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Investment in Electric Energy Storage Under Uncertainty: A Real Options Approach

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Problem description

The growing portion of renewables in the generation mix has led to an increasing need for ancillary services in the electricity grid. As a part of this green shift, the role of storage in the electricity market has changed. Traditionally, the motivation for investing in storage was based on time arbitrage of the spot price. Today, the investments in storage are being linked with the need for improving the power quality and balancing the grid.

Recent research papers point out that investments in small storage facilities are not profitable today without public support. This thesis will apply the real options framework, and investigate the profitability of energy storage under uncertain electricity prices, balancing prices and investment cost. It will further consider how policy makers can trigger investments in electric energy storage.

Preface

This is a master thesis written within the field of Financial Engineering at the Department of Industrial Economics and Technology Management, Norwegian University of Science and Technology (NTNU). We would like to thank our supervisors, Verena Hagspiel and Stein-Erik Fleten, for professional guidance throughout the project. We also wish to thank Professor Sonja Wogrin at Universidad Pontificia Comillas de Madrid for technical assistance, PhD candidate Lars Ivar Hagfors at NTNU for valuable input and Statkraft for providing market data.

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Abstract

The transition from conventional power sources to renewable energy sources is taking place in a number of European countries. Electric energy storage has been proposed as an environmentally friendly solution to make this transition possible. This thesis analyzes the profitability of investing in a battery bank in Germany and the UK, using a real options model. The model determines the option value and the optimal investment time, under the conditions of uncertain revenues and investment cost. The results show that it is profitable to invest in both countries, given that the battery banks can participate in both the spot and balancing market. The valuation also gives insight into how the battery bank should be operated between the two markets to maximize its expected profits and discovers that the battery earns over 70 % of its profit from ancillary services. This finding underlines the importance for investors to not only consider revenues from the spot market. The thesis further analyzes how uncertainty affects investor behavior and explains why there is a reluctance to invest in storage technology under the current market conditions; the investor is favoring the option to wait for more information.

Sammendrag

Overgangen fra konvensjonelle energikilder til fornybare energikilder finner sted i en rekke europeiske land. Elektrisk energilagring har blitt foreslått som en miljøvennlig løsning for å gjøre denne overgangen mulig. I denne masteroppgaven utvikler vi en realopsjonsmodel for å analysere lønnsomheten ved å investere i batteribanker i Storbritannia og Tyskland. Modellen bestemmer opsjonsverdien og optimal investeringstid, under forutsetningene at investeringskostnaden og inntektene er usikre. Resultatene viser at det er lønnsomt å investere i begge land, gitt at batteribankene kan delta både i spot- og balansemarkedet. Verdsettelsen bidrar også med innsikt i hvordan batteribanken bør opereres i de to markedene for å maksimere forventet fortjeneste og viser at 70 % av batteriets totale inntekter kommer fra deltagelse i balansemarkedet. Dette funnet understreker hvor viktig det er at investorer ikke bare vurdererer mulige inntekter fra spotmarkedet. Masteroppgaven analyserer videre hvordan usikkerhet påvirker investoratferd og forklarer hvorfor investorer er motvillige til å investere i lagringsteknologi under dagens markedsforhold. Når de fremtidige inntektene og investeringskostnaden er usikre, velger investorer å utsette investeringen i påvente av ny informasjon.

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Abbreviations

EES	=	Electric Energy Storage
EM	=	Expectation-Maximization
GBM	=	Geometric Brownian Motion
LSM	=	Least Square Monte Carlo
LTSC	=	Long Term Seasonal Component
MRS	=	Markov Regime Switching
NPV	=	Net Present Value
PHS	=	Pumped-Hydroelectric Storage
RES	=	Renewable Energy Sources
ROV	=	Real Options Valuation
STSC	=	Short Term Seasonal Component

Chapter 1

Introduction

The European Union introduced the EU2050 target to make the transition to a competitive-low-carbon society by 2050. To meet this long-term goal, additional targets, EU2020 and EU2030, have been implemented. The European Council agreed on the 2030 climate and energy policy framework in October 2014. They endorsed a binding target of at least 27 % renewable energy sources in the generation mix by 2030 (European Council, 2014). As a consequence of these frameworks, the electricity markets have experienced extensive changes during the last decades, creating an uncertain environment for investors.

This green shift of electricity generation results in an increasing portion of renewable energy sources in the transmission grid and an increasing need for ancillary services (Divya and Østergaard, 2009). A solution that would reduce the impact of an increased portion of renewables is to install electrical energy storage (EES) in the grid to improve reliability and performance. The EES systems can offer a time dimension, which makes it possible to store electricity when the demand is low and discharge when the demand is high.

Battery banks are one of the EES technologies that have received most attention recently due to favorable characteristics like quick response time, high round trip efficiency and pollution free operation. Tesla CEO, Elon Musk, announced in May 2015 that battery storage is their new focus area and further said that: ”*batteries for businesses and utilities is essential fostering a clean energy ecosystem and helping wean the world off fossil fuels*”. Further, Citigroup (2015) announced that grid batteries were the most important growth market in the electricity sector. However, recent research papers point out that investments in small storage facilities are not profitable today without public support (Reuter et al., 2012).

The main research question addressed in this thesis is therefore:

Is it profitable for an investor to invest in battery banks under the new condition of high share of renewable energy sources in European power markets?

A series of sub-questions follow:

1. *Does the profitability change between different markets?*

2. *How should the battery be operated and in which market should it participate to maximize its expected return?*

3. *How does uncertainty affect investor behavior?*

This thesis proposes a valuation model for battery storage. The results of the valuation show that investors should rethink how they choose to operate a battery to maximize its profit. Participation in the balancing market accounts for over 70 % of the battery banks total revenues, and realizing this opportunity will greatly increase the expected value of the investment. Today, peak-power plants with high emission and low energy efficiency provide most of these balancing services. EES can reduce the need for peak-power plants, by offering peak shaving and load leveling (Dunn et al., 2011). The main contribution of this thesis is a research paper: "Investment in Electric Energy Storage Under Uncertainty: A Real Options Approach". The research paper is planned to be submitted to Energy, a journal by Elsevier.

In this research paper a real options valuation method is developed that estimates the value of a battery bank. It considers both uncertainty in investment cost and market prices. Further, it applies regime-switching models to forecast spot and balancing prices, and apply a fast optimization algorithm to find the optimal economic dispatch. The results show that investments in battery banks can be profitable when considering them with both the net present value and real options approach. They can further be used to explain investor reluctance to invest in storage technologies due to uncertainty in the investment cost.

The structure of the thesis is as follows: in Chapter 2 we give an overview of the real options framework. In Chapter 3, the history, applications and economics of electric energy storage are presented. The structure of the deregulated electricity market are explained in Chapter 4. Then follow the different electricity and balance price models in Chapter 5. In Chapter 6, we present the most applied optimization algorithms used to find the economic dispatch of EES. Finally, in Chapter 7 we propose possible extensions of our model for further research.

Chapter 2

Valuations in the Energy Sector

Large investment costs and uncertain revenue streams characterize projects in the energy sector. Therefore, it is valuable to not only decide whether to invest, but also when to invest. Traditional net present value (NPV) analysis is often used to evaluate investment opportunities in this sector. However, real options valuation has the advantage over NPV of comparing the current value of the project with the expected value of waiting. This allows for a maximization of the project value with respect to, for example, investment time or expected profit. Dixit and Pindyck (1994) provide a detailed overview of the real options framework. The real options value can be expressed as follows:

$$ROV = max[P - I, C], \tag{2.1}$$

where ROV is the real options value, P the present value of the project, I the investment cost and C the expected value of postponing the investment often referred to as continuation value. It is optimal to invest when the NPV exceeds the continuation value.

The real options framework applies financial option theory to quantify the value of flexibility in a world of uncertainty. In addition to the flexibility in investment timing and sizing, the real options framework makes it possible to explicitly incorporate individual elements of risk in the analysis and evaluates how changes in individual elements affect the option value and investment decision.

Investing in grid scale batteries has gained attention in recent years due to an increased focus on the environment and as a possible solution to be able to integrate large amounts of renewables. We are not aware of any investment analyses which use real options to value battery banks. However, there are several papers that apply the net present value approach to battery storage (Kazempour et al., 2009; Sioshansi et al., 2009; Ekman and Jensen, 2010; Ma et al., 2014; Bradbury et al., 2014; Cho and Kleit, 2015).

The real options framework has been applied to conventional storage technologies, like pumped-hydroelectric storage (PHS) (Muche, 2009; Reuter et al., 2012; Fertig et al., 2014). Muche (2009) considers the option of operating the storage plant flexibly in response to the spot price. In addition, Reuter et al. (2012) include the option to wait for more information. Further, Fertig et al. (2014) extend the model by taking into account the option to choose the capacity of the pumped hydropower storage. However, this research paper fails to include any long-term uncertainty in the prices and therefore there is no real option to consider.

To our knowledge, all of the papers which evaluate the profitability of a single storage device consider the investor to be a price taker. A battery bank got limited capacity compared to a large scale pumped hydropower plant, and will not affect the prices by itself. Despite this, if the investment cost decreases substantially from a breakthrough in the technology, it might lead to widespread investment in battery banks that alter the spot and balancing price.

The uncertainty in the future development of battery cost is therefore important to consider when developing a valuation approach. The investment cost has traditionally been considered fixed or deterministic in the real options literature (Dixit and Pindyck, 1994; Reuter et al., 2012; Fertig et al., 2014). However, in real life it will change over time due to changing market conditions, demand and technology development. A few papers consider the investment cost to follow a stochastic process. The most applied processes to replicate the development in investment cost are Brownian motion (Saphores, 2003), geometric Brownian motion (Reed and Clarke, 1990; Berk et al., 1999; Fischer, 1978), geometric Brownian motion with jumps (McDonald and Siegel, 1982) and processes dependent on a Poisson random variable (Murto, 2007; Fuss and Szolgayov, 2010). Other processes have also been used to model the cost. Jaimungal et al. (2013) point out the mean reverting behavior of the investment cost and assume that it follows the exponential of a mean reverting process. In the paper of Elliott et al. (2009), the investment cost is considered to follow a two state Markov Regime Switching (MRS) model, where the two states represent ”low costs” and ”high costs”.

Chapter 3

Electric Energy Storage

Electricity is different from other commodities in the sense that it needs real time balancing. The reason for this is that electricity cannot be stored on a large scale in a cost efficient way. However, small to medium-scale storage can be profitable under certain market conditions. EES can be dated back to the early 20^{th} century, when utility companies started to recognize the importance of flexibility offered by storage. The first modern PHS was installed in 1929 (Baker and Collinson, 1999).

EES refers to a process of converting electrical energy into a form that can be stored, and at a later point in time can be converted back to electrical energy (Baker and Collinson, 1999; Chen et al., 2009). PHS is the most common type of EES and accounts for over 99 % of the installed storage capacity worldwide (Dunn et al., 2011). Other types of EES that are under development for large-scale storage are compressed air energy storage, fuel cell, battery, solar fuel, superconductors, flywheel and super-capacitors.

The number of PHS stations peaked in 2005, with over 200 plants in operation around the world providing more than 100 GW of generation capacity (Chen et al., 2009). After 2005, investment in PHS lost popularity due to increased uncertainty inflicted by deregulation of electricity markets worldwide and growing concern of the environmental impact of its operation. However, in the last couple of years the interest for EES has increased, not only for PHS but for other EES technologies as well. This can be explained by several factors: penetration of renewables in the transmission grid, increasing reliance on electricity in the industry, power quality issues, increased imbalances, negative spot prices and the need to find environmental friendly solutions to meet global emission targets.

EES technologies have two main applications: power quality and energy management (Chen et al., 2009). Technologies that are used to improve power quality are characterized by high power ratings with relative small energy content, while technologies aiming for energy management contain large quantum of energy but have lower power rating. From this, it is clear that a battery bank will have power quality as its main application, while for PHS it is energy management.

The reason for the increased interest in EES has to do with its benefits. The benefits can be divided into two groups: technical benefits and economic benefits (see Table 3.1). Technical benefits refer to benefits that improve reliability and quality of the transmission grid, while economic benefits are the potential revenues, or reduced losses, from employing EES.

Table 3.1: Technical and economic benefits of electric energy storage (Rodrigues et al., 2014)

Technical benefits	Economic benefits
Bulk energy time-shifting	Cut cost for electricity customers
Integration of renewable energy in the grid	Arbitrage of the spot price
Stand-by power sources for distribution lines	Reduce the need for peak generation
Keep voltage and frequency constant	Reduce transmission congestion charges
Reduce pollution	Reduce transmission capacity upgrades

3.1 Battery Storage

The interest in battery storage systems has exploded the last couple of years. In January 2015, Citigroup (2015) highlighted battery storage as a growth market and important investment theme in 2015. Tesla is another company that is showing interest and announced in May 2015 that they are developing battery storage for utility applications. These batteries can be grouped or scaled to more than 10 MWh (Tesla, 2015). A study by GTM Research and the Energy Storage Association also confirms this by showing that energy storage in the U.S. will more than triple this year (GTM Research, 2015).

Batteries can offer a number of important operating benefits to utilities, such as improved grid service reliability, black-start support and stand-by power to transformers. They also possess some major advantages over other storage technologies, with favorable characteristics as low maintenance cost, high round trip efficiency and quick response time. However, the willingness to pay for these services has been low due to the large portion of controllable production in the grid. With an increasing portion of renewables in the grid, the need for balancing increases due to unregulated production.

The main advantages of battery storage compared to PHS are that they can respond very rapidly to load changes, have low standby losses and can have a high energy efficiency of up to 98 % (Leadbetter and Swan, 2012). However, there have been few investments in large-scale utility battery storage due to low energy capacity and high investment cost. On the other hand, the total investment cost for battery storage is on average only a fraction of the PHS's. Additionally, the cost of battery storage is decreasing and is low per kWh compared to other storage technologies such as flywheels and capacitors.

Battery storage converts grid-interconnected electricity to chemical potential energy by a redox reaction between the chemical components in the battery (Dunn et al., 2011). The battery will charge during off-peak periods, when the spot price is low, and then convert the stored energy back to its original form during peak periods by exploiting the chemical energy the battery has stored in earlier hours. The business model for a battery bank is therefore time arbitrage of the spot price. There is however another market where the battery bank can participate, by providing ancillary services in the balancing market. Battery banks should maximize total benefits based on a trade-off between the revenues from the day-ahead spot market and balancing market.

Table 3.2: Battery technologies and their characteristics

Storage technology	Energy density [Wh/L]	Power density [W/kg]	Efficiency [%]	Cycles	Capital cost [$/kWh]
LA	50-80	75-300	63-90	500-1200	200-600
NaS	150-250	150-230	75-90	2000-5000	350
Li-ion	200-500	100-5000	80-98	1000-10000	600-1200
VRB	16-33	N/A	75-80	13000+	150-1000

Main reference for the table is: Leadbetter and Swan (2012). NaS and Li-ion power density and cycles: Ferreira et al. (2013)

Battery technologies that are either in use/or are potentially suitable for grid application include lead acid, vanadium redox battery (VRB), sodium sulphur (NaS) and lithium ion (li-ion). Table 3.2 presents some of their characteristics. The most widely used worldwide are lead acid, due to its availability and low cost. VRB has potentially the lowest cost and highest cycle life, but the lowest efficiency and energy density of the four. This means that it requires a large amount of space and that it is only suitable for small or medium applications. NaS competes with lead acid due to its higher energy density and longer lifetime. However, NaS batteries must be kept at 300-350 °C. The heat source uses the battery's stored energy, partially reducing performance. Li-ion has the most favorable characteristics with respect to efficiency, energy and power density. The main obstacle is its capital cost.

Li-ion batteries are currently the most actively researched battery technology due to the range of applications and performance. Companies interested in investing in grid batteries consider lithium-ion batteries as the best option (Citigroup, 2015; Tesla, 2015). These batteries have achieved significant penetration in the consumer electronics and electric vehicle markets due to rapid decrease in cost. At the end of the 1990s, the cost was more than $3000 per kWh, falling by more than 10 % each year since. Based on this history, Citigroup (2015) assumes the cost of grid-scale li-ion batteries to be high in the nascent market stage and then steadily decline from economies of scale.

Chapter 4

The Electricity Market

This section will present the fundamentals of the electricity market. It will further look into specific characteristics of the UK and German market, which are the markets we consider in our paper. The reasons for choosing these two markets are that we find them well suited to describe characteristics of other European markets; they are deregulated and exhibits characteristics which can be profitable for a battery bank.

The process of delivering electricity from producers to consumers consists of a number of different services such as generation, transmission, frequency control and balancing control. These services are designed to ensure safety, efficiency and reliability. The European electricity markets generally consist of a day-ahead spot market and a balancing market. The spot market is a day-ahead market with high liquidity. The balancing market is a market for different type of ancillary services, which are required by the system operator to ensure reliability in the transmission and distribution grid. The UK market also consists of a capacity market, which is a mechanism to ensure enough generation capacity in scarcity events (Cramton and Ockenfels, 2012).

The available generation capacity in a given country is linked to market design and security of supply. The reason is that the source of generation determines how much the price fluctuates (Painuly, 2001; Sensfu et al., 2008) and the need for ancillary services (Hammons (2008)). Systems that are characterized by a high share of slow generation capacity (i.e. unregulated renewables, nuclear and coal), will experience greater price fluctuations than systems with a high share of quick responsive generation capacity (i.e. hydro and peak-power plants). This can be explained by hydro and peak-power plants ability to rapidly change their output in response to changes in demand. This also explains why there is more need for ancillary services in a system dominated by slow generation capacity.

The gross electricity generation in Germany and the UK for 2014 is given in Table 4.1. It shows that Germany has a large fraction of is electricity production covered by slow regulating capacity, while the UK has a large portion of its production covered by fast responsive peak-power plants. The fact that generation technology determines the need for ancillary services explains why the price for these services in Germany has increased the last years. When the portion of unregulated renewable energy sources penetrates the market and cause gas peak-plants to be out of money, the amount of regulated capacity decreases. This further affects the systems ability to respond to changes in demand and supply. Therefore the need and price for balancing increases.

Table 4.1: Gross electricity generation by fuel in Germany and the UK

Source	The UK	Germany
Coal	29.1 %	43.6 %
Gas	30.2 %	9.6 %
Renewables	19.2 %	25.8 %
Nuclear	19.0 %	15.9 %
Other	2.5 %	5.1 %

4.1 The Day-Ahead Spot Market

In most European countries, including Germany and the UK, the spot markets are organized as power exchanges where the market operator will maximize social welfare (Zachmann, 2008). Here, contracts are made between sellers and buyers for delivery of power the following day, the price is set and the trade is agreed. It is designed to clear hours before the time of physical delivery. One reason for this is that some technologies are not flexible when it comes to power output and need sufficient time to coordinate production, i.e. coal and nuclear plants.

A buyer, typically the utility, needs to assess how much energy it will need to meet demand the following day, hour by hour. It also needs to decide how much it is willing to pay for this volume in every hour. The seller needs to determine how much power it can provide in a given hour and at what price. The buyers and sellers then submit their hourly bids the day before delivery and these bids are sorted by price. This constitutes the demand and supply curves.

In the electricity market the supply curve is referred to as the merit order curve, as way of ranking the available sources of energy in a system. At a specific time, the spot price and traded quantity (Q) are determined by where the demand and merit order curve intersect (see Figure 4.1). It is the most expensive plant that needs to be operating to meet demand that determines the price. All trades are settled at this market price. The bids are binding, so from 00:00 the next day, power contracts are physically delivered hour for hour according to the settled trades. Since the market is settled before real time, the spot market is an ex ante market (Wangensteen, 2012).

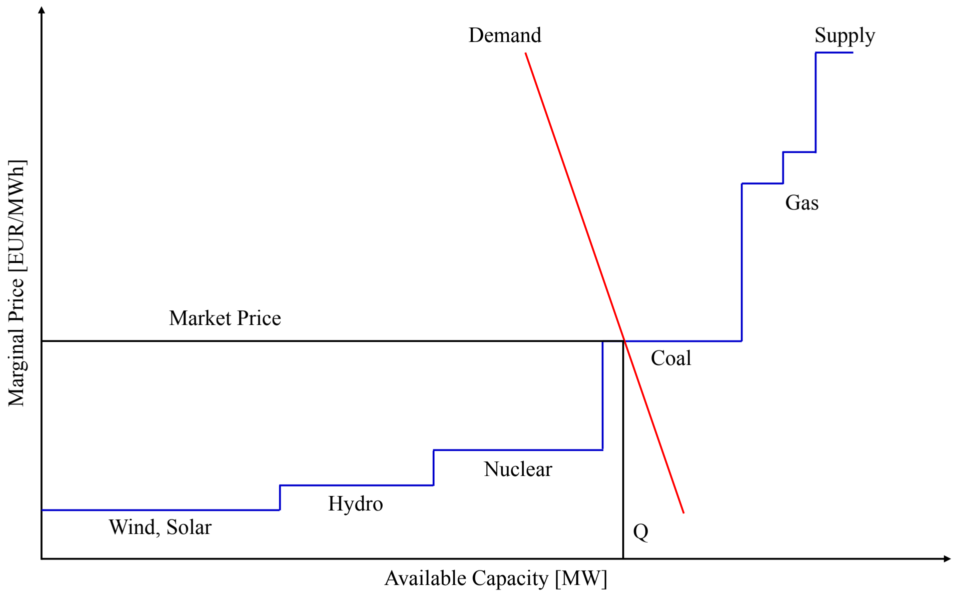

Figure 4.1: Merit order curve and demand

4.2 The Balancing Market

The reliability and quality of supply in the power system are dependent on that the technical systems connected has the necessary functionality to ensure safe operation (Statnett, 2014). With increasing portion of renewable generation in the electricity markets, there is a growing concern of how to ensure security of supply. Ensuring reliability in the transmission of electricity is one of the most important tasks of the modern society, since it is increasingly dependent on reliable and secure electricity supply to ensure economic growth. To ensure such reliability, the electricity market also consists of a balancing market.

The balancing market is an auction where the system operator buys generation from suppliers to ensure quality of supply and system reliability. It is designed to be cost efficient, so it use a merit order based on marginal cost of generation to set the price in the balancing market. Bidding takes place either the day before or during the operation day, depending on the market design. Different manufacturing technologies have different costs associated with regulation. It is effective first to utilize the resources that have the lowest cost of balancing. An important difference between the spot and balancing market is that the time solution varies. In the UK the spot bids are hourly, while the bids in the balancing market have a time frame of a half hour. In Germany they operate with quarterly bids in the balancing market.

There are strict criteria for suppliers to be able to participate in the balancing market and they change from country to country. The system operator requires different kinds of ancillary services to ensure reliability. Ancillary service are divided in six different categories: real-power balancing, voltage stability, transmission security, economic dispatch, financial trade enforcement and black start. The system operator must provide transmission security, trade enforcement and economic dispatch directly. The other services are what is known as the balancing market, where the system operator demand and pay for the provided services (Stoft, 2002).

The capacity made available for system operators through the balancing market have to be ready for delivery immediately after being called for. This restricts the suppliers to participate in one of the two markets, because they cannot reserve the same capacity in both markets at the same time. The balancing market is divided in two price mechanisms, an availability payment for reserving the capacity for the transmission system operator and utilization payment for delivery of energy (Koliou et al., 2014). This way, the suppliers are paid when they participate in the balancing market, even though they are not called to deliver.

The balancing market is complex due to its many different sub-markets, where each sub-market has its own design, participation criteria and prices. Stoft (2002) divides the market in two broad categories depending on the services it provides; balancing reserves and system reserves. The balancing reserve are further distinguished by the speed of the available technology, and are classified as primary, secondary and tertiary reserves (see Table 4.2). Battery banks are considered primary reserves due to their quick response time. However, there are strict criteria for minimum capacity batteries have to be able to deliver to participate in the balancing market as primary reserves. The minimum capacity required is 3 MW in the UK and 1 MW in Germany.

Table 4.2: Balancing reserve in a system dominated by thermal generation

Type	Control	Time response
Primary reserves	Automatic	Seconds
Secondary reserve	Automatic	A few minute
Tertiary reserve	Manual	10-30 minutes

Chapter 5

Spot and Balancing Price

5.1 Spot Price

In this sub-section we give a short introduction to some of the many different spot price models proposed in the literature. The modelling of the spot price is complicated due to its characteristics; mean-reversion, seasonality, spikes and volatility clustering. Spot price models can be divided into two groups depending on the time horizon of the dynamics they try to capture: short-term and long-term. Different long-term models that have been proposed are among others geometric Brownian motion (Boomsma et al., 2012) and Schwartz-Smith (Schwartz and Smith, 2000), while Markov Regime Switching (MRS) (Janczura and Weron, 2010, 2012; Arvesen et al., 2013), GARCH (Garcia et al., 2005) and mean-reverting jump diffusion (Deng, 2000; Weron et al., 2004; Cartea and Figueroa, 2005; Geman and Roncoroni, 2006) have been proposed as short-term models.

The need for real time balancing, in combination with rapidly changing consumption, results in seasonal patterns in the spot price. The spot price exhibits daily, weekly and yearly seasonality. The price is varying during the year due to changing climate conditions and throughout the week and day due to business cycle. Countries with a large portion of renewables can also experience an increase in the seasonality of the spot price due to seasonal variation in the underlying resource. An example which illustrates this is a generation system which is dominated by hydro units. In such a system, the spot price is heavily dependent on snow melting and precipitation.

One important characteristic of the spot is spikes, i.e. sudden increases and decreases in price. Positive price spikes occur when the demand reaches its limit of available capacity, because of a sudden increase in consumption. Negative price spikes occur as a response to low demand and/or oversupply. When the demand is low the least expensive generation technologies on the merit order curve are exercised, and the price is therefore very low (See Figure 4.1). Oversupply on the other hand is caused by technical limitations in generation technologies. For example, large thermal generators with high start-and stopping costs will in some situations choose to operate even though the spot price is below their marginal cost. The reason for this is that it would be more costly to stop and restart production, than the cost of operating the plant.

One of the explanations to the high volatility in the spot price is the price inelasticity of demand. This is because consumers do not either face or pay real-time prices, and therefore have no incentive to respond to changes in the spot prices. By evaluating historical spot price data from the two countries being considered in this thesis, it is evident that the prices are highly volatile. They also exhibit mean reversion, seasonality and spikes. In Germany the spot price also drops below zero in some hours.

Three of the models that best captures the characteristics of the spot price mentioned above are mean-reverting jump diffusion, MRS and Schwartz-Smith. In the following paragraphs, these three will be described in more detail.

One of the first to apply the mean-reversion jump diffusion model was Deng (2000). Since then, this way of modeling the spot price has been applied by several authors (Weron et al., 2004; Cartea and Figueroa, 2005). There are various types of jump-diffusion models used to model spot prices, which all can be obtained as special cases of:

$$dX_t = \mu(X_t, t)dt + \sigma(X_t, t)dW_t + q(X_t, t), \tag{5.1}$$

where μ is the mean level of the price, σ the volatility, dW_t the increments of a standard Wiener process and $dq(X_t, t)$ increments of a pure jump process. When the drift takes the form $\mu(X_t, t) = (\alpha - \beta X_t)$ it is called a mean-reverting jump diffusion process. For simplicity, the volatility is often set to constant ($\sigma(X_t, t) = \sigma$). The jump term can be assumed to follow a Poisson process ($q(X_t, t) = Jdq(t)$), where J is a normal or log-normal random variable and q(t) is a homogeneous Poisson process.

One of the main drawbacks of the jump-diffusion models is that they cannot exhibit consecutive spikes, which is a regular occurrence in the spot price. They also have a slow speed of mean reversion after a jump. A rate of mean reversion that would force the price back to the mean quickly would be highly overestimated in hours when the spot price is not considered a spike. The MRS model allows for this in a natural way, by having a transition matrix, which contains the probability of the spot price having a consecutive spike.

There are many different variations of the MRS model, which have been applied to forecast the spot price (Janczura and Weron, 2010, 2012; Arvesen et al., 2013). These approaches varies in the number of regimes employed and the processes applied in the different regimes. In a much cited paper by Janczura and Weron (2012), they choose to model the spot price with three regimes. In their model, one regime represents the 'normal' behavior of the spot price, one regime the sudden price jump (positive spike) and the third regime the sudden price drops (negative spikes).

The model parameters can either change between the different regimes or the independent regimes can be represented by different processes. For the spot price, where we would like to represent very different behaviors in the different regimes (with radically different behavior between the normal behavior and the spikes), a natural choice is independent regimes. A MRS model with three independent regimes, X_t, is given by:

$$X_t = \begin{cases} X_{t,1} & \text{if } R_t = 1, \\ X_{t,2} & \text{if } R_t = 2, \\ X_{t,3} & \text{if } R_t = 3, \end{cases} \tag{5.2}$$

where $X_{1,2,3}$ are the different regimes and $R_{1,2,3}$ the actual state of the market, i.e. normal behavior, spike or drop. Typically, the base regime is given by a mean-reverting diffusion process, sometimes with a heteroskedastic volatility term $\sigma(X_t, t) = \sigma|X_t|^\gamma$:

$$dX_{t,i} = (\alpha_i - \beta_i X_{t,i})dt + \sigma_i |X_{t,i}|^{\gamma_i} dZ_{t,i}. \tag{5.3}$$

The other regimes can be modeled by independent and identically distributed random variables. The random variables can for example have an exponential (Paraschiv et al., 2015) or log-normal distribution (Janczura and Weron, 2012).

None of these models capture the long-term dynamics in the price. Schwartz and Smith (2000) propose a model where the short term variations is captured by a mean-reverting process and the long term variations are assumed to follow a Brownian motion process. In the short-term/long-term model the spot price, S_t, is divided in two stochastic components $ln(S_t) = X_t + \varepsilon_t$, where X_t is the short-term deviations in the prices and ε_t is the long-run mean. The short-run dynamics are assumed to follow a mean reverting process with zero mean:

$$dX_t = -\beta X_t dt + \sigma_X dZ_X, \tag{5.4}$$

and the long-term dynamics follow a Brownian motion process:

$$d\varepsilon_t = \mu_\varepsilon dt + \sigma_\varepsilon dZ_\varepsilon, \tag{5.5}$$

here dZ_X and dZ_ε are correlated increments of the Brownian motion processes. This model on the other hand is not a good fit when trying to capture the short-term deviations in the price such as spikes. Therefore, the model should only be applied when these deviations can be disregarded.

5.2 Balancing Price

The modelling of balancing price has received less attention than the modelling of the day-ahead spot price. An explanation for this is that the balancing markets have more country specific rules than the spot market. There will therefore be more variations in the behavior of the prices between countries, and not possible to find one model that fits all. There are papers which develop models for the balancing price. However, these are not general and can therefore only be applied to a specific market.

The balancing prices in the markets we are considering have many of the same characteristics as the spot prices. They are reverting to a mean, the volatility is high, there are sudden increases and decreases in price (spikes) and they exhibit seasonal effects. Therefore, when forecasting the balancing price, the choice is between spot price models and statistical models, which are most applied in literature (Jaehnert et al., 2009; Klæboe et al., 2013; Boomsma et al., 2014).

Two common types of statistical approaches used to forecast the balancing price are ARMA and SARIMA. Klæboe et al. (2013) and Jaehnert et al. (2009) both applies the statistical method ARMA(1,1) to simulate the balancing price. In both papers they include the spot price as an exogenous factor:

$$(1-\phi L)(\rho_t^{BM} - \beta \rho_t^{spot}) = \epsilon_t, \tag{5.6}$$

here ϕ is the auto-correlation coefficient, L the lag operator, ρ^{BM} the balancing price, β is the coefficient of the external input, the spot price ρ^{spot}, and ε is the random error. This model does not include seasonal effects, something we find the balancing price to possess. In order to deal with this seasonality, some authors use a SARIMA model (Boomsma et al., 2014). The SARIMA(1,1,2)$\times$(1,1,2)$_{24}$ model of Boomsma et al. (2014) describes hourly and daily cycles:

$$(1-\phi L)(1-\varphi L^{24})(1-L^{24})(1-L)\rho^{BM} = (1-\gamma_1 L^{24} - \gamma_2 L^{48})(1-\theta_1 L - \theta_2 L^2)\epsilon_t, \tag{5.7}$$

where ϕ, φ, γ and θ are model parameters. In the UK electricity market we find evidence of correlation between the spot and balancing price. This model do not take this into account. Also, in the presence of spikes, statistical methods perform rather poorly (Weron, 2014).

Chapter 6

Optimization Model

In this section we give a short introduction to frequently used optimization approaches for optimal dispatch of electric energy storage. Most of the algorithms, which have been proposed are suited for PHS. However, in recent years there have been developed alternative algorithms for other types of EES technologies.

EES can earn revenues either by selling electricity in the spot market or reserving its capacity in the balancing market. In the spot market the EES generates revenues by selling electricity at a high spot price in the discharging mode and purchasing electricity when the spot price is low in charging mode. The second source of revenues for a storage owner is to offer its services in the balancing market. This way, the storage owner will be paid a market price for participating in the balancing market and an additional spot price if it is called to generate.

Optimization models in the energy sector can be divided in two groups; deterministic and stochastic models (Kallrath et al., 2009) . Deterministic models assume perfect knowledge of future prices, while stochastic models include price uncertainty. A further distinction can be made for optimization models for EES, those that are considering economic dispatch (Bathurst and Strbac (2003); Kazempour et al. (2009)) and those that optimize based on technical considerations (i.e. voltage output, power quality etc.) (Choi et al. (2012); Tant et al. (2013)). For the economic dispatch the models can further be divided in two groups, those that only consider the spot market and those that consider several markets.

In the last decade there have been an increasing amount of papers which consider optimization of EES. Most of these models consider economic dispatch with only participation in the spot market. In order to compare the different optimization algorithms and point out their differences, we present the commonly used objective functions these algorithms are using.

First we consider two common types of objective functions applied for PHS (Muche (2009) and Lu et al. (2004)) and then two for battery storage (Bradbury et al. (2014) and Kazempour et al. (2009)). In the paper of Muche (2009), he proposes an optimal dispatch algorithm for PHS that maximizes the revenues of arbitrage of the spot price.

$$Obj = \sum_{i=1}^{t} P_S(i)\big[Q_G(i)U - Q_P(i)M\big], \tag{6.1}$$

where P_S is the spot price, Q_P and Q_G the amount charged and discharged, and U and M binary variables telling if the PHS is in pump or generating mode at time i. The main drawback of such a model is that it only considers participation in the spot market alone and it uses binary variables, which make the algorithm speed slow compared to an integer programming problem. The paper of Lu et al. (2004) is one of few papers that propose an algorithm that allows for revenues in more than one market. In their model they use spot and balancing price forecasts on an hourly basis with an optimization period of one week:

$$Obj = \sum_{i=1}^{t_g} Q_G(i)P_S(i) + Q_A P_A t_p + Q_R P_R(T - t_g - t_p) - \sum_{j=1}^{t_p} Q_P(j)P_S(j) - C, \quad (6.2)$$

where C is the operation and maintenance cost, P_A and P_R are the prices of different balancing services,T the end of a cycle, Q_A and Q_R the amount reserved for balancing at time i. The main drawback of this approach is that they assume that the price of the ancillary services (P_A and P_R) are constant. By looking at the historical data of the different ancillary services, it is clear that this is not a valid assumption as we easily see that the price change over the day, week and year.

The first optimization algorithms for batteries were considering investments that combined energy storage with renewable energy sources such as wind and solar (Bathurst and Strbac (2003); Yang et al. (2007)). Lately, optimization algorithms have been developed, which consider optimal dispatch of a battery alone. Bradbury et al. (2014) developed an optimization algorithm of a battery which operated in the spot market alone:

$$Obj = \sum_{i=1}^{t} P_S(i)\big[Q_G(i) - Q_P(i)\big]. \quad (6.3)$$

Kazempour et al. (2009) developed a weekly-based optimization algorithm aiming to maximize the profit of a natrium sulfur battery. The algorithm considers the weekly forecasted prices in both the spot, spinning and regulation markets simultaneously.

$$Obj = \sum_{i=1}^{t_g} Q_G(i)P_S(i) + \sum_{j=1}^{t_A} Q_A(j)P_A(j) + \sum_{k=1}^{t_R} Q_R(k)P_R(k) + \sum_{l=1}^{t} Q_P(l)P_S(l) - C. \quad (6.4)$$

The approaches for optimizing electric energy storage are not only distinguished from each other by their objective function, but also by their constraints. Some papers include constraints such as limited amount of cycles, degradation in efficiency and storage capacity with time, maximum storage level and maximum charging/discharging capacity. It is important to include constraints which best estimate the objective being considered, but at the same time keep the number of constraints and decision variables at a minimum to ensure fast computational speed.

Chapter 7

Further Research

In the research paper we use MRS models without long term uncertainty to forecast the spot and balancing price. Since the battery bank earns its revenues by short-term fluctuations in prices, we chose a price model that best captured these fluctuations. The historical price data shows however that there is long-time uncertainty in the prices too. An extension of our model is therefore to include such long-time uncertainty in both spot and balancing price. This will help the understanding of how the long term uncertainty in the prices affect the investment decision. The reason for this is that we are valuing assets with a lifetime of several years. One possibility is to use an MRS model where the base regime is given by a Schwartz-Smith model.

In our model we assume that the capacity of the battery bank is fixed. Battery storage have however a scalable capacity, meaning that they can be tailored to meet a specific capacity. Including this option will make it possible for investors to find the optimal storage capacity as well as the optimal investment time. Dangl (1999) was one of the first to apply a model that included both investment timing and size. Since then there have been several others which include the choice of capacity sizing (Bøckman et al., 2008; Armada et al., 2011; Hagspiel et al., 2012; Fertig et al., 2014). A general result when including capacity choice is that greater uncertainty results in larger investments that take place at a later point in time. In future research we would like to extend our model to include the decision to choose between a number of different capacities. One approach is to let the investor choose between a number of discreet capacities (Fertig et al., 2014), while another is to model it as a choice between continues capacities (Hagspiel et al., 2012).

From the time an investor decide to invest in a battery bank until the battery is operating it takes approximately half a year. This time is not included in our model. This lagging period caused by construction reduces the value of the investment and could affect the timing of the investment. Several authors have considered this lagging period and find that when the uncertainty increases, so does the option value. The reason for this is that the value of waiting increases and therefore the investment is postponed (Bar-Ilan and Strange, 1996; Alvarez and Keppo, 2002; Costeniuc et al., 2008). To further extend the valuation, it would be favorable to include a lagging period when valuing the real option. This time lag can be modelled by applying the method developed by Linnerud et al. (2014), which includes the construction lag as a parameter in the electricity price.

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Investment in Electric Energy Storage Under Uncertainty: A Real Options Approach

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Abstract

Promoting renewable energy has been a key ingredient in energy policy seeking to de-carbonize the energy mix. This will continue given that the European Union keeps up its ambitions to reduce carbon emission. Electric energy storage (EES) has been proposed as a solution to make this transition possible. In this paper we develop a real options approach to evaluate the profitability of investing in a battery bank. The approach determines the optimal investment timing under conditions of uncertain future revenues and investment cost. It includes time arbitrage of the spot price and profits by providing ancillary services. Current studies of battery banks are limited, because they do not consider the uncertainty and the possibility of operating in both markets at the same time. We confirm previous research in terms of that when a battery bank participates in the spot market alone, the revenues are not sufficient to cover the initial investment cost. However, under the condition that the battery bank also can receive revenues from the balancing market, both the net present value (NPV) and the real options value are positive. The real options value is higher than the NPV, confirming the value of flexible investment timing when both revenues and investment cost are uncertain. This further explains why investors historically have been reluctant to invest in storage technology; the investors are favoring the option to wait for more information.

Keywords: Real Options, Electric Energy Storage, Markov Regime Switching, Economic Dispatch, Least Square Monte Carlo.

1. Introduction

Electric energy storage (EES) has recently received increasing attention. This is linked with more frequent imbalances in the transmission grid, which are caused by the integration of large amounts of renewable energy sources (RES) and society's focus on environmentally friendly solutions [1]. One of the advantages of electricity is that it can be produced in a clean and efficient way, i.e. hydro, solar and wind power. Today, ancillary services are however mostly provided by peak-power plants with high emissions and low energy efficiency. The reason for this is that peak-power plants are the cheapest available technology which can provide peak-power due to their quick-response time and high power output. With an increasing portion of RES, which have fluctuating power output, the need for balancing increases. So does the need for units with quick response time that can quickly change their power output. The development of additional EES capacity is therefore a necessary solution to favor the deployment of RES and to reduce emissions worldwide [2].

Investments in EES technologies have been a popular topic in the real options literature over the last decade [3–5]. Pumped hydroelectric storage has received the most attention, due to the fact that it is the dominant technology accounting for 99% of the world's storage capacity. In spite of this, there are a number of other storage technologies in the market such as compressed air energy storage, batteries, fuel cell, solar fuel, superconductors, flywheel and thermal energy storage [6, 7]. The choice of which storage technology an investor chooses depends on a number of factors; market design, characteristics required, costs, location, expected revenues etc. For markets with large imbalances and large portion of RES, there is demand for quick-response technologies such as batteries.

In this paper we apply a real options framework to value investments in lithium-ion battery banks (i.e. grid scale battery) in Germany and the UK. It is interesting to consider battery technology, due to the rapid decrease in battery cost and its favorable characteristics (i.e quick response time and regulated power output). Batteries also possess a number of other desirable features such as pollution-free operation, high round-trip efficiency, scalable power and energy output, long life cycle and low maintenance costs [1, 8, 9]. Despite their anticipated benefits and the needs of the markets, there has been a reluctance to invest in batteries due to high investment cost and uncertain revenues [10].

To consider the potential revenues, we must study the electricity market in more detail. The reason for considering investments in the UK and Germany is that they cover specific features that are common for markets in Europe, such as the need to integrate RES, need for more balancing power and the electricity generation is dominated by thermal plants. In the past two decades electricity markets around the world have been deregulated [11, 12]. Deregulated electricity markets are divided in two parts, the spot market and the balancing market. The spot market is a day-ahead market with high liquidity, where the suppliers are paid for the amount of electricity they provide. The balancing market consists of different types of

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ancillary services which are required by the transmission system operator in order to balance demand and supply, as well as to ensure security across the transmission system. In the balancing market suppliers are receiving two forms of payments; availability payments for making their unit available for ancillary services and utilization payments for the energy delivered as instructed by the system operator. Battery banks can participate in both markets, but not reserve the same capacity in both at the same time.

The spot price in general exhibits strong seasonality on the annual, weekly and daily level, mean reversion, high volatility, clustering effects and extreme price changes known as spikes or jumps. In Germany and the UK, the balancing price exhibits the same characteristics. Two of the most common approaches to model the spiking behavior of the power price are jump diffusion models and Markov regime-switching (MRS) models [13]. The jump-diffusion model introduces spikes through a Poisson jump component. It is however not able to generate consecutive spikes, because the jumps are independent [14, 15]. The MRS model are able to generate these with a transition matrix that includes the probability of the spot price having a consecutive spike [15]. It has therefore been extensively used to capture the unique behavior of the spot price [15–19].

Previous papers that consider investment in batteries find that it is not profitable. Some authors obtained this result assuming that the battery can only operate in the spot market [20, 21]. Our results support this finding, that a battery that only operates in the spot market is not lucrative. Ekman and Jensen [22] found the investment to be unprofitable when the battery could operate in either the spot or balancing market. In our model we add the flexibility to receive revenues from both markets. Research papers which include such flexibility, still not find it profitable [10, 23]. However, Cho and Kleit [10] assume that the battery could only charge and discharge once a day, when a battery in fact got the potential to change state every hour due to its quick response time. Kazempour et al. [23] consider another battery technology, with a lower efficiency than the lithium-ion battery, and have no spikes in their forecasted balancing prices. Our results contradicts these papers, by showing that a lithium-ion battery that receives revenues from both markets and can discharge more then once a day are profitable. This demonstrates that it is essential to include revenues from both markets, as well as capturing the characteristics of the prices to discover the total value of the investment.

The investment cost has generally been considered to be fixed or deterministic [24]. However, for real-world investment decisions the investment cost will change over time due to changing market conditions such as rise in commodity prices, decrease in demand and technology development. Still, there are some papers that include a stochastic investment cost. Stochastic investment cost has traditionally been modelled with a Brownian motion process [25], a geometric Brownian motion (GBM) [26–28] or a GBM with jumps [29]. More recently, Murto [30] and Fuss and Szolgayová [31] let the investment cost be dependent on a Poisson random variable. Jaimungal et al. [32] point out the mean reverting behavior of the investment cost and assume that it follows the exponential of a mean reverting process. In the paper of Elliott et al. [33] the investment cost is considered to follow a two state MRS model, where the two states represent "low costs" and "high costs". The investment cost of lithium-ion batteries has historically been decreasing with time without jumps. A possibility is therefore to assume that the battery cost development follows a GBM.

The main contribution of this paper is a quantification of the value of investing in a battery bank. For transmission systems with increased use of intermittent RES and a world in need of environmentally friendly solutions, the fact that battery banks are a cost-effective way of balancing supply and demand is an important result. In addition, we use a state of the art MRS model for the spot price that captures the characteristics of the prices. We are also the first to propose a MRS model for the balancing price. Further, the model for optimal hourly dispatch of the battery bank includes participation in both the spot and balancing market. Finally, the model takes into account the uncertainty of the investment cost and the revenues by applying the real options framework. To the best of our knowledge, there are no other investment analyses which use real options to value battery banks.

The paper is structured as follows: In Section 2 we describe the data used and the characteristics of the spot and balance price in Germany and the UK. In Section 3 we explain the model for the valuation of the battery bank. This consists of the real options valuation, the optimal dispatch of the battery bank and the MRS models for the spot and balancing price. Results are presented in Section 4, which includes the value of the battery bank and how parameters such as the growth rate and volatility of the investment costs affects the valuation. In Section 5 we conclude.

2. The datasets

The datasets in this study include market data from Germany (2010-2014) and the UK (2010-2014). This allows for an evaluation of investment under different market conditions. The two markets are ideal for a comparison of investments between countries, because they both are well suited for battery characteristics and at the same time have different market features. The UK market is isolated due to its location on an island, which creates a need for balancing. The price level for both spot and balancing is also high. The German market on the other hand is much more interconnected and the spot price has fallen with over 32 % since 2010. However, it exhibits variable market behavior with extreme spikes and it has a rapidly growing portion of RES installed. This in combination with the decision to close down all nuclear plants by the end of 2020, escalates the need for balancing which increases the prices in the balancing market. Both markets also have several similar properties to other markets in Europe; the growing investments in RES in combination with a high share of thermal plants in their generation mix.

2.1. Historical market prices for the UK (2010-2014)

The dataset includes the hourly market clearing price from the Amsterdam Power Exchange (APX Power UK) and the hourly balancing price from the system operator National Grid. The time series were constructed using data downloaded from Reuters, and processed accounting for missing values, leap years and daylight saving time. We also include the day of the week and hour of the day in the data set. This is necessary to be able to filter out the seasonal components of the prices. The market data for the balancing price is given in half-hour prices. We transform them to hourly prices to be able to compare balancing and spot prices in the optimization model.

The historical data for both the spot and balancing prices are mean reverting. There are however hours with extreme values, which we define as negative and positive spikes. To see how we classify spikes please see Appendix B. By looking at the historical data, it is also clear that the prices have diurnal, weekly and seasonal patterns. The volatility is greater in some periods than others, indicating a clustering effect. Another important finding is that the spot price is non-negative. This is due to the market design which forbids participants to enter trades with a negative spot price [11], as opposed to Germany. The price still show negative spikes, but they do not pass below zero. The prices in week 5 in 2014 are presented in Figure 1.

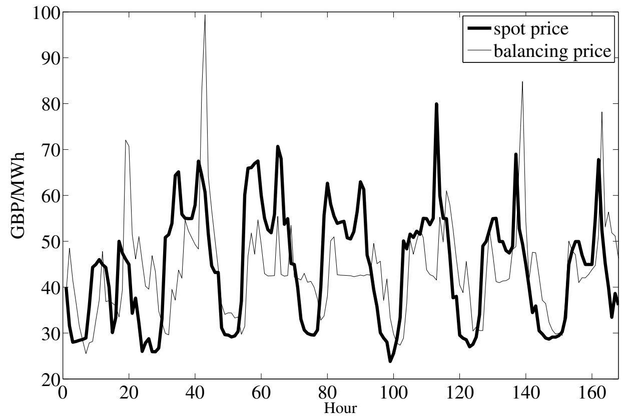

Figure 1: Spot and balancing price UK week 5, 2014.

2.2. Historical market prices for Germany (2010-2014)

This dataset includes the hourly market clearing price from the European Energy Exchange AG (EEX) and hourly balancing price from the system operator TenneT. The dataset was processed the same way as the UK dataset, except for the balancing price which was transformed from quarterly to hourly prices.

By evaluating historical data from the German market, it is clear that the spot and balancing prices have the same characteristics as in the UK market. The only exception is the spot price which has no price floor and a drop in the average spot price from 2010. The reason why the spot price in Germany has dropped is due to three main factors: 1) subsidies of new RES, 2) low carbon price and 3) coal being cheaper than gas in Europe [12]. To examine the potential financial gain by operating a battery bank, we have therefore based the price forecast of the spot and balancing prices on the market data from 2010-2014. Figure 2 shows the prices in week 5 in 2014.

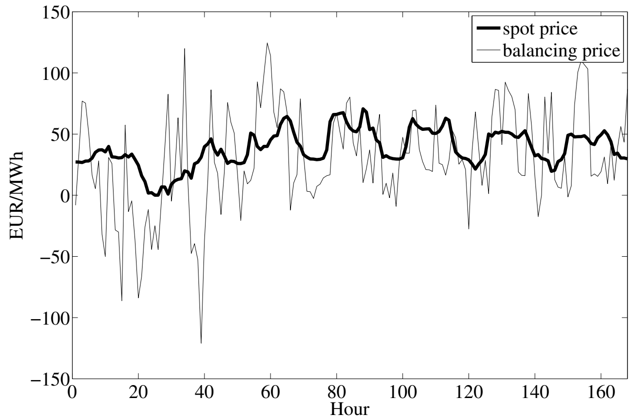

Figure 2: Spot and balancing price Germany week 5, 2014.

3. Model description

The valuation of the battery bank consists of four steps: price forecasts of the spot price and balance price, an optimization model for optimal operation of the battery bank, investment cost model and a real options valuation (see Figure 3). To be able to value a battery bank, we need to accurately forecast the power price and balance price. The forecast must capture the characteristics of the two prices and the correlation between them. The simulated future spot and balance prices serve as input to the optimization model. The economic dispatch is found by maximizing the revenues of the battery bank. Annual revenues from the optimal operation of the battery bank serve then as input to the real options valuation together with the investment cost forecasts. The real options model in turn returns the optimal investment time.

3.1. Price dynamics

The future spot and balancing price are both forecasted using Markov regime switching models with three independent regimes. In the following subsections we will go through the procedures we have used to develop the different models, the calibration of the parameters and the final results.

3.1.1. Spot price

The spot price is characterized by mean-reversion, with diurnal, weekly and yearly seasonal patterns. It is also highly volatile and exhibits spikes with clustering effects. The explanation for these characteristics is the highly non-linear supply-demand curve and that the market requires real-time balancing since electricity cannot be stored in large scale.

The seasonal patterns can be explained by the consumption of electricity. It is varying during the year due to changing weather conditions and throughout the week and day due to the business cycle. In addition, the generation is increasingly weather dependent, with the growing portion of unregulated RES.

Spikes are typically interpreted as the result of a sudden increase or decrease in demand [34]. At the times when the de-

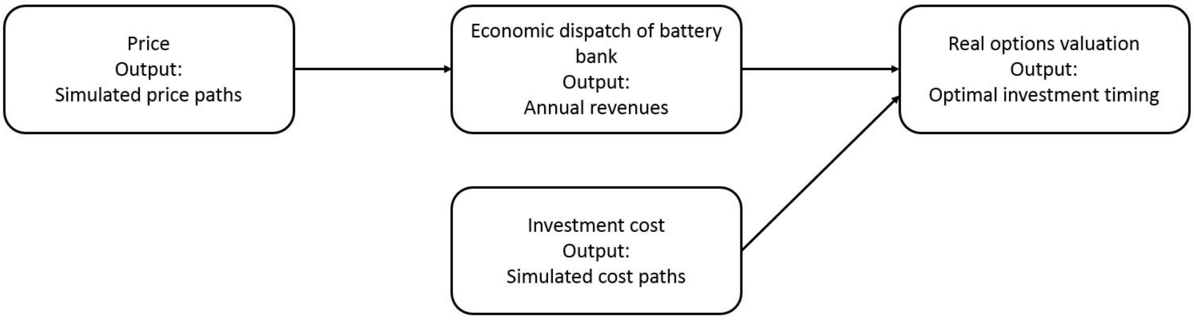

Figure 3: The structure of the analysis.

mand reaches the limit of available capacity, the spot price exhibits positive price spikes. Negative price spikes may occur in periods of low demand and/or periods of oversupply. Price jumps on the other hand can occur due to unexpected supply shortages or failures in the power grid.

The spot price model must be able to capture the seasonal patterns and the stochastic behavior of the spot price. We therefore choose to let the spot price, P_t, be a sum of two independent parts: a deterministic seasonal component (f_t) and a residual stochastic component (X_t); $P_t = f_t + X_t$.

The deterministic component

We let the deterministic component be composed of a daily (h_t) and weekly (s_t) periodic part (i.e. short-term seasonal component, STSC) and a long-term seasonal component (LTSC), T_t. The STSC is caused by variations in consumption throughout the day and business cycles, while the long term-component is explained by the changing climate throughout the year. The deterministic component can therefore be expressed as:

$$f_t = s_t + h_t + T_t. \tag{1}$$

There are different ways of handling the seasonality of the spot price. Some authors use dummy variables for each month, day of the week or hour of the day [16, 35]. Other use sinusoidal functions or sums of sinusoidal functions [18, 36]. Wavelet decomposition and smoothing is another possibility that is less sensitive to outliners and less periodic [36, 37]. Wavelets offer a very good in-sample fit to the data, but wavelets ability to forecast is poor [38]. As we are considering an investment that use the forecasted spot prices, wavelet decomposition is not suited. We therefore choose to apply the method presented in the paper of Janczura and Weron [18], where the LTSC is represented as a sum of sinusoidal functions.

The historical data is deseasonalized in three steps; first by subtracting T_t from P_t, then subtracting the daily component, and finally by removing the weekly seasonality. The daily periodic part (h_t) is found by calculating the 'average day' from the detrended data ($P_t - T_t$). The weekly periodic part (s_t) is found the same way as for the day, by calculating the 'average week', from the detrended data ($P_t - T_t - h_t$). The approach used to calculate the STSC is the same as having seasonality expressed by dummy variables [17]. The estimated seasonal components for the UK spot price is shown in Appendix B. The deterministic component is found by adding all the seasonal components as in Equation 1.

The stochastic component

We use a Markov regime-switching model to represent the stochastic component of the spot price. It represents the observed stochastic behavior of a specific time series by more than one separate regime with different underlying stochastic processes [17]. The switching mechanism between the different regimes is assumed to follow a Markov chain, i.e. the underlying process does only depend upon the current state.

To capture the characteristics of the spot price, the stochastic component (X_t) is represented by a MRS model with three independent states:

$$X_t = \begin{cases} X_{t,1} & \text{if } R_t = 1, \\ X_{t,2} & \text{if } R_t = 2, \\ X_{t,3} & \text{if } R_t = 3. \end{cases} \tag{2}$$

R_t describes the actual state of the market, i.e. normal behavior, spike or drop. The three regimes are independent and the switching mechanism between the regimes is assumed to be a latent Markov chain, R_t. It can be described by a transition matrix $\mathbf{P}$, which contains the probabilities of switching from one regime i at time t to regime j at time t+1.

$$\mathbf{P} = P(R_{t+1} = j \| R_t = i) = \rho_{ij} = \begin{pmatrix} \rho_{11} \, \rho_{12} \, \rho_{13} \\ \rho_{21} \, \rho_{22} \, \rho_{23} \\ \rho_{31} \, \rho_{32} \, \rho_{33} \end{pmatrix}. \tag{3}$$

The base regime ($X_{t,1}$) describes the statistical "normal" price behavior and is given by the Chan-Karolyi-Longstaff-Sanders (CKLS) differential equation:

$$dX_{t,1} = (\alpha_1 - \beta_1 X_{t,1})dt + \sigma_1 |X_{t,1}|^{\gamma_1} dZ_{t,1}, \tag{4}$$

where $\alpha_1, \beta_1, \gamma_1$ and σ_1 are constants and $dZ_{t,1}$ is the increment of the standard Wiener process. β_1 describes the speed of mean reversion, $\frac{\alpha_1}{\beta_1}$ the long-time equilibrium level, σ_1 the volatility of the process and γ_1 the volatility's dependence on the price level.

The upper regime ($X_{t,2}$), which represents the sudden price jump (positive spikes), is given by independent and identically distributed (i.i.d.) random variables from the shifted log-normal distribution:

$$log(X_{t,2} - X(q_2)) \sim N(\alpha_2, \sigma_2),\ X_{t,2} > X(q_2). \quad (5)$$

The lower regime ($X_{t,3}$), which represents the sudden price drops (negative spikes), is given by i.i.d. random variables from the shifted inverse log-normal distribution:

$$log(-X_{t,3} + X(q_3)) \sim N(\alpha_3, \sigma_3),\ X_{t,3} > X(q_3). \quad (6)$$

3.1.2. Balancing price

In the balancing market, the market closure is either the day before or immediately prior to delivery hour depending on market design. The units that have received their capacity in the balancing market can suddenly be told to generate. This feature makes the market accessible only to market players that can quickly adjust production or consumption.

The modelling of balancing prices has received less attention than the modelling of day-ahead spot prices. One of the explanations is that the design of the balancing market varies according to the country. Therefore, there will be no model that suits all balancing price processes. This explains why Skytte [39] finds that the balancing price can be explained by the day-ahead market price, while Jaehnert et al. [40] results indicate no correlation between the spot and balancing prices. Jaehnert et al. [40] model the balancing price as the difference to the day-ahead market price, while both Olsson and Soder [41] and Klæboe et al. [42] model it directly including correlation with the spot price.

Characteristics of the UK and German balancing price include positive and negative spikes, mean-reversion and volatility clustering. To capture these price characteristics, we choose to use a MRS model with three regimes: base- , upper- and lower regime. We also find that the balancing prices have seasonal components, which changes during the day, week and year (see Appendix B). We therefore apply the same methods as in the last sub-section to determine the deterministic seasonal components of the balancing price.

Since the balancing price is dependent on market design, the correlation between the spot price and balancing price will differ. We therefore tested the correlation between the spot and balancing price in our datasets, and found opposite results. For the German market, we find no significant correlation between the spot and balancing price. The price forecast of the balancing price is therefore modelled in the same way as for the spot price in Section 3.1.1. However, for the UK market, the correlation between the spot and balancing price increments were found to be 0.25. We incorporate this correlation in the UK balance price below, ensuring that the balancing price does not move unrealistically high or low compared to the spot price.

Balancing price in the UK

The balancing price is modelled by a MRS model (X_t), with the same deterministic seasonal component (f_t) as for the spot price, i.e. $P_t = X_t + f_t$. The MRS model is given by three independent regimes:

$$X_t = \begin{cases} X_{t,4} & \text{if } R_t = 1, \\ X_{t,5} & \text{if } R_t = 2, \\ X_{t,6} & \text{if } R_t = 3. \end{cases} \quad (7)$$

R_t describes the actual state of the market, i.e. normal behavior, spike or drop, and is assumed to follow a latent Markov chain (see Section 3.1.1). The three regimes are assumed to be independent, where the base regime ($X_{t,4}$) is a mean-reverting process, the upper regime ($X_{t,5}$) has a shifted log-normal distribution and the lower regime ($X_{t,6}$) a shifted inverse log-normal distribution.

The base regime captures the "normal behavior" of the balancing price and it includes the correlation between the spot and balancing price. To take into account the correlation we use the bivarate conditional expectation when determining dZ_4.The base regime ($X_{t,4}$) is given by the following equation:

$$dX_{t,4} = (\alpha_4 - \beta_4 X_{t,4})dt + \sigma_4 |X_{t,4}|^{\gamma_4} dZ_{t,4}, \quad (8)$$

where the balance price increment (dZ_4) is correlated with the spot price increment (dZ_1) by a factor ρ equal to 0.25.

3.1.3. Model calibration

To estimate the parameters in the Markov regime-switching price models, we apply the Expectation-Maximization algorithm (EM) developed by Dempster et al. [43] and applied to the MRS models by Hamilton [44]. The reason for applying such a method is that the calibration process of MRS models is not straightforward due to the state processes being latent. To overcome this, the EM algorithm lets us infer the parameters and state processes at the same time. The algorithm is an iterative two step procedure that starts with computing the conditional probabilities, $P(R_t = j|x_1, ..., x_T; \theta)$, for the process being in regime j at time t, with an arbitrary guess, $\theta^{(0)}$, for the parameter vector, θ, of the underlying stochastic process (E-step). The second step (M-step) computes the new maximum likelihood estimates of the parameter vector, θ, based on the conditional probabilities estimated in the E-step. These two steps are repeated until a local maximum of the likelihood function is achieved.

We estimate the parameters by applying the EM procedure described in Janczura and Weron [17]. This procedure can be applied to all MRS models where at least one regime is described by a mean-reverting process. The main advantage of this approach is that it reduces the computational complexity of the E-step. The EM procedure is formulated and applied to the historical data using Matlab.

The results from the parameter calibration of the historical EEX and APX prices are shown in Table 1 and 2. The parameters clearly show a difference between the two electricity markets we are considering. Comparing the deseasonalized spot prices, the UK has the highest speed of mean reversion (β) and mean level (α/β). All of the probabilities, p_{ii}, of staying in the same regime are quite high for each of the regimes, 0.525 to 0.992, except for the lower regime for the UK spot price. This is consistent with a more pronounced clustering effect in the

German spot market in combination with the less frequent negative spikes in the UK spot market. The same clustering effect is apparent for the two balancing prices. The German balancing price has the highest volatility. This indicates a higher potential for revenues, since the battery bank receives payments when reserving its capacity in this market. So when there is more extreme values occurring in the prices, it results in higher revenues. Simulated spot and balance price paths for the UK for a week are illustrated in Figure 4. The figure illustrates that we have managed to capture characteristics of the prices, such as seasonality and correlation between the prices.

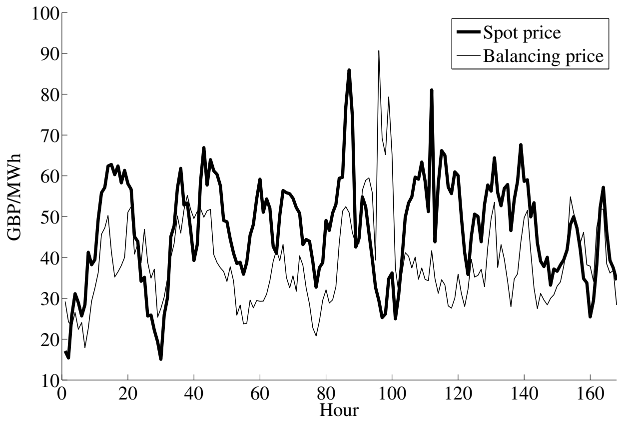

Figure 4: Simulated spot and balance prices for one week for UK.

3.2. *Optimal dispatch of the battery bank*

The optimization model we develop in this paper generates the optimal dispatch and expected profit of the battery bank for an average year, given the hourly spot price, $P_{spot,t}$, and balancing price, $P_{bal,t}$. We assume that a battery bank has the flexibility to operate in both the spot and balancing market. The economic dispatch determines the highest expected profit based on participation in both markets. At each hour t, the battery will be in one of the following states: charging, discharging or idle. When operating in the spot market the owner of the battery bank either receives or pays the spot price, depending on the state of operation. In the balancing market, it receives the hourly balancing price and additionally the hourly spot price if the battery is called to discharge. The probability of being called to generate is given by U and is based on historical data [23, 45].

The battery bank is optimized over a planning horizon of one day. The daily profits are summed up over the first year. This allows new information to be incorporated on a daily basis without assuming future knowledge of prices beyond a day. This means that the battery make price-dependent bids, which will result in an overestimation of the profits from operation. At the same time, we do not assume complete future knowledge of the prices so it will not be that different from scheduling based on knowledge of the price distribution. Contreras et al. [46] found that with a good forecasting model, the error applying daily forecasted prices would be maximum 11 %. We penalize the yearly revenue by multiplying by a constant of 0.9 (M) to adjust for knowing the prices the next day.

The objective of the storage owner is to optimize the operation of the battery to maximize the profit, i.e. revenues less operation and maintenance costs. The following linear programming problem maximizes the profit over a day:

$$\max\Big(\sum_{t=1}^{m} P_{spot,t}(q_t - b_t + Ur_t) + \sum_{t=1}^{m} P_{bal,t}r_t - \sum_{t=1}^{m} OM(q_t + b_t + Ur_t)\Big), \quad (9)$$

subject to:

$$W_t = W_{t-1} - \frac{q_t}{\eta_1} + b_t\eta_2 - \frac{Ur_t}{\eta_1} \quad (10)$$

$$q_t + r_t \le Q_{max} \ \ \forall t \quad (11)$$

$$0 \le W_t \le W_{max} \ \ \forall t \quad (12)$$

$$0 \le b_t \le B_{max} \ \ \forall t \quad (13)$$

$$0 \le q_t \le Q_{max} \ \ \forall t \quad (14)$$

$$0 \le r_t \le Q_{max} \ \ \forall t. \quad (15)$$

Table 1: Calibration results for MRS models with three independent regimes fitted to the deseasonalized EEX and APX spot prices.

	Parameters								Probabilities		
	α_1	β_1	σ_1	γ	α_2	σ_2	α_3	σ_3	p_{11}	p_{22}	p_{33}
EEX	4.26	0.10	4.15	0.00	2.46	0.83	2.29	1.18	0.992	0.750	0.851
APX	8.20	0.18	4.71	0.01	2.17	1.19	2.54	0.6	0.990	0.551	0.000

Table 2: Calibration results for MRS models with three independent regimes fitted to the deseasonalized EEX and APX balance prices.

	Parameters								Probabilities		
	α_4	β_4	σ_4	γ	α_5	σ_5	α_6	σ_6	p_{11}	p_{22}	p_{33}
EEX	12.30	0.34	24.18	0.08	3.36	1.22	4.22	0.88	0.977	0.704	0.591
APX	7.57	0.2	0.35	0.7	2.27	1.01	2.42	1.31	0.982	0.633	0.525

Variables and parameters in the economic dispatch are summarized in Table 3. The operation is controlled by three hourly operation variables: the discharge in the spot market, q_t, what is reserved in the balancing market, r_t, and the charging in the spot market, b_t. We assume that the storage level is zero at the beginning of operation. Further, operation and maintenance cost, OM, and efficiency for both charging, η_1, and discharging, η_2, are assumed constant.

The objective function, Equation (9), consists of three components. The first term calculates the revenue from delivering power in the spot market and the costs of charging the battery. The second term calculates the revenue from reserving capacity in the balancing market. The third term accounts for the operation and maintenance costs of operating the battery.

Equation (10) balances the energy storage level of the battery. The energy storage level is equal to the storage level at the previous time step, plus the energy charged minus the energy discharged. The energy discharged consists of two terms, the energy discharged to sell at the spot market and the energy discharged from participating in the balancing market at time period t. Both terms are divided by the discharge efficiency. The energy charged is the product of the charging rate and the charging efficiency.

Equation (11) sets a fixed maximum battery capacity. The energy sold in the spot and balancing markets in each hour can not exceed the maximum capacity of the battery.

Equations (12)-(15) are production limit constraints, putting an upper and lower bound on charging, discharging and storage level.

This model of economic dispatch with linear decisions variables is solved by a linear programming algorithm. To obtain this solution the model is formulated in the General Algebraic Modeling System (GAMS) and solved by the CPLEX solver.

From the economic dispatch we get the present value of operating a battery during a one year period for a given spot and balance price path. To get the total value of the battery bank, we need to sum up the revenues throughout the lifetime of the battery assuming the investor receives a fixed payment once a year. When summing up all yearly payments, we have to account for the time value of money and discount the profit flow. We assume an interest rate of 4 % and a lifetime of 15 years for the battery bank. We find the present value of the profit flow by applying the following formula:

$$PF = \sum_{k=1}^{z} \frac{C \times M}{(1+r)^k} = C \times M \Big[\frac{1-(1+r)^{-z}}{r} \Big], \tag{16}$$

where z is the total number of years the investor receives payments, C is the size of the payments, M is the penalty of knowing future prices and r is the risk free-rate.

The optimization algorithm is repeated for the 10 000 different spot and balancing price paths, i, we generated from the price models in Section 3.1. We use the results, PF_i, as an input variable in the real options valuation.

3.3. Investment cost

The cost of lithium-ion batteries for consumer electronics and electrical vehicles have decreased rapidly the last decade, with over 10 % each year. The main reasons for this are economy of scales and technology development. However, none of the papers which consider investment in battery storage include such uncertainty in technology development for grid scale batteries [10, 20–23]. If investors fail to take into account the uncertainty of technology development, they risk underestimating the value of the battery as well as investing before the optimal investment time.

In this paper we consider the investment cost, I_i, to follow a stochastic process due to the uncertain nature of battery development. Since the cost for comparable technology (i.e. small and medium scale lithium-ion batteries) have steadily decreased the last decade, we assume that the cost for battery banks also

Table 3: Parameters and variables in operation of battery bank.

Symbols	Explanation	Value	Unit
$P_{spot,t}$	Forecasted spot prices	-	€/MWh
$P_{bal,t}$	Forecasted balancing prices	-	€/MWh
OM	Fixed operation and maintenance costs	0.1	€/MWh
m	Length of operation period	24	hours
q_t	Spot discharge	-	MW
r_t	Capacity reserved in balancing market	-	MW
b_t	Battery charging	-	MW
U	Utilization factor	0.1	-
Q_{max}	Maximum production capacity	5	MW
B_{max}	Maximum discharging capacity	5	MW
W_0	Initial storage level	0	MWh
W_{max}	Maximum storage level	10	MWh
η_1	Efficiency of battery discharge	0.975	-
η_2	Efficiency of battery charging	0.975	-
M	Penalty	0.9	-

Subscript t denotes quantities that may change hourly will develop in a similar manner. Therefore, we let the investment cost follow a geometric Brownian motion with a negative growth rate:

$$dI_i = \alpha_I I_i dt + \sigma_I I_i dz_{I,i}, \tag{17}$$

where $\alpha_I < 0$ is the growth rate, $\sigma_I > 0$ is the volatility and $dz_{I,i}$ is the increment of the Wiener process. Table 4 shows the parameters of the investment cost.

Table 4: The parameters of the investment cost.

Parameters	Value
Investment cost (€/kWh)	1350
Capacity (MWh)	10
Growth rate (α)	-0.1
Volatility (σ)	0.2

3.4. Real options valuation

Classical methods of investment planning states that an investment should only be undertaken if its net present value (NPV) is positive. This strategy ignores the value of postponing investment to wait for more information. Real options valuation accounts for the value of such flexibility [24].

We are considering the following investment opportunity: at every year y, the firm can pay an investment cost, I_i, in order to buy a battery bank, given the profit flow from operation of the battery bank PF_i (see Figure 3). The battery bank investment decision is characterized by a large sunk cost and a time interval during which investment is possible. We therefore choose to value the investment as a Bermudan call option. A Bermudan option is a combination of American and European options, where the option can be exercised only on predetermined dates. This type of exotic option allows the owner to exercise the option only once, but has flexibility to choose the optimal exercise date between a number of given discrete times during the lifetime of the option T. The lifetime of the option is set to 10 years. Although an investment opportunity can be considered more often than once per year, this time step still gives insight about the investments in battery banks. The value of the investment opportunity is calculated as:

$$ROV = \max_{0 \le y \le T} \Big(\mathbb{E}[e^{-ry}(PF_i - I_i)], 0 \Big). \tag{18}$$

It is challenging to solve this optimal stopping problem with several exercise dates in the real options framework, particular when more than one stochastic factor affects the value of the option. This is primarily because finite difference and binomial techniques become impractical. The key to optimally exercising a Bermudan option is identifying the conditional expected value of continuation. We will therefore apply Least Square Monte Carlo described in the paper of Carriere [47] and further extended by Longstaff and Schwartz [48]. This is a mathematical approach based on random sampling where the idea is to evaluate an integral as an expected value. We use Matlab to find the value of the Bermudan option, applying the Least Square Monte Carlo algorithm.

The inputs for the Least Square Monte Carlo valuation are two exogenous variables: PF_i from the optimization model and I_i. Both of these consists of 10 000 unique paths (i). The algorithm optimizes the exercise date based on the trade-off between immediately exercising and the continuation value of keeping the option alive for each individual in-the-money path. The payoff vector $p_i(y)$ at each time y is given by:

$$p_i(y) = \begin{cases} PF_i(y) - I_i(y) & \text{if } PF_i(y) - I_i(y) > C_i(y) \\ C_i(y)e^{-rdy} & \text{else,} \end{cases} \tag{19}$$

where C_t is the continuation value of keeping the option alive. The option value is calculated by averaging the sum of all payoff paths at year zero. If the value of the option is greater than zero, the value of investing in a battery bank is positive. If the option value is zero or less, it is never optimal to invest. See Appendix A for a more detailed description of the approach.

4. Results

The results are based on a base case considering an interest rate of 4 %, battery bank and option lifetime of 15 and 10 years, and initial investment cost of 1350 €/kWh with volatility of 20 % and negative growth rate of 10 % .

The results from the real options valuation of the battery bank investments are given in Table 5. To compare the investments in the two countries, we convert the option value of investing in the UK from pounds to euro applying an exchange rate of 1.3 €/ £. The option values of investing in Germany (6.5 million) and the UK (9.9 million) are both positive. Therefore, it is profitable to invest in a battery bank in both countries in our base case.

Table 5: Results of the valuation.

	Germany	UK
NPV (mill. €)	6.1	9.6
Option value (mill. €)	6.5	9.9
Payback period (year)	7.6	6.3
Investment time (year)	2	1

The project with the highest option value is in the UK, with a 34 % higher option value than the project in Germany. This is due to a higher price level in the UK, compared to Germany. However, the results show that it can be profitable to invest in markets with different characteristics This is an important finding, which confirms that battery storage can be a cost efficient alternative to peak power plants to cover peak demand and to improve grid stability.

The lifetime of a battery bank is 15 years, resulting in additional profits past the first six (the UK) and seven (Germany) years (see Table 5). The payback time for both investments are therefore longer than six years. If we compare this benchmarks to another electric energy storage technology, pumped hydroelectric storage, the battery bank has a much shorter payback time. The reason for this is that the upfront investment cost on average is many times larger for pumped hydroelectric storage. This makes an investor more likely to invest faster in storage batteries than pumped storage, even though pumped storage investments are considered to be more profitable.

The average time to invest is after two years in Germany and after one year in the UK. We find this by calculating the average optimal investment time of the 10 000 independent paths. For investors following a traditional NPV rule, they will invest immediately since both investments have positive NPV of 6.1 and 9.6 million. When considering the flexibility to postpone the investment decision for up to ten years, to wait for a decrease in investment cost, the value of the investment opportunities are 6.5 and 9.9 million. This is an increase of only 7% for Germany and 3% for the UK. However, this difference is highly dependent upon the parameters of the investment cost. If the growth rate of the investment costs were to change from -10 % to -15 %, the differences between NPV and real options value increase to 25 % (Germany) and 15 % (the UK). In other words, the higher the uncertainty and negative growth rate for battery storage cost, the more profitable is it to value the investment as a real option.

The real options framework can help policy makers increase their insight on how to trigger investment in battery storage. As stated earlier, there has been a reluctance to invest in storage technologies. This investor behavior can not be explained by the traditional NPV methodology, which assumes that an investment will be undertaken as long as the project has a positive NPV. The real options valuation however explains this behavior by showing that when there is great uncertainty, investors are favoring the option to wait for more information. This shows that the reason why investors are not investing in batteries is not because they are not profitable, but rather that investors are waiting for the cost of batteries to decrease.

From the economic dispatch we find that batteries most of the time will offer their services in the balancing market, with the only exceptions being when there are spikes in the spot price. This result indicates that battery banks earn most of their profit from ancillary services, and only makes a small profit from time arbitrage of the spot price. In fact, participation in the balancing market accounts for over 70 % of its total revenues. This further demonstrates the importance of convincing investors to rethink how they choose to operate the battery to maximize its profit. By only considering revenues from the spot market, investors risk underestimating its value. The main reason why it is so profitable to participate in the balancing market is that the battery does not necessarily have to recharge every time after it has participated, which is the case in the spot market.

The main result of this paper is that a battery bank can be profitable under the conditions given in our base case. This is a contrast to recent published papers [3, 20, 21]. They assume that a battery will only operate in the spot market and revenues are therefore only gained by time arbitrage of the spot price. When we use this assumption we also find it unprofitable to invest. We find that in this case both investments have a negative NPV of -12.6 (Germany) and -11.8 million (the UK). From our valuation we also find that both projects have an option value equal to zero, which means that it is never optimal to invest. These results clearly demonstrates that it is essential for the profitability of a battery bank to operate in both markets.

4.1. Sensitivity analysis

In this subsection we perform a sensitivity analysis of the option value and the investment threshold. Only one parameter is changed at a time, while keeping the other parameters fixed. This increases the comparability of the results. We choose to only consider the German market, as the effects are the same as for the UK market.

The discount rate plays an important role when determining the value of a real option, it affects both the value and timing of investment. A low discount rate encourages waiting, which increases the value of the option. This is because the revenues are discounted less heavily, while at the same time the investment cost is expected to decrease. On the other hand, a high discount rate triggers earlier investment, which reduces the value of the option. Figure 5 illustrates how the option value for Germany changes with the discount rate. When the discount rate is low, the option value is large and vice versa. When the discount rate gets sufficiently high ($discountrate > 15\%$), the option value is equal to zero. The reason for this is that the total profit never gets large enough to cover the up-front investment cost. Considering the current market situation in Europe, with very low discount rates, the probability that the discount rate will increase above 15 % is small.

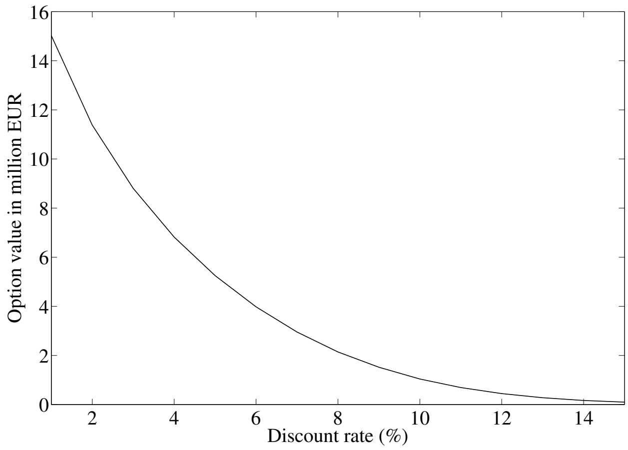

Figure 5: Sensitivity of option value to discount rate.

There are two uncertainties considered in the model, the investment cost and the profits from operating the battery. In order to analyze the investment cost's impact on the option value and optimal timing, we keep the parameters of the profit constant.

First we look at the investment cost threshold, i.e. what is the highest cost an investor is willing to pay to invest in a given year. In Figure 6, this investment threshold (line) is given as a function of investment cost and year. If the investment cost in a given year is less than the investment threshold, it is optimal to invest immediately. If the investment cost is higher than the threshold boundary, it is optimal to postpone the investment decision. For an investment to be optimal in year 1, the investment cost has to be less than 12.1 million. Further we see that the investment threshold decreases as the option approaches its maturity. In year 10, the investment cost has to be lower than 5.2 million for the investment to be optimal. This is an expected result. When the investors postpone possible profit flow, it is because they expect a lower investment cost in in the future.

Figure 7 illustrates how the growth rate affects the option value and timing of the investment. With a low negative growth rate ($\alpha > -4\%$), the value of the option is constant. The reason for this is that it is optimal to invest immediately. Therefore, the option value is equal to NPV which is independent of the growth rate. For high negative growth rates ($\alpha < -4\%$), the option value increases due to an increased value of waiting for more information. The optimal timing of investment would also change from immediately, which was optimal when the negative growth rate was small, to wait for one ($-6\% < \alpha \leq -4\%$) or two ($-30\% < \alpha \leq -6\%$) years. From this it is clear that increased negative growth rate has two main effects on investment decisions: it increases option value and the optimal investment timing increases.

Examining the sensitivity of the option value to volatility in investment cost, Figure 8 shows how the option value changes with an increase in volatility from 0 to 30 %. The figure illustrates that the option value increases with volatility, when the volatility changes from 2 to 30 %. As the volatility increases, the flexibility of postponing the investment to wait for more information is more valuable, i.e. the option holder is encouraged to wait. However, a surprising result of the analysis is the non-monotonic behavior of the option value as the volatility increases. When the volatility increases from 0-2 %, the option value decreases. This is not consistent with the characteristic feature of the Black-Scholes model; that the sensitivity of the option price with respect to the underlying assets volatility is always positive, i.e. the option value increases with volatility. Permana et al. [49] argued that this does not contradict the Black-Scholes model. They reasoned that by increasing one of the volatilities it can lead to a lower variability of the spread, which ultimately drives down the option value. This is exactly the same result we obtain in our analysis, by increasing the volatility from 0-2 % the option value decreases due to reduced difference between the investment cost and the profit flow. This suggests that for options that has more than one source of uncertainty, the option value can decrease in some intervals.

Next we will consider the sensitivity of the profit flow, keeping the parameters of the investment cost constant. An important benchmark for investors is the average yearly revenue required to make the investment profitable. Figure 9 shows the option value with respect to average yearly revenues. Without public support, the investment would not be profitable when the yearly profit is expected to be under 0.5 million. We find that when only participating in the spot market, the annual revenue is 0.2 million. When considering operation in both markets, the annual revenue is 1.8 million. Policy makers therefore have two options when wanting to trigger investment in battery banks, they can either give public support or allow batteries to participate in the balancing market.

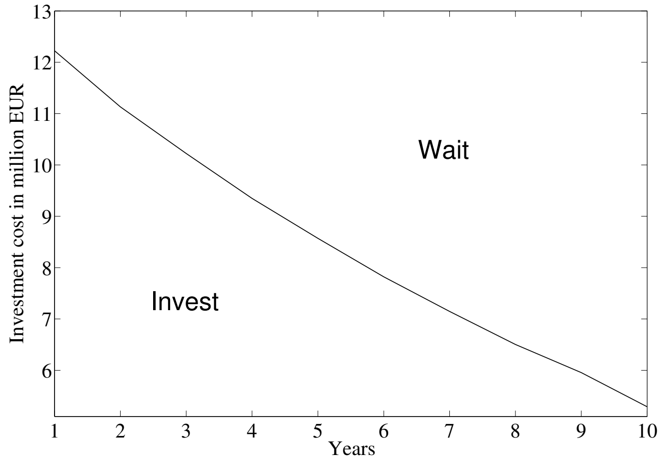

Figure 6: The investment cost threshold.

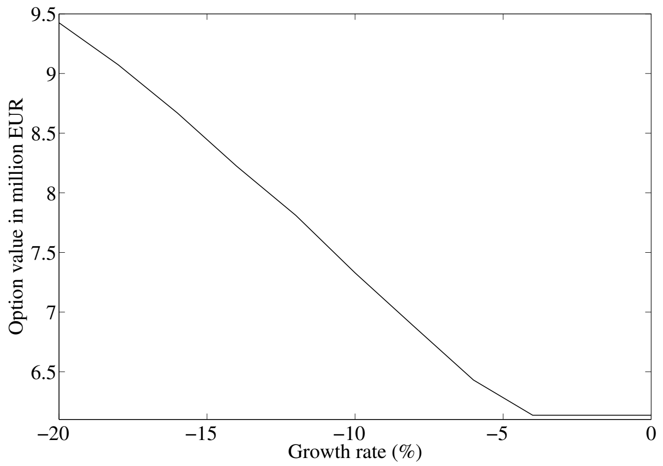

Figure 7: Sensitivity of option value to growth rate of the investment cost.

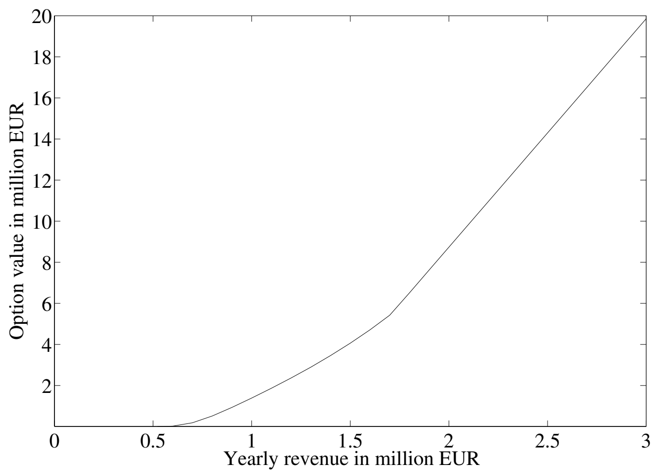

Figure 9: Sensitivity of option value to the yearly revenue

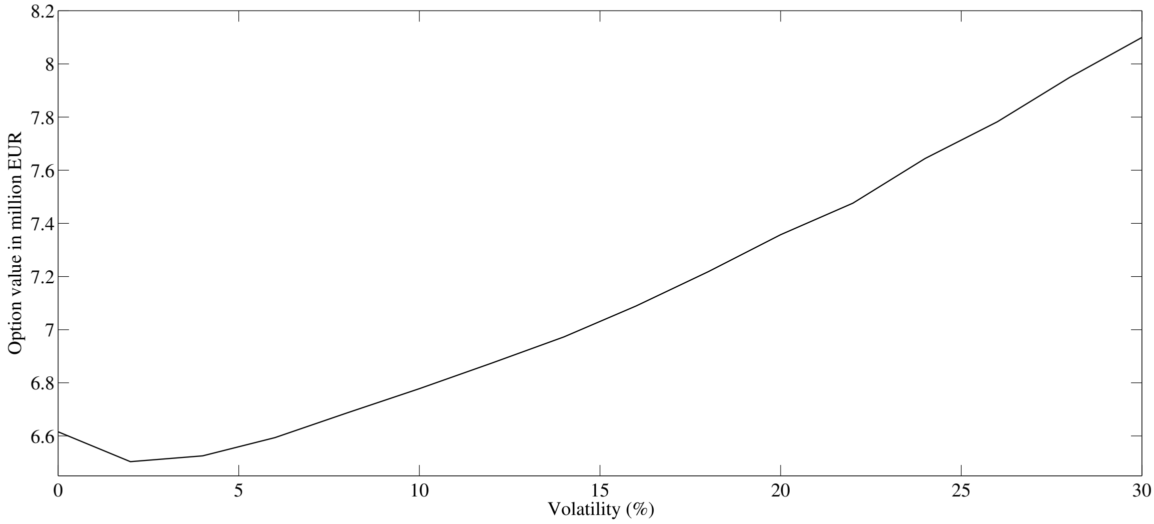

Figure 8: Sensitivity of option value to volatility of the investment cost.

5. Conclusion

We have analyzed the profitability of investing in a lithium-ion battery bank in Germany and the UK, considering the opportunity to operate in both spot and balancing market. The value of the investments are found by applying a real options model, which determines the option value and optimal investment time for a battery bank under the conditions of uncertain revenue stream and investment cost. Our results show that batteries can be a cost efficient and environmentally friendly solution to help the green transition in Europe. They further show that investment is profitable in both countries considered, and that it is optimal to postpone any investment for at least a year.

The real options model developed in this paper can help policy makers increase their insight on investor behaviour and how to trigger investments. The results from our analysis shows that the reluctance to invest in storage batteries can not be explained by batteries being unprofitable, but rather by high uncertainty. We find that high uncertainty in the development of battery costs leads investors to favor the option to wait for more information.

From the economic dispatch of the battery bank, we find that operating the battery bank on the sole purpose of time arbitrage of the spot price is not generating high enough revenues to cover the initial investment cost. This result shows that investors should rethink how they choose to operate the battery to maximize its profit. Participation in the balancing market accounts for over 70 % of the battery banks total revenues. Realizing this opportunity will greatly increase the expected value of the investment. We therefore point out the importance of including revenues from the balancing market when valuing investment in quick responsive electrical storage.

Appendix A. Least Square Monte Carlo

Least Square Monte Carlo is a recursive algorithm that at each time step, y, evaluates the value of all in-the-money-paths. The speed of the algorithm is fast, since it only considers these paths. We use Least Square Monte Carlo to value the Bermudan option. The value is obtained by evaluating the profit flow (PF) of each in-the money path and the discounted payoff vector (C), at each time-step. The algorithm can be mathematically explained by equations (A.1)-(A.4).

The stochastic investment cost and payoff from the operation of the battery are inputs of the Least Square Monte Carlo algorithm. Starting from year T and working back to year 0, at each time step y, the C vector is regressed onto PF. The continuation values at each time y, is given by:

$$C(X) = \sum_{k=0}^{n} \alpha_k f(PF)^k, \tag{A.1}$$

such that the quadratic error is minimized:

$$\sum_{j=1}^{M} \left(PF_j - \sum_{k=0}^{n} \alpha_k f(PF)^k \right)^2. \tag{A.2}$$

The approximate continuation values in our model follows the following distribution:

$$C_i(X) = \alpha_0 + \alpha_1 PF_i + \alpha_2 PF_i^2, \tag{A.3}$$

where a_0, a_1 and a_2 are the constants that are being estimated at each time step. The formula for C gives the continuation value i.e. the value of waiting to the next time step before exercising the option. This is a quite simple approximation, but several numerical tests confirm that even simple powers of the state variable gives accurate results [48].

The payoff of a Bermuda option is valued as the trade-off between immediately exercising and waiting. If the value of the option today is positive and greater than the continuation value, the option will immediately be exercised. In the other case, the option owner will keep the option alive. This is expressed by the following formula:

$$p_i(y) = \begin{cases} PF_i(y) - I_i(y) & \text{if } PF_i(y) - I_i(y) > C_i(y), \\ C_i(y)e^{-rdy} & \text{else.} \end{cases}$$

The value of the option is determined by summing all the payoff paths at time zero and average the payoff from the number of paths. This is expressed by the following formula:

$$\text{Option value} = \frac{1}{N} \sum_{i=1}^{N} p_i(0). \tag{A.4}$$

Appendix B. Price

In this appendix we show the results from the analysis of the spot and balancing price in the UK from 2010 to 2014. The results from the price analysis are divided in a stochastic and deterministic part. From the stochastic part we determine the spiky behaviour of the price. Figure B.10 and B.11 illustrate how we classify spikes from a fragment of both the spot and balancing price. The positive spikes are denoted by circles while negative spikes are denoted by $\times s$.

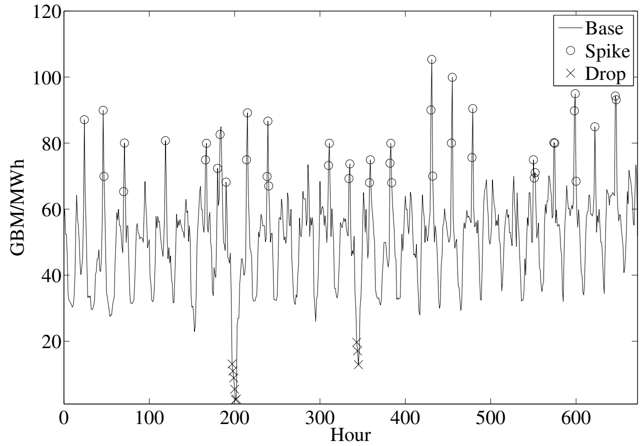

Figure B.10: The UK spot price classified as spike or drops

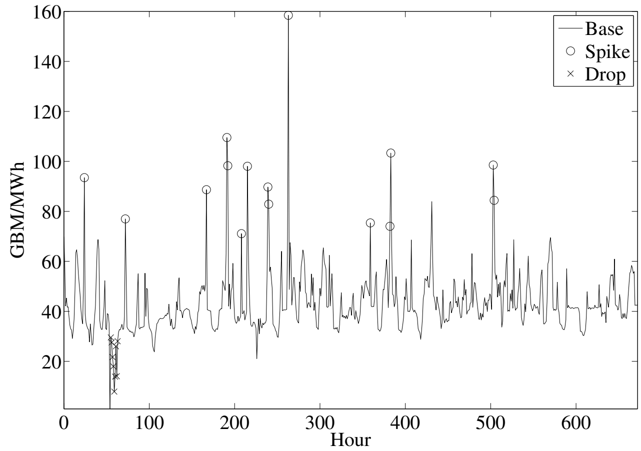

Figure B.11: The UK balancing price classified as spike or drops

The results from the analysis of the deterministic components of the spot and balancing price forecasts are given in Figure B.12 - B.17. Figure B.12 and B.13 show the hourly and weekly short term seasonal component (STSC) of the spot price, while Figure B.15 and B.16 show the same for the balancing price. This is the typical daily and weekly pattern of the spot and balancing price. Figure B.14 and Figure B.17 show how the long term seasonal component (LTSC) develops during one year for the spot and balancing price. The LTSC are plotted together with a simulated spot and balancing price path, to get an understanding of how they are related.

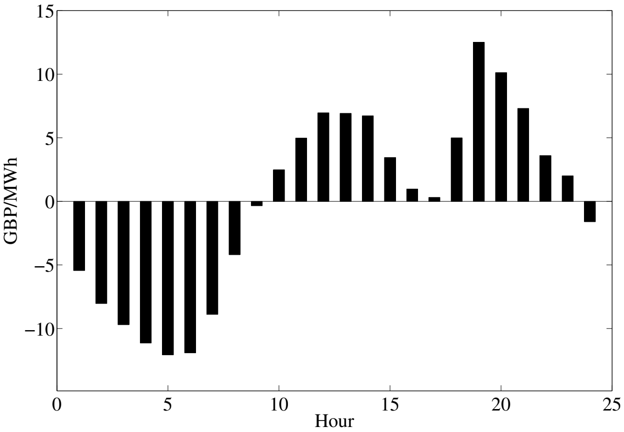

Figure B.12: The hourly STSC for the spot price.

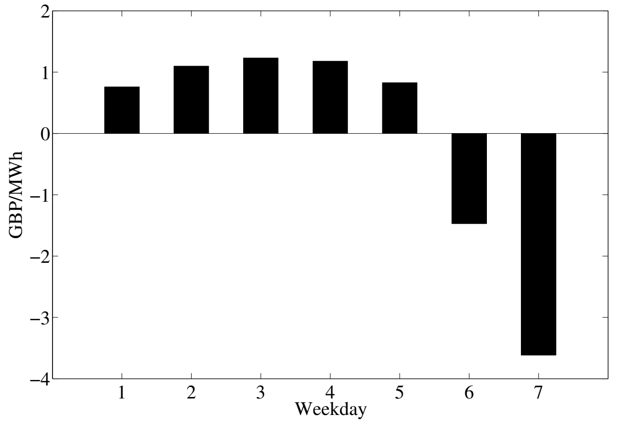

Figure B.13: The weekly STSC for the spot price.

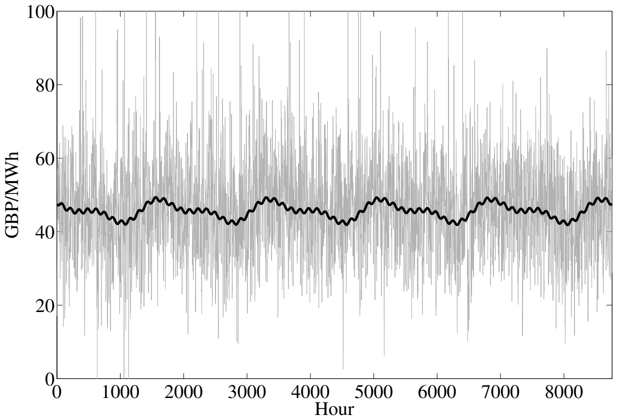

Figure B.14: The LTSC for the spot price.

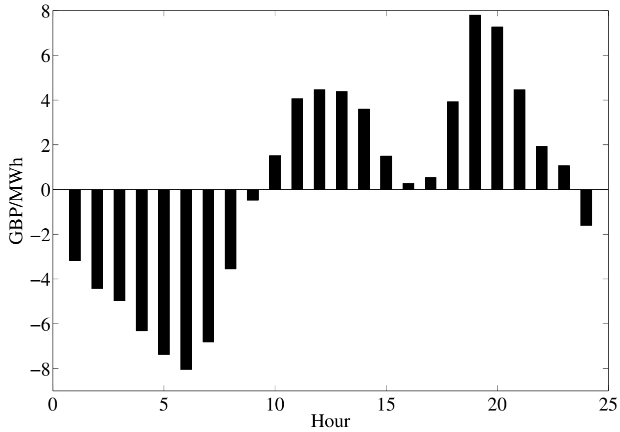

Figure B.15: The hourly STSC for the balancing price.

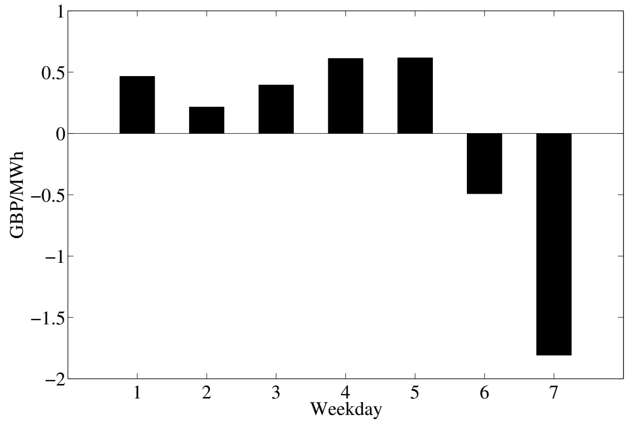

Figure B.16: The weekly STSC for the balancing price.

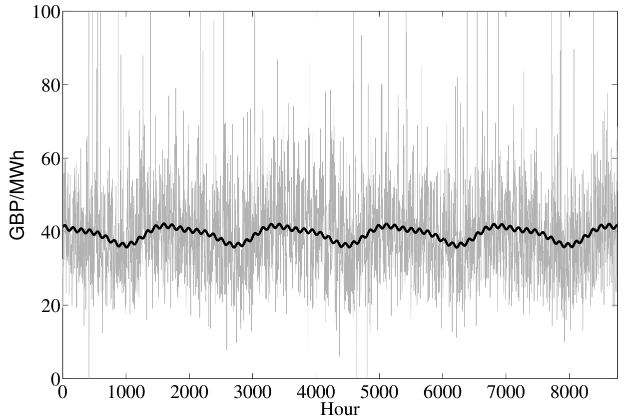

Figure B.17: The LTSC for the balancing price.

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