must it grant access for distributed agents to the considered market places, but it must also enable storage operators to dispatch their storage device for several applications at once, as long as the provision of the contracted service is guaranteed.

6.5 Impact on Electric Demand

Based on the results from Chapter 5, this case study will analyse the impact of distributed storage systems on the German electric system assuming a storage implementation growth rate. Hence, in addition to the individual impact of storage systems on grid demand which has previously been established in Chapter 5, this case study will look at the cumulative impact from a system perspective. Furthermore, the immediate financial impact on affected entities will be estimated. While such an analysis requires a wide range of assumptions, it provides a high-level understanding of the consequences of storage investments and potential feedback reactions on initial investment considerations.

For this case study it will be assumed that the storage systems are installed for time shifting locally generated energy. While the provision of ancillary services was shown to be profitable, it does not directly affect the energy market. Further motives will likely not result in a significant number of installations over the next years, as most applications are either not yet profitable (such as pursuing arbitrage, see Section 6.2) or face other implementation hurdles such as regulatory barriers (see Section 2.3). Therefore, they are not considered in this case study.

Analogous to the case study in Section 6.1, residential consumers will be considered as they face the highest electricity cost and will likely be the first ones for which storage becomes profitable. In addition, contrary to minimum-return hurdles on investment projects required by most companies, private investors are driven by motivations beyond pure economic incentives [132], such as technological interest, ecological motives or the desire to be (partially) independent from the grid. Hence, a significant share of the storage installations over the next years can be expected to be from residential consumers.

As detailed in Section 5.2.1, it will be differentiated between three implementation cases: storage installed in combination with a photovoltaic system, in combination with a photovoltaic system and a cogeneration unit as well as the refitting of existing photovoltaic systems with a new storage device.

6.5.1 Data and Assumptions

First, the assumptions about the growth of storage installations will be presented. Second, potential system configurations will be discussed. Following, the demand and generation profiles are defined.

Storage Growth Rate

The forecast of new installations is associated with a high degree of uncertainty due to the magnitude of influencing factors, such as the expected decrease in investment cost, the evolution of the regulatory framework as well as the development of electricity cost.

According to [132], from May 2013 until January 2016 about 34 000 storage devices were installed with a cumulative effective capacity of 200 MWh. The authors estimate that up to 60% of all new PV installations are equipped with a storage system.

The forecast of new storage systems is based on the idea that storage installations will follow a similar growth pattern as photovoltaic installations did after their introduction to the mass market in the past. [204] applied the historic growth rates of private photovoltaic installations from the years 2004 – 2011 to the market for private storage installations for the years 2015 – 2022, which predicts an increase in annual installations from about 32 000 in 2016 to more than 100 000 in 2022.

As the impact of storage differs according to its deployment, the number of total installations will be broken down as follows:

- The expected number of installed cogeneration units is relatively low. Based on data from the Federal Office of Economics and Export Control [205], which is responsible for the handling of subsidy payments for cogeneration units, on average 1 300 units with an electric output of less than 2 kW were installed annually over the last five years. For the following analysis it will therefore be assumed that out of the total forecasted storage installations, 1 300 systems are also equipped with a cogeneration unit besides the photovoltaic system and the storage device.
- Since the year 2000, the feed-in of photovoltaic generation in Germany has been regulated by the Renewable Energy Sources Act [126], which guarantees a fixed feed-in tariff for 20 years. Hence, from 2020 onwards, many existing PV installations will lose their attractive feed-in tariff. According to [206], from 2020 until 2022, installations with a total capacity of 226 MW will be affected. For consumers, whose installation is still operational, it will be economic beneficial to install storage to increase their self-consumption. Therefore, it will be assumed that 15% of these installations will be refitted with a storage device.
- The number of new combined photovoltaic and storage installations is defined by the difference between the total forecast and the previous two motives.

Both the historical growth and the expected storage installations as well as their breakdown according to the installation motive are shown in Figure 6.99. The growth of storage installations over the coming years is therefore clearly driven by new photovoltaic systems.

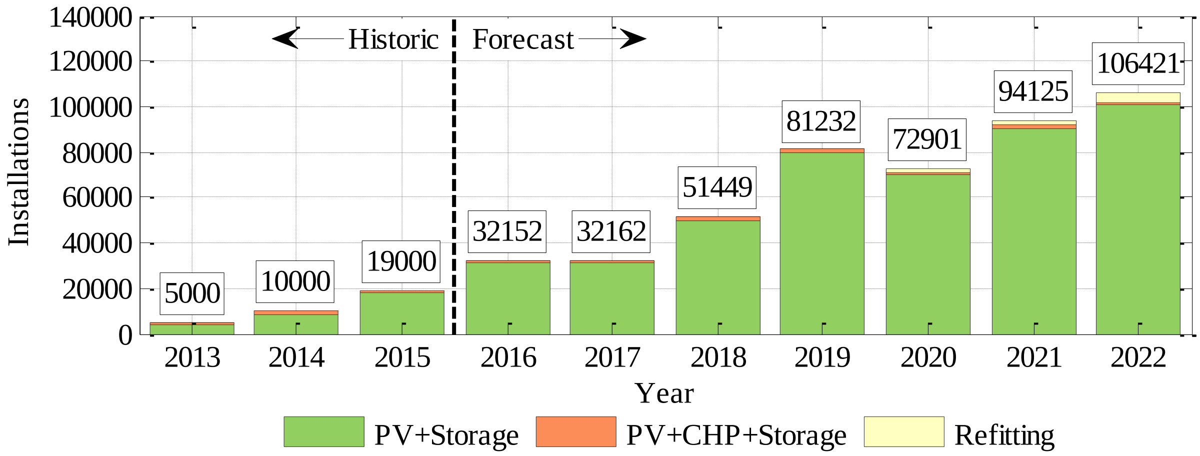

Figure 6.99: Historic growth ([132]) as well as forecast of new storage installations ([204])

System Configurations

The annual monitoring report [132] for the subsidy program for storage systems in Germany provides some insights about realized storage installations. Based on their findings, the following assumptions about the implemented system parameters and capacities will be taken:

- Annual electricity demand of households which invest into storage devices was found to typically range from 3 000 to 8 000 kWh. For the simulation, a normal distribution with $\mu = 5\ 000\ kWh$ and $\sigma = 2\ 000\ kWh$ will therefore be assumed.
- Most photovoltaic systems were found to have a peak generation capacity of 5 – 10 kW. Following, a normal distribution with $\mu = 6.5\ kW$ and $\sigma = 1.5\ kW$ will be assumed. Furthermore, the authors determined a positive correlation (assumed to be *0.5*) between photovoltaic capacity and annual electricity demand.
- Most installed storage systems have an effective capacity between 2 – 10 kWh. Therefore, a normal distribution with $\mu = 5\ kWh$ and $\sigma = 2\ kWh$ will be assumed. Furthermore, the capacity of the photovoltaic system is assumed to be correlated with *0.5* to the annual electricity demand as well as to the capacity of the storage system.

The capacity of a cogeneration unit for residential consumers is typically driven by the thermal demand. It is assumed that only some comparatively large households would invest into such a unit. Therefore, in the simulation, it is assumed that only consumers with an annual electric demand of at least 6 000 kWh install a cogeneration unit. The capacities are assumed to be normally distributed with $\mu = 1\ kW$ [205] and $\sigma = 0.2\ kW$.

From the sampled combinations, all sets with an annual demand below 1 500 kWh, a capacity of the photovoltaic system of less than 2 kW or a storage capacity of less than 2 kWh were discarded. Furthermore, if a cogeneration unit is installed, it must have a capacity of at least 0.5 kW.

Figure 6.100 shows an exemplary set of sampled combinations of electric demands and system capacities for all three cases.

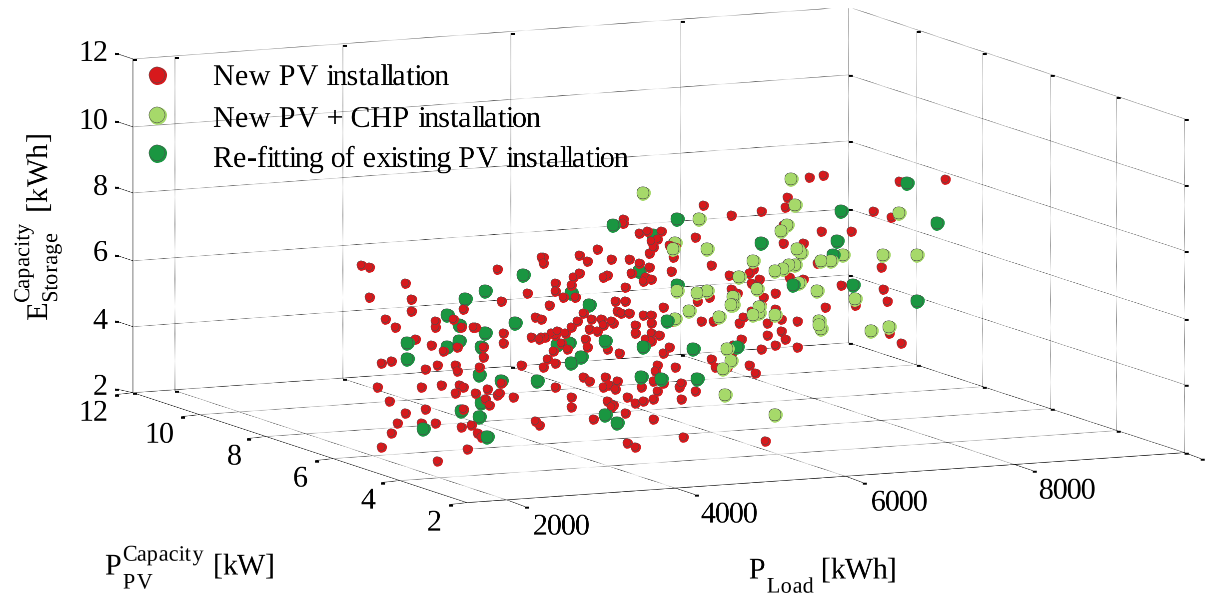

Figure 6.100: Sampled combinations of demand and system capacities

Demand and Generation Profiles

Demand is described by the standard load profile for residential consumers [191]. The profile was introduced and discussed in Section 5.2.1. It differentiates between the time of the year, with winter peak demand exceeding maximum load during the summer by 60%, especially during the evening hours. Figure 6.101 shows the profile along a week during a week in winter and in summer for the reference annual demand of 1 MWh.

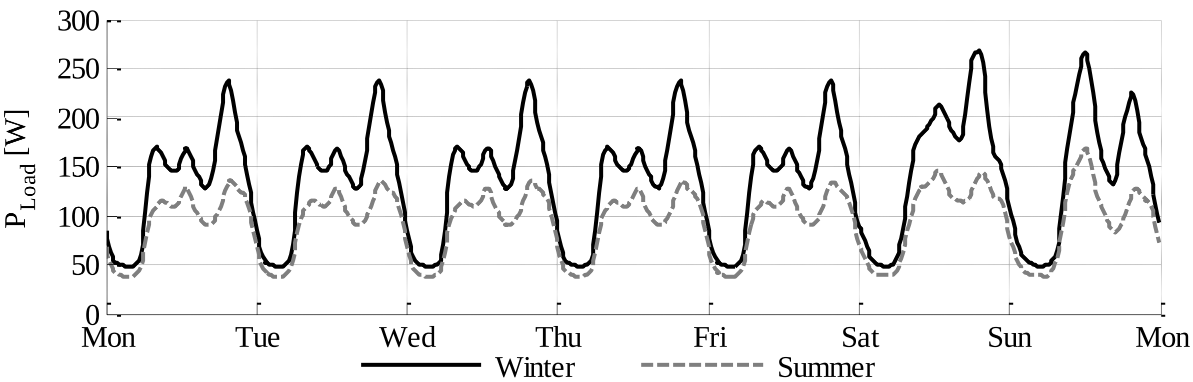

Figure 6.101: Load profile during a week in winter and in summer

The aspect of using smooth load profiles as compared to high-resolution data was discussed in the literature review in Section 2.4.4. Accordingly, short-term demand peaks and valleys are not correctly considered in the simulation, which results in an underestimate of both import and export of energy over the grid connection. However, as the interest of the case study is to derive some general findings and no individual high-resolution load profiles over a wide range of consumers were available, the resulting error is accepted.

The usage of average solar data could potentially introduce major errors, as intermittent solar yields fluctuate strongly from day to day and affect all operators of solar systems at the same time. Hence, the potential impact on the results is much more substantial. Therefore, historical data was used, which was introduced in Section 6.1.1. The monthly distribution as well as the generation along the year was shown by Figure 6.6 and Figure 6.7. Despite using high-resolution historical data, a further error is introduced at that point, as only data for one location was used, whereas in reality an overall smoother generation profile due to the geographic dispersion can be observed.

The output of the cogeneration unit is assumed to be proportional to the annual distribution of residential heat demand as presented in Section 6.1.1. It is assumed that the cogeneration unit is constantly dispatched, however oftentimes working only at part-load, such that at the rated output it would operate during 6 000 hours. Total demand seen by the grid is based upon data from [194].

6.5.2 Model Implementation

Following the approach presented in Chapter 5, in a first step the impact on grid demand will be established. In order to reduce the required computational effort, a typical portfolio of installations for each implementation case will be simulated and scaled to the number of installations instead of simulating thousands of installations individually. Therefore, these steps will be followed:

- First, for each of the three implementation cases, a set of 250 random system configurations is created. The resulting distributions and correlations are compared to the initial assumptions to ensure the proper implementation.
- Second, the optimal dispatch is determined for each system configuration following the methodology presented in Section 3.3.4.
- Third, based on the optimal dispatch for each configuration, the impact on grid demand is determined following the approach discussed in Section 5.2.1.
- Forth, the expected impact on grid demand for each implementation case is obtained by averaging across the 250 dispatches.
- Last, the expected impact on grid demand from the previous step is scaled according to the assumed growth rate of storage installations.

6.5.3 Results

Figure 6.102 shows exemplary both the individual as well as the average impact from 250 simulated photovoltaic and storage installations. It is obvious that the impact varies significantly across the considered system configurations as well as from day to day due to the variability of the solar radiation and the difference in installed capacities.

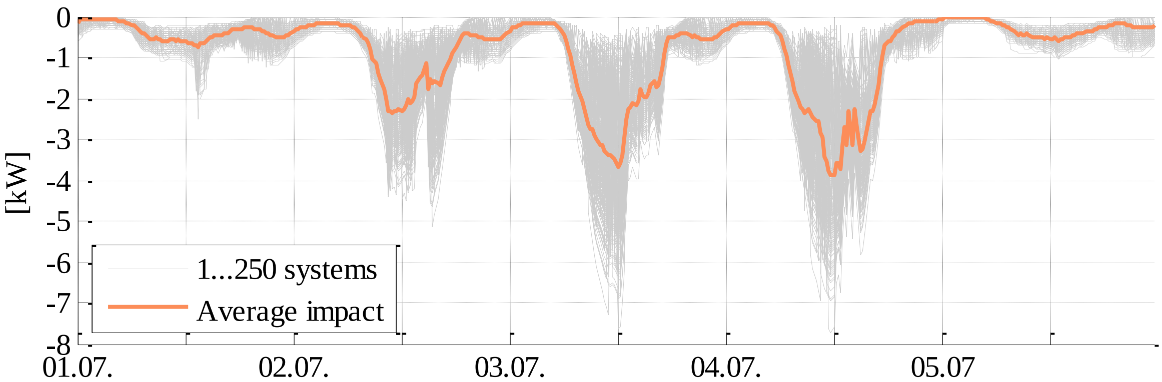

Figure 6.102: Average impact from new photovoltaic and storage installations

The absolute impact on the energy exchange with the grid is shown in Figure 6.103. It is clearly dominated by new combined photovoltaic and storage systems, which also provide the majority of storage installations according to the growth forecast (see Figure 6.99). The expected absolute change in demand from time shifting applications increases from 440 GWh in 2016 to 3 157 GWh in 2022. Despite the strong growth, this represents less than 1% of the current total demand.

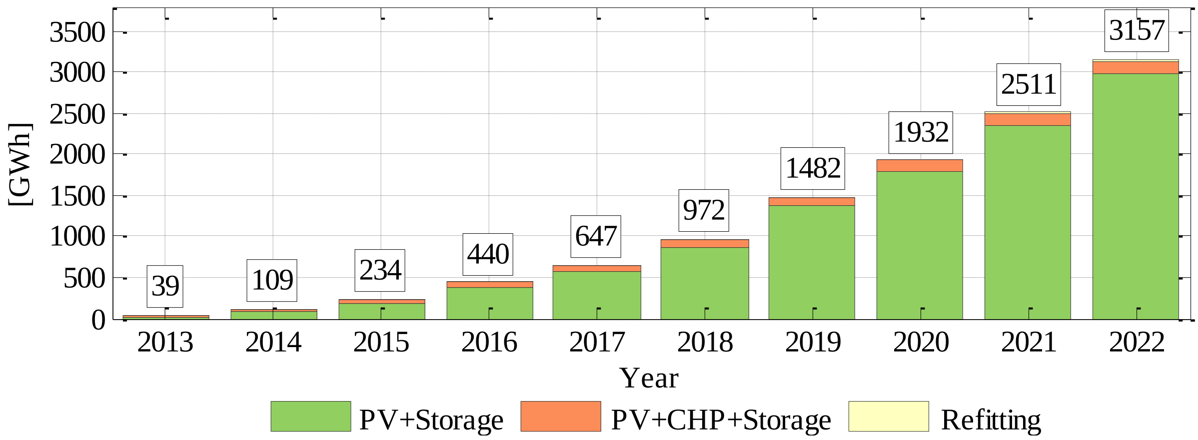

Figure 6.103: Estimated absolute impact on power exchange with the grid

Figure 6.104 shows a duration curve of the expected impact on grid demand from the storage installations. In 2016, the impact is still negligible when compared to overall load which is typically (90% of the time) between 38 and 66 GW. During 2022, however, the change in net load exceeds two GW during 544 15-minute intervals and one GW during more than 1 000 hours.

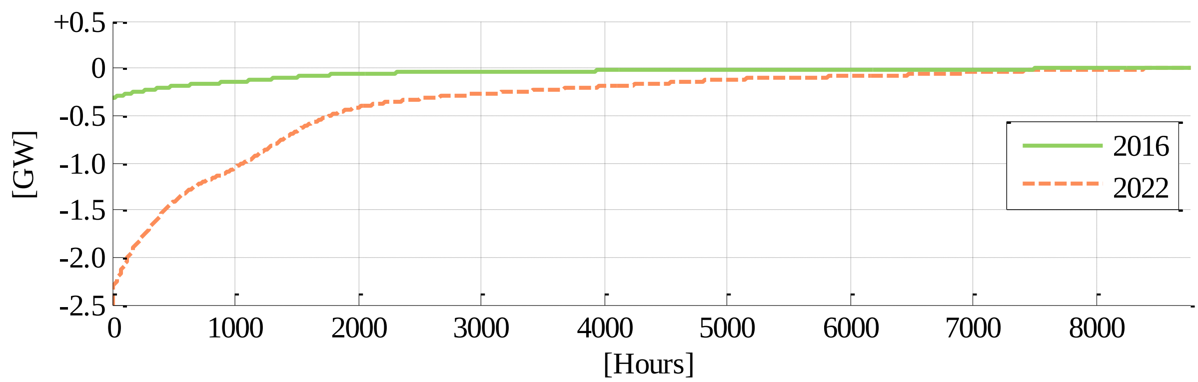

Figure 6.104: Change in the load duration curve

The impact on the grid can be further differentiated by looking at the different load levels (see Figure 6.105). At higher load levels (in this case, above 60 GW), generally a reduction in demand can be identified, which results in an increase in number of hours where the grid sees slightly lower demand levels (55-60 GW). Furthermore, the number of hours during which low demand levels (up to 45 GW) are experienced also rises.

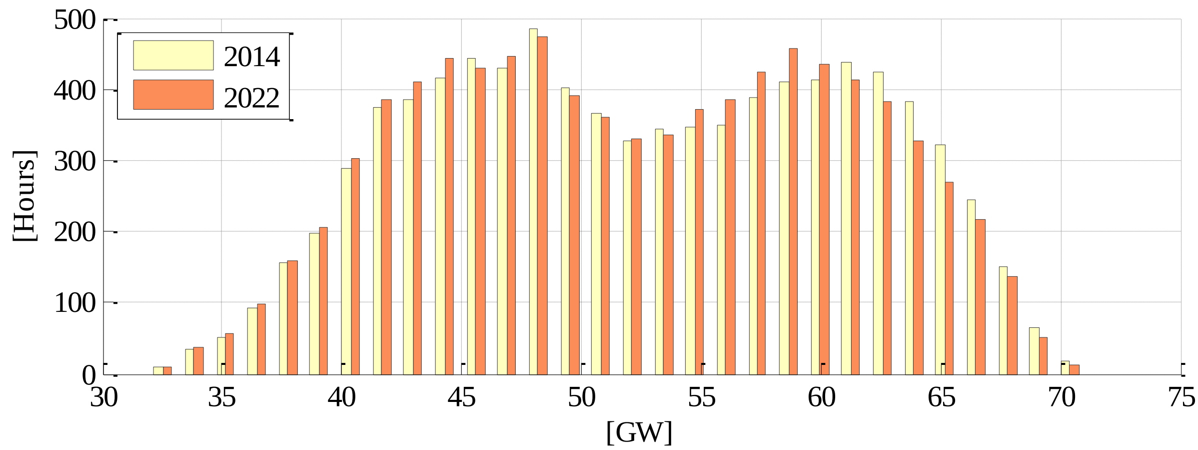

Figure 6.105: Comparison of net grid load

As has already previously been established (see Section 5.2.1), there is a substantial difference in the impact across seasons due to the varying solar yields, generation from cogeneration units as well as energy demand. However, these factors also result in significant different impact levels from day to day. Figure 6.106 shows the estimated impact along the year 2022, where every bar represents the change in net load during one day. As expected, the impact during the summer time is larger than during the winter. Furthermore, the impact varies significantly from day to day, even during the summer.

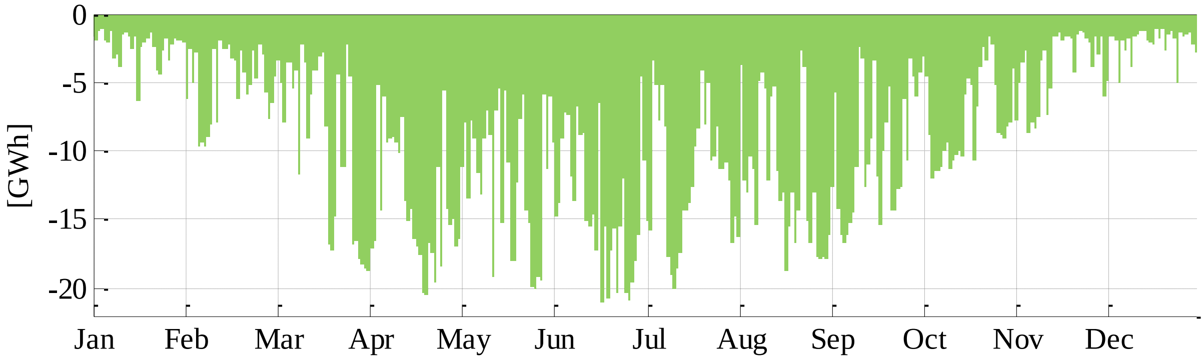

Figure 6.106: Daily impact along the year 2022

6.5.4 Analysis

Besides the analysed impact on the electric grid, storage implementations also have a financial impact on several entities. Only a fraction of the retail electricity tariff is determined by market prices. The majority of the final price is constituted by fees, surcharges and taxes. Table 6.27 breaks down the cost structure of an average retail tariff (year: 2015) for a residential consumer [197]. In addition, it also provides the recipient for each of these cash flows.

Price component	**Recipient**	**[ct/kWh]**
Energy procurement, administration and margin	Retailer	7.57
Network charge	DSO	5.94
Metering charge	DSO	0.65
Concession fee	Municipality	1.63
Surcharge under the renewable energy sources act [126]	Transfer	6.17
Surcharge under the act on combined heat and power generation [201]	Transfer	0.25
Surcharge under the electricity network tariffs regulation [125]	Transfer	0.24
Surcharge for offshore liability	Transfer	-0.05
Surcharge for interruptible loads	Transfer	0.01
Electricity tax	Government	2.05
Value added tax	Government	4.65
Total		29.11

Table 6.27: Composition of retail electricity price [197]

According to Table 6.27, only about one fourth of the total energy bill is retained by the retailer to cover the procurement of energy as well as administrative cost. Network charges are transferred to the related DSO. In addition, metering charges are also attributed to the DSO, as they typically operate the meter [197]. The concession fee is paid to the local municipality. A major portion of the total electricity cost corresponds to surcharges, primarily for the renewable energy sources act. These surcharges are levied and administered by the TSO in a transfer account to offset the associated cost such as the feed-in tariff for renewable energy resources in the case of the surcharge under the renewable energy sources act. Last, both electricity as well as value added tax are collected by the government.

From a taxation perspective, the analysis assumes that the storage devices are installed and operated by private persons and not as a corporate entity. In the second case, investors could reclaim the value added tax on the investment amount but would in turn become liable to pay value added tax on the generated energy. Assuming a private person, the absolute amount of value added taxes over time is reduced as less energy is taken from the grid. However, there will be a substantial payment on the initial investment amount. In the following, this initial tax payment will be broken down to an annual value according to the life expectancy of the component lifetimes (as assumed in Section 6.1) to facilitate comparison.

Under the current legislation, excess local generation can be fed into the grid at a pre-set feed-in tariff, both for generation from cogeneration units as well as from photovoltaic systems. Hence, if some of the energy is not fed into the grid but stored and later consumed locally, less compensation must be paid. On the other hand, as less energy is taken from the grid due to the usage of storage systems, consumers will also pay less surcharges. Table 6.28 compares the energy and the resulting cash flows under different implementation scenarios to a reference case, where all energy is taken from the grid. Therefore, the average energy flows from the 250 simulated systems were considered.

	Reference	Only photovoltaic	Photovoltaic + storage
P_{Grid}^{Import}	5 000 kWh	2 908 kWh	2 024 kWh
$P_{Grid}^{Export\ PV}$	0 kWh	4 116 kWh	3 136 kWh
C_{PV}^{Invest}	0 EUR	8 778 EUR	8 778 EUR
$C_{Storage}^{Invest}$	0 EUR	0 EUR	5 046 EUR
Energy bill	1 456 EUR	847 EUR	589 EUR
Value added tax on C^{Invest} (annualized)	0 EUR	83 EUR	147 EUR
Received feed-in tariff	-0 EUR	-494 EUR	-376 EUR
Total	1 456 EUR	436 EUR	360 EUR

Table 6.28: Comparison of payments

Under the reference case, all energy was taken from the grid, which results in an annual energy bill of 1 456 EUR. The addition of a photovoltaic system decreases the energy bill to 847 EUR. As the operator receives a significant compensation for the feed-in of excess local generation, the total net payment amounts to only 436 EUR.

As expected, the addition of a storage device further reduces the energy bill to 589 EUR, as even less energy is taken from the grid. Compared to the individual installation of only a photovoltaic system, however, the value added tax on the investment amount increases slightly and less compensation is received for the feed-in of excess local generation. The net total payment is reduced to 360 EUR, about one fourth of the initial amount.

However, not all entities are affected in the same way. Table 6.29 breaks down the payments to the different entities, where the sum of each column is equal to the total of energy bill and paid value added taxes in Table 6.28.

Entity	Reference	Only photovoltaic	Photovoltaic + storage
Retailer	378.50 EUR	220.19 EUR	153.24 EUR
DSO	329.50 EUR	191.68 EUR	133.40 EUR
Municipality	81.50 EUR	47.41 EUR	33.00 EUR
Transfer	331.00 EUR	192.55 EUR	134.01 EUR
Government	335.00 EUR	278.27 EUR	282.94 EUR

Table 6.29: Break-down of payments to different entities

The retailer, DSO and the municipality see a reduction of their income in line with the reduced grid demand. While the transfer accounts were previously a net receiver, they are a net payer after the installation of the combined photovoltaic and storage systems. The government also sees a reduction in tax income. However, due to the additional income from the value added tax on the system components, the reduction is lessened. In reality, the government would even benefit in the short-term, as the value added tax on the system components is due as a lump-sum at the moment the system is purchased, whereas the taxes on imported energy only accumulate over time.

Considering the forecasted installation growth as shown in Figure 6.99, the impact on tax revenues, collected surcharges and further payments can be estimated. To simplify the analysis, it was assumed that all new installations are combined photovoltaic and storage systems.

Figure 6.107 shows the cumulative funding gap until the year 2022. Whereas the government and the municipality see only minor income reductions, the other entities experience significant revenue reductions. The impact on the transfer accounts is especially pronounced and amounts to a total of -41 million EUR until the year 2022, which has to be financed for example by increasing the surcharge.

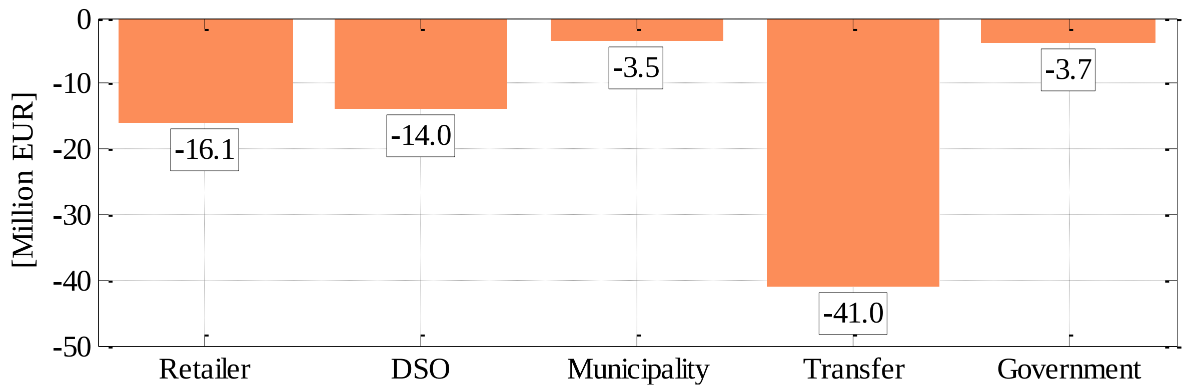

Figure 6.107: Cumulative funding gap until the year 2022

The previous analysis was restricted to an evaluation of the immediate cash flows and did not consider any indirect implications storage installations might have. For example, the roll-out of storage for time shifting was shown to reduce the electricity market prices, which in turn would increase the relative profit margin of the retailer across all consumers.

6.5.5 Conclusions

Assuming a growth rate for storage devices analogous to the growth rate that photovoltaic systems experienced in the past, annual installations will rise from about 19 000 systems in 2015 to more than 100 000 systems in 2022. The change in energy flows of these clients is estimated to amount to 3 157 GWh in 2022, less than 1% of total annual demand.

Generally, a reduction of demand at very high load levels can be identified. In addition, low load levels also tend to occur more frequently. Furthermore, the impact is more pronounced during summer than winter. However, as the change in demand varies substantially from day to day due to the intermittent solar generation, an almost unchanged level of traditional generation capacity is required. While the current analysis overestimates the impact, as no geographic dispersion was considered, it can be concluded that the introduction of storage systems together with photovoltaic systems increases the variability of grid demand significantly.

This threat is increased by the additional layer of uncertainty between the demand from the customer and the grid demand, which is distorted by the dispatch of the storage device and local generation. Therefore, from a system perspective, generation capacity is required to be sufficiently flexible to quickly react to changes in the net load levels. However, market price might not set the right incentives for generators to hold sufficient flexible generation capacity available. It is therefore up to policy makers to ensure that generation is flexible enough to avoid shortfalls in the near future, when for example after several days of no sunshine the majority of storage operators will demand energy from the grid at the same time.

Besides the impact on the energy exchange with the grid, this case study also analysed the financial impact on immediately affected third parties.

The biggest impact is on the transfer accounts for the balancing of surcharges and related cost, most notably surcharges under the renewable energy sources act. If no other counter measures are taken by policy makers, this will likely require an increase of the surcharges in the long-term in order to keep the account balanced. However, over the next years, the estimated impact of 41 million EUR by the year 2022 is still negligible in comparison to the current annual transfer amount of more than 20 billion EUR for the surcharge under the renewable energy sources act alone [207].

Second, retail companies will see a strong decline in revenues. For clients operating a storage system, the annual income of the retailer declines from 378.50 EUR to 153.24 EUR. Assuming an average energy procurement cost of 30 EUR / MWh, the margin for administration and profit would decrease from 228.50 EUR to 92.52 EUR. Assuming that the fixed cost per client is independent from the actual energy consumption and therefore is constant, it is less interesting for retailers to contract with storage operators. A potential reaction would be to either exclude storage operators or demand an additional fee.

Payments to the network operators also see a significant decrease. In order to recover the previous revenues and cover the expenses of the operator, network charges will likely increase. DSO's in rural areas and small towns will likely be more affected, as there are relatively more buildings available with sufficient roof space for additional photovoltaic installations.

The government will see a reduction in tax income from energy consumed. However, this reduction is mostly offset by additional value added tax income from the system components. Furthermore, as the tax is paid upfront, the government will benefit in the short-term. Last, the municipality will see a small reduction in revenues from lower concession income.

As previously discussed in chapter 5, one option to lessen the financial impact would be to introduce a fee for the required grid capacity (in EUR / kW) in addition to the energy related tariffs (in EUR / kWh). In the short-term, this would reduce the economic attractiveness of storage and likely the installation numbers. In the long-term, however, this would introduce an incentive for clients to become completely independent from the grid once the installation cost for storage and distributed generation technologies decrease further.

Last, contrary to photovoltaic systems with an expected calendric lifetime of oftentimes at least 20 years, the lifetime expectation of storage installations is more limited. Hence, consumers will have the opportunity to re-evaluate the utility and economics of a storage device after the initial lifetime before committing to a new installation or a refit of the existing device. Therefore, if storage installations lose their attractiveness, their impact will fade within a shorter period.

Chapter 7

7 Conclusions

Abstract

The final chapter of this thesis presents a review of the contributions. In addition, it discusses the main findings and summarizes the results obtained throughout this document. Last, a range of potential topics for future work is identified.

7.1 Contributions

This thesis contributes to the current state of the art in three principal areas:

- the formulation of storage dispatch models for commercial applications of storage systems in order to evaluate them from an economic point of view (Chapter 3),
- the consideration of uncertainty in the evaluation process (Chapter 4)
- and the estimation of the impact of distributed commercial storage implementations on electricity markets (Chapter 5).

In Chapter 3, a general framework to simulate the dispatch of a storage system (Section 3.1) as well as an economic evaluation approach (Section 3.2) were developed. In the following, these were adapted and extended to integrate the commercial applications previously identified in the literature review (Chapter 2).

- In Section 3.3, an extensive mixed integer program was developed to determine the profit maximizing dispatch for a storage device deployed for time shifting locally generated energy, considering a wide range of system components and parameters. In order to integrate cogeneration units, the problem formulation accounts not only for electric power flows but also for the thermal system. In addition, in order to identify the optimum system configuration, a metaheuristic search process was presented. Last, a simple dispatch using only historical information was proposed to estimate the value of perfect foresight.
- For the arbitrage of energy price (Section 3.4), a mixed integer program was formulated, which also accounts for negative market prices. To consider both the calendric lifetime as well as the limited cycle lifetime, a hurdle rate was integrated and the accompanying search routine for the

optimal rate was designed. Furthermore, a dispatch process based on only historic prices was presented.

- Section 3.5 presented an approach to determine the profitability from the provision of ancillary services.
- In order to increase the profitability of storage systems, in Section 3.6 a mixed integer program was developed integrating several applications simultaneously in the storage dispatch. Therefore, the time shifting of local energy resources, the provision of reserve control as well as peak shaving of grid demand were considered. The problem formulation not only optimizes the capacity allocation to each service, but also ensures that the resulting operational requirements and technical restrictions are followed.

In addition to the formulation of the dispatch process, every Section presented a valuation approach to determine the economic proposition of storage in the respective context.

In Chapter 4, the consideration of uncertainty and the resulting financial risk in the evaluation process were discussed.

- In a first step, it was demonstrated how the previously designed MIP models can be verified (Section 4.2) to ensure they are both correctly formulated as well as correctly implemented.
- Following, several tools commonly applied to evaluate investment projects were discussed and adapted to the specific storage context: sensitivity analysis (Section 4.3), scenario analysis (Section 4.4) and Monte Carlo simulation of parameters (Section 4.5.1). These methodologies can be used to quantify the uncertainty as well as determine its impact on the financial evaluation and the economic viability of storage.
- In Section 4.5.2, an approach was designed to decompose historic market price data into several components. Based thereupon, it was shown how synthetic price paths can be simulated, either having similar characteristic as the historical data or reflecting particular changes, such as an increased probability of price jumps.
- Following, in Section 4.6 a methodology was presented applying Monte Carlo Simulation to estimate the probability of realizing a certain outcome.
- Last, Section 4.7 demonstrated how the previously introduced scenario analysis or Monte Carlo simulation can be applied to consider uncertainty in the decision making process.

Chapter 5 analyzed the impact of distributed storage installations on electricity markets.

- In Section 5.2 an approach is proposed to determine the change in demand seen by the grid when a storage device is installed and dispatched for a particular application.
- Based thereupon, in Section 5.3 two approaches were demonstrated to determine the impact from a change of demand on market prices.
- Furthermore, an approach was proposed to estimate the market potential for arbitrage, before the entrance of additional market agents deteriorates the business case and market conditions to a point where revenues are no longer sufficient.

7.2 Main Findings

The proposed models and methodologies were implemented in several case studies in Chapter 6.

First, storage in a consumer setting dispatched for time shifting of locally generated energy from a photovoltaic system and / or a cogeneration unit was considered (Section 6.1).

- It was shown that significant savings are available by satisfying the major part of the electric demand locally and hence reducing the amount of energy taken from the electric grid. The required systems however require high initial investments.
- Given today's investment cost, storage was found to be not yet economic viable. While the storage system was shown to be beneficial as electricity imports could be further reduced, the associated cost from the depreciation still outweighed the value added.
- Taking uncertainty into account, it was demonstrated how the inclusion of storage into the system can be beneficial. While storage does not yet compete on a cost basis, it protects against a range of adverse outcomes, such as rising electricity prices.
- Major drivers for the viability of storage are, besides falling investment cost, decreasing feed-in tariffs and increasing consumption tariffs.
- Having perfect knowledge about future demand as compared to a simple dispatch approach based on historical data was shown to reduce the energy related cost by about 15%.
- It was found that integrating local generation resources reduces the grid demand substantially. However, the implementation showed that the required connection capacity does not decrease if no financial incentives are set.

Even though arbitrage is oftentimes mentioned as a potential application for storage, the results from Section 6.2 show that currently no economic incentive for this application exist.

- Even under optimistic assumptions, small-scale storage systems were found to be unprofitable as depreciation charges significantly outweighed realizable revenues.
- For storage systems with a limited cycle lifetime, it was shown that the net present value should be maximized instead of revenues in order to take the negative impact of frequent cycling on the expected lifetime into account.
- 15-minute contracts were found to have a higher revenue potential and therefore present an attractive alternative to 1-hour contracts.
- It was shown that higher power-to-energy ratios improve the financial viability, even though revenues were still not sufficient.
- More volatile prices would create a more favorable environment for storage systems. In order to justify a storage investment at current cost, it was estimated that price jumps need to occur five times as frequently with a significantly higher magnitude than empirically identified.
- Having good forecasts about future prices was found to be of high relevance in order to identify the most attractive charging- and discharging opportunities, especially for storage devices with a high power-to-energy ratio and when considering 15-minute contracts.

Contrary to pursuing arbitrage, the provision of primary reserve control was found to be financially attractive (Section 6.3).

- Under the taken assumptions, a return on equity of about 10% was determined.
- The provision of primary reserve control was found to provide very steady cash flows.
- About 80% of the theoretic optimum revenues could be obtained with a simple bidding process. Overall, it was found to be advantageous to bid rather low but be considered in the tender at all times.
- Besides the investment cost, the expected lifetime is a major driver of profitability.

In Section 6.4, it was demonstrated that the value proposition of a storage device can be significantly improved when multiple services are provided simultaneously.

- While the applicability and availability of revenue sources is very specific to the considered context, dispatching a storage device for several purposes was found to significantly enhance its value proposition up to the point that storage becomes attractive at today's cost.
- The value contribution of the individual services is not additive. Pursuing several applications at once has implications on the operation of each individual application. However, the identified value gap due to the resulting interference was found to be small.

Storage operations were found to have a range of impacts on the overall grid demand (Sections 5.2, 6.1 and 6.5).

- The dispatch of storage for time shifting was shown to reduce net grid demand significantly, both due to reduced demand as well as feed-in of excess local generation.
- The impact has a strong temporal component due to the availability of local generation especially from photovoltaic systems, both in the course of the day as well as along the year.
- Storage dispatched for arbitrage was found to increase the overall demand due to efficiency losses but leads to a temporal shift.
- Most frequently, storage dispatched for arbitrage would be charged from midnight to the early morning hours and hence would increase the demand seen by the grid during those times. Discharging operations, which would be seen as generation by the grid, typically occur during the morning as well as evening hours.
- Charging operations from arbitrage were found to typically occur at times with a relatively low overall load level. Contrary, the storage device was found to be more frequently discharged during periods with high overall load.
- The reduced grid demand was shown to result in a reduced income of public entities.

The changed demand was found to have a range of consequences for market prices (Section 5.3).

- Storage dispatched for time shifting was found to decrease the overall price level slightly, both due to the lower demand seen by the grid as well as the feed-in of excess generation.
- Arbitrage operations were found to reduce the occurrence of extreme prices, both on the up- as well as on the down-side. In addition, it was shown that on average prices decline slightly.

Based on the obtained results, the following recommendations are derived:

- It is up to policy makers and regulators to ensure that distributed agents can access the discussed revenue streams. It was shown that participating in the ancillary service market can greatly enhance profitability, especially if tender periods would be shortened to intervals of twelve hours or less. However, a suitable legal framework is required. The current regulation lacks a harmonization across different technology options and hence creates an uneven playfield. Therefore, besides granting access to markets, regulations and policies must further evolve to clarify the status of storage. In addition, regulations should also enable storage operators to dispatch their storage device for several applications at once, as long as the provision of the contracted service is guaranteed.
- A low feed-in limit for local generation is helpful to incentivize consumers to dispatch their storage device in a grid-beneficial way. Furthermore, a lower limit can also act as a financial incentive to install a storage system to avoid the curtailment of surplus generation.
- Manufacturers should focus on reducing cost and extending lifetime instead of improving technical characteristics such as efficiency, as the former were found to be more significant drivers of profitability. Furthermore, consumers should demand a uniform and open interface to control the storage device in order to enable the communication with both generation resources and load to improve the efficiency of the dispatch. This is also an important prerequisite to integrate storage closer into the smart-grid and participate in pools such as virtual power plants.
- The reduced grid demand is a thread to the income of electricity generators as well as public funds. The former should therefore invest into flexibility instead of capacity to benefit from periods where higher prices prevail, for example due to a shortage of local generation. To retain income from surcharges and fees, a shift to a capacity based fee structure for the grid interconnection is recommended. While storage can be dispatched in such a way that a large share of this fee increase would be mitigated again, actual infrastructure requirements and hence cost would decrease in line.

7.3 Perspectives for Future Work

The following considerations might provide interesting opportunities for future work:

- Besides primary reserve control, a range of further ancillary services exist. Their provision either individually or stacked jointly with further applications presents a potential additional income source for storage operators.
- This thesis addressed only applications with an immediate commercial benefit. However, storage can also add value with only indirect benefits such as a deferral of grid upgrades. It is unclear how a private storage operator could benefit from these and what their value is.
- For arbitrage operations, only 1-hour and 15-minute electricity auctions were considered. The continuous intraday market offers an additional income opportunity.
- The dispatch process was shown to be a major value driver. Further efforts should be spent on developing dispatch processes, which do not require perfect foresight.

The author is confident that the presented work provides a useful framework for the evaluation of electrical storage systems and serves as a foundation for further research in this direction. Hopefully, the obtained results and main findings can be of help to overcome existing barriers to further storage investments and support the transition to a clean power system.

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