Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Information Technology and Electrical Engineering
Department of Electric Power Engineering

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Impact of Industrial Size Battery Storage Systems on Electricity Price Distribution

Master's thesis in Energy and Environmental Engineering
Supervisor: Gro Klæboe & Sjur Westgaard
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Abstract

Battery Storage Systems (BSS) have emerged as a promising technology for addressing the energy security-related challenges caused by the intermittent nature of Variable Renewable Energy (VRE). To investigate the impact of large-scale BSS implementation on the electricity price distribution, the German electricity market is modeled as a cost-minimization problem with varying levels of BSS storage capacity. Subsequent market prices undergo analysis through the lens of descriptive statistics and multi-variable quantile regression. The thesis also aims to establish a mathematical relationship to explore the dynamics between BSS, VRE, and electricity price quantiles.

The results show that BSS lowers the most extreme prices and raises the lower prices, making the price distribution denser and less variable around its central tendency. Further examination of the prices through quantile regression unveils a linear relationship between BSS storage capacity and electricity price quantiles. The gradients of the lower quantiles demonstrate a positive yet modest value, while the upper quantiles exhibit a more significant negative gradient in comparison to the lower quantiles.

When investigating the dynamics between BSS and VRE, the VRE exhibits improved efficiency in reducing prices when paired with BSS in the system, particularly for upper price quantiles. This suggests that the presence of BSS enhances the system's ability to effectively utilize and store excess VRE generation, leading to lower electricity prices.

Sammendrag

Batterilagringssystemer (BLS) har vokst frem som en lovende teknologi for å håndtere energisikkerhetsutfordringene forårsaket av de uregelmessige egenskapene til Variabel Fornybar Energi (VFE). For å undersøke effekten av storskala BLS-implementering på prisfordelingen til strøm, modelleres det tyske strømmarkedet som et kostnadsminimeringsproblem med ulike nivåer av batterilagringskapasitet. Videre analyseres markedsprisene ved hjelp av deskriptiv statistikk og multi-variabel kvantilregresjon. Oppgaven har også som mål å etablere en matematisk sammenheng for å belyse dynamikken mellom BLS, VFE og elektrisitetspris-kvantiler.

Resultatene viser at BLS senker de mest ekstreme prisene og øker de lave prisene, noe som gjør prisfordelingen mer kompakt og mindre variabel rundt sin sentrale tendens. Videre analyse av elektrisitetsprisene gjennom kvantilregresjon avslører en lineær sammenheng mellom BLS-lagringskapasitet og priskvantiler. Gradientene til de nedre kvantilene viser en beskjeden, positiv verdi, mens de øvre kvantilene viser en betydelig mer negativ gradient sammenlignet med de nedre kvantilene.

Angående dynamikken mellom BLS og VFE, viser VFE forbedret effektivitet i å redusere priser når den kombineres med BLS i systemet, spesielt for de øvre pris-kvantilene. Funnene viser at implementeringen av BLS styrker systemets evne til å effektivt utnytte og lagre overskuddsgenerering fra VFE, som igjen fører til lavere elektrisitetspriser.

Preface

This thesis is a result of an interdepartmental collaboration between the Department of Industrial Economics and Technology Management and the Department of Electric Power Engineering at NTNU, Trondheim. The thesis is written as a part of the courses *TIØ4900 - Financial Engineering, Master's Thesis* and *TET4900 - Electric Power and Energy Systems, Master's Thesis*. The thesis is part of corresponding Master's degrees in Industrial Economics and Technology Management for Sander Haugen and Energy and Environmental Engineering for Ferdinand Lindal, respectively.

Subsection 3.1 of the related literature review in the thesis is re-used from the corresponding project thesis [1], written in the fall of 2022. The same is true for the introduction to subsection 4.1 in the data section.

We want to thank our supervisors, Gro Klæboe and Sjur Westgaard, for facilitating this collaboration and for their outstanding guidance and support throughout the semester. Furthermore, we would like to express gratitude towards Tor Reier Lilleholt and Volue Insight for granting us access to their data API. Finally, we would like to thank our families for their support and encouragement.

Sander Haugen & Ferdinand Lindal
Trondheim, June 2023

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Acronyms

API Application Programming Interface. 16, 18, 19

BATSTORM Battery-based Energy Storage Road Map. 23

BLS Batterilagringssystemer. ii

BSS Battery Storage Systems. i, v–ix, 1–4, 7–10, 12–15, 22–32, 34, 36–56, 63

CVaR Conditional Value at Risk. 13

EES Energy Storage Systems. 12

EEX European Energy Exchange. 17

GARCH Generalised Autoregressive Conditional Heteroscedasticity. 14

KDE Kernel Density Estimation. 35, 39

OLS Ordinary Least Squares. 48

RES Renewable Energy Sources. 14

SOC State of Charge. 25–27

SPV Solar Photovoltaic. 14

SRMC Short Run Marginal Cost. viii, ix, 4, 17–19, 22, 23, 28, 34, 41, 62

TSO Transmission System Operators. 16

UMM Urgent Market Messages. 17

VaR Value at Risk. 13

VFE Variabel Fornybar Energi. ii

VRE Variable Renewable Energy. i, vi–ix, 1–3, 7, 12–15, 17, 22, 29–32, 36, 37, 41–56, 62–64

1 Introduction

1.1 Background and Motivation

VRE has grown increasingly vital in the global energy mix, primarily due to international goals of reducing climate gas emissions and the exponential decrease in VRE costs over recent decades. These cost reductions have reached a point where investments in VRE technologies can compete with other power-generating units, even without subsidy schemes [2]. Despite these advantages, the intermittent nature of VRE sources presents challenges to the security of supply in electrical systems that require a constant balance between production and consumption.

Large-scale energy storage has emerged as a potential solution to the challenges posed by excess VRE production. Several promising technologies have been explored in academia and practice, such as pumped hydro storage, hydrogen fuel cells, and thermal energy storage. However, these solutions still face technological and cost-related constraints, making them more suitable for long-term rather than short-term energy storage [3].

For short-term energy storage, BSS has gained recognition as a promising technology capable of handling some of the challenges associated with VRE. Storing energy from cheap or excessive electricity production can be used for several applications. Small-scale peak shaving and spot-price arbitrage are some that have shown promise, as demonstrated in behind-the-meter battery systems [4]. Moreover, BSS has seen significant cost reductions in recent years, with projections indicating this trend will continue [5].

As battery capacities increase, the aggregated battery fleet could become a key player in the electricity market, impacting price formation and distribution [6]. Although extensive research has examined the individual effects of high VRE and BSS shares on electricity price volatility, a notable research gap remains regarding their combined impact in large-scale systems on electricity price distribution. More specifically, how the introduction of BSS impacts the overall shape of the price distribution, as well as the various quantiles within the distribution. Understanding the influence of BSS on the shape of the electricity price distribution in high-share VRE markets is critical for all market participants. Producers and end-users rely heavily on price expectations to plan future expansion and consumption. Therefore, any potential lasting changes in the price distribution shape, due to the introduction of BSS, must be taken into account. Additionally, risk managers overseeing electricity market operations must carefully monitor substantial price shifts, especially at the extreme ends of the price scale. These shifts can lead to significant costs if not anticipated accurately. Understanding the influence of BSS on upper and lower price quantiles provides these risk managers with crucial insights, enabling them to make well-founded decisions during project planning stages.

As a result, this paper aims to address the impact of BSS on electricity price distribution by examining the German electricity market, which features a significant presence of both VRE and industrial-sized BSS [7]. By examining the dynamics between BSS and VRE in the German market, the hope is to gain a deeper understanding of the role of batteries in the electricity market and pave the way for future research and innovation.

1.2 Objective and Contribution

This thesis aims to explore the impact of industrial-size BSS storage capacity on electricity price distribution in real electricity markets with substantial shares of VRE. The goal is to uncover the underlying dynamics and contextualize the findings in comparison to the small sample size of similar research and relevant literature. Specifically, the thesis aims to answer the following questions:

- *How is the electricity price distribution affected by BSS storage capacity?*
- *Are the various quantiles of electricity prices affected differently by BSS storage capacity?*
- *Can we draw inferences on the mathematical relationship between BSS storage capacity and electricity price quantiles?*
- *Will increased VRE capacity affect the impact of BSS on electricity price distribution?*

The research questions are addressed through the following contributions of this thesis: Firstly, the German electricity market is modeled using real market data supplied by Volue Insight, a leading power market analysis firm in Europe. Different levels of BSS storage capacity are introduced into the system, and their impact on electricity price distribution is analyzed and compared to a base scenario without BSS. The results show that the BSS creates a denser and less variable price distribution, where the prices are closer and more symmetrically positioned around its central tendency. The influence of BSS across price quantiles demonstrates varying patterns, where lower price quantiles increase while upper price quantiles decrease. This trend is amplified with increasing BSS capacity.

Quantile regression analysis reveals a linear relationship between BSS storage capacity and all quantiles. The lower quantiles display a positive but modest influence, whereas the upper quantiles exhibit a larger negative impact compared to the lower quantiles. The results are unique in the sense that they are the first to explicitly describe a mathematical relationship between BSS storage capacity and electricity price quantiles.

Lastly, the dynamic between BSS and VRE is explored through an extended quantile regression model that considers both variables. VRE demonstrates enhanced efficiency in terms of price reductions when operating alongside BSS in the system, especially for the upper price quantiles. This indicates that the presence of BSS enables the system to more effectively utilize and store excess VRE generation, resulting in lower electricity prices.

1.3 Outline

The remainder of this thesis is organized as follows: Section 2 introduces relevant information on electricity markets and modelling, BSS, statistical properties of electricity prices, and quantile regression. Next, section 3 explores the existing academic literature and research on BSS and their applications in electricity markets. In addition, a review of the application of quantile regression models in electricity markets is presented. Section 4 describes the data utilized for modelling the German market, and section 5 elaborates on the market optimization model framed as a cost-minimization problem, in addition to the analysis of price distribution through quantile regression. Section 6 presents the comprehensive results across all BSS and VRE scenarios, followed by a discussion of notable observations and implications in section 7. Finally, section 8 offers a summary of key findings and conclusions while providing directions for further work.

2 Theory

This section offers essential background for understanding the thesis' methodology and is structured as follows: Firstly, the concept of deregulated electricity market operation is explained before emphasizing the characteristics of the German electricity market. Subsequently, the basics of electricity market modelling are introduced. This leads to a concise overview of state-of-the-art BSS. The statistical properties of electricity prices are subsequently discussed, followed by an introduction to quantile regression analysis to end the section.

2.1 Electricity Markets

2.1.1 Deregulated Electricity Market Operation

Deregulated electricity market operation has become an increasingly popular approach to promote competition, improve efficiency, and reduce costs in the electricity industry [8]. One approach to achieving these objectives is market pooling, which deviates significantly from conventional utility models. In a market pooling system, all electricity generators in an exclusive market area sell their electricity into a common bidding pool, regardless of their individual costs of production and other factors. The pool is managed by a market operator or a similar entity and sets the price of electricity in a particular area, based on the total supply and demand in the market.

The price of electricity in the pool is typically determined by the merit order and set to the Short Run Marginal Cost (SRMC) of the most expensive generator needed to meet the demand for electricity. An exception occurs in markets characterized by a high volume of water-value-based power or regions implementing green energy policies, such as feed-in tariffs and tax incentives [9]. The merit order guarantees that all generators in the pool are paid the same price for their electricity, regardless of their individual costs. An illustration of this process is given in Figure 1.

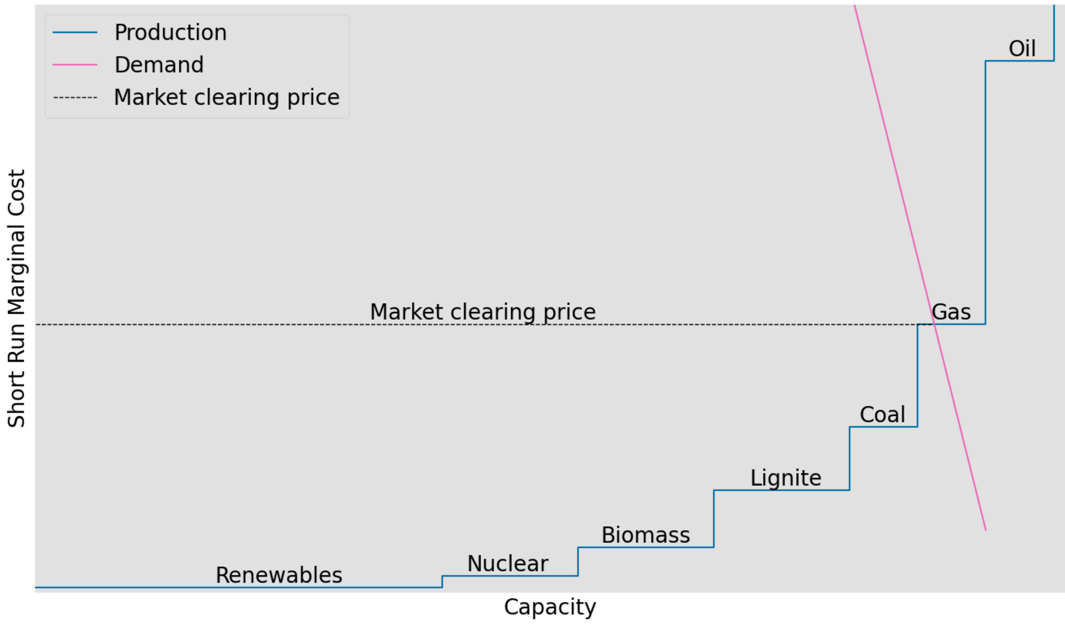


Figure 1: Market clearing - A merit order of production vs the demand curve.

No axes - Visual example only

Market pooling can help reduce the production cost of electricity by promoting competition and efficiency among generators [8]. This is achieved by establishing the market price of electricity at the level of the marginal unit's cost, thereby ensuring a uniform price for all production units. Consequently, the more cost-effective units yield a profit, stimulating generators to propose their most competitive pricing. This pricing aligns with the marginal cost curve, a situation where marginal costs exceed average costs. Additionally, market pooling can prevent price manipulation by individual generators, as the price is determined through a competitive market rather than the bids of individual generators [8].

2.1.2 The German Electricity Market

The German electricity market is very complex and one of the largest in Europe. It has undergone significant changes in recent years due to Germany's ambitious energy transition goals, which include phasing out nuclear power and significantly increasing the share of renewable energy in the electricity mix [10]. The market is characterized by a mix of conventional thermal power plants and renewable energy sources such as wind and solar, illustrated in Figure 2.

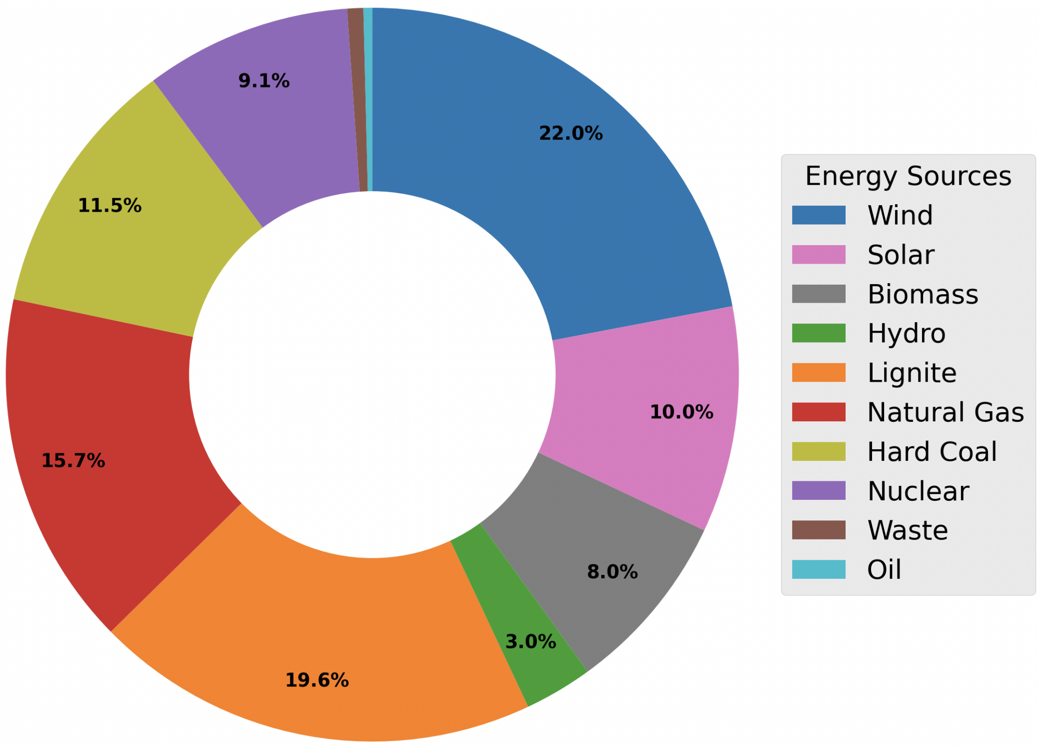


Figure 2: Production mix in Germany 2021-2023 - Source: Volue Insight [11].

Table 1: Production mix in Germany 2021-2023 - Source: Volue Insight [11].

Generation tech.	Share
Wind	22.0%
Solar	10.0%
Biomass	8.0%
Hydro	3.0%
Lignite	19.6%
Natural Gas	15.7%
Hard coal	11.5%
Nuclear	9.1%
Oil	0.4%
Waste	0.7%

The market operates within a framework of regulations designed to promote competition and protect consumers and is overseen by the Federal Network Agency (Bundesnetzagentur) and the Federal Cartel Office (Bundeskartellamt). One of the main challenges facing the German electricity market is balancing the intermittent supply of renewable energy sources with the demand for electricity, which can lead to volatility in prices and grid stability issues [12]. However, Germany has also been a leader in developing innovative market mechanisms to manage these challenges, such as the integration of renewable energy sources into the wholesale market through auctions and feed-in tariffs [13]. Despite these challenges, the German electricity market is likely to continue to play a leading role in shaping the future of the European energy sector.

2.2 Electricity Market Modelling

Electricity market modelling can be viewed as a cost minimization problem where the goal is to determine the lowest cost dispatch of electricity, which is the amount of power each source should generate at any given time. Formulating the problem by cost minimization is equivalent to a perfectly competitive market where producers face a market price equal to the marginal cost of production. A generator maximizes profits by bidding its marginal cost curve where the marginal cost is above average cost [14]. The complexity in market models comes from satisfying the fundamental principles of power system operation, which include operational and physical limitations. This is done while attaining a balance between the supply and demand of electricity in the most efficient way possible.

In this context, the total cost of electricity is the sum of costs from different sources of power generation, such as thermal power plants, renewable generation units, and hydroelectric power plants. Each source of power generation has different operational and technical characteristics, including the variable cost of generation, minimum and maximum output levels, ramp-up and ramp-down rates, and start-up and shut-down times. The complex nature of generator characteristics presents challenges in capturing the true market dynamics, often posing obstacles to accurately capturing market volatility [15].

In its most general form, the least-cost problem of the central planner can be formulated as:

$$\min \quad \boldsymbol{c}(\boldsymbol{x}) \tag{1a}$$

$$\text{s.t.} \quad \boldsymbol{g}(\boldsymbol{x}) = d \tag{1b}$$

$$\boldsymbol{a}(\boldsymbol{x}) \leq \boldsymbol{K} \tag{1c}$$

The objective function, 1a, minimizes the total generation cost of the system given the generation units $\boldsymbol{x}$. The constraint in 1b states that total system generation $\boldsymbol{g}(\boldsymbol{x})$ must equal total system demand d. This is known as the power balance constraint. The last constraint, 1c, forces system generation and transmission $\boldsymbol{a}(\boldsymbol{x})$ to stay within their limits and capacities, $\boldsymbol{K}$, to ensure system stability.

This formulation presents a constrained optimization problem. Here, the Lagrange multiplier of the power balance constraint in 1b, known as λ, signifies the system's marginal cost. Under marginal pricing, this cost sets the market price for electricity [16]. The decision on the most suitable method for solving the problem is influenced by various factors, such as the characteristics of the objective function and constraints, as well as the available computational resources. It is important to tailor the chosen method to the specific market model being analyzed [17].

2.3 Battery Storage Systems

BSS have emerged as one of the most promising technologies for short-term storage of electrical energy. These systems provide a critical solution to challenges posed by the intermittency and variability of VRE, such as wind and solar power [18]. BSS are capable of storing excess electricity during periods of low demand and discharging it during peak hours. This not only reduces reliance on costly peaking power plants but also enhances grid stability. Among the impressive features of BSS are fast response times, low standby losses, and high energy efficiency up to 95% [3]. Furthermore, compared to other storage technologies, these systems boast one of the shortest construction times. In addition to fuel flexibility and environmental benefits, they can also offer important operating benefits to the electricity utility, such as voltage regulation, frequency control, uninterruptible power supply, and spinning reserves [3]. Lastly, BSS has experienced a remarkable cost reduction in recent years, with projections suggesting that the trend will persist [5]. This is illustrated by the decreasing costs of lithium-ion systems in Figure 3.

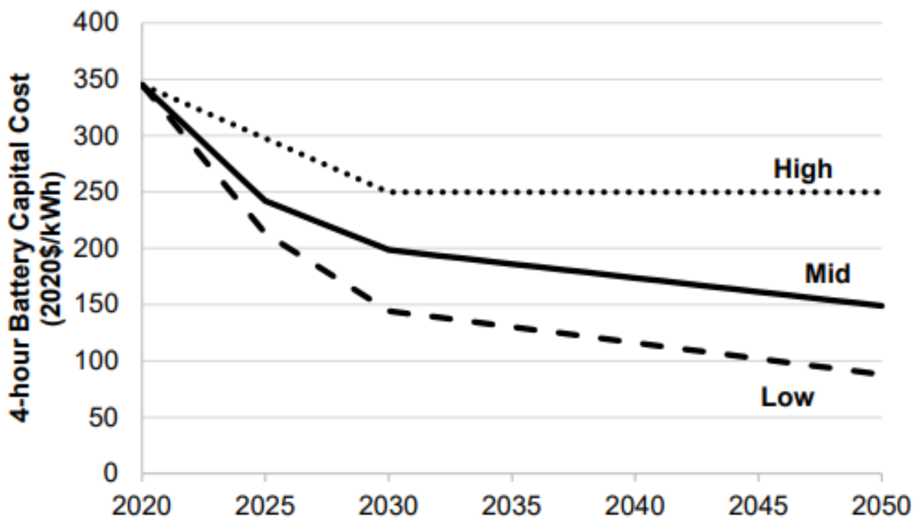


Figure 3: Battery cost projections for 4-hour lithium-ion systems as of 2021. The figure is obtained from the National Renewable Energy Laboratory [5].

2.4 Statistical Properties of Deregulated Electricity Prices

Understanding the behavior of electricity prices is crucial for effective decision-making in the electricity industry [19]. In deregulated electricity markets, prices are determined by supply and demand and thus can exhibit significant fluctuations over time [20]. This section will provide an overview of the main statistical properties of electricity prices, including price distribution and volatility. Factors influencing electricity prices, such as physical limitations, fuel prices, and demand trends, are discussed. Relevant statistical tests and test statistics will also be introduced. The analysis of the statistical properties of electricity prices can provide insights into the dynamics of electricity markets and help stakeholders make informed decisions regarding risk management [19].

2.4.1 Price Distribution

The price distribution of electricity prices in deregulated markets shows evidence of variation depending on a number of factors related to the dynamics between supply and demand [21]. The instantaneous nature and limited storage potential of electricity make prices sensitive to rapid changes in the availability of different energy sources and varying levels of demand. The availability of generation technologies is highly influenced by weather, prices of thermal fuels, plant outages, and other market conditions. Varying levels of demand are caused by daily, weekly, and seasonal demand patterns.

Empirical research indicates that electricity prices in deregulated markets tend to follow a log-normal distribution [22]. The advantage of using a log-normal description is due to the flexibility and ability to capture a wide range of the characteristics of electricity prices. The log-normal shape of electricity prices is characterized by a skewed, right-tailed shape, where the majority of the observations are clustered around a lower price range. The tail of the distribution on the right-hand side represents extreme observations or outliers, where prices can diverge strongly from the mean or median. The shape of this distribution reflects the tendency of electricity prices to be relatively stable and low in normal conditions, but are characterized by frequent sharp spikes during periods of high demand or supply shortages [23].

2.4.2 Volatility

Volatility can be defined as the measure of the spread or dispersion of a set of data. Analyzing this dispersion is critical when assessing the uncertainty, or risk, associated with the data [24]. The volatility of electricity prices in deregulated markets is a result of several factors, and often combinations of them. The primary reason is the instantaneous nature of electricity combined with storage constraints. These characteristics make prices sensitive to changes in the availability of power-generating sources. Combined with a high level of inelastic demand, price spikes are very frequent and unpredictable in deregulated markets. Secondary factors include commodity prices, carbon prices, weather, and demand patterns, among others [21]. These factors can affect the dynamics between supply and demand strongly, and thereby influence pricing patterns. A comprehensive analysis of all drivers behind electricity price volatility is outside the scope of this thesis. However, given the fast response time of BSS and its ability to fully charge and discharge within hours, it seems that the effects of BSS are closely tied to short-term intra-day demand-driven fluctuations in electricity price. Consequently, it is reasonable to assume that the primary impact of BSS is on the intra-day volatility factor. In conclusion, the volatility of electricity prices can create both opportunities and risks for all market participants, and careful analysis and management are required to effectively navigate [19].

2.4.3 Descriptive Test Statistics

Test statistics are statistics used in statistical hypothesis testing. Statistical hypothesis testing is used to make probabilistic statements about population parameters [24]. In this thesis, both raw price data and price results from modelling will be subject to hypothesis testing in order to describe the statistical characteristics of the data. The tests include the Jarque-Bera test for normality and the Augmented Dickey-Fuller unit root test for stationarity [24]. The testing procedure and mathematics behind the tests will not be described in this section as it is considered outside the scope of this thesis. Detailed derivations of the tests are described by Brooks [24].

2.5 Quantile Regression

Quantile regression is a statistical approach to mathematically describe the relationship between a dependent variable and one or more independent variables through estimating the conditional quantiles of the dependent variable [25]. In contrast, traditional linear regression estimates the conditional mean of the dependent variable given the independent variables. Quantile regression allows estimations of conditional relationships at various quantiles. As a result, it is advantageous in the presence of outliers or non-normal distributions compared to linear regression. In other words, it does not make assumptions about the relationship between the dependent and independent variables. This is favorable for this thesis, as there is little previous evidence of any specific mathematical relationship between electricity prices and BSS storage capacity. Also, electricity prices show strong evidence of non-normal distribution [26], which favors the use of quantile regression as no assumptions are made on the distribution.

As no assumptions are made on the relationship between electricity price quantiles and BSS storage capacity, nor on the distribution of electricity prices, quantile regression is deemed the favorable method for describing this relationship. The general formulation of a quantile regression model can be mathematically described as:

$$Q_\tau(\mathbf{y}|\mathbf{X}) = \mathbf{X}\boldsymbol{\beta}^\tau \tag{2}$$

Where Q_τ is the conditional τ-quantile function of the dependent variable $\mathbf{y}$, and $\mathbf{X}$ is a vector of independent variables. $\boldsymbol{\beta^\tau}$ is a vector of the estimated coefficients for the predictors $\mathbf{X}$ associated with the quantile τ.

The obtain the coefficients in $\boldsymbol{\beta}$, one must minimize the corresponding loss function that measures the distance between the observed values of the dependent variable and the predicted values of the conditional quantiles. The loss function is defined as:

$$L(\boldsymbol{y}, \boldsymbol{X}, \boldsymbol{\beta}) = \rho\tau(u)(\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta}) \tag{3}$$

where $\rho\tau(u)$ is a function that measures the distance between u and zero, depending on the quantile level τ. Typically, $\rho\tau(u)$ is defined as:

$$\rho\tau = u(\tau - I(u < 0)) \tag{4}$$

where $I(u < 0)$ is an indicator function that equals 1 if $u < 0$ and 0 otherwise.

Estimating the coefficients in β can be difficult due to them being unavailable in the closed form [27]. To estimate the coefficients, the minimization of loss function L must therefore be reformulated as an optimization problem.

$$\min_{\boldsymbol{\beta}^\tau} \quad \sum_{i \in I} (\tau - 1_{\boldsymbol{y}_i \leq \boldsymbol{\beta}^\tau X_i})(\boldsymbol{y}_i - \boldsymbol{\beta}^\tau X_i) \tag{5a}$$

where

$$1_{\boldsymbol{y}_i \leq \boldsymbol{\beta}^{\tau} X_i} = \begin{cases} 1, & \text{if } \boldsymbol{y}_i \leq \boldsymbol{\beta}^{\tau} X_i \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

The minimization problem can be solved using either simplex methods or interior point methods, depending on whether the problem is linear or non-linear [25]. The resulting estimates of the regression coefficients provide information about the influence of the independent variables on different quantiles of the dependent variable.

3 Related Literature Review

The following section contextualizes the thesis within the relevant literature. The first subsection presents a general introduction to batteries, small-scale BSS, and their applications in electricity systems. Advantages of large-scale BSS in electricity markets with high shares of VRE are subsequently highlighted. Secondly, the history and application of quantile regression in electricity markets are summarized. Finally, a summary explains how this thesis differs from previous work and what it can add to the academic domain of electricity markets. Subsection 3.1 is reused material from an unpublished project thesis by the same authors [1].

3.1 Battery Storage Systems in Electricity Markets

BSS of varying scales can be applied for different behind-the-meter applications. The peak shaving ability of BSS has been frequently examined in academia, with both optimal management and sizing being assessed [28][29]. The concept of price arbitrage has also been explored using BSS and proven to be profitable for both small-scale [4] and large-scale [30] battery systems. In applications such as peak shaving and price arbitrage, the BSS often acts as a price-taker, i.e., it does not affect the electricity market equilibrium because of limited battery storage capacity. With large-scale BSS, however, the market equilibrium can be affected. Mathematical models for determining this effect have been derived and tested numerically by Awad et al. [31]. It is found that energy storage size and location directly impact electricity market prices and arbitrage benefits. The results point towards lower price differences between peak and off-peak hours. Some results even claim that energy storage increases market equilibrium prices [32], as off-peak prices increase more than peak prices are reduced.

An auspicious aspect of large-scale BSS is its application in high-share VRE electricity markets. The term "large-scale BSS" generally describes large single battery sites and aggregated small-scale batteries in an area. Large-scale energy storage could become crucial in future electricity markets, due to the potential of VRE, which offers the lowest lifetime cost per delivered unit of power. Consequently, VRE may displace traditional generators burdened by higher marginal costs [18]. This is known as the merit-order effect [33]. Botterud & Korpås [18] find that combining large-scale Energy Storage Systems (EES) and VRE will remove substantial base-load thermal generation from the market, while peaker thermal generation will essentially remain unchanged. This is because EES seem to trigger significant amounts of additional VRE capacity in the system optimum. The paper states that this is the most important factor of the EES (and BSS), i.e., EES enables VRE capacity expansion but does not directly affect the price of electricity. However, VRE capacity expansion will subsequently reduce the price of electricity in addition to the level of CO_2 emissions from the system. The benefits of BSS in high-share VRE electricity markets proposed by Botterud & Korpås [18] are supported by Li et al. [34] where the uncertainty of wind power forecasts are considered as well. Lastly, the effects of BSS on peak and off-peak prices by Awad et al. [31] is supported in a future scenario in the Belgian electricity with high shares of VRE and BSS [35].

Academia has briefly addressed the impact of BSS in reducing price volatility. Yang & Ozdaglar [36] suggest that the value of energy storage could be significantly underestimated if its potential contribution to volatility reduction is neglected. Several of the aforementioned papers comment on price volatility implicitly by highlighting price differences in peak and off-peak hours [35][31], and the annual cost of energy [18] respectively. Nevertheless, no detailed volatility assessments are presented. Masoumzadeh et al. [37] present a bi-level optimization model for finding the optimal nodal BSS storage capacities for reducing price volatility levels in a nodal electricity market. The optimal size of storage devices at two price areas in Australia and a 30-bus IEEE system is determined. However, there is no explicit price volatility modelling or analysis. The approach is instead described as a price volatility management framework. The most explicit work on how BSS affects price volatility in high-share VRE electricity markets is performed by Gissey et al. [38], where the aggregated electrical storage capacity of consumers in Britain is integrated into the market clearing, either by consumer-led (decentralized) or aggregator-led (centralized) coordination. The volatility of electricity prices in four different future scenarios is presented. The volatility is found to decrease for increasing levels of BSS storage capacity in the market. Centralized coordination of the aggregate storage capacity decreases the mean and volatility of electricity prices compared to decentralized operation.

3.2 Quantile Regression in Electricity Markets

In order to gain a deeper understanding of the relationship between electricity price distribution and BSS, the establishment of a sound framework is necessary as a foundation for analysis. As a result, quantile regression is utilized in this thesis to differentiate the research methodology from previous research by examining the relationship on a quantile level. To the best of the authors' knowledge, quantile regression has not been applied in the context of the relationship between electricity price distribution and BSS. However, quantile regression analysis has been broadly applied in academia. This subsection will briefly discuss the history and relevant application of quantile regression analysis in finance and electricity markets.

Koenker & Basset Jr first introduced quantile regression in 1978 [39]. Since then, the mathematical principles of quantile regression have been applied within a broad range of academic fields [25]. In finance, there is a growing interest in quantile regression modelling with an emphasis on risk management [40]. Specifically, the application of quantile regression within Value at Risk (VaR) estimations has received growing interest. Relevant results of using quantile regression in VaR estimations include identifying previously undetected periods of increased risk exposure [41]. Similarly, Conditional Value at Risk (CVaR) assessments have benefited from quantile regression models as they do not require any of the extreme assumptions invoked by existing methodologies, such as normality or independent and identically distributed returns [42]. Instead, quantile regression models move the focus of attention from the distribution of returns directly to the behavior of the quantile. Other examples of financial fields where quantile regression is applied, include portfolio optimization and volatility spillover effects [40][43].

Quantile regression has gained significant attention within academic research pertaining to electricity markets, as it offers a flexible and robust analytical framework for examining the complex relationships between various market factors. Patterns of electricity demand have been investigated using quantile regression, showing the varying impact of demographic, socioeconomic, and household characteristics on domestic electricity consumption [44]. The effects of the predictor variables are found to differ across quantiles and change over time. Analysis and forecasting of electricity price risk is another example of quantile regression application within the field. Accurate risk measures have considerable value in trading and risk management with the topic being actively researched for better techniques [45]. Using a multi-factor, dynamic, quantile regression formulation, extended to include Generalised Autoregressive Conditional Heteroscedasticity (GARCH) properties, the specification effects of mean reversion, spikes, and time-varying volatility are captured by Bunn et al. [45]. The results demonstrate how the prices of gas, coal, and carbon, forecasts of demand, and reserve margin influence the electricity price quantiles. Hagfors et al. [26] characterize the impact of fundamental factors on UK electricity prices by means of linear quantile regression. Positive elasticities for the underlying fuel commodities are found, while the sensitivity to changes in demand is generally positive. However, the sensitivity to different factors varies substantially both across the day and within the price distribution.

Quantile regression models have also been used to estimate the merit order effect [33] for different quantiles of electricity prices in markets with VRE. In a preliminary study on the impact of Renewable Energy Sources (RES) on prices in the German electricity market, Hagfors [46] finds that RES overall has a mild price-dampening effect. The influence of wind and Solar Photovoltaic (SPV) on the magnitude and variability of the German electricity spot price is analyzed by Maciejowska [47]. The findings indicate that both types of renewable generation have a similar, negative impact on the price level, approximated by the price median. However, the effect of two renewable sources deviates when employing inter-quantile range measures. Conditional on the level of the total demand, wind production is found to either increase when demand is low or decrease when demand is high. On the other hand, the increase in solar power stabilizes the price variance for moderate demand levels. As a result, the paper underscores the significance of maintaining a balance between wind and solar power in policy recommendations for the development and integration of VRE.

3.3 Summary

Applications of behind-the-meter and large-scale BSS in electricity systems have been widely covered in academia [3][28][30]. The impact of fundamental factors, including VRE, on electricity price volatility has been examined using quantile regression analysis [26][45][47][46]. Optimal operation and sizing of BSS in electricity markets with and without VRE has also been investigated [37][38][18][31][33]. The impact of BSS storage capacity on market equilibrium has been investigated, and price volatility has been commented on implicitly by studying price patterns in peak and off-peak hours [36][37][38][18][31][34][35]. Although the value of energy storage in reducing price volatility is emphasized [36], only Masoumzadeh et al. [37] and Gissey et al. [38] explicitly investigate the relationship between BSS storage capacity and price volatility. However, these studies do not explicitly examine the varying impacts of BSS on the different quantiles of the price distribution. Furthermore, no comprehensive framework, such as quantile regression, has been employed in previous studies to investigate the relationship between BSS and the distribution of electricity prices.

In conclusion, the authors of this thesis believe that there exists a research gap concerning the impact of BSS on electricity price distribution in high-share VRE markets, and how BSS affects the different quantiles of the price distribution. This thesis aims to investigate this relationship, and if possible, draw mathematical inferences between BSS and the various price quantiles. Relevant findings are compared with the small sample size of similar research and relevant literature. As BSS becomes an increasingly more important part of electricity market operation, the findings of this thesis can help gain a deeper understanding of the dynamics between BSS and electricity prices which may be beneficial to all market participants.

4 Data

The power market analytics company Volue Insight has provided the data used in this thesis. The firm originates from Markedskraft which was established in 1992. Since then, they have become an international company and have over 35 million daily data calls to their Application Programming Interface (API) [48]. Volue Insight is a part of the publicly traded company Volue ASA. The introduction of Subsection 4.1 is reused material from an unpublished project thesis by the same authors [1].

4.1 Fundamental Market Data

Volue Insight uses fundamental data gathered from Transmission System Operators (TSO) and other external sources to construct their data curves, i.e., time series of fundamental data related to the power market. In Germany, the measured data comes from the four TSOs: Amprion, TenneT, TransnetBW, and 50Hertz Transmission. These operators ensure that power is produced and transported optimally, and as a byproduct, they also measure the produced power accurately. These measurements make a solid foundation for the models produced by Volue.

This thesis uses fundamental data for prices, production, consumption, and capacities of relevant generation technologies. This data also serves as input for state-of-the-art forecasting models. These models include the EMPS- and Plexos-model [49], which simulate power systems with constraints on transfer capacity and hydrological differences between areas. Forecasts from these models are either used for further analysis or published directly to users. An example of the data curves used in this thesis can be seen in Figure 4 below. The curves show actual solar production in Germany between January 1st and January 8th, 2023.

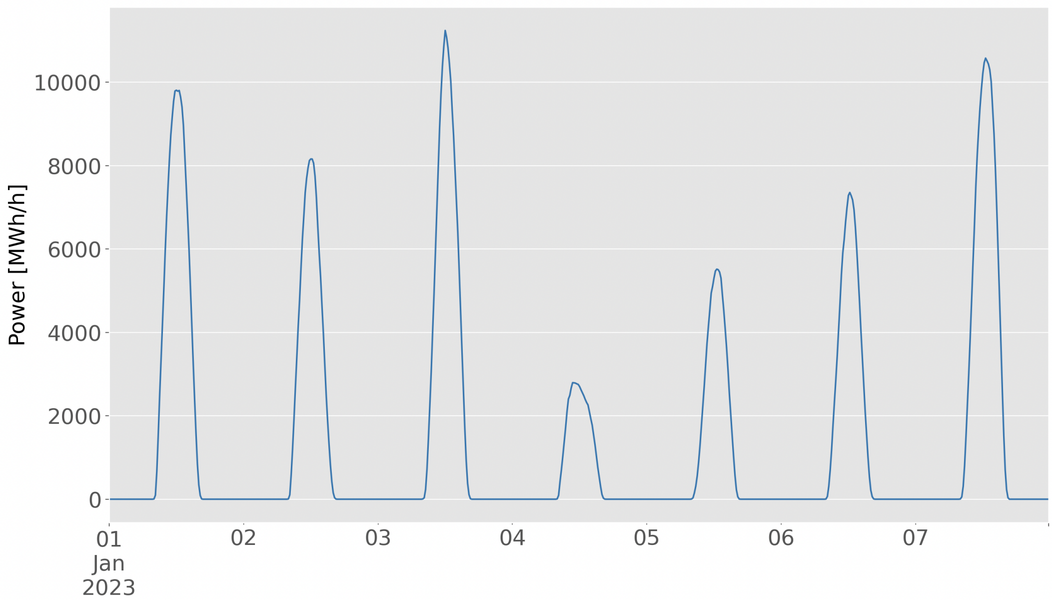


Figure 4: Actual solar production in Germany between the 1st and 8th of January, 2023, measured at a frequency of 15 minutes. Source: Volue Insight [11].

Volue Insight has preprocessed the API data, removing outliers and filling in missing values, so no further cleaning is required. To minimize timezone complications, the data is converted from local to a neutral timezone before the analysis (CET to UTC) and is reverted after. To facilitate comparison, the time series are aggregated from a mix of monthly and 15-minute frequencies to a consistent hourly frequency.

4.1.1 Thermal Generation

Thermal generation of electricity is generally referred to as power produced from heat, that drives rotating generators [50]. The most common thermal energy sources are natural gas, coal, oil, and nuclear, while greener alternatives such as biomass and waste burning are growing industries. Production data from these plants are reported to the European Energy Exchange (EEX) by all production plants in Europe, which creates a transparent market. The data is observed hourly and is measured in MWh/h. The platform incorporates plant-specific capabilities, forthcoming maintenance activities, and Urgent Market Messages (UMM) to generate publications that inform both current and future production in addition to available capacity[51]. Subsequently, this data is distributed to energy market operators, including Volue Insight.

The publications on future available generation capacities from EEX form the basis for capacity assumptions in this thesis. The capacity forecasts represent the most recent forecasts for the period under investigation. This methodology is employed to obtain the most precise and up-to-date information possible. Nonetheless, a drawback of using these forecasts is that they are hypothetical rather than empirical values, thereby elevating the possibility of data imperfections caused by underlying modelling assumptions.

4.1.2 Renewable Generation

Renewable generation technologies included in this thesis are solar photovoltaic, onshore and offshore wind, and hydropower. Volue Insight receives the data for renewable generation through EEX. The data is observed every 15 minutes, updated daily, and measured in MWh/h. It is then aggregated to an hourly frequency to align with the thermal generation capacities.

Reported production data is used instead of generation capacities for renewable technologies. This is equivalent to an assumption of a perfect forecast of VRE where the availability of VRE capacity is expressed implicitly. Given that renewables consistently operate at nearly full available capacity due to their low SRMC [33], utilizing actual production data is considered justifiable as it closely aligns with the available production capacity. If installed capacities of VRE were to be used, the model would strongly overestimate the available capacity as varying weather conditions would not be considered. This is visualized in Figure A.1 in the Appendix.

Using actual production data to model renewable power generation is considered especially beneficial for hydropower as this approach eliminates the need to model water values [12], reducing the complexity of the model without significantly impacting the results. Hydropower has limited production and installed capacity in Germany, coupled with a low SRMC. As a result, it is rarely the price-setting technology in the German electricity market [33].

4.1.3 Cost of Power Generation

In thermal power generation, the SRMC is mainly affected by the cost of fuel and the price of CO_2 quotas. The cost of fuel is decided by several factors, including the price of the thermal fuel itself, along with costs related to transportation and storage. These factors can change drastically over a short period due to scarcity [52]. In addition, the historical prices of CO_2 quotas have increased notably in recent years [53]. As a result, the SRMC of thermal power generation can vary significantly over time. The SRMC of thermal power generation for a given efficiency η is calculated as follows:

$$SRMC = \frac{fuelCost}{\eta} + \frac{CO_2Cost}{\eta} + fixedCost \tag{7}$$

Accurately representing the SRMC of thermal generation is imperative to the performance and accuracy of electricity market modelling as the market price is set by the marginal cost of production (see: Subsection 2.1.1). An overview of all fundamental generation data and corresponding SRMC used in the thesis is seen in Table 2 below. Elaboration on historical costs and justification of assumptions for historical averages follow in the paragraphs below the table.

Table 2: Overview of fundamental generation data and corresponding SRMC.

Generation Technology	Generation Input Data	SRMC
Wind	Actual Production[1]	0
Solar	Actual Production[1]	0
Hydro	Actual Production[1]	Assumption[2]
Gas	Available Capacity	Historical Cost
Coal	Available Capacity	Historical Cost
Oil	Available Capacity	Historical Cost
Lignite	Available Capacity	Historical Cost
Biomass	Available Capacity	Historical Cost
Nuclear	Available Capacity	Historical Average[3]
Waste	Available Capacity	Historical Average[3]

[1] Equivalent to deterministic forecast.
[2] Assumed to be zero. Low hydro capacity and is rarely price setter [54].
[3] Historical SRMC average values are found in Table 21 in the Appendix.

For gas and coal, historical SRMCs are provided directly from the Volue Insight API. Efficiencies of gas and coal power plants are based on internal Volue Insight assumptions [54].

Regarding lignite, no explicit data on SRMC of German power generators are available and time-series must resultingly be constructed. SRMC of lignite is highly correlated with coal historically but has been priced lower than coal as lignite is both mined and consumed in Germany [55]. As a result, the SRMC of lignite is priced accordingly:

$$SRMC_{lignite} = SRMC_{coal} - \Delta SRMC \tag{8}$$

where $\Delta SRMC$ is an estimate of the historic difference between SRMC of lignite and coal in Germany based on internal Volue Insight assumptions [54].

The SRMC of German oil generation is constructed using Equation 7. Fuel costs are based on historic forward contracts for heavy fuel oil in Germany. The price of forward contracts is provided to Volue Insight by Metanoploy. Historic prices of CO_2 quotas are used to calculate CO_2 costs and are provided by Volue Insight [11]. The installed capacity of oil power production in Germany is very low compared to gas, coal, and lignite. However, the SRMC of oil is often found to be the marginal production unit historically [55]. Thus, a realistic representation of the SRMC of oil is important for the accuracy of modelling the German electricity market.

As for thermal biomass generation, the SRMC has historically shown high levels of correlation with North Western Europe pellets [56]. However, as biomass is assumed to rarely affect the marginal cost of electricity [54], a varying SRMC based on the historic average price of North Western Europe pellets [56] is assumed. The SRMC varies between 75 and 200€/MWh.

Nuclear generation is assumed to have a constant SRMC, an assumption used in similar research [57]. The modest installed capacity of power production from thermal waste is also assumed to be produced at a constant SRMC based on a historic average [54].

Renewable electricity generation has a very low SRMC as there are no fuel costs. Due to state-driven compensation, the costs can even be negative [58]. As a result, the SRMC of wind and solar, is assumed to be zero. Regarding hydropower generation, the SRMC is assumed to be zero as well. Firstly, hydropower has a very low variable cost of production. In addition, hydropower generation is rarely a marginal technology in Germany [54] which justifies the assumption further.

4.2 German Spot Prices

To evaluate the performance of the optimization model, the results of the base scenario are compared with actual German spot prices for the period under investigation. The spot prices used as the basis for comparison are gathered from Nordpool and distributed through the API of Volue Insight [11]. The spot prices are displayed at an hourly frequency and in €/MWh. The German spot prices for electricity for the period under investigation can be seen in Figure 5 below.

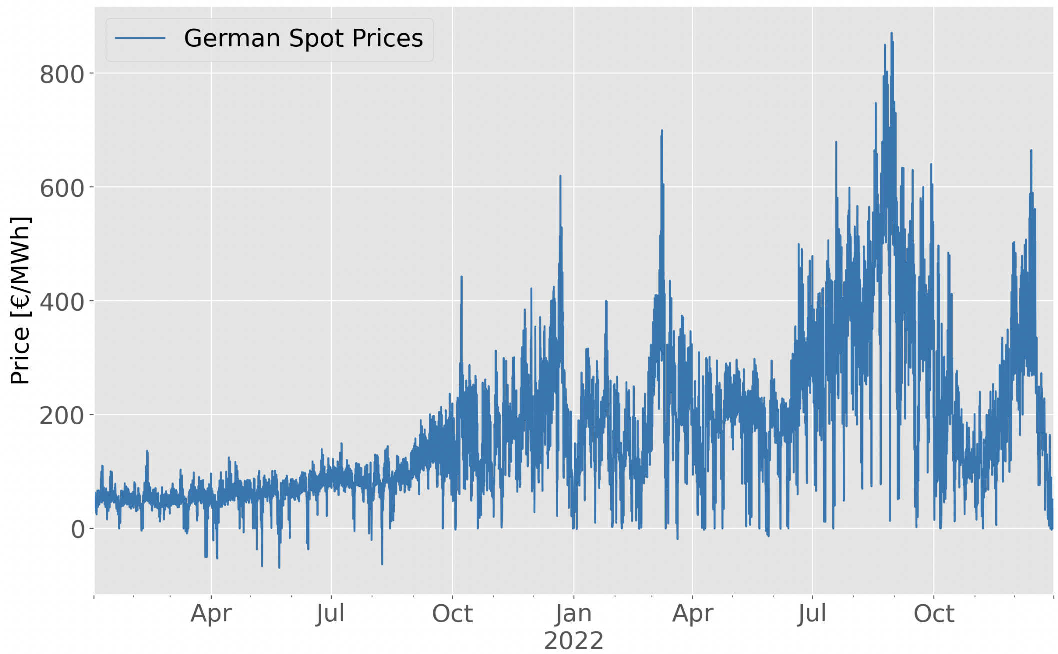


Figure 5: German spot prices for electricity from January 2021 to January 2023. Source: Volue Insight [11].

The figure above reveals high volatility in German prices throughout the period. This is especially evident from the fall of 2021 until the end of the period. It is as if two distinct paradigms exist within the time series: one from January 2021 until fall 2021, and another thereafter. The first period is more in line with the spot price profile for the years before 2021, while the latter deviates significantly from historical pricing patterns. The high prices and volatility seen from the fall of 2021 must be contextualized with the tightening of Russian gas exports to Germany [52], and later as a result of the Russian invasion of Ukraine in February 2022 [59]. These events massively impacted energy prices across Europe [60]. The extreme price spikes during this period are in line with theory (see: Subsection 2.4.2 on the volatility of electricity prices), and are an example of how sudden changes in supply dynamics can affect price volatility. More specifically, how scarcity of fuel can affect the costs of marginal production technologies and thereby influence market prices.

A summary of relevant descriptive statistics from the German spot prices is seen in Table 3 below.

Table 3: Descriptive statistics for German spot prices from January 2021 to January 2023.

Test Statistic	Numeric Value
Min	-69.00
Max	871.00
Mean	166.54
Median	123.32
Standard Deviation	133.06
Skewness	1.39
Kurtosis	2.04
Jarque-Bera	8681.47*
ADF	-5.22*
N	17472

* Indicates that the respective null hypothesis is rejected at the 1% level.

The minimum and maximum observation over the period is -69.00€/MWh and 871.00€/MWh respectively. The standard deviation is 133.06€/MWh compared to the mean of 166.54€/MWh. The median, of 123.32€/MWh, is significantly lower than the mean, which is in line with the discussion in subsection 2.4.1 of right-skewed electricity price distribution. The spot price density distribution is visualized in Figure 6 below.

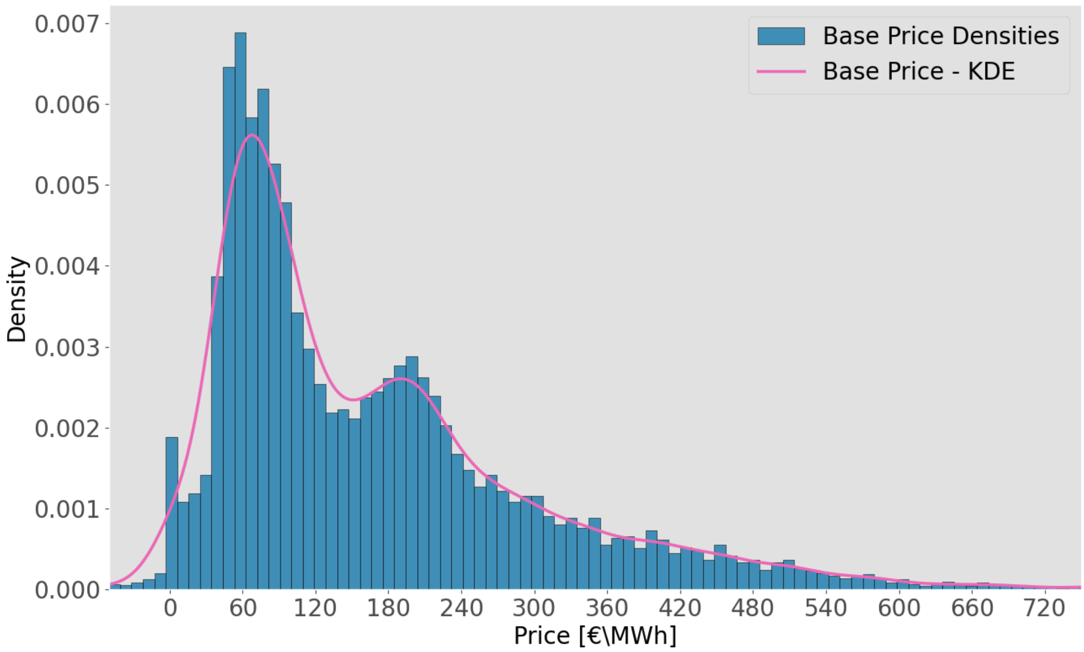


Figure 6: Density plot for German spot prices from January 2021 to January 2023. KDE is the Kernel Density Estimation [61] of the probability density function of spot prices.

The skewness and excess kurtosis, from Table 3, is displayed in the figure above. Here, the median is positioned left of the mean and suggests that lower prices are the most common. The excess kurtosis, visualized by the fat tail on the right-hand side of the mean, represents high prices that significantly deviate from normal prices. These results support the claim from Subsection 2.4.1 on how electricity prices tend to be relatively stable and low in normal conditions, while also having high spikes during periods of supply shortages. The Jarque-Bera test of Table 3 reject the hypothesis of German electricity prices being normally distributed. This is also evident by examining the shape of the distribution seen in Figure 6. Lastly, the test statistic from the ADF test for stationarity confirms the presence of stationary and mean-reverting prices.

The prices at different quantiles are presented in Table 4 below. These results will be compared with the quantiles of the base scenario of the model. The comparison will be of interest due to the peak shaving ability of BSS. In theory, the BSS should remove the most extreme price pikes due to discharging of the batteries while also increasing the prices in off-peak hours as a result of charging activity (see: Subsection 3.1). As a result, prices at lower quantiles are expected to increase, while prices at higher quantiles are expected to be reduced.

Table 4: German spot prices at different quantiles from January 2021 to January 2023 measured in €/MWh.

Quantile	1%	5%	25%	50%	75%	95%	99%
Price	-0.03	29.66	67.70	123.32	225.98	444.95	593.49

To motivate the investigation of the dynamics between BSS and VRE, the correlation between German spot prices and thermal SRMCs, wind, and solar generation are presented in Table 5 below.

Table 5: Correlation between German spot prices and thermal SRMCs, wind, and solar generation at different quantiles from January 2021 to January 2023.

Quantile	5%	25%	50%	75%	95%	Overall
SRMC gas	0.08	-0.23	0.25	0.73	0.60	0.81
SRMC coal	0.04	-0.27	0.29	0.45	0.37	0.69
SRMC oil	0.05	-0.29	0.24	0.30	0.28	0.61
Wind	0.03	-0.47	-0.26	-0.20	0.03	-0.35
Solar	-0.28	-0.20	-0.10	0.01	0.06	-0.05

As evident from the table, there is a negative correlation between low prices and both wind and solar generation. Through the implementation of BSS, surplus VRE generation during low-priced hours can be utilized to reduce prices during peak hours when thermal generation serves as the marginal units. The high correlation, seen between the SRMC of thermal generation technologies and the upper quantiles of German spot prices, clearly visualizes how expensive thermal generation affects prices in hours of high demand. These correlations illustrate the potential for BSS to replace expensive thermal generation with VRE generation, thereby contributing to a more cost-effective and sustainable energy mix.

4.3 Battery Storage System Data

To perform the analysis regarding the impact of BSS, a battery index with BSS storage capacities is created from external sources. The Battery-based Energy Storage Road Map (BATSTORM) report [7] has been the primary source of information when creating the index. The index is created by asserting capacity values to specific dates when BSS storage capacities are commissioned and production goals are set. These values are aggregated to show Germany's total BSS storage capacity at a given time. This data is used to create a time series with a desired length and frequency, where there is a linear increase in storage capacities between the original data points from the report. The BSS capacity ranges from $\sim$1GWh, which corresponds to the present non-aggregated BSS capacity in Germany [7], to 20GWh, with increments of 1GWh. The upper limit is chosen based on future predictions for installed BSS storage capacity in Germany [62]. The BSS is assumed to have a charge and discharge rate of half its storage capacity, i.e., it can be fully charged or discharged in two hours. This is known as the C-rate of the battery.

For the BSS, the SRMC is defined as the cost of discharging. The discharge cost should ideally reflect the opportunity cost of conserving the energy for later use, similarly to water-values of hydro-power plants [12]. As this is considered outside the scope of this thesis, the marginal cost of discharging is assumed to be zero, similar to hydro-power generation. This reflects the sunk investment cost of the BSS and the low variable cost per cycle.

5 Methodology

5.1 Electricity Market Modelling with BSS

The German electricity market is modeled between January 2nd, 2021, and January 1st, 2023 using the data presented in Section 4. BSS is introduced in the system, with varying levels of storage capacity. This capacity represents the total industrial-sized electrical battery storage within Germany. Under the assumption that the market operator controls the BSS (i.e., centralized control), this approach mirrors the storage coordination used by Gissey et al [38]. Previous studies have shown that the aggregation of storage can increase social welfare and decrease electricity costs compared to the decentralized operation of storage [63][64].

5.1.1 Formulation of the Optimization Model

The optimization problem is formulated as a deterministic cost minimization problem, in line with relevant deregulated electricity market modelling theory (see: Subsection 2.2). This is equivalent to a perfectly competitive market where producers face a market price equal to the marginal cost of production. The market price is represented by the Lagrangian multiplier associated with the power balance constraint [16].

The least-cost dispatch problem of the central planner is specified as presented below. All model sets, indices, parameters, variables, and problem formulation are included.

Sets and indices

T : set of hours, $t \in T$

S: set of scenarios, $s \in S$

I: set of generation technologies, $i \in I$

Parameters

$c_{i,t}$: cost of generation type i in hour t

$\bar{x}_i$: generation capacity of technology i

$\bar{e}_t$: storage capacity of BSS in hour t

$\bar{b}$: charge and discharge power capacity of BSS

η^+: discharge efficiency of BSS

η^-: charge efficiency of BSS

d_t: power demand at hour t

Variables

$x_{i,t}$: power generation of technology i in hour t

$b_{soc,t}$: State of Charge (SOC) in BSS in hour t

b_t^+: power discharge of BSS in hour t

b_t^-: power charge of BSS in hour t

The complete model formulation:

$$\min_{x,b^+,b^-,b_{soc}} \quad C = \sum_{t\in T}\sum_{i\in I} c(x_{i,t})\cdot x_{i,t} \tag{9a}$$

$$\text{s.t.} \quad d_t = \sum_{i\in I} x_{i,t} + b_t^+ - b_t^- \qquad \forall t \in T \tag{9b}$$

$$0 \leq x_{i,t} \leq \bar{x}_{i,t} \qquad \forall t \in T, \quad \forall i \in I \tag{9c}$$

$$0 \leq b_t^+ \leq \bar{b} \qquad \forall t \in T \tag{9d}$$

$$0 \leq b_t^- \leq \bar{b} \qquad \forall t \in T \tag{9e}$$

$$b_{soc,t+1} = b_{soc,t} + \eta^- \cdot b_t^- - \eta^+ \cdot b_t^+ \quad \forall t \in T \tag{9f}$$

$$0 \leq b_{soc,t} \leq \bar{e}_t \qquad \forall t \in T \tag{9g}$$

$$b_{soc,0} = 0 \tag{9h}$$

The objective function in 9a minimizes the production cost of the system. The power balance equality is represented by 9b, while upper limits for generation capacities are accounted for in 9c. Power charge and discharge limitations for the BSS are expressed in 9d and 9e, respectively, while the BSS energy balance is given by 9f, including round-trip losses. The storage capacity of the BSS is expressed in 9g. Lastly, the initial state of the BSS is set to zero in 9h.

The objective function minimizes the sum of costs for all electricity generating sources, storage, and import. The total cost is the product of production and cost for every technology in the system. The cost of each thermal generation technology is modeled to vary in accordance with the energy produced, simulating the volume-based bidding process employed by producers. This representation of thermal costs is achieved using a quadratic function as presented in Equation 10 below.

$$c(x_{i,t}, \bar{x}_{i,t}) = C_{min,t} + (C_{max,t} - C_{min,t})(\frac{x_{i,t}}{\bar{x}_{i,t}})^2 \tag{10}$$

$C_{max,t}$ and $C_{min,t}$ are the maximum and minimum marginal costs for a generation technology at time t as a result of varying plant efficiencies within the same technology. $(\frac{x_{i,t}}{\bar{x}_{i,t}})$ is the ratio between the current generation and the maximum generation capacity of the given generation technology. Figure 7 visualizes the quadratic cost curve, where the x-axis represents the ratio between the current generation and the maximum generation capacity of the specified generation technology. The cost function for import and each thermal generation technology follows the same curve, as shown beneath, but with distinct parameter values.

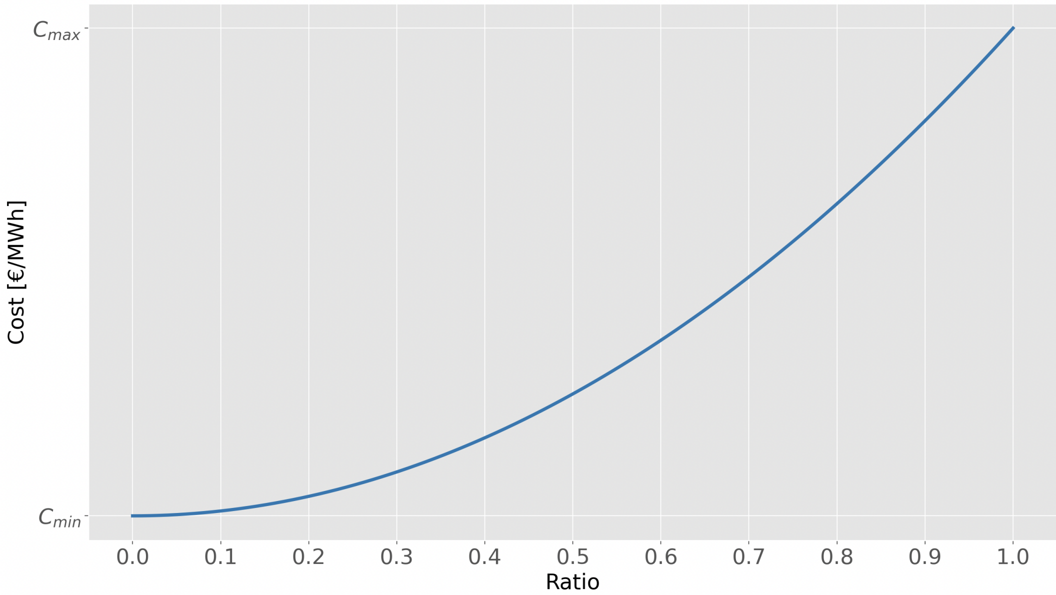


Figure 7: General cost curve for thermal generation and import in the system.

Using this curve, the thermal generation costs vary with utilized capacity. By letting the modeled costs vary with the dispatched generation, the costs reflect the difference in efficiencies between generation units within the same technology. This induces an effect of disaggregating a general cost of production within a unique technology into individual unit costs, where the cheapest units are dispatched first.

The model is implemented and run in Python, using the optimization modelling language Pyomo. Optimal production mix and BSS operation are obtained directly, while the market price series is expressed as the dual value of the power balance in constraint 9b.

5.1.2 Decomposition of the Optimization Model

The process of breaking down a model into smaller, more manageable parts and running them separately is known as model decomposition. This approach allows for a more in-depth analysis of each component of the model and can simplify the modelling process, especially for complex systems [65].

The introduction of a quadratic cost function in the model for thermals and import increases the complexity of the optimization problem. As a result, it makes the optimization problem unsolvable for periods longer than 11 days, when solved directly. The added complexity arises from the transformation of the objective function from linear to non-linear, which demands a higher solving capacity. To address this issue, a decomposition method is applied.

In electricity market modelling with storage, accurate time representation and endpoint constraint management are essential for a precise analysis. When solving for the complete period, only one SOC endpoint must be addressed. However, when decomposing the problem, more SOC endpoints are created. Assessing this increase in endpoint complexity when integrating the individual decomposed components is essential. Combining decomposed periods consecutively would assume fixed endpoint values, leading to unrealistic or sub-optimal resource allocation decisions as it fails to account for the dynamic nature of the problem.

To overcome this limitation, a rolling horizon approach is applied. This allows for a more accurate representation of inter-period dynamics in BSS management by considering the continuity of the SOC across different periods [66]. Incorporating overlap between periods enables the model to account for carryover storage, ensuring optimal allocation of stored electricity over time.

The rolling horizon decomposition is illustrated in Figure 8 below.

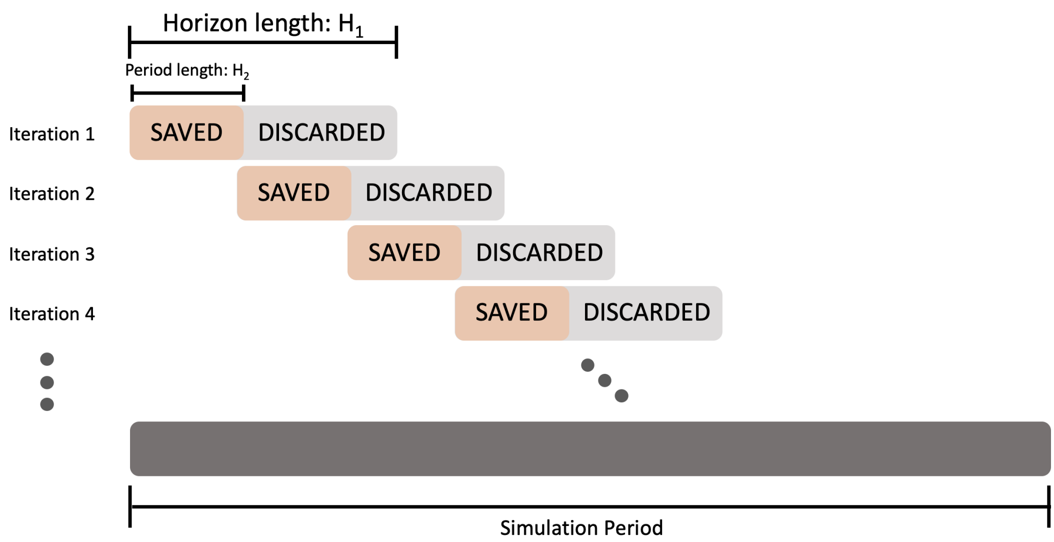


Figure 8: An illustration of the rolling horizon decomposition.

To implement the rolling horizon decomposition, the set of hours T is divided into N overlapping sub-horizons with length H_1. The starting point of each sub-horizon is denoted by 0, and the corresponding ending time by H_1. The overall horizon is divided into N non-overlapping sub-periods denoted p, where

$$\text{Length of } p = H_2 = \lceil \frac{T}{H_1} \rceil \tag{11}$$

Thus, the rolling horizon optimization problem is formulated as follows:

$$\begin{aligned}
\min \quad & C_p = \sum_{t=0}^{t=H_1} c(x_{p,t}) && \text{(12a)} \\
\text{s.t.} \quad & g(x_{p,t}) \leq 0 \qquad \forall t \in [0, H_1] && \text{(12b)} \\
& b_{soc,p+1,0} = b_{soc,p,H_2} && \text{(12c)}
\end{aligned}$$

$\forall p \in [0, N-1]$.

The objective function in 12a minimizes the cost over the period of length H_1, where the cost function is the same as in equation 10. The constraint in 12b represents all the constraints of the complete model formulation, except the BSS energy balance equation which is represented in 12c. Here, the constraint sets the initial state of the BSS equal to the last state of the previous period p. Note that the initial state of the new period is equal to the state at time H_2 in the previous period, and not at time H_1 which is the optimization horizon. Consequently, only the decisions made from time 0 until time H_2 are taken into account when moving on to the next period. This is illustrated by the SAVED and DISCARDED boxes in Figure 8.

The length of the overlapping period must be carefully examined to avoid endpoint inaccuracies. The overlap period is required to be longer than the battery's charge cycle to ensure an optimal storage allocation [67][66]. In the simulations, the BSS displays a charge cycle of three days at its maximum. Consequently, endpoint challenges are addressed by running the model for 10 days and using only the results from the first seven days. This approach satisfies the overlapping requirement.

As long as the remaining period length is longer than 10 days, the model will decompose the problem as described above. The last period, which lacks overlap data, is used directly in the solution. With the addition of an endpoint handling approach inspired by hydro reservoir modelling, the decomposition method applied in this thesis ensures an accurate representation of the battery constraints within the electricity market model. This leads to improved optimization results and a more realistic market operation.

5.1.3 Model Assumptions

Import

The model assumes zero power exchange between Germany and connected countries to reduce model complexity arising from power exchange dynamics and price interactions between countries. As electricity prices in Germany are highly correlated with surrounding areas [11], this simplification of the system must be handled appropriately. To simulate the effect of high prices in periods of generation shortage in Germany, the optimization model uses historical correlations between peak gas prices in Germany and levels of import. In times of high import, German electricity prices are highly correlated with SRMC of gas power plants [11]. The price of imported power due to generation shortage is therefore priced as SRMC of gas power multiplied with a factor accounting for price effects caused by import. This factor varies between C_{min}=1.1 and C_{max}=2.0, depending on the level of power import and is based on the historical correlation between SRMC of gas and German electricity prices during import [54].

Other Assumptions

To concentrate the scope of this thesis, certain simplifications regarding the German electricity market are made. The complexity-reducing measures are considered to not significantly impact the established indications made by the thesis. The assumption of a deterministic forecast for VRE and hydropower are accounted for in Subsection 4.1.2. In addition, relevant simplifications and assumptions include demand flexibility, internal transmission congestion, ancillary services, and ramping costs. These aspects are neglected because the model's intended application is on an aggregated level. The effects of these simplifications should be a topic for discussion and will be highly relevant concerning future research.

5.2 Model Scenarios

5.2.1 Base Scenario

The model is initially run without any BSS storage capacity, to imitate the current German electricity market with no centralized BSS operation. The base scenario is considered to be a proxy for the performance and quality of the model. Resultant production mix and market prices generated by the base scenario will be analyzed and compared with actual production and prices during the period under investigation. Subsequently, the market prices generated by the model will be subject to the same examination as the authentic German spot prices analyzed in Subsection 4.2. The resultant descriptive statistics will be compared with corresponding authentic statistics, where both differences and similarities will be highlighted. Moreover, the results of the base scenario will in addition serve as a basis for comparison when introducing BSS and additional VRE to the system.

5.2.2 BSS Scenario

Varying levels of BSS storage capacities are subsequently introduced in the model. The storage capacity ranges from ∼1GWh, which corresponds to the present non-aggregated storage capacity in Germany [7], to 20GWh, with increments of 1GWh. The upper limit is chosen based on future predictions for installed BSS storage capacity in Germany [62]. The obtained production mixes and BSS operation will be analyzed and compared with the base scenario. The same applies to descriptive statistics acquired from market prices from BSS iterations. The inferences drawn on the relationship between BSS and market prices will be compared with relevant literature. Furthermore, the BSS market prices at various quantiles will serve as inputs for the subsequent quantile regression.

5.2.3 BSS & VRE Scenario

In addition to evaluating the effects of BSS on electricity market prices, the interactions between VRE and BSS are investigated. Current literature emphasizes the importance of sufficient VRE capacity in the context of BSS [18]. To further dissect the role of BSS in future electricity markets, the installed capacity of VRE is increased in various iterations of the model. The VRE capacity increase ranges between zero and one, with increments of 0.2, and represents the percent increase in installed VRE capacity in each iteration. In this context, installed VRE capacity is defined as the aggregated capacities of solar and wind generation. The upper limit of the VRE capacity increase is based on future

VRE capacity predictions by Volue [54]. The goal is to observe and draw inferences on the dynamics between BSS and VRE, and how they collectively influence the production mix and market prices. Findings will be compared with previous model iterations and relevant literature. The price dynamic caused by BSS and VRE interaction will also be investigated by means of quantile regression.

An overview of all model scenarios is presented in Table 6 below.

Table 6: Overview of model scenarios.

Scenario	Base	BSS	BSS & VRE
BSS Capacity [GWh]	0	1-20	0-20
VRE Capacity Increase	0	0	0-1

5.3 Quantile Regression

5.3.1 BSS

As stated in the introduction, one of the main objectives of this thesis is to investigate the relationship between BSS storage capacity and electricity prices at different quantiles, and if possible, draw inferences on the mathematical relationship between them. In order to accomplish this objective, quantile regression is applied. The linear quantile regression model utilized in this thesis follows the approach described in the theory section (see: Subsection 2.5). The conditional τ-quantile function of the quantile regression model is formulated as follows:

$$Q_\tau(P_s|X_s) = \alpha^\tau + \beta^\tau_{BSS} X_s + \epsilon^\tau_s \tag{13}$$

where P_s is the τ-quantile electricity price related to BSS scenario s, and X_s is the BSS capacity in scenario s. α^q is the constant term of quantile τ for all BSS scenarios, and β^τ_{BSS} is the gradient of quantile τ for all BSS scenarios. ϵ^τ_s is the τ-quantile error term for BSS scenario s.

To estimate the coefficients α^τ and β^τ_{BSS} a linear optimization algorithm is applied. The minimization problem for a given quantile τ becomes:

$$\min_{\alpha^\tau, \beta^\tau_{BSS}} \quad \sum_{s \in S} (\tau - 1_{P_s \leq \alpha^\tau + \beta^\tau_{BSS} X_s})(P_s - (\alpha^\tau + \beta^\tau_{BSS} X_s)) \tag{14a}$$

where

$$1_{P_s \leq \alpha^\tau + \beta^\tau_{BSS} X_s} = \begin{cases} 1, & \text{if } P_s \leq \alpha^\tau + \beta^\tau_{BSS} X_s \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

The minimization problem seeks to estimate coefficients that minimize the weighted sum of the residuals (i.e. error terms). The residuals are the differences between the actual observed electricity prices and the estimated values provided by the quantile regression model. Equation 15 equals one if the residual is negative and zero if it is positive. If the residuals are positive (i.e., under-predictions), their weight is equal to τ. On the other hand, if the residuals are negative (i.e., over-predictions), their weight is equal to $|\tau - 1|$. As a result, the model minimizes the weighted absolute distances between the observed values and the predicted values.

The quantile regression is run in Python, using the Python package Statsmodels [68]. Estimated gradients and plots are presented in the results. The gradient plots include quantile intervals, or bands, estimated by asymptotic analysis, as they do not assume normally distributed prices [69].

5.3.2 VRE

To distinguish potential synergy effects between BSS and VRE on the electricity price distribution from the individual impact of VRE, a separate quantile regression is run using VRE capacity as the independent variable. The regression model utilizes prices derived from scenarios featuring different levels of additional VRE capacity and a constant zero BSS storage capacity. The conditional τ-quantile function of the quantile regression model for the single-variable VRE scenarios is thus defined as:

$$Q_\tau(P_r|Y_r) = \alpha^\tau + \beta^\tau_{VRE} Y_r + \epsilon^\tau_r \tag{16}$$

where P_r is the τ-quantile electricity price related to VRE scenario r, and Y_r is the VRE capacity increase in scenario r.

The coefficients α^τ and β^τ_{VRE} are estimated using the same methodology as described in Subsection 5.3.1. Estimated gradients and plots are presented in the results.

5.3.3 BSS and VRE

To investigate the interconnection between BSS and the implementation of VRE, a multivariate quantile regression model is formulated. The purpose of an additional model is to create a basis for comparison with the work of Botterud & Korpås [18]. They have shown that increased implementation of VRE capacity has positive synergies with BSS, as it lowers the average cost of electricity. This is due to the ability of BSS to take advantage of the fluctuations of VRE, mainly by storing energy in times of excess VRE generation. To explore the relationship between BSS, VRE, and the electricity price distribution, the following quantile regression model is formulated:

$$Q_\tau(P_{s,r}|X_s, Y_r) = \alpha^\tau + \beta^\tau_{BSS} X_s + \beta^\tau_{VRE} Y_r + \epsilon^\tau_{s,r} \tag{17}$$

where $P_{s,r}$ is the τ-quantile electricity price related to BSS scenario s and VRE scenario r. The error, $\epsilon^\tau_{s,r}$, is the τ-quantile error term for BSS scenario s and VRE scenario r.

The coefficients α^τ, β^τ_{BSS} and β^τ_{VRE} are estimated using the same methodology as described in Subsection 5.3.1. Estimated gradients and plots are presented in the results.

6 Results

6.1 Electricity Market Modelling with BSS

The following section presents the results of the electricity market modelling. First, the generation mixes and market prices from the base scenario are introduced. They are then compared with actual production and prices, before the price distribution and quantiles are investigated. The same procedure is subsequently repeated for the single-variable *BSS* scenario and the multi-variate *BSS & VRE* scenario, where the base scenario serves as the basis of comparison.

6.1.1 Base Scenario

The results of the base scenario are presented in the following subsection. In the base scenario, no BSS storage capacity or additional VRE capacity has been implemented.

Generation Mix

The German electricity market is simulated for a span of two years, from January 2nd, 2021, to January 1st, 2023. For a clearer illustration of the optimal production mix, a 10-day time frame is selected. This choice is made as changes in the price profile due to BSS occur on an intra-day and intra-week basis, and would not be easily visible in a yearly plot. The specific time frame selected for analysis spans from July 16th to July 25th, 2022, as shown in Figure 9 below. During this period, there is a combination of both high and low VRE production in relation to the demand. Since significant price fluctuations typically coincide with high VRE production, this particular time frame may offer valuable insights as it illustrates this phenomenon well. In the figure, demand is visualized by a black curve and generation as a stacked bar plot. Please note that this figure does not differentiate between individual thermal generation technologies.

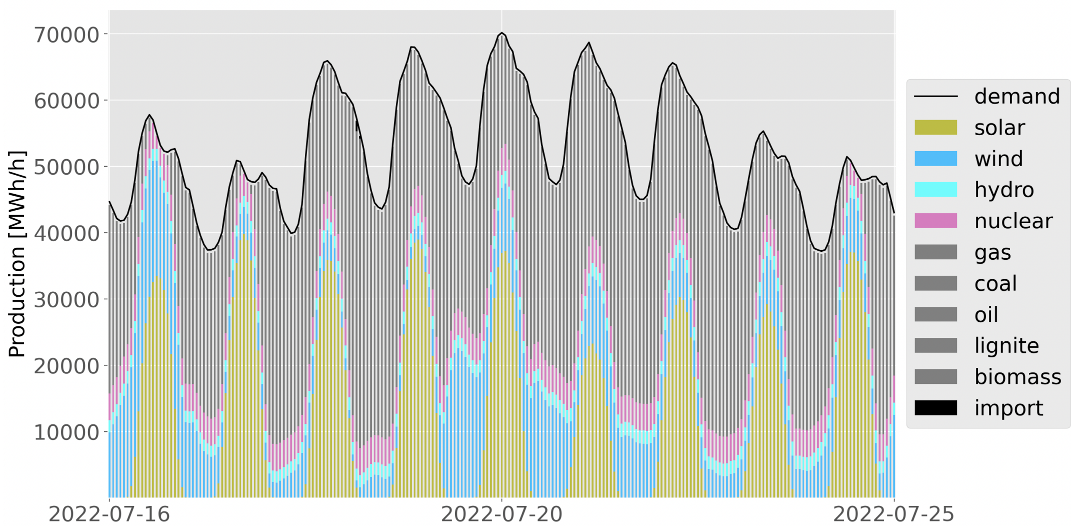


Figure 9: Market mix for the base scenario from 16th to 25th of July, 2022.

Figure 9 above demonstrates that all available VRE is generated during all hours in an attempt to cover demand, a pattern that remains consistent throughout the two-year period. However, consumption is rarely fully covered by VRE, leading to thermal generation technologies becoming the marginal generators in most hours. The complete generation mix for the two-year period can be seen in Table 7 below.

Table 7: Generation mix for the base scenario and actual generation from January 2021 to January 2023. Absolute deviations are relative to the actual generation.

Generation tech.	Base [%]	Actual [%]	*Dev. [%]*
Wind	22.8	22.0	*0.8*
Solar	10.3	10.0	*0.3*
Biomass	3.4	8.0	*-4.6*
Hydro	3.1	3.0	*0.1*
Lignite	21.7	19.6	*2.1*
Natural Gas	8.0	15.7	*-7.7*
Hard coal	17.9	11.5	*6.4*
Nuclear	9.7	9.1	*0.6*
Oil	0.9	0.4	*0.5*
Waste	0.7	0.7	*0.0*
Other	1.4	0.0	*1.4*

The generation mix for renewables in the base scenario closely resembles the actual production in Germany, with the exception of biomass production. However, there are significant deviations in thermal generation, particularly in natural gas generation. The base scenario appears to favor lignite and hard coal generation over natural gas. Additionally, the base scenario is unable to meet the demand during all hours, which accounts for the 1.4 % discrepancy in the *Other* category. In this thesis, *Other* represents the additional generation required to meet demand in situations where the existing generation is insufficient, analogous to imports in a real market.

The discrepancy in generation mixes could be linked to the model's disregard for ramp-up costs in thermal plants, permitting these plants to switch production on and off every hour. Such behavior would be less likely in an actual market due to the associated cost of varying production. Another factor possibly contributing to this discrepancy could be the model's lack of cross-boundary power transfer. As the model potentially overprices imported energy in some instances, overcompensation in local production because of the perceived energy shortfall might occur.

it might overestimate local production to compensate for the perceived energy shortfall.

Price Profile

The price profile for the base scenario is presented and compared to actual German spot prices in Figure 9 below for the period between July 16th and July 25th, 2022.

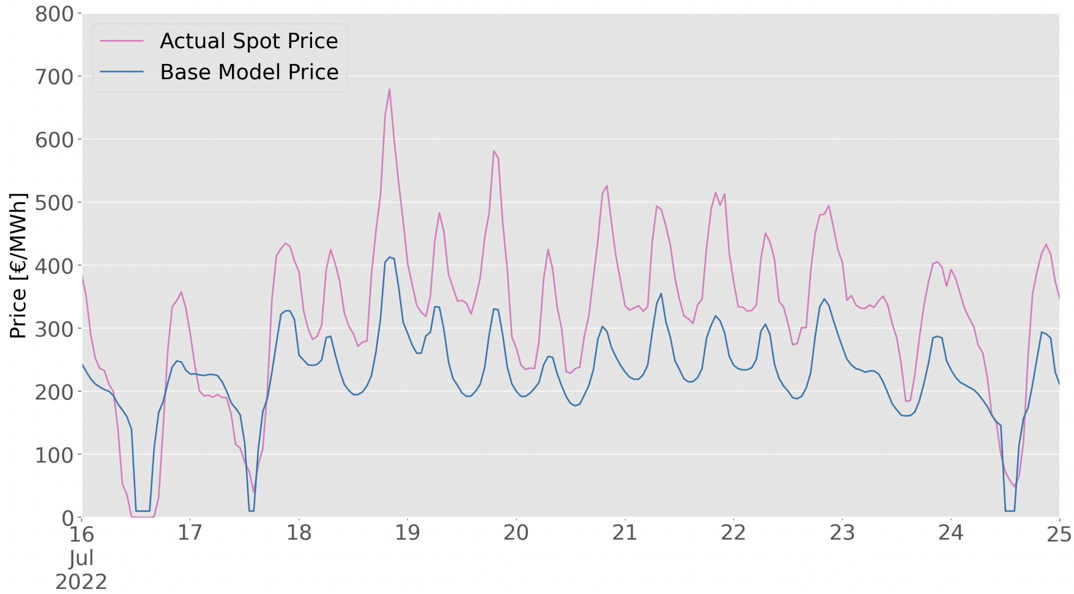


Figure 10: Market price for the base scenario from July 16th to July 25th, 2022.

The price profile of the base model successfully captures the overall price trends of the actual prices by accurately predicting when price peaks and valleys occur. Additionally, it effectively represents the varying price levels over the span of two years (see: Figure A.2 in the Appendix). This indicates that the capacities and SRMCs of different generation technologies reliably reflect the capacities and costs in the market.

The base model encounters difficulties in capturing volatility during hours when the most extreme price changes occur, whether they are negative or positive. Though the accurate representation of high volatility is a recurring challenge in electricity market modelling [15], there is most likely an added effect caused by the general volatility in the European and German electricity market during the period under investigation. The tightening of Russian gas exports has caused supply constraints and led to a substantially more volatile price level across the European countries, including Germany [52][60]. These sudden and unpredictable market conditions represent significant market challenges that are difficult to capture in modelling. However, the model's price prediction accuracy is considered satisfactory, given that it effectively replicates real market prices during periods of more stable volatility throughout the two-year period.

Price Distribution

The price distribution plot for the base scenario is presented in Figure 11 below.

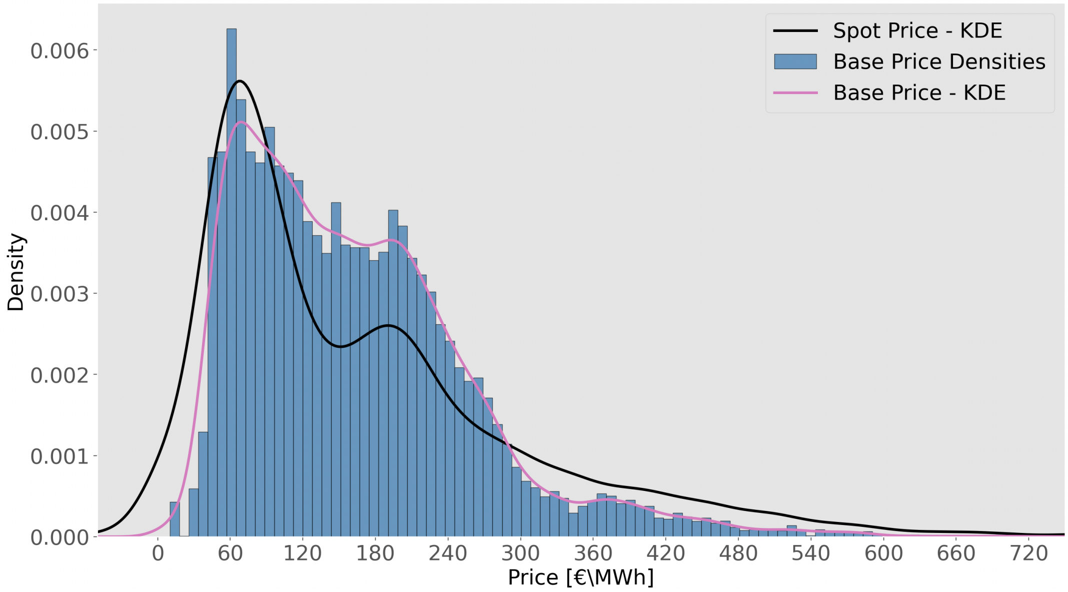


Figure 11: Density plot for base scenario prices compared to German spot prices from January 2021 to January 2023. KDE is the Kernel Density Estimation [61] of the probability density function of the prices.

The base scenario prices follow a log-normal distribution, a characteristic also found in German spot prices. This distribution shape mirrors the typical behavior of electricity prices, which tend to maintain a relatively low and stable level under standard conditions, but are characterized by frequent sharp spikes during periods of high demand or supply shortages [22][23]. These price spikes often originate from a reduced availability in power generation, linked directly to fluctuations in fuel availability [21].

The base scenario exhibits a more concentrated distribution of prices than the German spot prices, with reduced variability in the central region of the curve. This less pronounced spread is observed by the shorter tails on the Kernel Density Estimation (KDE) plot. In essence, the distribution exhibits lower kurtosis compared to the German spot prices.

Descriptive Statistics

Descriptive statistics are presented for the full period in Table 8. The table presents the statistical values for both the base and actual spot prices in the first two columns while the subsequent columns highlight the deviation between them. Deviations are expressed in both their respective units and as a percentage change.

Table 8: Descriptive statistics for base scenario market prices from January 2021 to January 2023.

Test Statistic	Base	Actual	*Deviation*	*Deviation [%]*
Min	10.00	-69.00	79	114.49
Max	794.69	871.00	-76.31	-8.76
Mean	162.26	166.54	-4.28	-2.57
Median	145.93	123.32	22.61	18.34
Standard Deviation	96.39	133.06	-36.66	-27.56
Skewness	1.26	1.39	-0.14	-9.82
Kurtosis	2.33	2.04	-0.28	-13.94
Jarque-Bera	8531.40*	8681.47*	-150.06	-1.73
ADF	-5.34*	-5.22*	-0.12	-2.24
N	17472	17472	N/A	N/A

* Indicates that the respective null hypothesis is rejected at the 1% level.

The minimum and maximum values indicate that the model does not reproduce negative prices and that the highest prices are not entirely captured. The absence of negative prices is due to the exclusion of ramp-up costs in thermal plants and the omission of VRE subsidy schemes in the model formulation [2][58]. The mean values are quite similar, while the median values suggest that the model's price level is typically higher than the actual prices. The standard deviation illustrates the variability in prices and reveals less variability in the modeled prices compared to the German spot prices. The values for skewness and kurtosis depict a model that is more symmetrical around its central tendency and has fewer extreme values, which is consistent with the base scenario price profile seen in Figure 10. The Jarque-Bera and ADF tests confirm the presence of non-normality and stationarity in the price series of the base scenario. Overall, the table conveys a model that captures general price trends but struggles with accurately representing the most extreme prices.

Table 9 below presents the distribution of prices across percentiles.

Table 9: Price quantiles for the base scenario measured in €/MWh. Deviations are relative to German spot prices.

Quantile	1%	5%	25%	50%	75%	95%	99%
Base	35.09	48.30	87.18	145.93	214.40	351.68	476.19
Actual	-0.03	29.66	67.69	123.32	225.98	444.95	593.49
Deviation	35.12	18.64	19.48	22.61	-11.58	-93.27	-117.31
Deviation [%]	N/A	62.86	28.78	18.34	-5.12	-20.96	-19.77

The figure reveals that in the base scenario, prices are higher than the actual spot prices for the lower quantiles. This pattern is evident until the 50% quantile. For the upper quantiles, especially the 95%, and 99%, the base scenario prices are lower than the actual prices. In general, the deviations indicate that the model does not capture the most extreme prices, both at the upper and lower ends. This is in line with the price peaks seen in Figure 10 and the distribution plot in Figure 11.

6.1.2 BSS Scenario

The results of the single-variable *BSS* scenarios are presented in the following subsection. In the BSS scenarios, varying levels of BSS storage capacity are introduced to the system. The BSS storage capacity ranges between one and 20GWh with increments of 1GWh per scenario.

Generation Mix

Similar to the base scenario, the generation mix with the addition of 20GWh BSS storage capacity is illustrated in Figure 12 below. The green bars below the x-axis represent BSS charging, while the red bars near the demand line indicate discharging. Of note is the intersection of the demand curve with the stacked bar plot, which represents production, when the BSS is charging. The demand does not account for BSS charging, and an excess of energy is required to accommodate the additional load from the BSS. The green bars, which demonstrate the BSS extracting power from the grid, will have the same absolute values as the excess production due to the power balance constraint from Equation 9b in the model formulation.

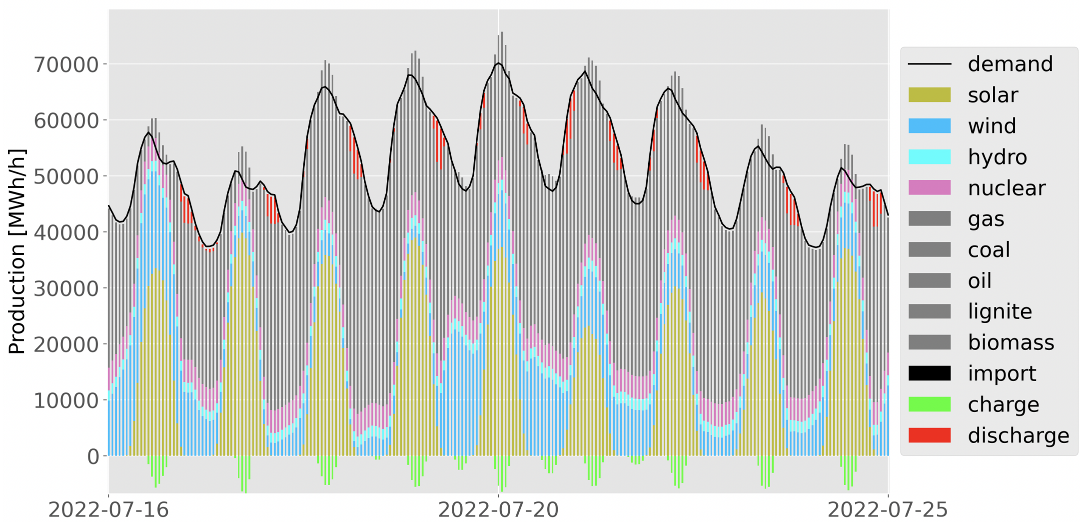


Figure 12: Market mix for the 20GWh BSS scenario from 16th to 25th of July, 2022.

Typically, charging of the BSS occurs in hours when power generation from VRE is high. However, the marginal technology in instances of charging is usually thermal, rather than VRE. When discharging, the BSS replaces more expensive thermal generation with stored, cheaper thermal generation, resulting in cost savings. The complete generation mix for the 20GWh BSS scenario is presented in Table 10 below.

Table 10: Generation mix for the 20GWh BSS scenario from January 2021 to January 2023. Absolute deviations are relative to the base scenario.

Generation tech.	**20GWh** [%]	***Dev.*** *[%]*
Wind	22.7	*-0.1*
Solar	10.3	*0.0*
Biomass	3.4	*0.0*
Hydro	3.1	*0.0*
Lignite	22.1	*0.4*
Natural Gas	7.8	*-0.2*
Hard coal	18.2	*0.3*
Nuclear	9.6	*-0.1*
Oil	0.9	*0.0*
Waste	0.7	*0.0*
Other	1.1	*-0.3*

The generation mix with increased BSS capacity is very similar to the base scenario but shows minor differences in the mix of thermal generation. The table indicates that BSS moves some of the generation from more expensive technologies, such as import and natural gas, to cheaper technologies, including lignite and hard coal.

Price Profile

The price profile for two BSS scenarios are presented in Figure 13 below. Specifically, the price profiles for the 10GWh and 20GWh BSS scenarios are compared to the base scenario.

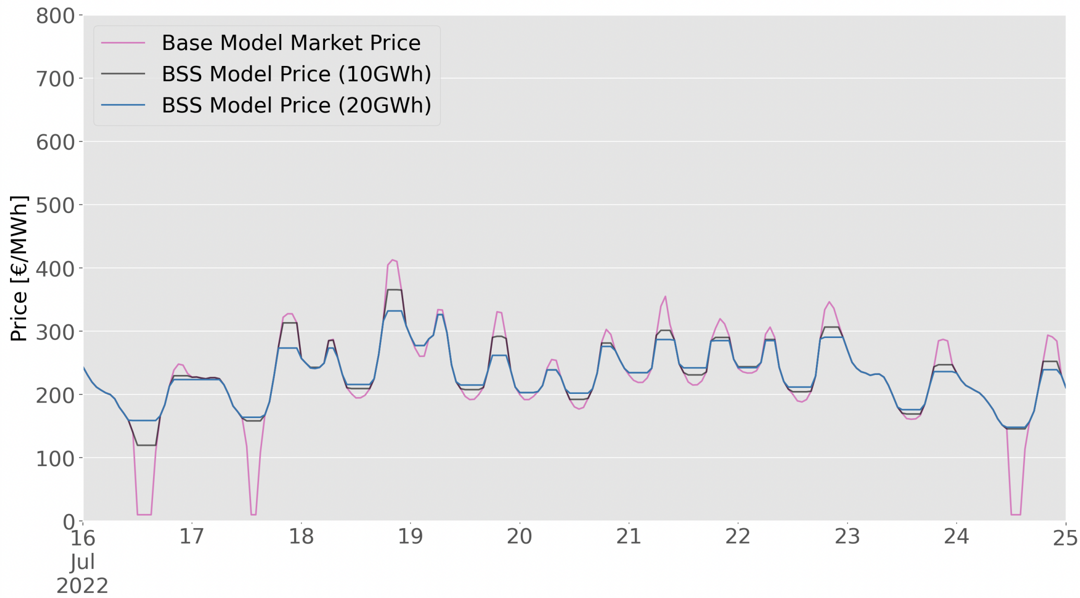


Figure 13: Market prices for the 10GWh and 20GWh BSS scenarios from July 16th to July 25th, 2022.

The 20GWh BSS scenario demonstrates lower maximum prices and higher minimum prices in comparison to the base prices represented by the pink line in the plot. The black line, representing the 10GWh scenarios, follows a trend similar to that of the 20GWh scenario. However, its overall impact is less pronounced. Consequently, the 10GWh scenario remains within the visual limits established by the two extreme cases.

Price Distribution

The price distribution plot for the 20GWh BSS scenario is illustrated and compared to the base scenario in the KDE plot in Figure 14 below.

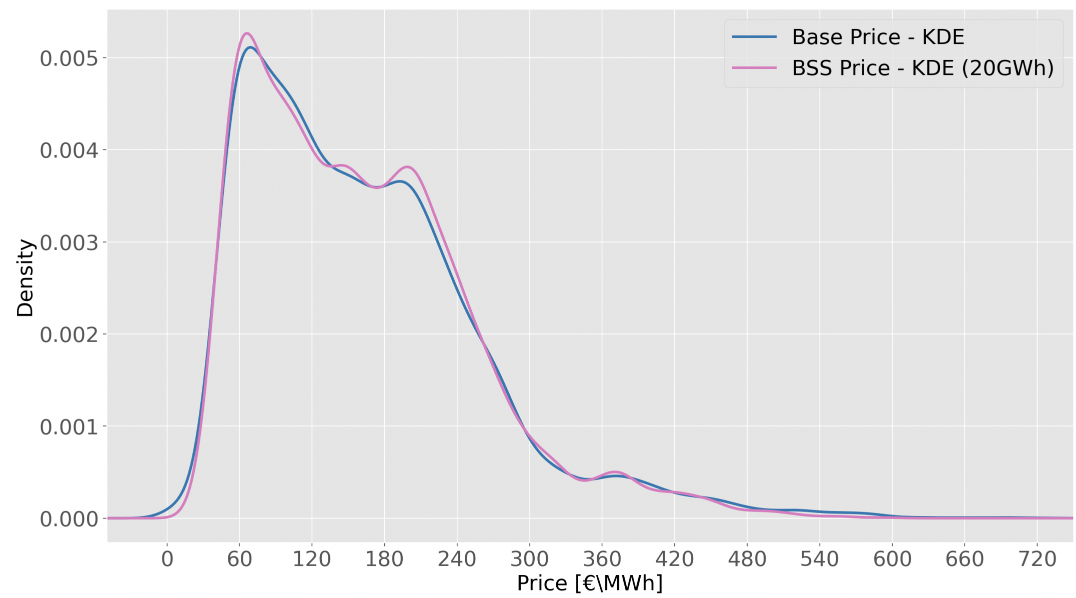


Figure 14: Density plot for the 20GWh BSS and base scenario prices from January 2021 to January 2023. KDE is the Kernel Density Estimation [61] of the probability density function of the prices.

The figure reveals a higher concentration of prices between 50 and 240€/MWh, signifying a denser price distribution. The curve representing the 20GWh BSS scenario is consistently below the blue curve at both ends of the spectrum, more specifically, near zero and from 380€/MWh to 650€/MWh. As a result, the 20GWh BSS scenario demonstrates a reduced density at both tails of the curve.

Descriptive Statistics

As with the base scenario, descriptive statistics for the full two-year period are presented for two BSS scenarios in Table 11. The table displays statistical values for the 10GWh and 20GWh scenarios, respectively. Additionally, deviation from the base scenario in terms of percent change is presented.

Table 11: Descriptive statistics for the 10GWh and 20GWh BSS scenario market prices from January 2021 to January 2023.

Test Statistic	**10GWh**	*Deviation [%]*	**20GWh**	*Deviation [%]*
Min	10.00	*0.00*	30.70	*207.01*
Max	647.94	*-18.47*	593.32	*-25.34*
Mean	161.67	*-0.36*	161.08	*-0.73*
Median	146.76	*0.57*	147.43	*1.03*
Standard Deviation	92.94	*-3.58*	90.72	*-5.89*
Skewness	1.10	*-12.74*	0.99	*-20.81*
Kurtosis	1.50	*-35.35*	1.08	*-53.44*
Jarque-Bera	5142.21*	*-39.71*	3733.59*	*-56.24*
ADF	-5.35*	*-0.09*	-5.17*	*3.14*
N	17472	N/A	17472	N/A

* Indicates that the respective null hypothesis is rejected at the 1% level.

The minimum price remains unchanged for the 10GWh scenario, while it increases from 10 to 31€/MWh for the 20GWh scenario. The opposite is true for the maximum price, which decreases by approximately 54€/MWh between the BSS scenarios alone, though both scenarios significantly reduce the maximum price compared to the base scenario. The mean and median values do not exhibit substantial changes, indicating that the BSS primarily influences price outliers on both ends of the spectrum, thus reducing price volatility. This observation is supported by the negative change in standard deviations. The changes in skewness and kurtosis suggest that the distribution is more symmetrical and has fewer price outliers with increased BSS storage capacity. Notably, the kurtosis decreases significantly in both BSS scenarios. The decreased values for skewness and kurtosis are consistent with the shape of the BSS price distribution in Figure 14. As with the base scenario, the Jarque-Bera and ADF tests still reject the hypotheses of a normal distribution and non-stationarity. In summary, the less extreme minimum and maximum prices, paired with reduced values for kurtosis, skewness, and standard deviation, illustrate how the BSS contributes to a more compact and less variable price distribution. As a result, the prices are closer and more symmetrically positioned around its central tendency.

Table 12 displays the distribution of prices across quantiles and between the two BSS scenarios.

Table 12: Price quantiles for BSS scenarios measured in €/MWh. Deviations are relative to the base scenario.

Quantile	1%	5%	25%	50%	75%	95%	99%
10GWh	39.15	49.13	87.31	146.76	213.50	344.04	458.70
Dev. from base [%]	11.58	*1.72*	*0.15*	*0.57*	*-0.42*	*-2.17*	*-3.67*
20GWh	39.82	49.58	87.58	147.43	214.02	332.69	440.96
Dev. from base [%]	*13.50*	*2.64*	*0.46*	*1.03*	*-0.18*	*-5.68*	*-7.40*

The price deviations from the base scenario are, in general, more evident in the 20GWh scenario compared to the 10GWh scenario. The deviations in the middle quantiles are minimal and comparable for both BSS scenarios. In contrast, for the upper and lower quantiles, there is a difference in the extent of deviations between the two BSS scenarios. Compared to the 10GWh scenario, the 20GWh scenario exhibits a greater increase in the lower quantiles and a larger reduction in the upper quantiles.

Relative to the base scenario, the absolute deviations are significantly greater for the upper quantiles. This phenomenon can be explained by assessing the smaller differences in SRMC among lower-cost technologies, compared to the significant differences in SRMC between expensive technologies. When BSS alters the generation mix, cost disparities result in larger price differences when switching between expensive technologies compared to shifting between cheaper technologies.

6.1.3 BSS & VRE Scenario

The results of the multi-variate *BSS & VRE* scenarios are presented in the following subsection. In the multivariate scenarios, varying levels of both BSS storage capacity and additional VRE capacity are introduced to the system. The BSS storage capacity ranges between zero and 20GWh, while the VRE capacity increase is between zero and one with increments of 0.2.

Generation Mix

The generation mix for the multivariate scenario with 20GWh capacity and a VRE increase of 0.6 is presented in Figure 15 below. The figure employs the same description for the BSS charging cycle and the balance between production and demand as presented for Figure 12 illustrating the production mix for the single-variable BSS scenario.

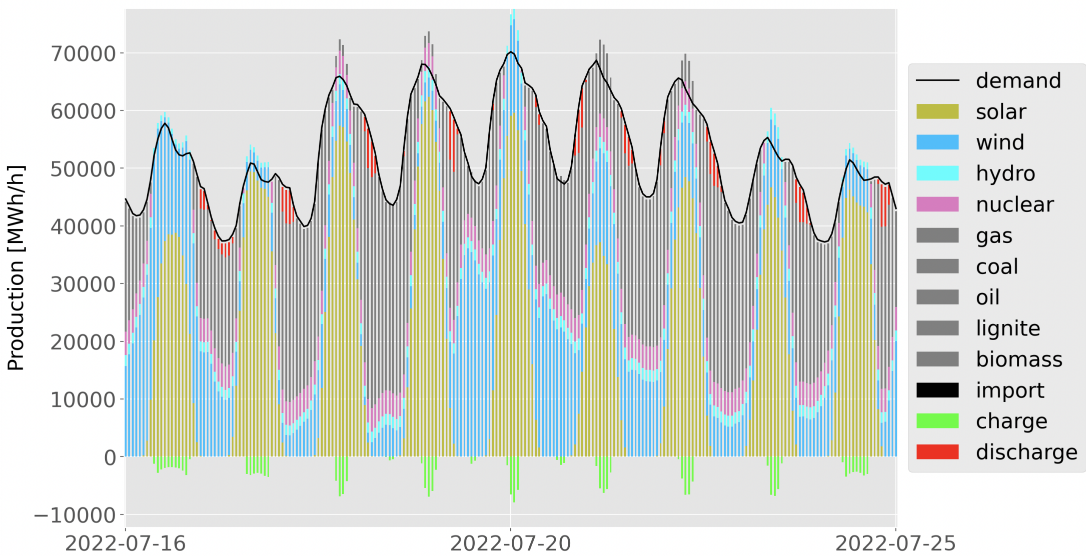


Figure 15: Market mix for the multivariate 20GWh BSS and 0.6 VRE increase scenario from July 16th to 25th, 2022.

When introducing additional VRE capacity into the system, the VRE can more frequently meet the demand compared to the base and single-variable BSS scenario. With more VRE capacity entering the system, the VRE is more often the main source when charging the BSS.

The complete generation mix for the multivariate scenario with 20GWh BSS and 0.6 VRE increase is presented in Table 13 below. The single-variable BSS scenario in the table is the corresponding scenario to the multi-variate scenario where the BSS storage capacity is the same but the VRE increase is zero.

Table 13: Generation mix for the multivariate 20GWh BSS and 0.6 VRE increase scenario from January 2021 to January 2023. Absolute deviations are relative to the single-variable 20GWh BSS and base scenario.

Generation technology	**20GWh & 0.6 VRE** [%]	*Dev. from BSS [%]*	*Dev. from base [%]*
Wind	35.8	*13.1*	*13.0*
Solar Photovoltaic	16.1	*5.8*	*5.8*
Biomass	2.4	*-1.0*	*-1.0*
Hydro	3.0	*-0.1*	*-0.1*
Lignite	15.8	*-6.3*	*-5.9*
Natural Gas	4.4	*-3.4*	*-3.6*
Hard coal	12.3	*-5.9*	*-5.6*
Nuclear	8.6	*-1.0*	*-1.1*
Oil	0.5	*-0.4*	*-0.4*
Waste	0.7	*0.0*	*0.0*
Other	0.4	*-0.7*	*-1.0*

Due to the increased VRE capacity, the multivariate scenario generates significantly more wind and solar power compared to the single-variable BSS and base scenario. The increased VRE generation leads to a substantial reduction in the utilization of the most expensive thermal generation technologies. This is evident in the decreased generation of lignite, hard coal, and natural gas. In conclusion, it is clear that the inclusion of additional VRE capacity amplifies the merit order effect [33].

Price Profile

The price profiles of the multivariate scenarios are exemplified by the 20GWh and 0.6 VRE increase in Figure 15 below. The price profile is compared with both the base and single-variable 20GWh BSS scenario.

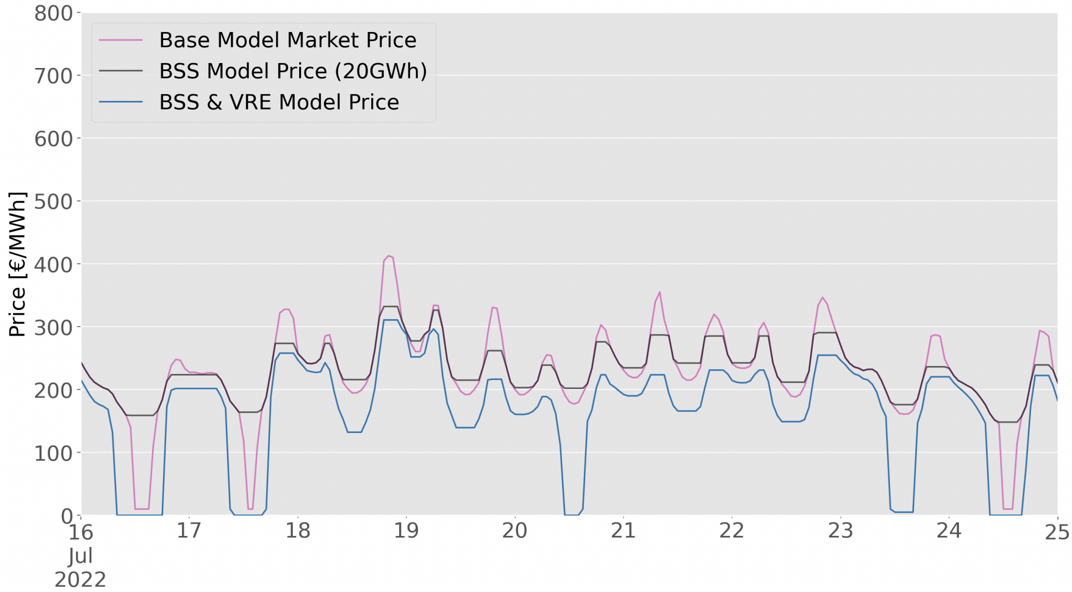


Figure 16: Market prices for the multivariate 20GWh BSS and 0.6 VRE increase scenario from July 16th to July 25th, 2022.

In general, the prices of the multivariate scenario seem to follow the same profile as the single-variable 20GWh BSS scenario. However, the price level of the multivariate scenario is significantly lower and reaches zero more often in comparison due to the high share of VRE generation at zero cost. This trend remains consistent throughout the two-year period. Despite the additional consumption from BSS charging, price valleys persist and, in some cases, are even more pronounced. In addition, the BSS contributes to peak price shaving because there is an excess supply of zero-priced VRE generation available to meet both the demand and the charging requirements of the BSS. Consequently, the combined implementation of increased VRE capacity and BSS leads to a price profile where the highest extreme prices are reduced, and the overall price level is lower compared to the base scenario and the single-variable BSS scenario. The price profile showcased in Figure 16 effectively demonstrates the combined effect of BSS and VRE.

Price Distribution

The price distribution plot for the multivariate 20GWh BSS and 0.6 VRE increase scenario is presented and compared with the 20GWh BSS scenario in Figure 17 below.

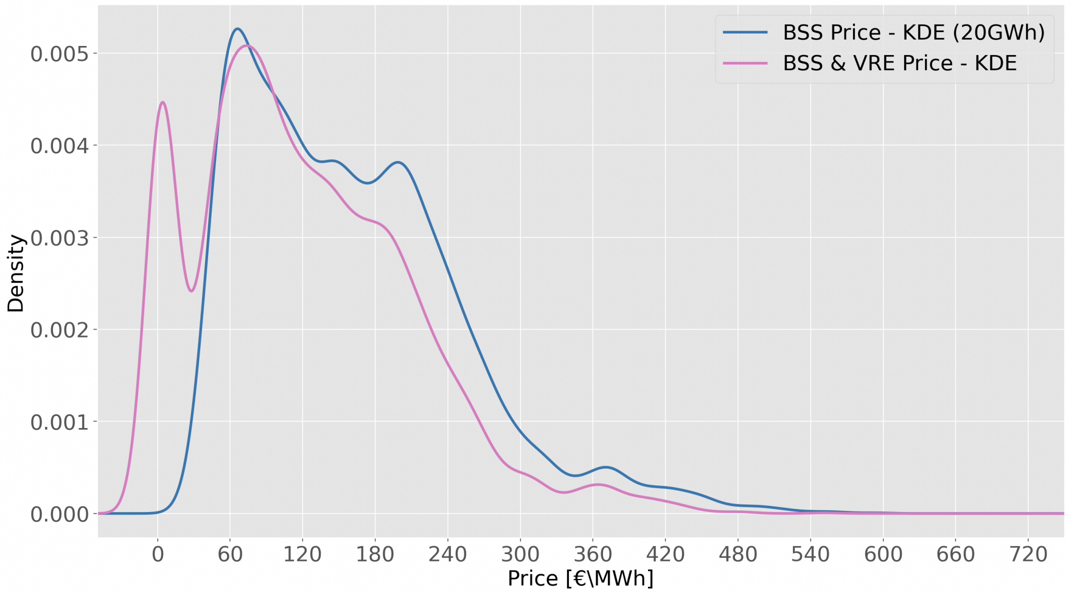


Figure 17: Density price plot for the multivariate 20GWh BSS and 0.6 VRE capacity increase scenario and the single-variable 20GWh BSS scenario from January 2021 to January 2023. KDE is the Kernel Density Estimation [61] of the probability density function of the prices.

When considering the price distribution, the combined impact of BSS and VRE results in a distribution that is more concentrated around its central tendency. The central tendency is significantly lower compared to other scenarios, as demonstrated in Figure 17 above. The introduction of BSS contributes to a reduction in skewness and kurtosis by removing the most extreme prices at the upper end of the distribution. In contrast, the increased capacity of VRE results in a significant rise in instances with zero prices, ultimately reducing the central tendency of the distribution.

Descriptive Statistics

Descriptive statistics for the full two-year period are presented for the multivariate 20GWh BSS and 0.6 VRE increase scenario in Table 14. Deviations from the single-variable 20GWh BSS and the base scenario are included.

Table 14: Descriptive statistics for the multivariate 20GWh BSS & 0.6 VRE increase scenario market prices from January 2021 to January 2023.

Test Statistic	**20GWh & 0.6VRE**	*Dev. from BSS [%]*	*Dev. from base [%]*
Min	0.00	*-100.00*	*-100.00*
Max	551.16	*-7.11*	*-30.64*
Mean	120.21	*-25.37*	*-25.91*
Median	107.10	*-27.36*	*-26.61*
Standard Deviation	87.81	*-3.21*	*-8.90*
Skewness	0.79	*-20.66*	*-37.17*
Kurtosis	0.64	*-40.56*	*-72.33*
Jarque-Bera	2111.50*	*-43.37*	*-75.22*
ADF	-7.25*	*-40.13*	*-35.73*
N	17472	N/A	N/A

* Indicates that the respective null hypothesis is rejected at the 1% level.

The new minimum value is zero, as seen frequently in both Figure 15 and 17. Although there is a decrease in maximum value, it is not as substantial as the reduction observed while transitioning from the base scenario to the single-variable BSS scenario. The central tendency, however, is significantly reduced as both the mean and median have decreased by approximately 25% and 27%, in the BSS scenario. The variability is slightly reduced, while both skewness and kurtosis have decreased substantially, which is in line with the observations in the density plot in Figure 17. Lastly, the price series is still non-normally distributed and stationary.

The price quantiles of the multivariate scenarios are illustrated by the 20GWh BSS and 0.6 VRE capacity increase scenario in Table 15.

Table 15: Price quantiles for the multivariate 20GWh & 0.6 VRE increase scenario measured in €/MWh. Deviations are relative to the single-variable 20GWh BSS and base scenario.

Quantile	1%	5%	25%	50%	75%	95%	99%
20GWh & 0.6VRE	0.00	0.00	55.63	107.10	177.10	271.82	380.54
Dev. from BSS [%]	*-100.00*	*-100.00*	*-36.47*	*-27.36*	*-17.25*	*-18.05*	*-13.70*
Dev. from base [%]	*-100.00*	*-100.00*	*-36.18*	*-26.61*	*-17.40*	*-22.71*	*-20.09*

The 1% and 5% quantiles are both zero. In addition, the 25%, 50%, and 75% quantiles have been reduced substantially compared to the single-variable 20GWh BSS and base scenario. The prices of the two upper quantiles have also decreased significantly. However, the reduction from the single-variable 20GWh BSS scenario is less evident than from the base scenario for the upper quantiles.

The price quantiles for a 0GWh BSS and 0.6 VRE increase scenario are presented in Table 16.

Table 16: Price quantiles the for a 0GWh BSS and 0.6 VRE increase scenario measured in €/MWh. Deviations are relative to the base scenario.

Quantile	1%	5%	25%	50%	75%	95%	99%
0GWh & 0.6VRE	0.00	0.00	53.33	105.83	178.06	284.19	418.84
Dev. from base [%]	*-100.00*	*-100.00*	*-38.82*	*-27.48*	*-16.95*	*-19.19*	*-12.04*

For the lower and middle quantiles, the price reductions from the base scenario are very similar to those seen in Table 15. This indicates that additional VRE leads to significant price reductions for most quantiles, regardless of the level of BSS storage capacity. However, for the two upper quantiles, there are differences between the two 0.6 VRE increase scenarios. Specifically, the scenario incorporating 20GWh BSS storage capacity exhibits even greater price reductions for the upper quantiles compared to the scenario without BSS.

To summarize the findings of Table 15 and 16, the additional capacity of VRE significantly reduces all price quantiles in comparison to both the base scenario and the single-variate BSS scenario. However, there are noticeable differences in the deviation levels between the multi-variate scenario and the base/single-variate BSS scenarios, particularly for the upper two quantiles. The differences in the two upper quantiles of Table 15 (with 20GWh battery capacity) and Table 16 (with 0GWh battery capacity) further emphasize the role of BSS in reducing the occurrence of the highest price extremes in scenarios with the same amount of VRE capacity. These findings suggest that BSS is particularly beneficial in mitigating the highest prices, as VRE alone cannot address these exceptional price levels fully.

6.2 Quantile Regression

In this section, the results of the quantile regression models are presented through plots of the regression lines and the gradients for the different quantiles. The gradients are also presented in a table format, providing the exact values. The results of the single-variable BSS scenarios and the single-variable VRE scenarios are presented first. Lastly, the partial impacts of both BSS and VRE on the multi-variable system are isolated and presented through plots of the gradients.

6.2.1 BSS

Before evaluating the results of the single-variable BSS quantile regression, and thereby drawing inferences on the mathematical relationship between BSS and electricity price quantiles, it is essential to evaluate the choice of selecting a *linear* quantile regression approach. While the impact of BSS on price concentration in Table 12 seems to emulate a linear relationship where the influence is proportional to the storage capacity of the BSS, the trend is more clearly visualized in Figure A.3 in the Appendix. The figure illustrates that as the BSS storage capacity increases, all price quantiles exhibit nearly perfect linearity with either negative or positive gradients. This characteristic makes a linear approach to the quantile regression favorable. A linear relationship can also be seen for the impact of VRE capacity on electricity price quantiles (see: Figure A.4 in the Appendix).

The scatter plot of hourly market prices for all BSS scenarios is presented in Figure 18 below along with the regression lines from the quantile regression model. The BSS storage capacity varies from zero to 20GWh, while the VRE increase is constant at zero, indicating that no additional VRE is added to the system.

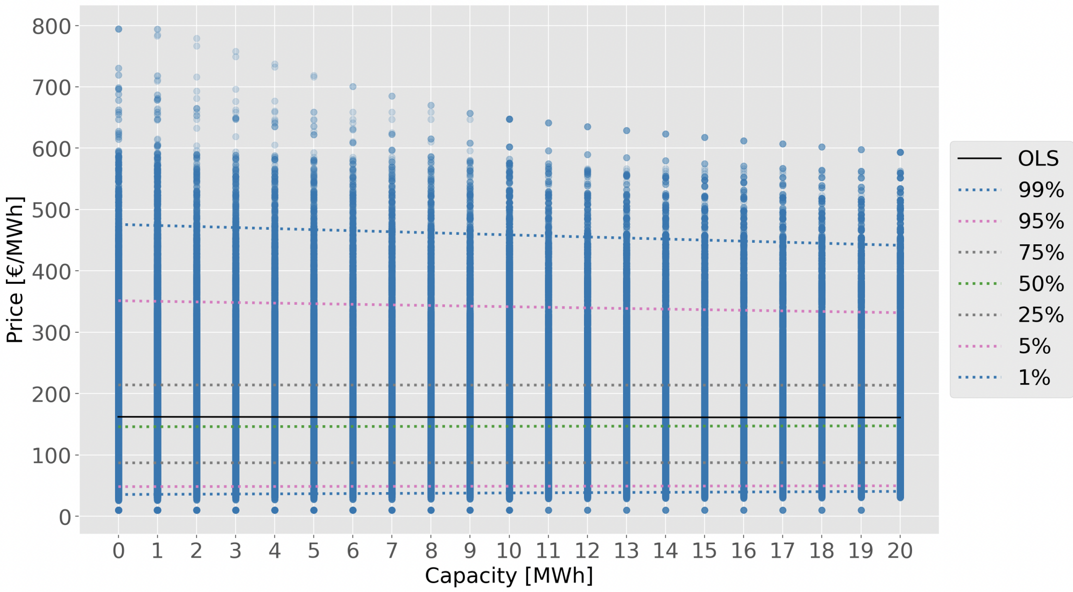
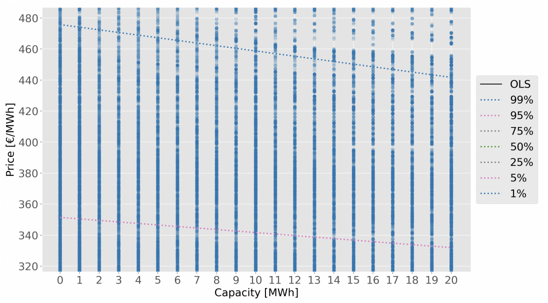
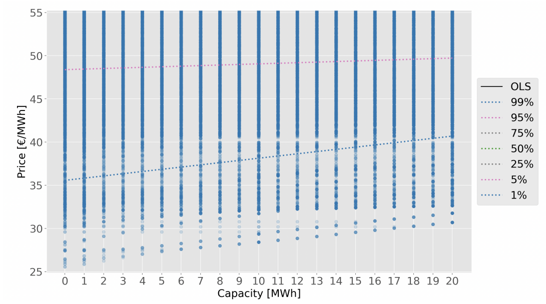


Figure 18: Price scatter plot and quantile regression lines for varying levels of BSS storage capacity and constant zero VRE increase.



(a) Zoomed-in view of the regression lines for the 99% and 95% quantiles.



(b) Zoomed-in view of the regression lines for the 1% and 5% quantiles.

The figure shows that the upper price quantiles are reduced as the storage capacity of the BSS increases, while the opposite trend is observed for the lower price quantiles. In simpler terms, the upper quantiles exhibit negative gradients, while the lower quantiles demonstrate positive gradients. The gradients are more clearly visualized in Figure 18a and 18b. These findings are in line with the price quantile deviations presented in Table 12 and indicate that the price distribution is turning more concentrated as the BSS capacity increases.

The gradient, β_{BSS}, exhibits variation across quantiles, as demonstrated in Figure 19 below. A positive linear relationship between BSS storage capacity and electricity price quantiles is associated with positive gradients for β_{BSS}. The blue, shaded area illustrates the quantile intervals, or bands, representing the range of uncertainty or variability around the estimated quantile regression line. The pink line in the plot represents a standard Ordinary Least Squares (OLS) regression with corresponding confidence interval lines, i.e., a regression where differences between quantiles are not taken into account.

Figure 19: Gradients for BSS across price quantiles in a system with varying levels of BSS storage capacity and a constant zero VRE increase.

Gradients for the lower and middle quantiles up to the 75% quantile are positive but modest in magnitude. In contrast, the gradients for the upper quantiles are negative. For the 95% and 99% quantiles, the gradients are considerably larger, in absolute value, than those of the lower quantiles. This implies that a greater BSS storage capacity exerts a progressively more substantial effect on higher prices. The quantile bands are narrow across all quantiles, indicating a low level of uncertainty in the estimations. As the impact of BSS varies across the price quantiles, it is evident that quantile regression provides a more accurate description of the relationship compared to a standard OLS regression. Unlike OLS, quantile regression captures the differing influence across the price quantiles.

The exact gradient values are presented in Table 17 below.

Table 17: Gradients for BSS across price quantiles in a system with varying levels of BSS storage capacity and constant zero VRE increase. The gradients are expressed in $\frac{[€/\text{MWh}]}{[\text{GWh}]}$.

Quantile	1%	5%	25%	50%	75%	95%	99%
β_{BSS}	0.26	0.07	0.02	0.07	-0.02	-0.98	-1.70

In absolute terms, the largest value is -1.70 in the 99% quantile. The value implies that the 99% quantile will be reduced by 34€/MWh when adding 20GWh BSS storage capacity to the system.

In summary, the findings show evidence of a linear relationship between all quantiles of the electricity price distribution and BSS storage capacity, where the impact varies from a modestly positive relationship up until the 75% quantile to a greater negative relationship for the 95% and 99% quantile.

6.2.2 VRE

The isolated impact of VRE capacity in a system without BSS is presented in Figure 20 below. The VRE capacity increase ranges between zero and one, with increments of 0.2, and represents how much the current installed VRE capacity is increased in percent for each iteration compared to the base scenario.

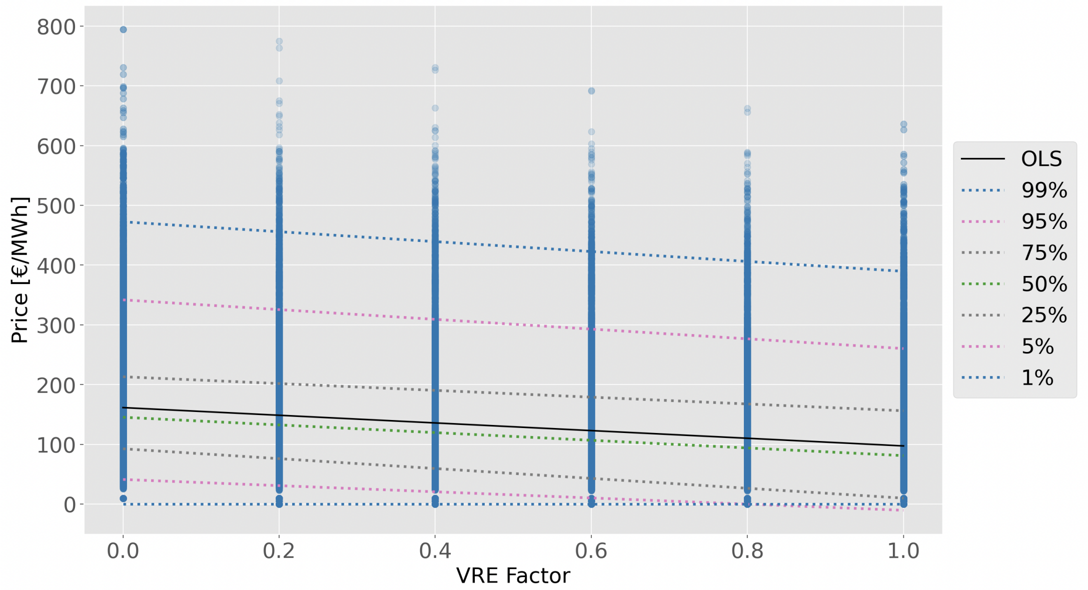
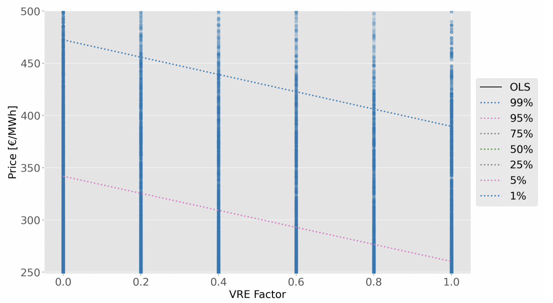
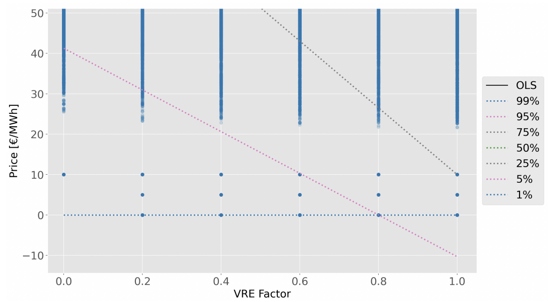


Figure 20: Price scatter plot and quantile regression lines for varying levels of VRE capacity increase and constant zero BSS storage capacity.



(a) Zoomed-in view of the regression lines for the 99% and 95% quantile.



(b) Zoomed-in view of the regression lines for the 1% and 5% quantile.

The upper price quantiles are reduced as VRE capacity increases, exhibiting a similar pattern as observed in the single-variable BSS scenarios seen in Figure 18a. The same trend is seen in the lower quantiles, where the prices decrease as VRE capacity is increased. In addition, the regression lines in the central region of the plot consistently reveal a negative trend as VRE increases. This implies that the impact of increased VRE capacity on the lower and middle quantiles stand in sharp contrast to the influence of BSS storage capacity on the same quantiles, distinguishing these results from those seen in the single-variable BSS scenarios.

The impact of increased VRE capacity on electricity prices for different quantiles is presented in Figure 21 below.

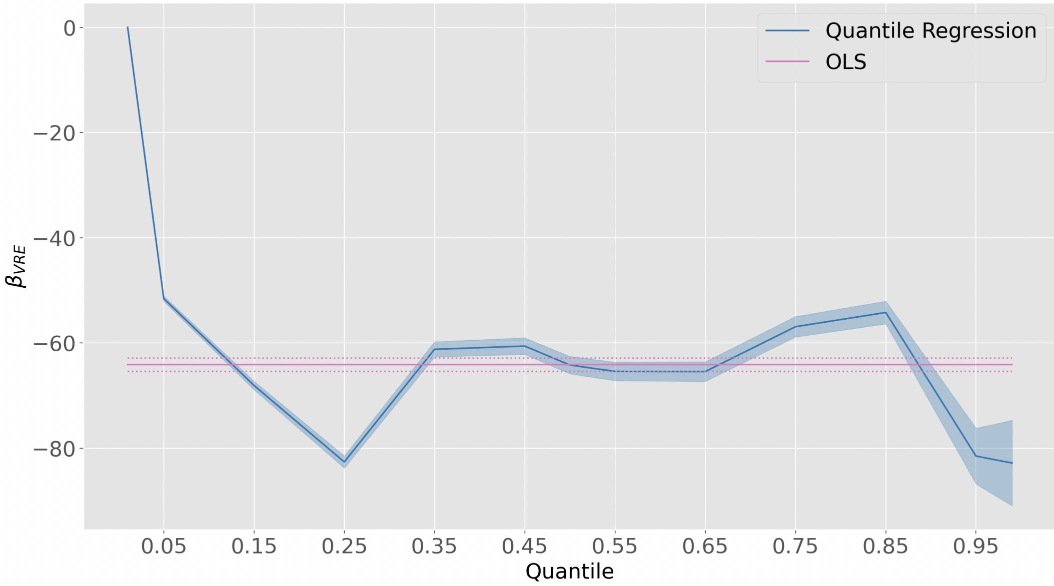


Figure 21: Gradients for VRE across price quantiles in a system with varying levels of VRE capacity and constant zero BSS storage capacity.

The figure displays a less consistent trend compared to the β_{BSS} plot, as the gradient of the VRE does not consistently decrease across the quantiles. However, the gradients are consistently negative, indicating that VRE has a negative impact on prices throughout all quantiles. Similar to the effect of BSS observed in Figure 19, the upper price quantiles exhibit the most significant sensitivities. The quantile bands are narrow across all quantiles, indicating a low level of uncertainty in the estimations. The exact gradients are presented in Table 18 below.

Table 18: Gradients for VRE across price quantiles in a system with varying levels of VRE and constant zero BSS storage capacity. The gradients are expressed in $\frac{[€/\text{MWh}]}{[\text{VRE increase}]}$.

Quantile	1%	5%	25%	50%	75%	95%	99%
β_{VRE}	0.00	-51.57	-82.62	-64.20	-56.91	-81.52	-82.83

In absolute terms, the largest value is -82.83 in the 99% quantile. The value implies that the 99% quantile will be reduced by 82.83€/MWh when introducing a VRE increase of 1, i.e., a 100% increase in the VRE capacity.

6.2.3 BSS and VRE

Quantile regression results for the multivariate system with varying levels of BSS and VRE are now presented by their respective gradient plots. The partial impact of BSS storage capacity on the multi-variable system is presented in Figure 22 below.

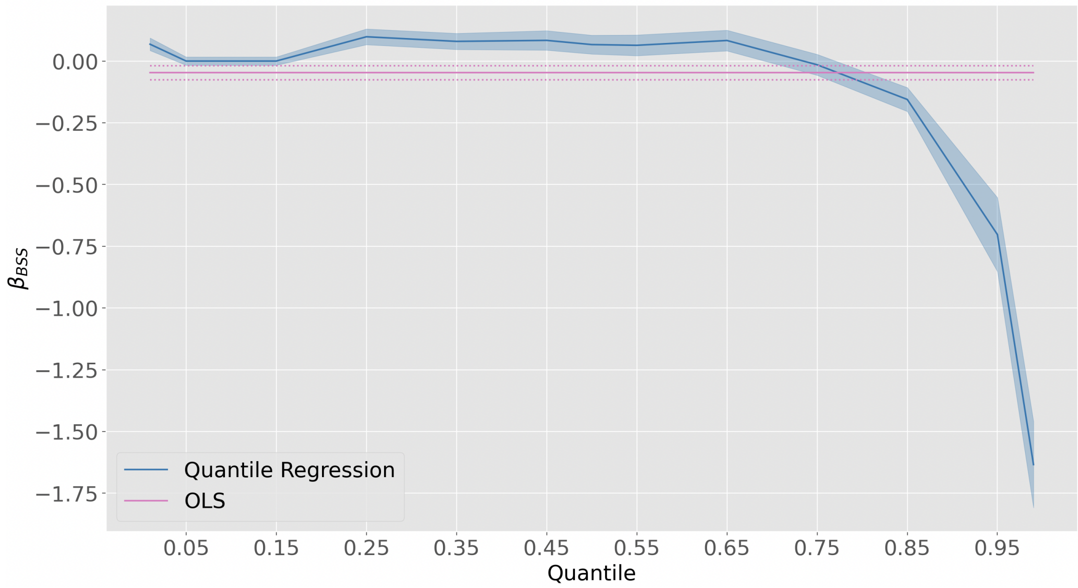


Figure 22: Gradients for BSS across price quantiles in a system with varying levels of both BSS storage and VRE capacity.

The gradients, β_{BSS} follow the same trend as in the single-variable BSS scenario seen in Figure 19. The gradients of the lower and middle quantiles up until the 75% quantile are modest, yet positive. The upper quantile gradients are negative, and for the 95% and 99% quantiles, the values are significantly larger than for the lower quantiles in absolute terms.

The gradients for BSS in the multi-variable scenario are presented in Table 19, including deviations from the single-variable BSS scenario.

Table 19: Gradients for BSS across price quantiles in a system with varying levels of both BSS storage capacity and VRE capacity, with deviations from the single-variable BSS scenario. The gradients are expressed in $\frac{[€/\mathrm{MWh}]}{[\mathrm{GWh}]}$.

Quantile	1%	5%	25%	50%	75%	95%	99%
β_{BSS}	0.07	0.00	0.10	0.07	-0.02	-0.70	-1.63
Deviation	*-0.19*	*-0.07*	*0.08*	*-0.00*	*0.01*	*0.27*	*0.07*

The reduced gradients in the two lower quantiles indicate that the BSS increases low prices less evidently in the multivariate scenario than in the single-variable scenario. For the upper price quantiles, the trend is the opposite as the high prices seem to be less reduced by the BSS in the multi-variable scenario than in the single-variable scenario. In absolute terms, however, the differences in BSS impact between the single- and multi-variable scenarios are modest. The largest deviation value, which is 0.27 for the 95% quantile, implies that the 95% quantile is only reduced by 5.40€/MWh less in the multivariate scenarios than the single-variable when introducing 20GWh BSS to the system. These findings imply that the BSS functions with consistent efficiency in a multivariate system relative to the single-variable BSS scenarios.

The impact of increased VRE capacity in the multivariate scenarios is illustrated in Figure 23 below.

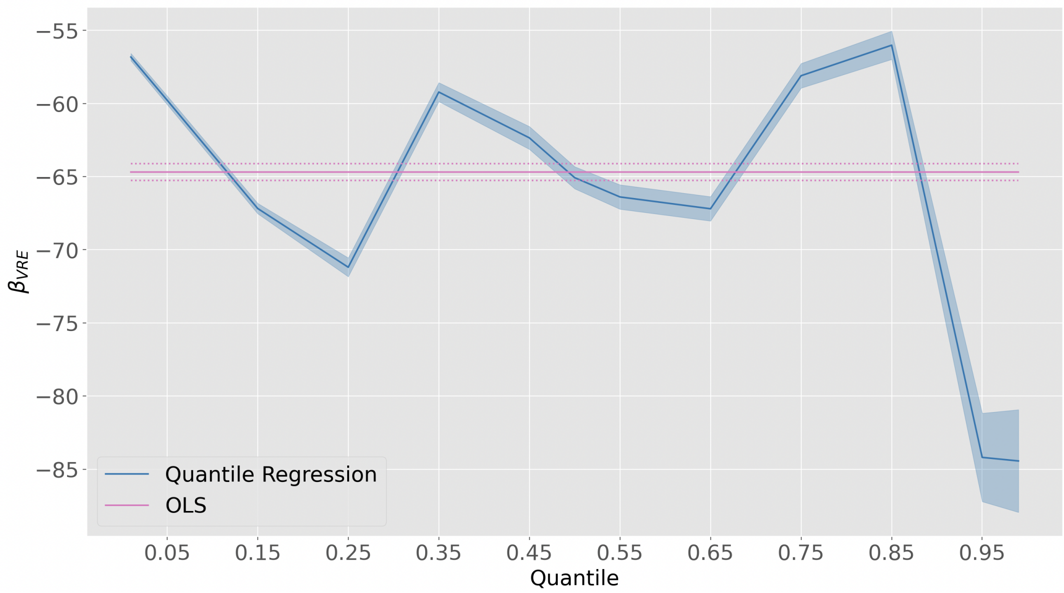


Figure 23: Gradients for VRE across price quantiles in a system with varying levels of both BSS storage and VRE capacity.

The shape of the figure is very similar to the gradient plot in the single-variable VRE scenario seen in Figure 21. However, the gradient of the 1% quantile has become significantly more negative. Regarding the upper quantiles, the gradients of the 95% and 99% quantiles exhibit a marginally more negative tendency. The exact VRE gradient values of the multivariate scenario are presented in Table 20 below.

Table 20: Gradients for VRE across price quantiles in a system with varying levels of both BSS storage capacity and VRE capacity, with deviations from the single variable VRE scenario. The gradients are expressed in $\frac{[€/\text{MWh}]}{[\text{VRE increase}]}$.

Quantile	1%	5%	25%	50%	75%	95%	99%
β_{VRE}	-56.82	-59.76	-71.19	-65.07	-58.10	-84.19	-84.44
Deviation	*-56.82*	*-8.19*	*11.43*	*-0.87*	*-1.18*	*-2.68*	*-1.60*

Most gradients exhibit further reductions compared to the single-variable VRE scenario. A clear difference is seen in the 1% quantile with a deviation of -56.82 from the single-variable VRE scenario. Thus, the 1% price quantile is reduced by an additional 56.82€/MWh in the multi-variable scenarios when increasing the VRE capacity increase from zero to one, compared to the same increase in the single-variable VRE scenario.

As the 1% price quantile of the base scenario is 35.09€/MWh (see: Table 9), the multivariate VRE 1% gradient suggests that the lowest prices would be negative for a VRE increase higher than 0.6, regardless of BSS storage capacity. Negative prices would occur if the VRE increase reduces prices beyond the given value of the 1% price quantile of the base scenario. Given the gradient value of -56.82 for the 1% price quantile, an VRE increase of 0.7 would reduce the 1% quantile by 39.77€/MWh, exceeding the current base scenario 1% price quantile of 35.09€/MWh. However, the current formulation of the electricity market model does not allow negative pricing. Therefore, the multivariate quantile regression seems to overestimate the impact of substantial VRE increases on the lowest prices.

In summary, the results of the multivariate quantile regression show that VRE exhibits increased efficiency in terms of price reductions when operating within a system that incorporates BSS. As evident from Table 20, most price quantiles experience further reductions compared to the single-variable VRE scenario. This indicates that the presence of BSS enables the system to more effectively utilize and store excess VRE generation, resulting in lower electricity prices across all quantiles.

7 Discussion

The price smoothing effect observed in the BSS scenarios is in line with the majority of pertinent literature regarding optimal BSS operation [37][38][31][35]. Increasing the storage capacity of the BSS reduces volatility, aligning with previous literature [36][37][38]. Regarding the impact of BSS on the generation mix, it is evident that the BSS replaces expensive generation sources with more cost-effective alternatives. These findings are consistent with the relevant literature [18][31][33] and further substantiates the optimal functioning of BSS. The influence of BSS on the generation mix particularly resonates with the research of Nyamdash & Denny [32], suggesting that introducing BSS does not necessarily lead to lower average prices when the generation mix remains close to constant. This is evidenced by the findings of the BSS scenarios, where the central tendency remains near unchanged regardless of BSS storage capacity. While previous research has implicitly discussed the varying impact of BSS on electricity price quantiles by examining peak and off-peak hours [37][31][35], this thesis is the first to explicitly describe the relationship between BSS storage capacity and electricity prices on a quantile level. The findings reveal a linear relationship between all quantiles of the electricity price distribution and BSS storage capacity, with varying impact across the quantiles in terms of sign and magnitude.

Consistent with related studies [18][46][47][33], this thesis suggests that VRE has the potential to reduce the overall price level. In contrast, the BSS primarily contributes to a more concentrated price distribution without significantly altering the central tendency of the price distribution. In real systems, the expansion of VRE capacity is often accompanied by expectations of increased demand, or changes to the generation mix, which may affect the observed price reduction compared to scenarios with constant consumption. Nonetheless, the main claim that VRE has a negative impact on prices across all quantiles remains applicable and aligns with related research [47][46].

The observed dynamics of price reduction between VRE and BSS are consistent with the findings of Korpås & Botterud [18], where BSS facilitates the storage of surplus VRE that would otherwise be curtailed, stimulating increased VRE generation. This increased VRE generation displaces thermal capacity from the market, resulting in reduced electricity prices.

An examination of BSS efficiency reveals that higher price volatility, similar to the levels seen in the actual German market, could enhance its operation. This observation suggests that BSS implementation could be even more efficient in the actual market as the potential for price concentration increases. A strategy to better replicate real market volatility could be through the introduction of stochasticity in VRE generation forecasts. In scenarios where stochastic VRE forecasts underestimate the wind and/or solar activity, the need for thermal generation increases, raising the market prices relative to a perfect forecast. The deterministic forecast, operating under the assumption of perfect foresight, would yield lower prices due to the assured maximum utilization of VRE capacity. Therefore, a stochastic forecast could more faithfully represent the uncertainties embedded in day-ahead bids, thus providing a closer approximation to the dynamics of the actual market. This may raise the volatility in the modeled prices and enhance the efficiency of BSS. However, the stochastic nature of VRE generation would prevent optimal operation of

BSS due to the absence of perfect foresight. This could potentially lead to sub-optimal operation and result in a less pronounced impact on the concentration of the electricity price distribution. While intriguing, the effect of these two factors proves hard to quantify and should be investigated further.

The findings of this thesis carry implications for all participants in the electricity market. For consumers, the adoption of BSS would result in a more predictable cost of electricity, with a decrease in the occurrence of extreme prices. This enhanced predictability of expenses reduces the risk associated with future financial commitments, enabling consumers to make better-informed decisions regarding their future activities. In essence, BSS has the potential to bring about a substantial transformation in risk management for both industrial and residential consumers.

From the perspective of producers, the adoption of large-scale industrial BSS will have an impact on revenues due to the reduced frequency of extreme prices. However, as long as there is no significant change in the generation mix, the average income for the aggregated pool of producers is expected to remain relatively similar. The concentration of prices, caused by BSS, can contribute to more predictable revenue streams. This enables producers to gain better insights into the future profitability of their operations. Furthermore, BSS increases the efficiency of VRE by storing otherwise curtailed generation. As a result, the additional VRE generation will increase the profitability of VRE. This enhanced profitability can have a profound impact on the energy market as it incentivizes investment in renewable energy projects and encourages the shift away from more expensive and carbon-intensive energy sources. In this way, the combination of BSS and VRE can contribute to a more sustainable and cost-effective energy landscape.

8 Conclusion

In this thesis, the impact of BSS on the electricity price distribution is investigated by modelling the German electricity market from January 2021 to January 2023. The results show that the BSS creates a denser and less variable price distribution, where the prices are closer and more symmetrically positioned around its central tendency. This trend is amplified with increasing BSS storage capacity. The influence of BSS across price quantiles demonstrates varying patterns, with modestly positive effects observed in the lower quantiles and larger negative impacts in the upper quantiles.

Quantile regression analysis reveals a linear relationship between BSS storage capacity and all quantiles, with varying sign and magnitude of the gradients. The lower quantiles display a positive but modest influence, whereas the upper quantiles exhibit a larger negative impact compared to the lower quantiles. The results are unique in the sense that they are the first to explicitly describe a mathematical relationship between BSS storage capacity and electricity price quantiles.

The introduction of additional VRE capacity to the system leads to a notable rise in instances with zero electricity prices, resulting in a decrease in the central tendency of the distribution. While the efficiency of BSS remains consistent regardless of the addition of surplus VRE capacity, VRE demonstrates enhanced efficiency in terms of price reductions when operating alongside BSS in the system, especially for the upper price quantiles. This indicates that the presence of BSS enables the system to more effectively utilize and store excess VRE generation, resulting in lower electricity prices.

8.1 Further Work

Future research can explore the dynamic interaction between BSS and VRE in a system where both consumption and the generation mix undergo changes with increasing VRE capacity. A possible approach is to incorporate additional variables, such as consumption and thermal generation technologies, in the quantile regression analysis. This investigation would be valuable considering the growing adoption of VRE, which is expected to significantly alter the generation mix and energy landscape in the future.

Furthermore, incorporating stochastic forecasts for VRE generation would contribute to a more realistic representation of the intermittency of VRE. This could result in a more accurate representation of BSS operation, which may be closer to real-world conditions.

Lastly, an in-depth analysis of the generation cost savings resulting from the implementation of BSS could be conducted. This analysis could contextualize the savings in relation to the installed capacity of the BSS, serving as a proxy for the cost of BSS and providing a measure of the potential profitability associated with an implementation in electricity markets.

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A Appendix

VRE production vs installed capacity

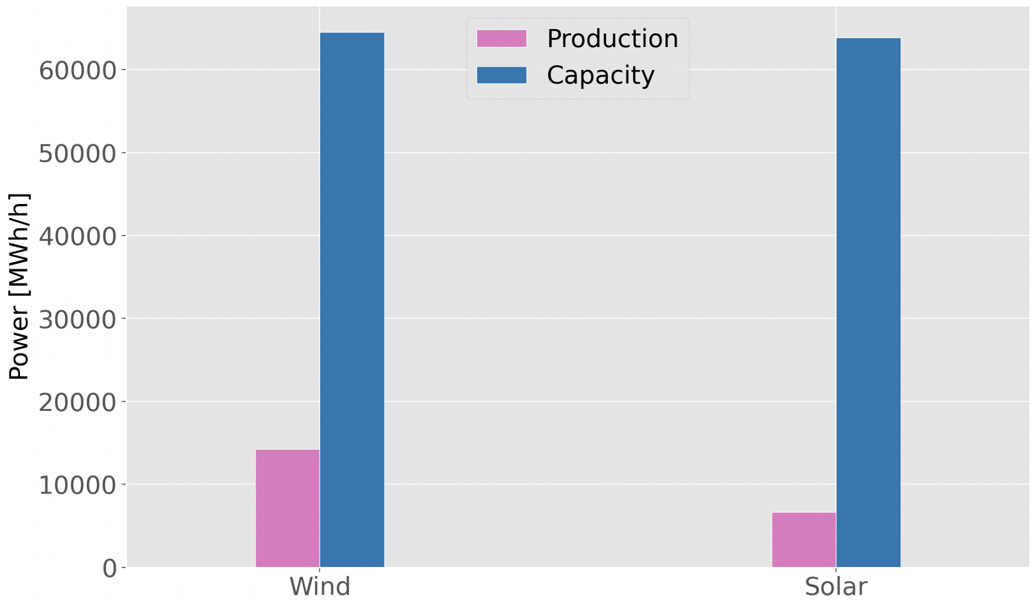

Figure A.1: Average VRE production versus total installed capacity for 2022. Source: Volue Insight [48].

SRMC assumptions

Table 21: Historical average SRMC of thermal generation technologies in Germany.

Type	SRMC [€/MWh]
Nuclear	10 [57]
Waste	5 [54]

Base model prices vs German spot prices

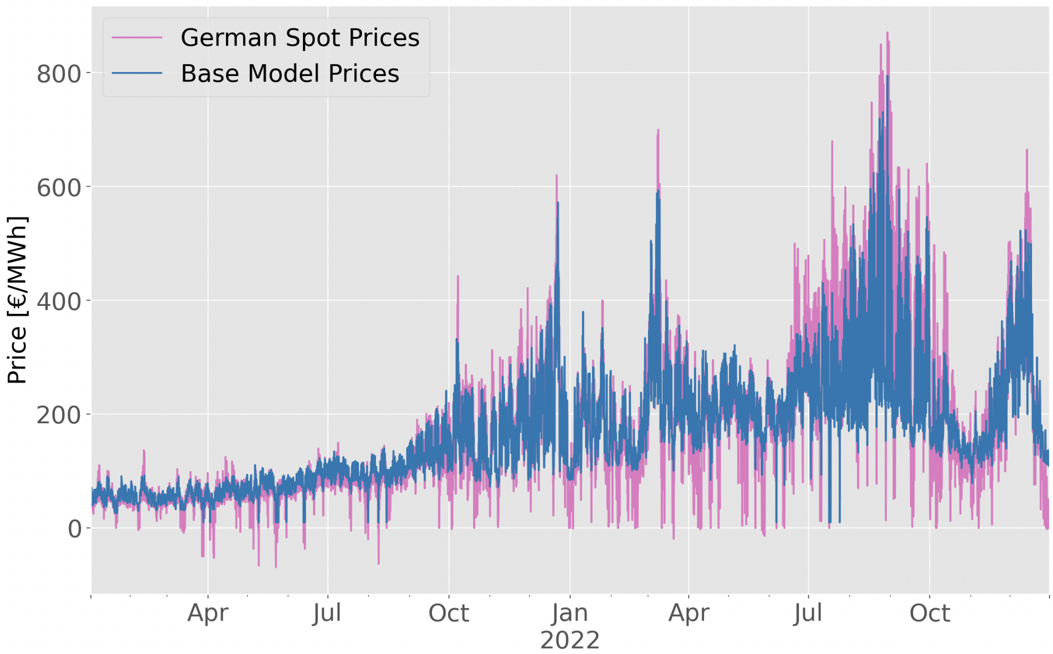

Figure A.2: Price profile for the base scenario and actual spot prices from January 2021 to January 2023.

Price quantiles for single-variable BSS and VRE scenarios.

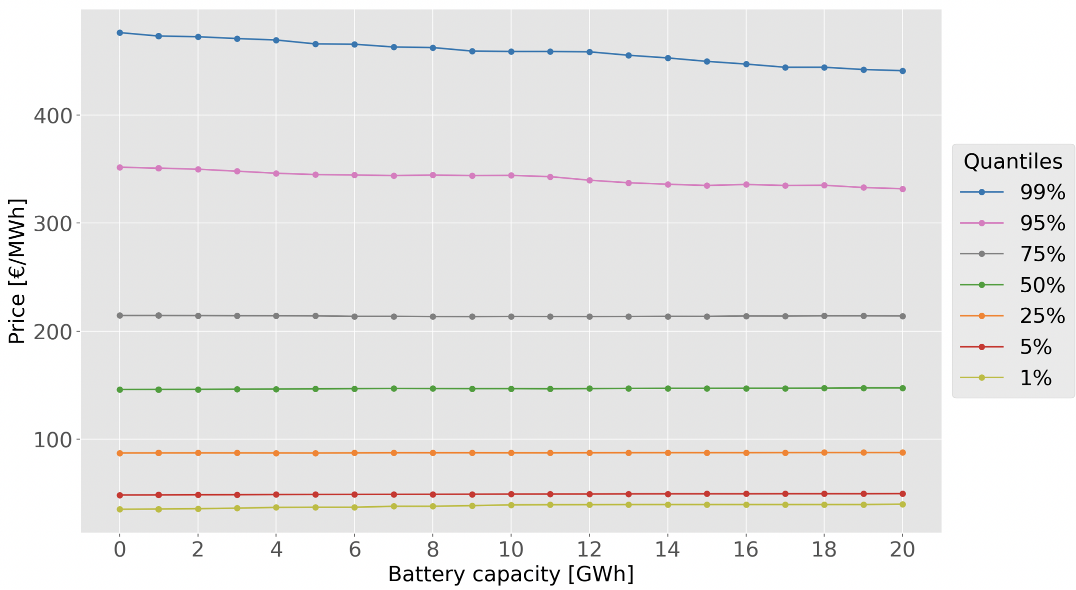

Figure A.3: Price quantiles for all single-variable BSS scenarios.

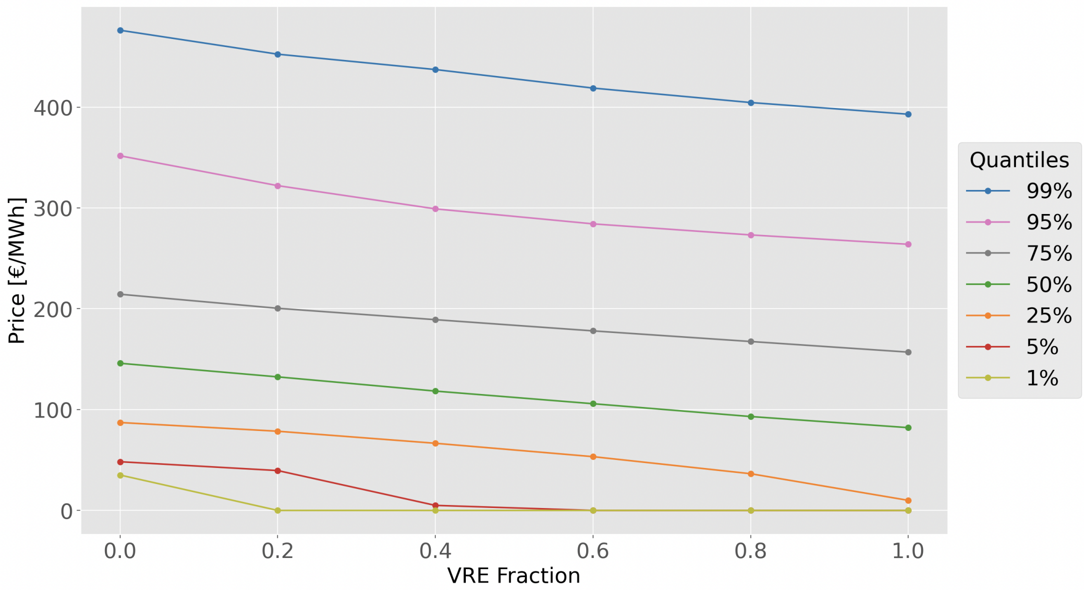

Figure A.4: Price quantiles for all single-variable VRE scenarios.

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