Benefits of local electrical energy storage for a distribution system operator

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Benefits of local electrical energy storage for a distribution system operator

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Acknowledgements

After using slightly more time for graduating than is indicated by the number of ECTS rewarded for this project, I can say that this is the end of a very nice chapter in my life. I have to thank many people for making my time in Delft enjoyable, but here I limit myself to my thesis.

The first step in any graduation project is the decision on a topic. For me, this topic was easily determined - anything contributing to the energy transition. Energy has increasingly gotten my interest during my time in Delft. I find it fascinating that everyone relies on a continuous availability of energy, yet only a few can fully grasp the complexity of the energy system.

I find the role of system operators in this matter interesting, as they possess an unique position for contributing to the energy transition. Therefore, I went to Stedin to talk about their ideas regarding the role of DSOs. Already in the first conversation, we were able to agree on a topic - the topic of this research.

Stedin - and especially the Strategy & Innovation team - has provided me with valuable insights, unique datasets, but most importantly with a very nice group of people. Henri, I want to thank you for supporting me, introducing me to the right people, and for stimulating me to be critical towards my own work and the work of others.

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I certainly learned a lot during this thesis. I hope others find it valuable to read as well and enjoy reading it.

M.E. (Mark) Klein Entink

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Executive Summary

Introduction In recent reports the Dutch network operators come to a number of conclusions regarding the electricity system and more specifically the distribution system. First of all, a strong increase in electricity demand is envisaged due to usage for heat and mobility. A trend that is already visible and that is expected to increase rapidly in the near future. Second, local production of electricity (e.g. solar panels) is already really taking off and will grow to substantial levels in the coming years. This will not only lead to a changed ratio between central en decentral production of electricity, but also to high peaks in local production that do not coincide with the demand for electricity on local level. Based on these developments local electricity networks have to be prepared for local production and supply of electricity and if possible for smart adjustments between production and supply. Next to that, the network needs to be reinforced to be able to distribute the higher loads related to the increase of electricity demand. Introduction of storage units on local level could limit the investments needed for reinforcements on the distribution system.

Based on these trends, the main research question is formulated as follows:

"What is the value of low-voltage electrical energy storage for a distribution system operator (DSO)?"

Analysing the value of electrical storage, one can distinguish the value of deferring investments in the distribution system on one hand and the possibility to use the storage unit for trading on electricity markets on the other hand. This leads to three subquestions for answering the main research question, being:

1. What is the value of low-voltage electrical energy storage when only used to defer investments by the DSO?
2. On which markets is it possible to trade with low-voltage electricity storage units?
3. What is the value of trading on these markets with low-voltage electricity storage, constrained by the usage by the DSO?

Methodology In line with the research questions a distinction has been made in the approach between the research on the possibility to defer investments in the distribution system and an analysis of the different electricity trading markets and the possibility of trading on these markets with low-voltage storage units.

For the first part of the research an analysis has been made of the demand pattern and peak pattern of five types of neighbourhoods, varying from 100% residential to nearly 100% non-residential connections. Insight in these patterns is required as they define the capacity that is needed in substations, which transform the electricity from 10 kV (medium-voltage) to 400 V (low-voltage) for neighbourhoods. Next to that, the development of electricity demand is investigated, based on scenarios as used within Stedin. Combining these two aspects gives insight in the expected deferral time for investments in substations. Furthermore, the required investments are estimated and by using the NPV method these deferred investments are translated into a value for the DSO.

For the second part of the research an analysis has been made of the six Dutch markets on which electricity is traded. This analysis also included the possibility to trade on that markets with low-voltage storage units. From this analysis it appears that two markets offer opportunities, being the Day-ahead market and the Secondary Reserve market. For these market a trading model has been developed that was tested on a trading period of one year for validation reasons.
This model is then used to determine the value of trading on mentioned markets with low-voltage electricity storage units.

Conclusions The main conclusion of the research carried out is that at this point in time the value of low-voltage electrical energy storage, obtained by deferral of investments and the use of storage facilities for trading purposes, does not outweigh the costs of these facilities (batteries). However, with the expected price developments of batteries the break-even point might come in sight in the next 5 to 10 years.

An analysis on demand pattern and peak pattern has been carried out for five different neighbourhoods. The outcome of this analysis shows that existing substations, the critical items in the low-voltage network in terms of capacity, are used at the moment at between 50% and 75% of their maximum capacity and hence still have spare capacity for future growth of electricity demand. This not only applies to the five neighbourhoods investigated, but also to approximately 45% of all substations in Stedin's network.

Growth scenarios as used by Stedin, taking into account further growth of electricity demand due to usage for heating and mobility, show that the five neighbourhoods reach their maximum capacity somewhere between 2022 and 2032. From that point in time the investment in new transformers can be deferred by installing storage capacity (batteries) to cover for peak load. For how long investments can be deferred depends on the existing load pattern and the growth scenarios. Future changes in load pattern have not been taken into account. Per neighbourhood the deferral time is determined and typically is between 2 and 7 years.

The investment costs for new transformers are in the order of magnitude of €50.000 per substation. Deferring these costs for the given deferral time leads to a value that has been calculated using the NPV method with a discount rate of 5% to 10%. The maximum "savings" that can be obtained are in the range of €24.000 to €37.000 and are still well below the investment costs of batteries, that are in the order of magnitude of €100.000. Figures vary per neighbourhood, depending on actual load pattern and type of consumers (residential or non-residential). The conclusion for research subquestion one is that using storage facilities solely for deferral of network investments does not create a positive business case.

The storage units (batteries) can also be used for trading on the electricity market and by doing so can add value to the overall business case. There are six electricity markets in the Netherlands and from the analysis of these markets it is concluded that two markets offer possibilities for trading with local storage units, being the Day-Ahead market and the Secondary Reserve market. For the Day-Ahead the minimum power offered is 100 kW. This threshold has been taken into account in the design of the storage units. For the Secondary Reserve market there are no limitations for trading.

In order to simulate the trading on these markets a regression analysis has been carried out on real market prices for a period of one year. The outcome of the analysis shows an explained variance of 66%, which is considered accurate enough for the purpose of this research. Furthermore, a trading model has been developed, using the outcome of the regression analysis, to calculate the value of trading with the storage units in the different neighbourhoods. These calculations show a value ranging from €5.500 to €16.600 for the different neighbourhoods, depending on the availability of spare capacity. In these calculations the constraints for trading, due to the fact that storage is first used by the DSO for peak demand, has been taken into account.

The combined value of deferral of investment plus the value of trading show a bandwidth of €30.000 to €51.000, which still does not outweigh the costs of storage units. In the best case, just below 50% of the investment costs can be covered by the value created. The prices of batteries however are expected, by both the industry and science, to decrease by approximately 50% in 2025, compared to 2014. This would bring a break-even within reach for certain neighbourhoods. Further usage of the storage units for system services or locally balancing the network, as local production of electricity by solar panels will increase, could create an additional values for the business case.

Next to conclusions for the business case of low-voltage storage, also conclusions regarding the scientific added value can be drawn. The scientific added value of this research lies on one hand in the development of a quantitative methodology for adjusting the design of the storage unit to the load characteristics in a specific neighbourhood. The analysed load characteristics of different neighbourhood types in this research can also be used for the determination of other benefits of local storage units. On the other hand, the scientific added value lies in developing an methodology for combined and related calculation of values created by both deferral of investment and trading on electricity markets. This novel methodology is applicable for other benefits of storage as well.

Recommendations From this research a number of recommendations have been formulated:

1. More insight is required in actual load profiles and demand pattern. Obtaining these data is now hampered due to privacy reasons. It is recommended to develop a mechanism that can obtain, store and analyse information in an anonymous way. This becomes even more important as local production will increase and will change existing load profiles.

2. The price level of batteries (or other mechanisms for storage) play an important role in the value analysis and is expected to go down substantially in the near future. It is therefore recommended to monitor this development closely and define a price level that would justify a pilot.

3. Define and develop a pilot for the most beneficial neighbourhoods to gain experience with local low-voltage electricity storage, that can be started as soon as certain conditions are met (e.g. price level batteries).

4. Initiate further research towards additional values that can be created with the storage units. These values can be either for the government (system services) or for consumers (storing locally produced electricity).

5. Further testing of the decision logic behind the trading algorithm in order to increase the reliability of the trading value and optimize the value of trading, taking into account future electricity price developments.

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List of Abbreviations

Abbreviation	**Meaning**
ACF	Auto-Correlation Function
APX	Amsterdam Power Exchange
BRP	Balance Responsible Party
DER	Distributed Energy Resource
DSO	Distribution System Operator
EES	Electrical Energy Storage
ENTSO-E	European Network for Transmission System Operators
GWh	Giga Watt hour
HHI	Herfindahl-Hirschman Index
Hz	Hertz
kV	kilo Volt
kVA	kilo Volt Ampere
kWh	kilo Watt hour
kW	kilo Watt
MW	Mega Watt
MWh	Mega Watt hour
NPV	Net Present Value
ODS	Optimal Dispatch Strategy
PACF	Partial Auto-Correlation Function
PCR	Primary Control Reserve
PTU	Program-Time Unit
PV	Photovoltaic
RSE	Relative Standard Error
SCR	Secondary Control Reserve
SPSS	Statistical Package for the Social Sciences
TCR	Tertiary Control Reserve
T&D	Transmission & Distribution
TSO	Transmission System Operator
V	Volt
VPP	Virtual Power Plant

1 | Introduction

This introductory chapter will concisely cover trends in the electricity system, the problem statement, the research questions, relevance, goal, and outline for this thesis.

1.1 Trends in the electricity system

During the last decade, the share of renewable sources in the world's electricity supply has significantly increased. With this increase, both central and decentral, the intermittent character of the electricity system also becomes more present. In order to keep an affordable and reliable system, extra flexibility is needed. Many experts in this field argue that storage of electricity would be a suitable option for this flexibility.

In a report supported by all Dutch network operators, a number of conclusions were drawn regarding the future scenarios for the electricity system. One of them is that the local demand for electricity will know a strong increase because of substitution for heat and mobility. Regarding the production of electricity, the conclusion is drawn that the fluctuations in supply will increase because of renewable sources. Decentral production will increase and therefore decrease the demand for central production. Decentral production has high peaks which do not coincide with the demand for electricity. Therefore, also a demand for central reserve-capacity will still be present (Netbeheer Nederland, 2011).

Some forecasts for the development of networks are made in the same report. Local networks have to be prepared for both supply and local production, as well as for smart adjustment of supply and demand. Next to that a reinforcement of capacity is needed, since the load will increase. However, if the supply and demand can be adjusted smartly, this reinforcement can be limited. This smart adjustment requires significant modification and acceptation on the consumer-level. This entails both investments in electricity storage and demand response management. The reinforcement of local networks requires a reinforcement of regional networks as well (Netbeheer Nederland, 2011).

Research towards the benefits of storage facilities in the electricity system have shown that using distributed storage systems can reduce costs for households (Ahlert and Block, 2010), that in-house electricity storage can reduce load (Klaassen et al., 2014), and that electrical energy storage (EES) can act as a normal reserve (Zakeri and Syri, 2014). The current available technologies can be divided into five categories: pumped hydro, compressed air energy storage, battery energy storage (multiple types), flywheel energy storage, and hydrogen-based storage (Zakeri and Syri, 2015). Behnam Zakeri and Sanna Syri have made a comprehensive overview of electrical energy storage technologies, both in terms of technical characteristics and costs. They based their findings on 27 different research projects towards electrical energy storage (Zakeri and Syri, 2015). Each of these technologies have their own characteristics which influence the usability of these technologies for different goals. Apart from the goal for which different storage technologies can be used, there must be a solid 'business case' before any organisation will invest in a storage facility.

In general, the business case of local electrical energy storage consists on one hand of income that could be generated from trading on electricity markets, and on the other hand of benefits from system services that could be performed. According to Eurelectric (Union of the Electricity Industry), the system services include anti-islanding operation, islanding operation, frequency control, security congestion management, firm capacity management, power quality management, and demand side management (Eurelectric, 2012). Moreover, these two elements of the business case do not necessarily exclude each other.

A distribution system operator (DSO) would most likely invest in local storage primarily to defer network investments. However, as stated by James Eyer and his colleagues, in many cases local demand peaks coincide with system peak demand. Moreover, there are most likely only a few hours per year when power is needed to defer network investments, which means that in the remaining hours storage mechanisms could be used for energy trading (Eyer et al., 2004). In another research, James Eyer concluded that a suitable next step in this field of research is to tailor the storage design to specific circumstances. This could be done by taking historic data and expectations for the development of demand (Eyer et al., 2005). In other words, Eyer and his colleagues conclude that a (quantitative) model would be an appropriate method.

1.2 Problem statement

The situation that leads to the problem is an expected growth of peak-demand for electricity, in combination with the legal obligation for distribution system operators to always be able to deliver electricity. Networks are often not designed on the maximum demand per household multiplied by the number of households in a specific area. The design is done with a so-called "simultaneity factor", which indicates the amount of households that are simultaneously demanding their maximum amount (determined by the grid connection they have). If however the amount of for example electric vehicles and electric stoves increase, this "simultaneity factor" probably will change - meaning that the DSO has to increase network capacity.

Distribution system operators are stimulated in the Netherlands to be economically efficient, for example by the RPI-X regulation (Haffner, 2010). Therefore, a DSO wants to keep investments in network capacity as low as possible, without loss of security of supply. Within this line of reasoning, local storage of electricity could be an alternative for investing in the grid (e.g. in transformers and cables). It is however unclear whether a local storage unit is a better investment than a new transformer and/or cable. It could also be beneficial for a distribution system operator to defer the investment in grid capacity using local storage units.

Next to this benefit, Eurelectric (Eurelectric, 2012) describes three other short-term benefits. These benefits are reliability and stability, providing interim power, and short-term flexibility. Eurelectric stresses that the short-term benefits help to devise a strategy for achieving the long-term goal, which is the development of a smart grid.

However, as stated before, a DSO is likely to invest only if the net present value (NPV) is positive. The value of the mentioned benefits of storage is unclear, and requires clarification to enable a DSO to take an substantiated decision in this respect. The problem statement is therefore:

"The value of low-voltage electrical energy storage, when primarily used for deferral of network investments and secondarily for other short-term benefits, is unclear"

1.3 Research question and subquestions

The problem statement leads to the following research question:

"What is the value of low-voltage electrical energy storage for a distribution system operator?"

In order to answer this main research question, three subquestions have been defined:

1. What is the value of low-voltage electrical storage when only used to defer network investments by the DSO?
2. On which markets is it possible to trade electricity with low-voltage electricity storage unit?
3. What is the value of trading on these markets with low-voltage electricity storage, constrained by the usage by the DSO?

A number of explanations are needed because of these questions. In the first place, the research question consists of three main elements: value, low-voltage storage, and distribution system operator. All these elements need a definition. Next to that, the second and third subquestion limit the scope of this research to a specific value of storage. This scope will be explained as well.

A distribution system operator (DSO) in the Netherlands is responsible for the medium- and low-voltage electricity grid (and often also the natural gas network, but that is not part of this research). Whilst there is only one transmission system operator in the Netherlands (TenneT - responsible for the high-voltage grid), there are multiple DSOs. Each of them own a specific part of the grid and are in their area responsible for the safety and reliability of the distribution. A DSO is also responsible for installing new grid connections and for checking the consumption (Ombudsman Energie, 2016).
An important legal limitation of the activities of a DSO is caused by the unbundling of the electricity sector. This separates the network operation from the production, delivery, and trade of electricity (NMa, 2006).

The second main element of the research question is low-voltage storage. This means a storage unit connected to the low-voltage electricity grid after the transformer. The low-voltage grid has a current of approximately 400 V.

1.4 Social and scientific relevance

The social relevance of this research lies in the first place in the role that storage plays in the energy transition and in the insights created for DSOs. This research starts by giving an overview of the potential benefits of local storage (decentralized storage) in the research framework (chapter 2). One of the consequences of the energy transition is a growing (peak) demand for electricity. All stakeholders in the value chain of electricity (production - transport - distribution - consumption) have to cope with this growth, preferably in an (economically) efficient way. Storage is considered an alternative compared to reinforcement of the network for coping with this growth, and this research provides insight in the economic efficiency of using storage. This means that the benefits of deferring network investments are compared to the costs of installing storage units.
This research creates a decision framework for DSOs for future investments, indicating when storage is likely to reach a break-even point in terms of benefits and costs. When the break-even point is reached, this research can be used as a base for designing the storage units in terms of location (which neighbourhood), placement (location in specific neighbourhood), capacity, and power.

The second social relevance is for electricity traders. This relevance for traders consists of two elements. The first element is an analysis of the Dutch electricity markets, including an overview of prerequisites for entering these markets. This analysis ex-

plains how these electricity markets function and what their characteristics are. This is especially beneficial for organizations that are considering to commence in electricity trading.
The second element is the statistical analysis of two Dutch electricity markets (only these two are accessible for storage units), resulting in the design of a trading algorithm. This analysis and the design of the trading algorithm can help incumbent traders to understand electricity markets better and potentially to further optimize their trading algorithms.

The scientific relevance of this research can also be divided into two main contributions. The first contribution is the development of a quantitative methodology for adjusting the design of the storage unit to the load characteristics in a specific neighbourhood. Data of load profiles on such decentralized level in the electricity system was not available (in the Netherlands) before as DSOs are not allowed to store this data for privacy reasons. This data has recently become available and this research uses that data for the calculation of the benefits of deferral of investments. This approach can be used for other benefits of storage as well. Moreover, the method developed and used in this research is one of the first to quantify the value of deferral of investments in the distribution network.
The second contribution in developing an methodology for combined and related calculation of values created by both deferral of investment and trading on electricity markets. In the first place, multiple scientific papers on trading on electricity markets are combined to develop a trading algorithm and to assess the value of trading with storage units. Second, this trading value is constrained by the usage of the DSO (for covering peak demand), which means that the storage unit is sometimes not available for trading. This creates a value of local storage units that consists of both the benefit of deferral of investments and of the benefits of trading.

1.5 Research goal

The goal of this research is to create insights in the value of local storage based on a holistic and quantitative approach. The goal is to give a substantiated order of magnitude for the value of local storage, which creates a basis for further research to quantify more exact values.
The approach used in this research has two goals. In the first place it should serve as a decision framework for DSOs to take further steps regarding using storage units in their operations. Second, the methodology should be useable for the calculation other benefits of storage as well.
Compared to the existing research on this subject, this research takes a step further in quantifying the research that has been done so far in this field and be a stepping stone for future research to add more benefits and/or further detail the methodology.

As this research was conducted in cooperation with Stedin, a Dutch DSO, another goal is to provide them with valuable insights.

1.6 Outline

The outline of this research is as follows. In chapter 2 the research framework and methodology are described. In chapter 3 a storage unit is designed for five different neighbourhoods. Chapter 4 gives an overview of the Dutch electricity markets and their short-term forecastability. Chapter 5 describes how a trading algorithm can be designed based on the analysis in chapter 4, and in chapter 5 this trading algorithm is also modelled in R (statistical software package) and tested. Chapter 6 covers the conclusions and recommendations.

Figure 1.1 gives an overview of the outline of this research. This figure clearly indicates the two storylines of this research. This research delivers two different values, namely the value for the DSO and the value of trading.

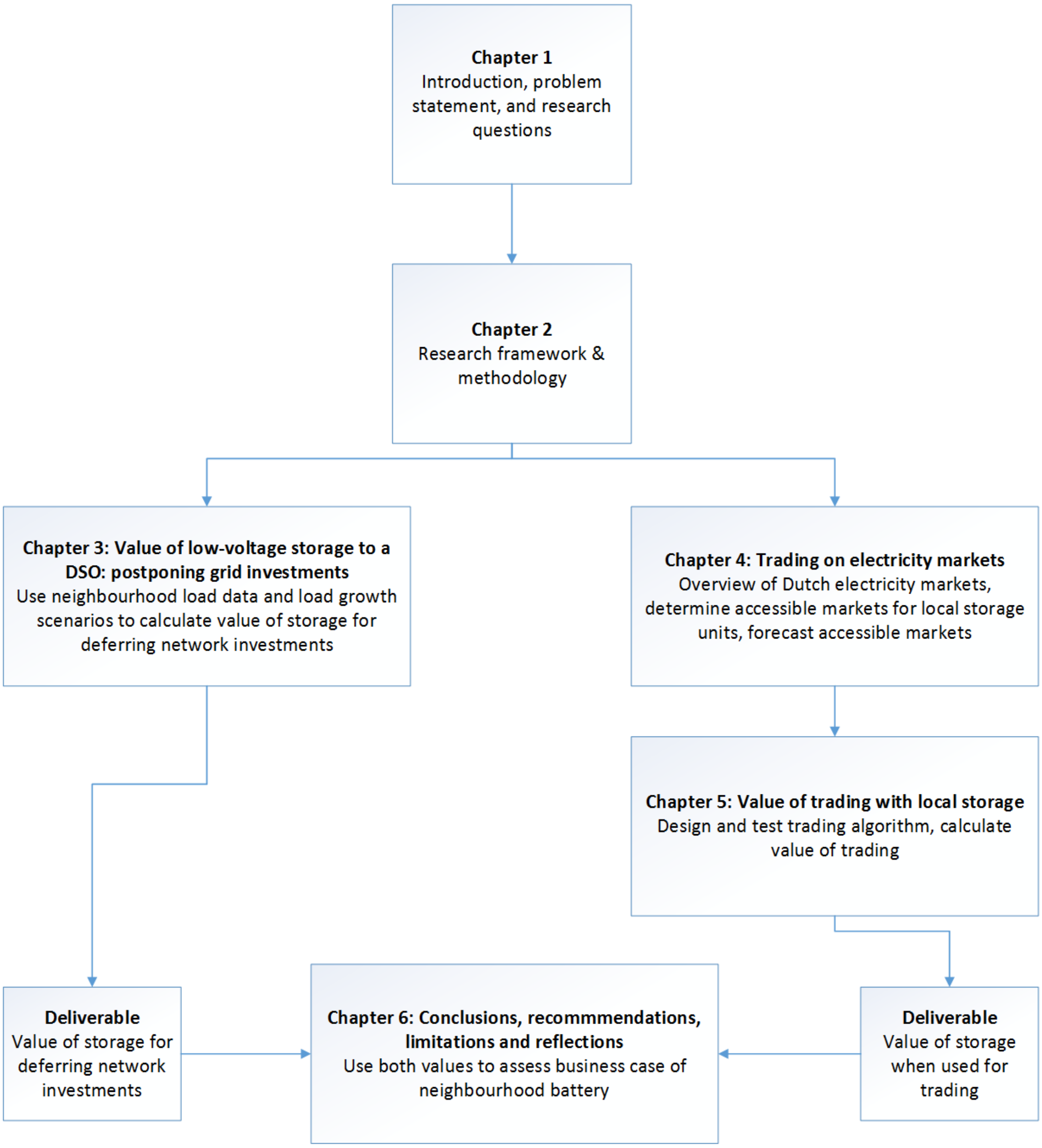

Figure 1.1: Outline of this research

2 Research framework and methodology

The previous chapter described the situation, problem statement, and research questions. This chapter describes the framework and methodology used throughout this research. This increases the scientific value of the research and creates more structure for the used analyses.

2.1 Framework

The Dutch electricity system is originally a central-oriented system; centralized production units deliver electricity via transmission and distribution networks to the end consumer. However, in the last decade, a more decentralised view has been developed among scientists but also among multiple industries. Consumers changed to prosumers, meaning that they also produce electricity instead of solely consuming electricity, and the growth in consumer-owned solar power is significant. This creates possibilities to supply electricity on a local scale. Next to that an increasing demand for electricity is expected due to usage for heating and mobility. Network operators foresee challenges in their operations, as they need to cope with (expected) higher peak demands. Especially DSOs have to cope with these demands.

The traditional approach of DSOs is to linearly increase their network capacity with the (forecasted) peak demand. If a certain area is expected to reach its maximum capacity in the next year(s), the transformers and distribution lines are replaced with equipment with higher capacity. However, DSOs are currently exploring alternatives for this traditional approach. One of these alternatives is installing local storage units to defer these traditional investments in their grid capacity. Among scientists this is referred to as "Deferral investments T&D" (transmission & distribution assets).

More and more scientists and policy makers look at these local storage units in a broader context, meaning that they acknowledge other benefits as well. A comprehensive overview of these benefits is made by the Union of the Electricity Industry (Eurelectric, 2012). Eurelectric represents the common interest of the electricity industry at pan-European level. The research was executed by 17 members of Eurelectric, originating from nine different countries. This overview can be found in figure 2.1.

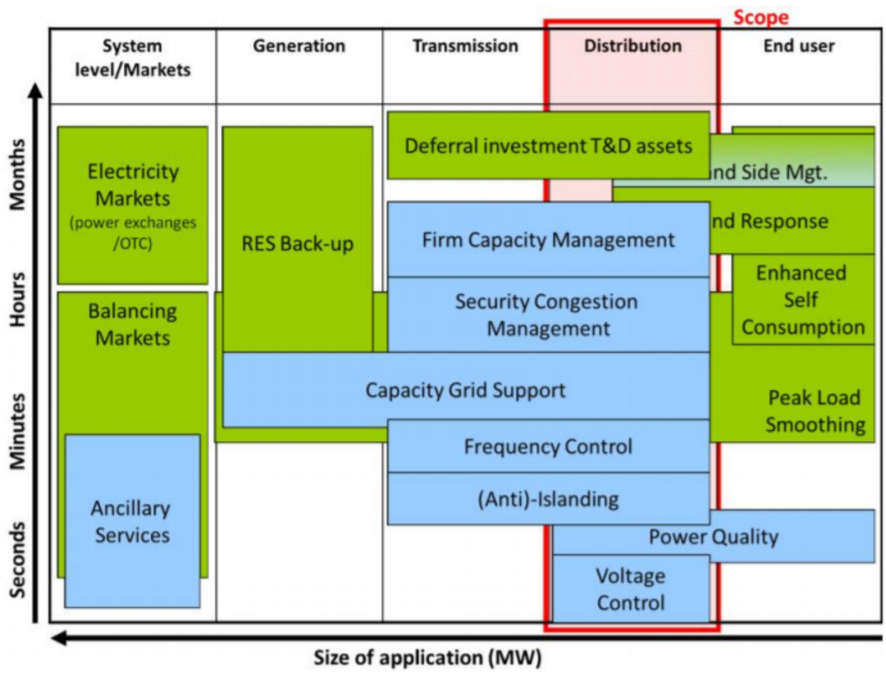

Figure 2.1: Overview of benefits of local storage (Eurelectric, 2012)

The green elements of this chart represent the Energy Management benefits, defined as *"Decoupling the generation of electricity from its instantaneous consumption"*. The blue elements represent the System Services, defined as *"Any service that is able to improve and support the quality of service and the security of supply in the electric power system"*(Eurelectric, 2012).

As this research is carried in cooperation with Stedin, a Dutch DSO, the first subject for research is the deferral of investment in T&D assets, and specifically the distribution assets.

Jim Eyer (2009) states that *"In simplest terms, the T&D deferral benefit is the avoided cost — the cost not incurred by utility ratepayers if the T&D upgrade is not made."*. He continues by saying that the distributed energy resources (DER) are well-suited in the following circumstances:
"1. Peak demand on a T&D node is at or near the T&D equipment's load carrying capacity (limit) - resulting in a "hot spot", and
2. A relatively small amount of DER capacity located downstream (electrically) from the hot spot can serve a portion of peak demand, on the margin, such that an upgrade of the T&D equipment is deferrable"(Eyer, 2009)

From these findings, it can be concluded that taking local characteristics into account is required to come to optimal solutions. Therefore, this research proposes a new method for valuing T&D deferral by local storage units. This new method is based on a design of the storage units tailored to the load profile in a specific neighbourhood. The possibility for this new method arises from newly available data about the load in specific neighbourhoods. By law, DSOs are not allowed to store load data. However, in the Netherlands, a number of projects are started recently where the DSO has permission to store this load data. Based on information of these projects the design of storage units is now possible. This enables more fact based and accurate conclusions about the benefits of storage units used for T&D deferral.

Other research towards the value of distributed energy resources for T&D deferral has been done as well by Gil and Joos (2006). They were one of the first to quantify the value of network capacity deferral. Their research focussed on distributed generation as means of deferral. Using the net present value calculation method, Gil and Joos came to the conclusion that the benefits of deferral depends on the timing of the planned or scheduled upgrades (Gil and Joos, 2006). Zhang et al. (2010) used the same method to evaluate the investment deferral caused by microgeneration for extra high voltage distribution networks. Although the application differs, the applied method for calculating the benefits is the same - which is net present value. Also Zhang et al. come to the conclusion that the location of microgeneration is of significant importance to the benefits of that microgeneration (Zhang et al., 2010).

In 2016, Farah Abi Morshed in her thesis also uses net present value calculations to determine the value of deferral of grid reinforcement by using demand-side flexibility (Morshed, 2016). She concludes that flexibility steering can on average postpone grid investment by 2 years. She does state that if grid investment postponement is feasible from a technical perspective, it does not necessarily mean that it is advisable from a financial perspective. Based on the outcomes of her analyses, she made the following conclusions (Morshed, 2016):
"1. The financial savings of grid investment postponement by means of demand-side flexibility is highly sensitive to the grid investment cost per kVA per household. Thus, savings from grid investments might be more significant in rural areas in comparison to urban areas.
2. The financial savings of grid investment postponement for the DSO are more signficant in large districts in comparison to small streets because in the former, more investments are needed to upgrade the city grid and its components.
3. Financial savings are more significant in areas where congestion is occasional and temporary, in comparison to areas where congestion is persistent and severe, because in the latter high flexibility ordering leads to high cost incurred that will probably outweigh savings gained from grid investment postponement."

Morshed's research proves once more that the location of DERs significantly influences the benefit. In summary of all of the above-mentioned research projects, three aspects become clear:

1. **Local stored electricity can have a value for DSOs in terms of deferral of grid investments;**
2. **Different locations of distributed energy resources in the grid can have significantly different benefits;**
3. **The net present value method seems to be the most accepted method for calculating the value of deferral of T&D investments.**

The new research carried out in the framework of this thesis, incorporates and further develops these three aspects. The design of the storage unit is tailored to specific neighbourhoods, meaning that locational effects are incorporated in the value. Moreover, this research uses the accepted NPV-valuation to actually calculate the value of distributed storage, which has not been done before. This represents the first research question of this thesis.

The methodology described above is believed to be applicable to other benefits shown in the figure 2.1 as well in the field of System Services (e.g. capacity management, congestion management, frequency control, etc.). These benefits are shown on the vertical axis in the diagram of figure 2.1 in the distribution column. However, this research has not further investigated these benefits, but has taken another route, looking at the possibilities and benefits on the horizontal axis. As local storage for peak demand is only utilized for a limited number of hours per day and has a seasonal pattern, there is remaining capacity that can be used for trading on the electricity market. Therefore, the second part of this research is focussed on the possibilities of local storage units on electricity markets. This includes research towards the accessibility of markets and the value that can be obtained, taking into account the fact that storage is primarily meant to be used by the DSO for peak demand.

As said in the introduction of this paragraph, the electricity system is originally a central-oriented system. The centralised production mostly consists of large power plants (coal and gas) and large wind farms. Decentralised energy resources have significantly less power and capacity. However, the electricity markets are designed for the large power plants. This is confirmed by the European Commission who reports a high market concentration, with the three largest electricity companies covering 83% of the retail market in 2012. The Herfindahl-Hirschman Index (HHI), a commonly accepted measure of market concentration, was 2.338 (European Commission, 2014). A market with an HHI higher than 1800 is considered highly concentrated (Diallo, 2015). One of the new developments in the Netherlands is a market for smaller power outputs, named Energy Trading Platform Amsterdam (ETPA). This development shows that there is a demand for a market place for smaller producers.

Witteveen (2016) described the Dutch secondary reserve capacity market as a monopsony, which is a single-buyer market. One of his conclusions is that *"The presumed entering of an additional producer in the market has a profound effect on the procurement cost for the TenneT, as the entering of an additional producer decreased the procurement with approximately 33 percent. This demonstrates how much there is to gain (and lose) with respect to the amount of competition in this market"* (Witteveen, 2016). From a consumer-perspective, it would therefore be economically beneficial when an additional producer would enter this market. However, the incumbent producers would most likely not be too happy with that. Next to the likely unwillingness of incumbent producers for an additional producer to enter the market, TenneT also put up a number of more technical entry prerequisites for trading. In this research, an overview of these prerequisites is made based and elaborated upon in chapter 4.

Research towards actual trading on electricity markets with a distributed energy resource (DER) has been done before. For example Bai et al. (2015) looked at an Optimal Dispatch Strategy (ODS) for a Virtual Power Plant (VPP). A VPP aggregates DERs and can thereby take part in the electricity market in the form of a single plant (Bai et al., 2015).

In another study, Xi et al (2013) concluded that there are *"numerous issues and nuances of storage that are not well addressed"* by literature. They give three issues:
1) Most literature only considers one storage application instead of co-optimizing multiple storage values;
2) The negligence of price and system uncertainty;
3) Most literature considers 'utility-scale' storage, meaning hundreds of MW. (Xi et al., 2013)

They therefore describe an *"SDP* (stochastic dynamic program) *model that co-optimizes multiple storage applications while accounting for market and system uncertainty"*. Their model is hour-based and incorporates their mentioned uncertainty. However, the amount of uncertainty incorporated in their model is limited (Xi et al., 2013). Other authors in this field also use an optimization algorithm, with or without a small amount of uncertainty. Using an optimization algorithm means that the authors assume perfect knowledge about future electricity prices. This research avoids making that assumption by developing a forecasting algorithm for the electricity prices based on forecasted demand. The model and input variables are based on prior research and elaborated upon later in this paragraph.

Models for forecasting electricity prices have been made in literature. Rafal Weron (2014) made an overview of electricity price models he found in literature and came to five categories: Multi-Agent, Fundamental, Reduced-form, Statistical, and Computational

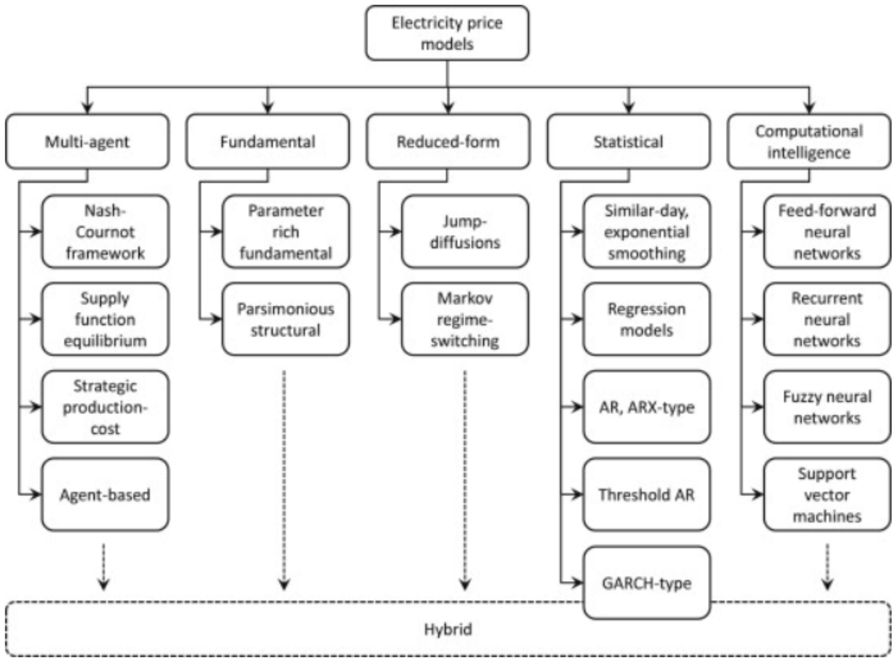

Figure 2.2: Overview of electricity price models (Weron, 2014)

Intelligence. All the categories contain multiple subcategories. This is shown in figure 2.2.

This thesis is not aimed at evaluating all electricity price models, but to generate a valid estimate of the value of trading. Therefore, only the "Statistical category" is used. For this category, Weron concludes that *"While the efficiency and usefulness of technical analysis (statistical models) in financial markets is often questioned, the methods stand a better chance in power markets, because of the seasonality prevailing in electricity prices processes during normal, non-spiky periods"* (Weron, 2014). Regarding regression models, he states that *"Despite the large number of alternatives, linear regression models are still among the most popular EPF (Electricity Price Forecasting) approaches"* (Weron, 2014). Therefore, a linear regression model is used in this research for developing a trading algorithm. In other research, explanatory variables, used as input for this linear regression model, have been investigated before.

Mulder and Scholtens (2013) investigated numerous possible explanatory variables for the electricity price on the Day-Ahead market. Their research indicated that the variables *demand*, the *gas price*, and *day of the week* have the most explanatory power. They suspected a strong link with the German market, but found that *"conventional power plants remain to be the marginal, price-setting power plants in the Dutch market"*. They do state that their results may be affected by the amount of interconnector capacity available (Mulder, 2013). As their datasets date from 2011, it is worth investigating these relations again. The variables to be taken into account in this research are therefore: *Load forecast* (Both Dutch and German), *Residual load forecast* (Both Dutch and German), *day of the week*, and *month of the year* (e.g. seasonal influence).

In summary of this paragraph, the total framework and contribution of this research is visualized in figure 2.3.

2.2 Methodology

The methodology used in this research in order to answer the research questions is described in this paragraph. A large part of this research has a quantitative character. The methods are discussed per research question. Table 2.1 gives the overview of the methods used in this research to answer the research subquestions and thereby the main research question. The research is divided in a qualitative part and a quantitative part. This methodology is made for the two values to be delivered by this research, of which an comprehensive graph can be found in chapter 1.6. As this research consists of a number of different methodologies, the more detailed description of the steps taken is given at the beginning of each chapter.

	Subquestion	**Method**	**Goal**
Qualitative research	1	Desk analysis	Determine price levels battery & transformer
	2	Literature review & desk analysis	Identify accessible markets
Quantitative research	1	Data analysis;	Design neighbourhood battery
	1	Scenario analysis	Determine deferral time
	2	Statistical analysis (regression)	Forecast electricity prices; Input trading algorithm
	3	Modelling	Testing trading algorithm

Table 2.1: Overview of research methodologies

2.2.1 Research subquestion 1

The first research subquestion, answered in chapter 3, concerns the value of a local storage unit when only used for the DSO, e.g. for deferral of investments in the grid. This question will be partly answered using desk analysis, but for a larger part using data

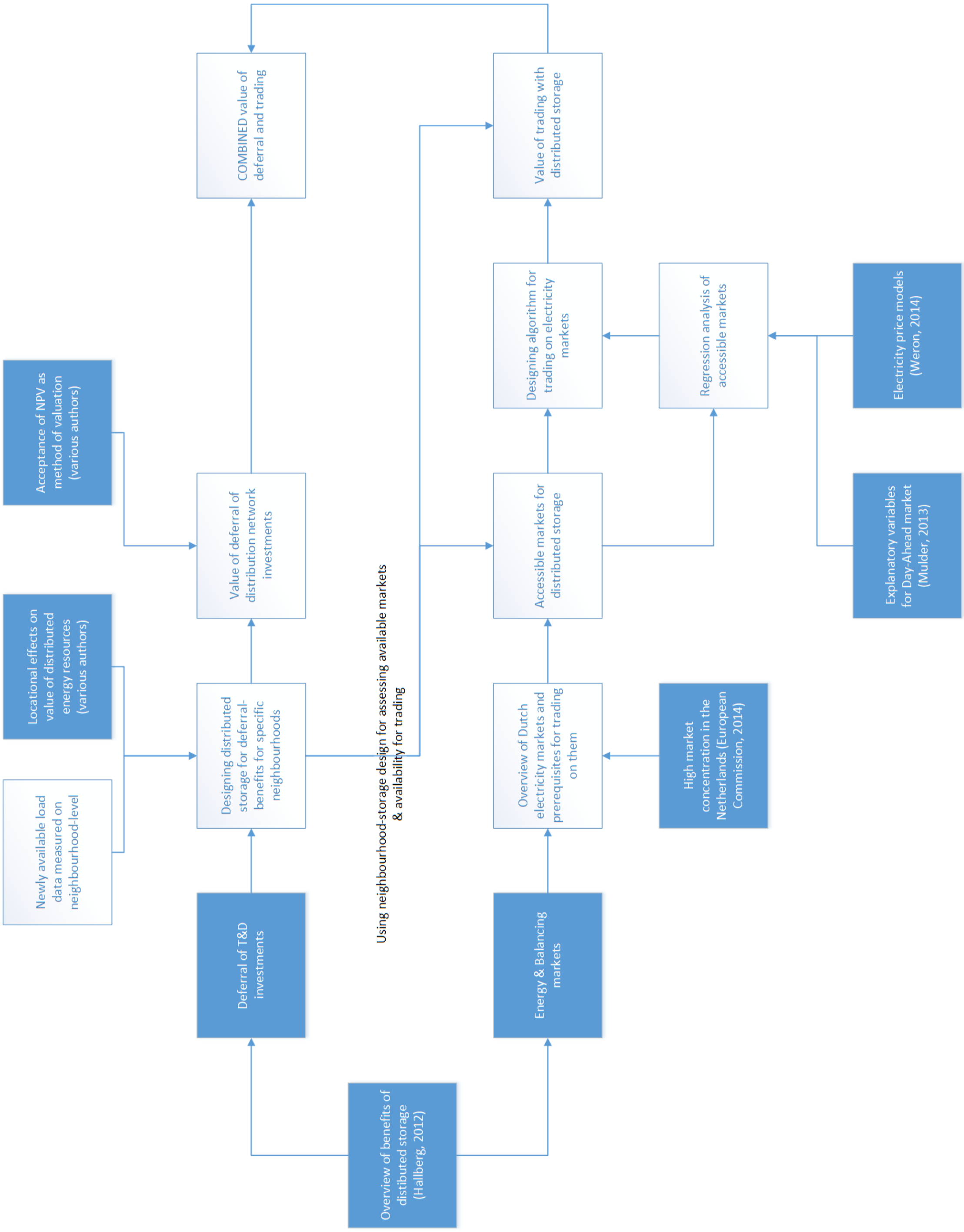

Figure 2.3: Total research framework (Blue elements = from other literature, white elements = contribution of this research)

analysis. The desk analysis is aimed at determining the price of a new transformer and the price of storage unit, given its capacity and power. The data analysis is used for calculating the capacity and power of a storage unit, using the neighbourhood load pattern as input. The storage unit is designed to support the transformer in times of peak demand. Peak demand for the purpose of this research is defined as the demand above the 75$^{\text{th}}$ quantile. Seasonal effect is also incorporated in this analysis. When the storage capacity and power is known, the deferral time of the storage unit can be determined using the growth scenarios defined by Stedin. This deferral time is used in the calculation of the Net Present Value (NPV) combined with the price of a new transformer to determine the value of deferral of investment. This value is then compared to the price of the storage unit. An overview of the method used for research subquestion 1 can be found in figure 2.4.

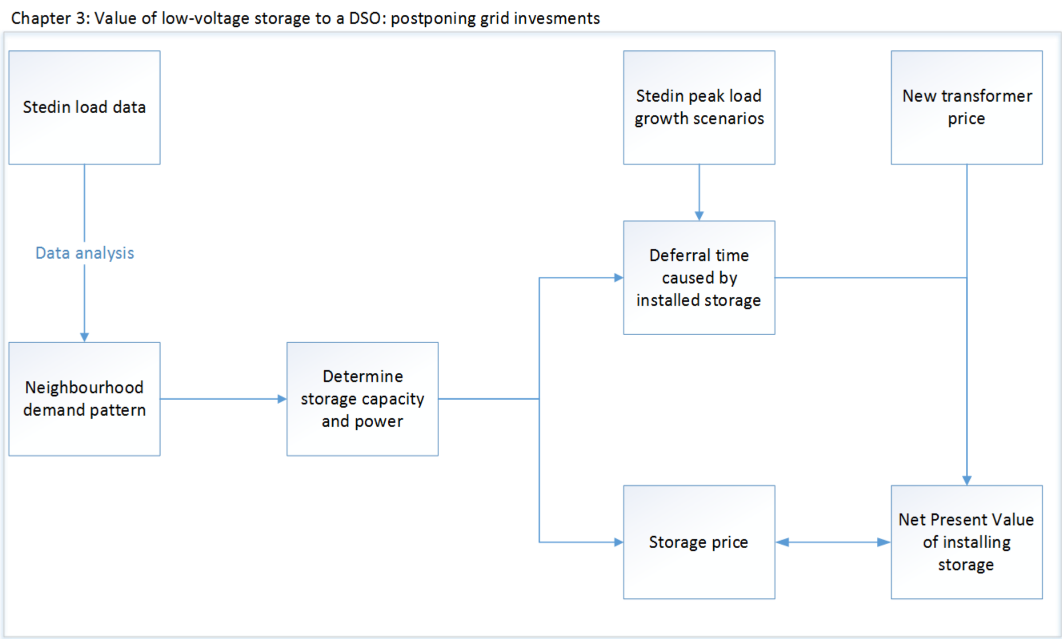

Figure 2.4: Overview of methodology for research subquestion 1

2.2.2 Research subquestion 2

The second research subquestion is aimed at determining the accessibility of electricity markets for local storage units. A literature review on documents provided by TenneT, the Dutch Transmission System Operator (TSO), and documents provided by the European Network of Transmission System Operators for Electricity (ENTSO-E), is used for creating an overview of the Dutch electricity markets. The prerequisites to trade on this market are used to determine the accessible markets for local storage units. The accessible markets are then analysed, using both basic time series analysis and regression modelling. This means that it will be assessed if either time of the day, or an explanatory variable, or combination of both is better to design the trading algorithm. The overview of the steps for research question 2 is given in figure 2.5.

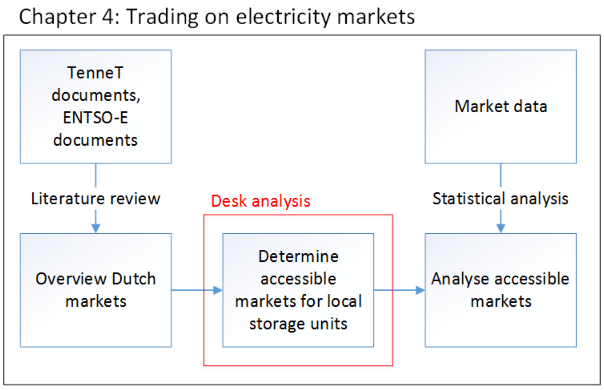

Figure 2.5: Overview of methodology for research subquestion 2

2.2.3 Research subquestion 3

The third subquestion is aimed at determining the value of trading on the accessible markets. The trading algorithm is then designed, based on a decision logic that results from the analysis of the accessible markets. The trading algorithm is implemented and tested in R. The algorithm forecasts the electricity prices based on the parameters from the analysis of the accessible markets. The verification and validation is not aimed at the trading algorithm, but at the testing environment. It is not the goal of this research to create the most optimal trading algorithm - which is an research in itself - but to get an indication what trading with local storage could realize in terms of revenue. It is however important that the trading algorithm is implemented correctly in R (verification) and that the testing environment reflects the environment of a 'real' trader (validation). The overview of the steps for research question 3 is given in figure 2.6.

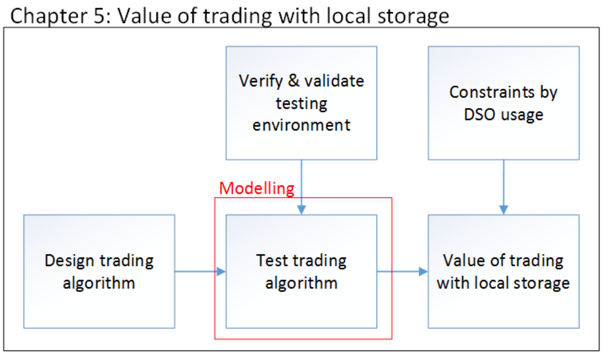

Figure 2.6: Overview of methodology for research subquestion 3

3 | Value of low-voltage storage to a DSO: postponing grid investments

As described in the previous chapters, local storage of electricity has value for a distribution system operator. This value arises from the postponement of grid investments. In this chapter, the value of this postponement of grid investments is determined. This will answer the first research subquestion.

In order to determine the value of postponement of grid investments, a framework is needed. This framework will be based on the netto present value (NPV) calculation method. The calculation of a NPV consists of one or multiple cash flows (C), the timing of the cash flow(s) (t), and the discount rate (r). The formula of the NPV is:

$$NPV = \sum_{i=1}^{n} \frac{C_i}{(1+r)^t} \tag{3.1}$$

This chapter will determine the elements of formula 3.1. First an overview of the Dutch electricity distribution system will be given to indicate where a DSO is able to place storage mechanisms. Thereafter the exact placement in a neighbourhood is described, as locating the storage unit in a neighbourhood proves to be the most suitable (see 3.2.1). These two paragraphs combined determine which components of the grid are being unburdenedd and thereby determine the value of the cash flow.

The timing of the cash flow (t in formula 3.1) is calculated in the paragraph 3.3. This will be done by using scenarios developed by Stedin and using different storage capacities. In paragraph 3.4 the netto present value of postponing grid investments is calculated for different discount rates, and compared to the cost of a battery. In 3.5 the conclusion will be given.

3.1 Description Dutch electricity distribution system

The Dutch electricity distribution system starts at the transformer (high voltage to medium voltage) and ends just before the meter at the consumer. These networks are operated by DSOs, and in the Netherlands, there are six different DSOs, covering various regions.

The main task of these DSOs is to distribute all demanded electricity to end-users. They have to make sure that there is sufficient capacity in the medium-voltage and low-voltage grid to supply this electricity. Figure 3.1 gives a simplified overview of the Dutch electricity system.

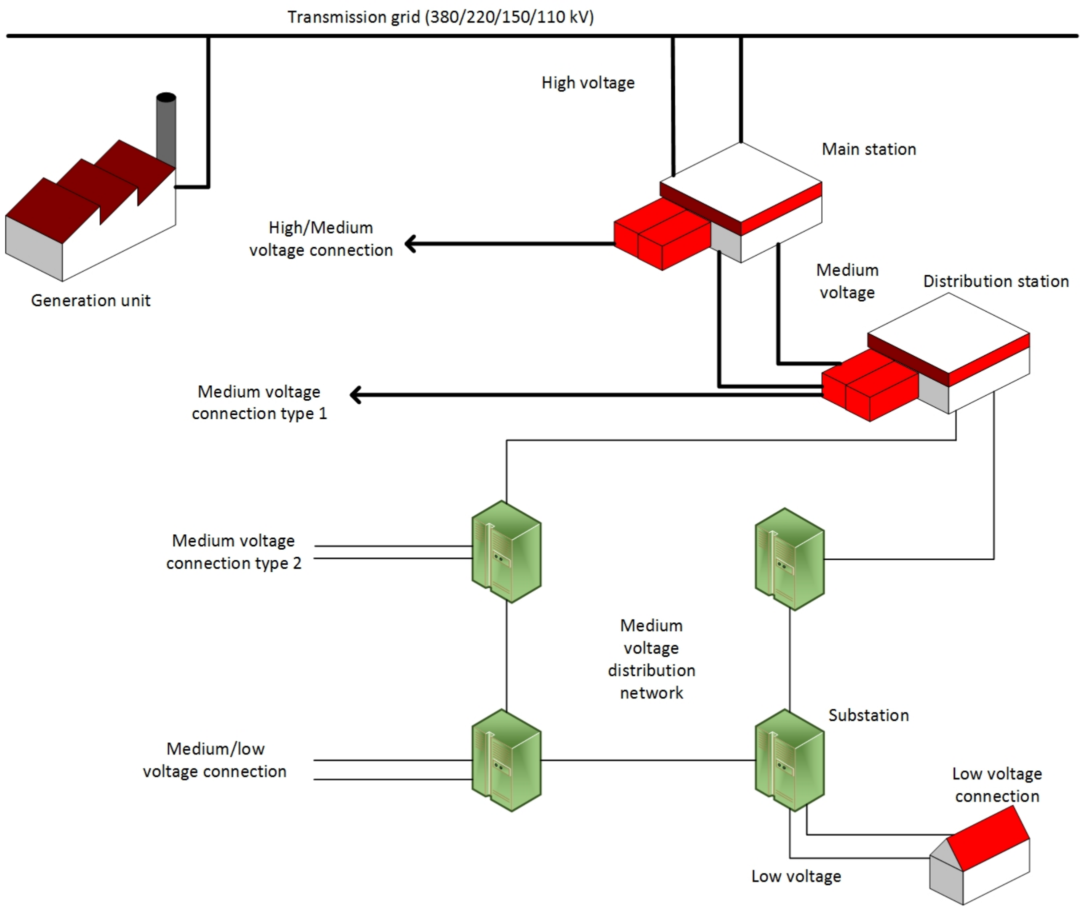

Figure 3.1: Overview of the Dutch electricity system

A generation unit produces electricity, which is transported using the transmission grid operated by TenneT. The voltage is high at this point in order to minimize transmission losses. This high voltage is then transformed into medium voltage at a main station and distributed to a distribution station. The transportation of electricity from the main station to the distribution station is done at 50 kV. At the distribution station, the voltage is decreases to 10 kV, which also classifies as medium voltage. The distribution stations are often located near villages, from where the low voltage lines go into the village. These lines reach local substations, where the electricity is once more transformed, in this case to 400 V. From here, electricity lines reach houses, shops, and small offices.

As can be seen in figure 3.1, there are other possible connections to the electricity grid. These connections are meant for large consumers, such as heavy industry. Another characteristic of the Dutch electricity grid is shown in figure 3.1, being the ring-structure to ensure security of supply. Every part of the network has two 'paths' through which it can be reached. The network that is operated by a distribution system operator starts at the main station and ends at the end-user.

3.2 Design of low-voltage electricity storage for postponing grid investments

For the purpose of this research, two technical design elements of low-voltage electricity storage are of importance: the placement and the size (power and capacity) of the storage. The possible placements of storage units are limited to the network that is operated by the DSO, as the storage unit's main task is to defer investments in the network operated by the DSO. A DSO is able to place a storage unit anywhere in the network between the main station and the low voltage connection (see figure 3.1). However, this research is limiting the placing of the storage unit to the low-voltage grid. This limitation is not without reason: the Asset Management department at Stedin expects that the substations and the underground low-voltage cables will be the first elements of their network to have insufficient capacity in the future. Since they are obliged to ensure sufficient capacity, they have to either replace these substations and cables, or find an alternative for this replacement. Low-voltage electricity storage is considered an alternative.
The size of the storage units depends on their placement (e.g. the network elements that are unburdened) and the time period for which these elements need to be unburdened. This time period also influences the NPV (formula 3.1), which creates a trade-off. More insight in this trade-off is given in paragraph 3.2.2.

3.2.1 Placement

In the low-voltage grid, there are four conceptual alternatives for the placement of storage units. These alternatives are at the substation, between the substation and the first bifurcation, between the first and last bifurcation, and after the last bifucation. These alternatives are visualized in figure 3.2.

The alternatives for placing storage units are evaluated in terms of their use (e.g. grid components unburdened) and their main disadvantage for implementation. There might be more criteria for evaluating the alternatives for placing, but these proved to

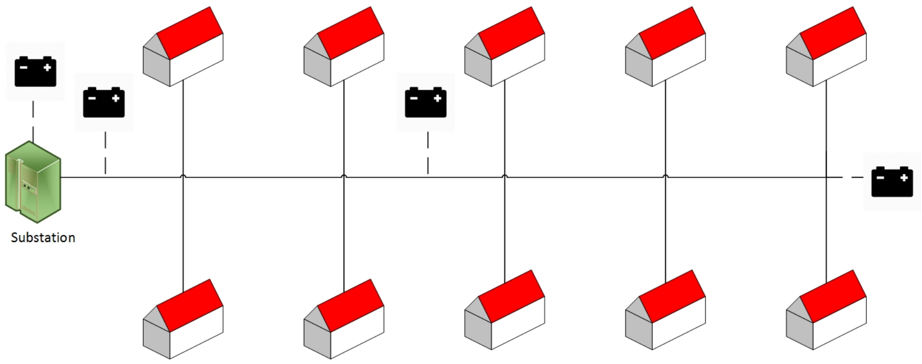

Figure 3.2: Possible placements of storage in a neighbourhood

Placement	**Use**	**Disadvantage**
Substation	Unburdening substation	Limited space in station
Substation - bifurcation	Unburdening substation and cable	New location
Bifurcation - bifurcation	Unburdening substation and cable	Nuisance for consumers
After last bifurcation	Maintain voltage quality	No deferral of grid investments

Table 3.1: Overview placements of storage, usage, and disadvantages

be unnessecary since one location will prove to be most suitable using these criteria.

The elements of this table will be explained per placement. If a storage unit is placed at the substation, the substation is unburdened (or more specifically: the transformer in the station is unburdened). The cable nor voltage quality is affected. The disadvantage of placing the storage unit in a substation is that the space in the station is limited, and therefore the capacity of the storage unit is limited. A lithium-ion battery for example has an energy density of about 400 Wh/L, which means that a 200 kWh battery will take up about 0,5 m^3.
Placement of the storage unit between the substation and the first bifurcation will unburden the substation and a part of the cable. This is visualized in figure 3.3 (top). The disadvantage of this placement is that the DSO has to obtain a new piece of land to place the storage unit.
The third placement, which is inbetween bifurcations, will unburden a larger part of the cable compared to the placement before the first bifurcation, and still unburdens the substation. This is also visualized in the bottom overview of figure 3.3. The disadvantage of this placement is nuisance for consumers. This nuisance arises from the storage unit often having a container-like casing and the experience with large batteries being that they make a 'humming' sound when (dis)charging.
The last placement, after the last bifurcation, can be used to maintain voltage quality

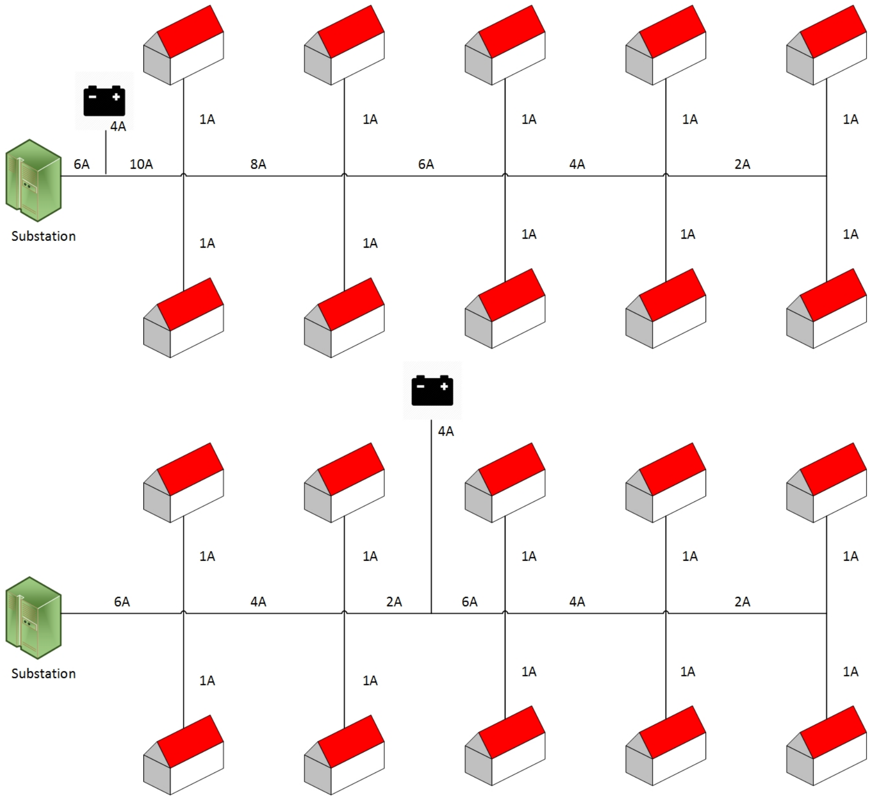

Figure 3.3: Current throughout a neighbourhood for two diffent storage locations

but not for unburdening grid components. This means that this location does not defer grid investments.

The use of the second and third mentioned location might not be obvious at first. Therefore, it will be explained here. The connections from the low-voltage cable to consumers are in parallel, because all consumers want to have 400 volts arriving at their home. This means that the voltage throughout the cables will be the same, but the amperage will change after each bifurcation. The amperage at the beginning of the cable is equal to the sum of all amperages of each bifurcation. So, the amperage will decrease after each bifurcation. This means that is it possible to unburden the transformer and a part of the cable.

The effect of placing storage at the substation would be the same as placing it between the substation and the first bifurcation - apart from a few meters of cable that is not unburdenend. The advantage of placing the storage unit at the substation is that this substation is in possession of the DSO. The benefits of locating the storage unit at the substation - namely unburdening the station and already owned ground - and the disadvantages of locating it next to consumers - namely the 'humming' sounds that the battery makes during charging - leads to the conclusion that the most suitable placement of the battery is at the substation.

3.2.2 Capacity and Power

As described in 3.2.1, the most suitable placement of local storage units is at the substation. In this paragraph, the most suitable capacity and power of those storage units is determined. The power of the storage unit depends on the power of the relevant substation, the time period for which the substation should be unburdened, and the expected peak demand growth in the relevant neighbourhood. The capacity of the storage unit is determined by the power of the storage unit times the expected time duration of peaks. This can be translated into formulas 3.2 and 3.3. A factor that is not included in these formulas is the amount of days per year that the peak demand reaches a certain height that creates a necessity to use the storage unit. This means that it could be possible that in the winter, the peak demand is very high - creating a need for using the storage unit - but during summer, the peak demand stays below the substation's capacity - meaning that the storage unit could be used otherwise. This seasonal influence will be used to determine suitable neighbourhood-types to place the storage.

$$P_{storage} = D_{peak} * (1 + r_t) - P_{substation} \tag{3.2}$$

$$C_{storage} = P_{storage} * Du_{peak} \tag{3.3}$$

P	Power	kW
C	Capacity	kWh
D_{peak}	Current peak demand	kW
r_t	Expect growth rate for year t	dimensionless
Du_{peak}	Duration of peak demand	h

To start with the only deterministic variable of both formulas (3.2 and 3.3): the power of the substation. The most occuring values of power of substations are 250, 400, and 630 kVA. This is the apparent power, and the true power can be calculated by multiplying it with the cosinus-phi value. This cosinus-phi value usually lies between 0.96 and 0.99. This results in a real power of a 630 kVA transformer of approximately 605 - 625 kW. It is worth mentioning that substations are able to 'run' at 120% of their maximum power for approximately three hours. However, this feature of the substations is used for emergency situations and is therefore not considered in the furhter analysis.

In order to determine the peak demand and peak duration, load data is necessary. However, in conversations with the Asset Management department at Stedin, it became clear that it is not allowed to store the load data per substation per minute or even per hour, for privacy reasons. Stedin does possess the following data:

1) Data of the load per substation per five minutes. There namely exists one project in their network where they have permission from the consumers to measure and store this load data. This dataset is from 01-01-2016 till 01-10-2016.
2) Data on the peak demand as a percentage of the power of the anonymised substation. The power of the substations is not available in this dataset. This dataset also contains a growth scenario for four different types of neighbourhoods.

In order to be able to use the datasets, a number of wrongly measured values need to be removed. These false measurements occur when the measuring equipment has a malfunctioning. The 'clean' datasets are used to determine the peak duration, the difference between weekdays and weekend, and the seasonal influence on the load. Moreover, the effect of different ratios between residential and non-residential connections on the peak duration and seasonal influence is tested. An overview of the used neighbourhoods and graphs can be found in table 3.2.

Neighbourhood	**Residential connections**	**Non-residential connections**	**Percentage residential**
1	167	0	100%
2	158	1	99%
3	66	32	67%
4	11	32	26%
5	1	15	6%

Graph	**Use**
Load characterisctics for all days of the week	Peak duration and height
Load characteristics for weekdays	Peak duration and height, difference weekdays and weekend
Load characteristics for weekend	Peak duration and height, difference weekdays and weekend
Maximum load per day	Seasonal effect

Table 3.2: Neighbourhood types and graphs used for the load analysis

The second available dataset (peak demand in percentage of substation's power) is used to determine the effect of local storage on the investments needed (e.g. replacement of substations) in Stedin's total network. The assumption is made that when the peak demand reaches 100% of the substation's power, it needs to be replaced. Stedin developed a number of scenarios for predicting the peak demand in the coming 30 years (till 2050). These scenarios are used to assess the years of deferral when a storage unit is installed in the five neighbourhoods.

In figure 3.4, the load of 167 residential connections, all attached to one substation, is visualized. The load was measured once per five minutes from the period 01-01-2016 till 01-10-2016. This should result in 275 days of data, but at some instants, the meter was malfunctioning. This results in 259 days of usable data. This data is used to calculate the mean, maximum, minimum, and 25th to 75th quantile of the load per five minutes of the day.

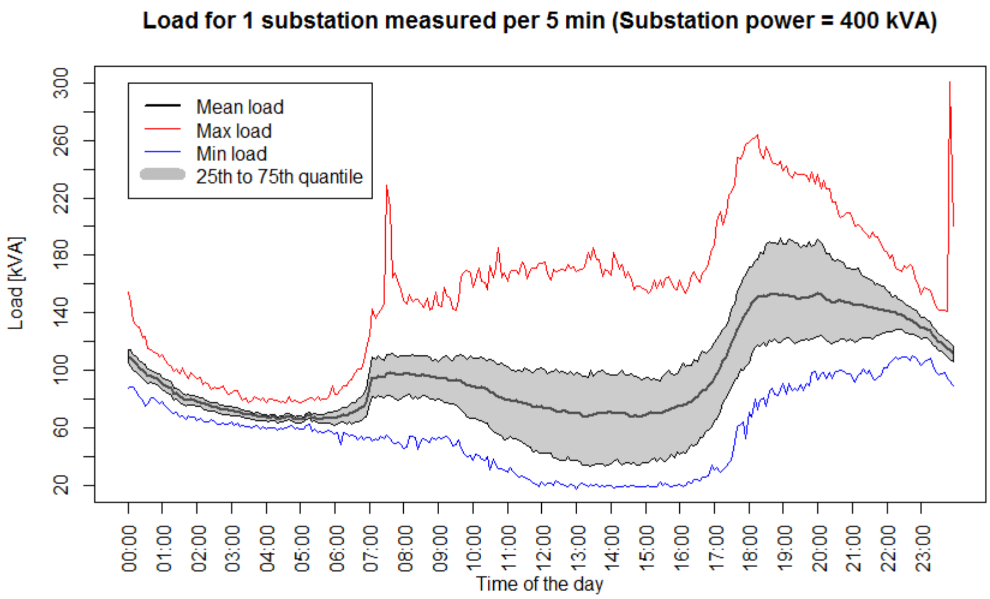

Figure 3.4: Load characteristics of substation 1 (167 residential connections) for 01-01-2016 till 01-10-2016

Before conclusions can be drawn from this graph (figure 3.4), the two peaks need to be addressed, as they fall outside the demand pattern. This is the peak at 7:30 and at 23:50. To be more certain that these peaks are the results of a measuring error, the exact measurements around these instants are shown in table 3.3.

Timestamp	**S [kVA]**	**Timestamp**	**S [kVA]**
2016-02-09 06:00:00	73.74	2016-01-27 22:15:00	154.82
2016-02-09 06:05:00	77.39	2016-01-27 22:20:00	149.98
2016-02-09 06:10:00	75.47	2016-01-27 22:25:00	158.46
2016-02-09 06:10:00	48.50	2016-01-27 22:26:00	148.70
2016-02-09 07:30:00	228.54	2016-01-27 23:50:00	300.52
2016-02-09 07:35:00	214.02	2016-01-27 23:55:00	200.61
2016-02-09 07:40:00	164.51	2016-01-28 00:00:00	154.68
2016-02-09 07:45:00	167.54	2016-01-28 00:05:00	147.07
2016-02-09 07:50:00	160.66	2016-01-28 00:10:00	134.11

Table 3.3: Timestamps and measured load for the two peaks in figure 3.4, showing the errors in measurement

From the exact measurements in table 3.3 it was concluded that six data points are not to be taken into consideration. These data points are at 06:10(2^{nd}), 07:30 and 07:35 in the left column in table 3.3, and at 22:26, 23:50 and 23:55 in the right column. These data points are either removed because they make no sense compared to previous and subsequent data points, or because there shouldn't be a data point at a specific time (the measuring equipment should only measure every 5 minutes). Now that the dataset is cleaned of wrongly measured values, the four graphs as described in table 3.2 are made. These graphs are shown in figure 3.5. This process is executed for all five neighbourhoods, but not described repeatedly.

A number of patterns are visible in figure 3.5. First, the mean load pattern is described. The mean load characteristics of all days of the week (top-left graph in figure 3.5, black line) show an abrupt increase around 07:00, most likely because people wake up at that time. From approximately 08:00, the load starts to decrease, as people leave their house to go to their work. Around 17:00 the load starts to increase and reaches its maximum around 18:00, at which it remains till 20:00. Thereafter, the load starts to decrease.

The maximum measured load follows the mean pattern of the load. The minimum measured load however declines from 05:00 till 12:00, whereas the mean load has the abrupt increase around 07:00. This can be explained by solar panels that are present in this neighbourhood, which decrease the load on the substation by providing a part of the demand for electricity.

The difference between weekdays and weekend is clearly visible in the graphs in figure 3.5. The increase in de morning is less abrupt, as people wake up later in the weekend and more spread out over time. The mean load during the weekend is slightly higher than during weekdays, as more people are home during the weekend. The peak around 18:00 till 20:00 is comparable for weekdays and weekend. It appears that the weekend-

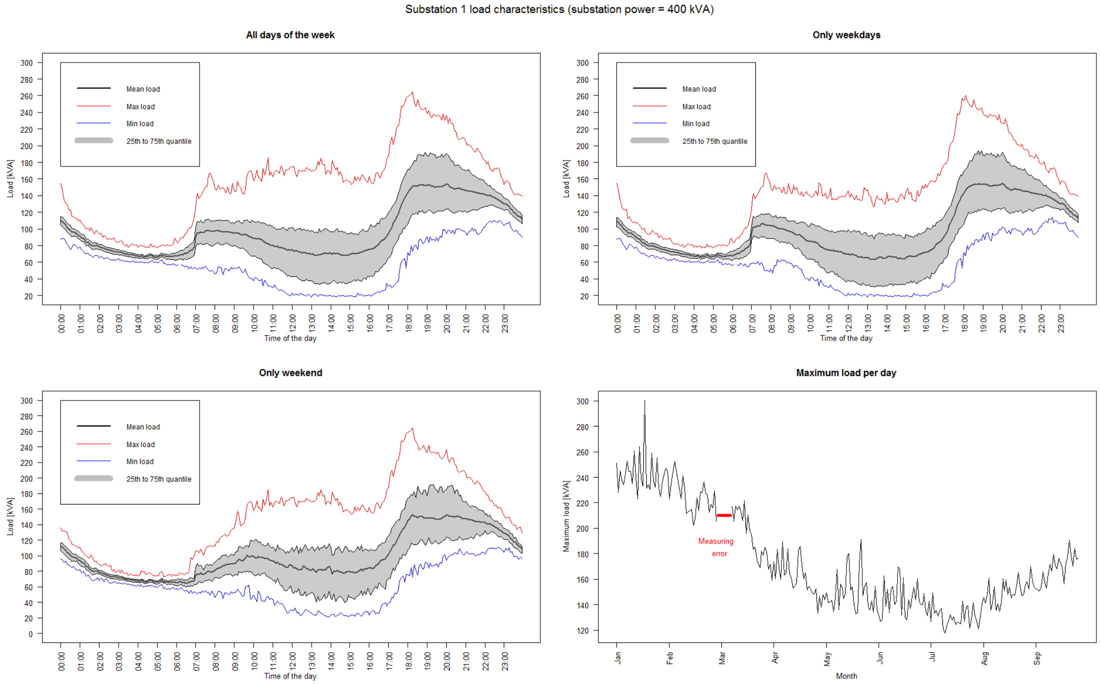

Figure 3.5: Corrected load characteristics of substation 1 (167 residential connections) for 01-01-2016 till 01-10-2016

behaviour is more fluctuant because of the less smooth curves, but this is most likely caused by the fact that the weekend-graph has less data points (as there are 5 weekdays and 2 weekend-days per week).

The seasonal effect is shown in the bottom-right graph in figure 3.5. This graph shows the maximum measured load per day, irrespective of the time of the day at which this maximum occurred. The graph shows that the maximum load declines in the summer months and starts to go up again in August and September (unfortunately, the first of October is the last date of the dataset). Another observation from this graph is that the maximum load does not reach the capacity of the substation; the capacity of the substation is 400 kVA and the maximum load was 280 kVA.

The graphs in figure 3.5 can be used to determine the peak duration and peak height. The maximum load line (the red line) and the 75$^{\text{th}}$ quantile (top of the grey area) are used to determine the peak duration and peak height. Looking at the seasonal effect on the peak load and thereby taking into account that the previous analysis does not cover the months October, November and December, it is concluded that for 4 months the daily peak load is at its maximum. It is thereby assumed that the load in the three missing months gradually increases to the load in January. For the other months, there is a daily peak load, but this load is significantly lower than during those 4 months (November, December, January, February). This means that for this specific substation, the peak load per day is for four months per year above 200 kVA and for eight months per year substantially lower than 200 kVA. Therefore the storage is designed for the load from the maximum value of the 75^{th} quantile and the maximum value of the maxima. This is visualized in figure 3.6 in the green area.

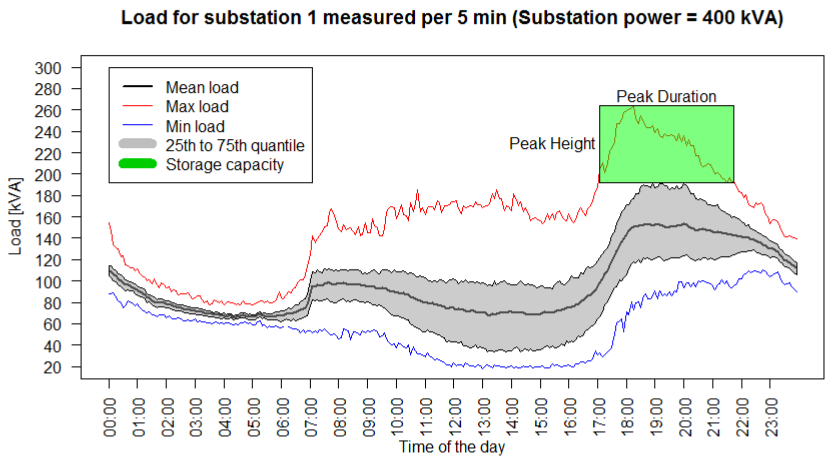

Figure 3.6: Load characteristics for all days of substation 1 (167 residential connections) with indication for the capacity of the storage

This method for determining the peak height and peak duration ensures the following. The starting point is the maximum of the 75^{th} quantile. This means that at least 75% of the time, the load is lower than this value. This means that the substation needs to have sufficient capacity at minimum 75% of the time. It is visible in the bottom-right graph in figure 3.5 that in the months March to October the load is not higher than 200 kVA - which is approximately also the maximum of the 75^{th} quantile. By designing the storage this way, the high loads in the months December, January, and February are captured by the storage unit, and from March onwards the storage unit can be used for other purposes.

This design results in a peak duration of 285 minutes, or 4.75 hours. The peak height is 72.1 kVA. This specific substation has a power factor of 0.99, which means that the peak demand is 71.4 kW. This means that the storage unit should have a power of 71.4 kW and a capacity of 340 kWh.

This analysis is executed for all mentioned substations. In figure 3.7 the same graphs as in figure 3.5 are visualized. As the percentage of residential connections of the second substation is nearly equal to the first substation, the load characteristics of substation 2 is also similar. This strengthens the analysis made for substation 1.

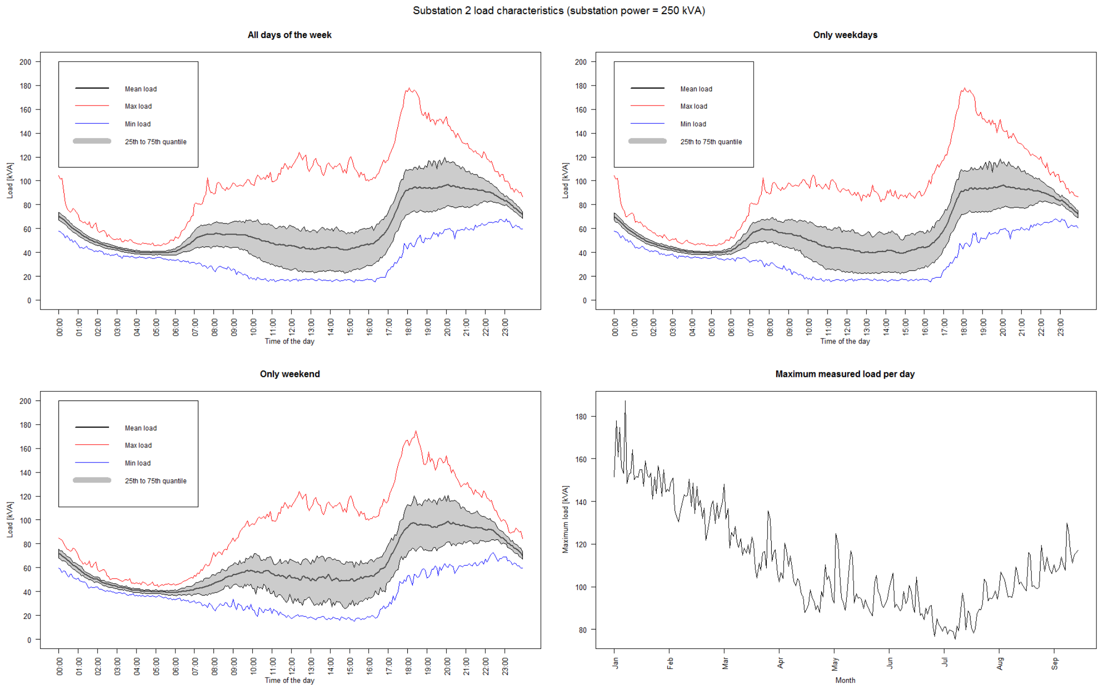

Figure 3.7: Load characteristics for substation 2 (158 residential connections, 1 non-residential) for 01-01-2016 till 01-10-2016

Figure 3.7 visualizes that the second substation has the same load characteristics as the first substation. These characteristics are a daily peak starting around 18:00 and lasting for two hours till 20:00, no significant difference between weekdays and weekend, and a large seasonal influence for the maximum load per day.
This neighbourhood however does have a number of differences with the first one. The load increase in the morning (at 07:00) is less abrupt and the difference between the mean load and the maximum load during peak (18:00-20:00) is larger. This last behaviour influences the necessary capacity of storage in the second neighbourhood. In figure 3.8, the necessary capacity is visualized. The determination method for this capacity is equal to the method used for the first neighbourhood.

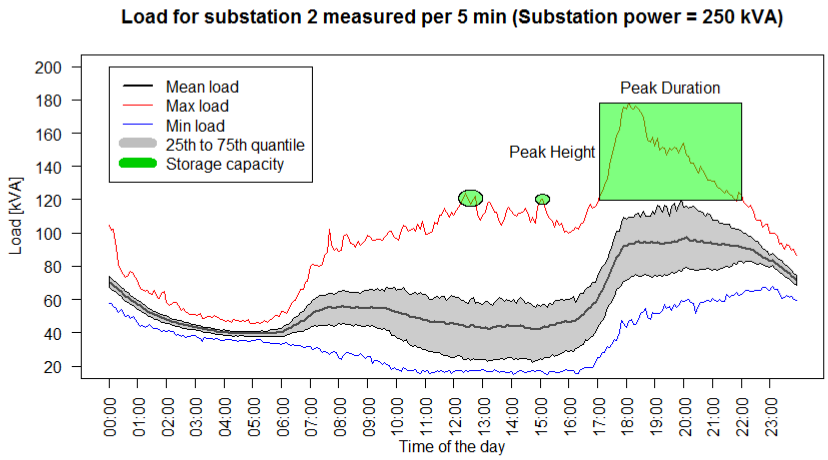

Figure 3.8: Load characteristics for all days of substation 2 (158 residential connections, 1 non-residential) with indication for the capacity of the storage

In the second neighbourhood, there is a main peak, but also two small peaks during the day. These smaller peaks are indicated by the green ovals. The storage is however not designed for these peaks, as they are too small to use the storage capacity for (meaning that the storage can be used for other purposes during this time of the day). Therefore, in this neighbourhood, the capacity of the substation itself needs to be higher than the maximum of the 75$^{\text{th}}$ quantile. The peak height then becomes 58.2 kVA and the peak duration is exactly 5 hours. The power factor of this substation is also 0.99, which results in a necessary power of 57.6 kW and a capacity of 288 kWh.

The third neighbourhood has 66 residential connections and 32 non-residential connections. This influences the load behaviour, as visualized in figure 3.9. Whereas the load in the second neighbourhood is similar to the first neighbourhood, the third neighbourhood differs from the first two. The load starts to increase around 06:00 and steadily grows till 09:00 and from 09:00 till 11:00, the load decreasingly grows. Shortly after 11:00, the load has another abrupt increase. After this increase, the load decreases for a short period of time. Then it slowly increases till around 18:00. Thereafter it slowly decreases till 21:00 and strongly decreases till 02:00, after which it remains constant till 06:00. This load behaviour is also visible in the only-weekdays graph and in the weekend-only graph. However, the weekend-only graph shows a larger 25$^{\text{th}}$ to 75$^{\text{th}}$ quantile. The seasonal effect is visible for this neighbourhood, but the load has a more constant pattern throughout the year compared to neighbourhood 1 and 2.

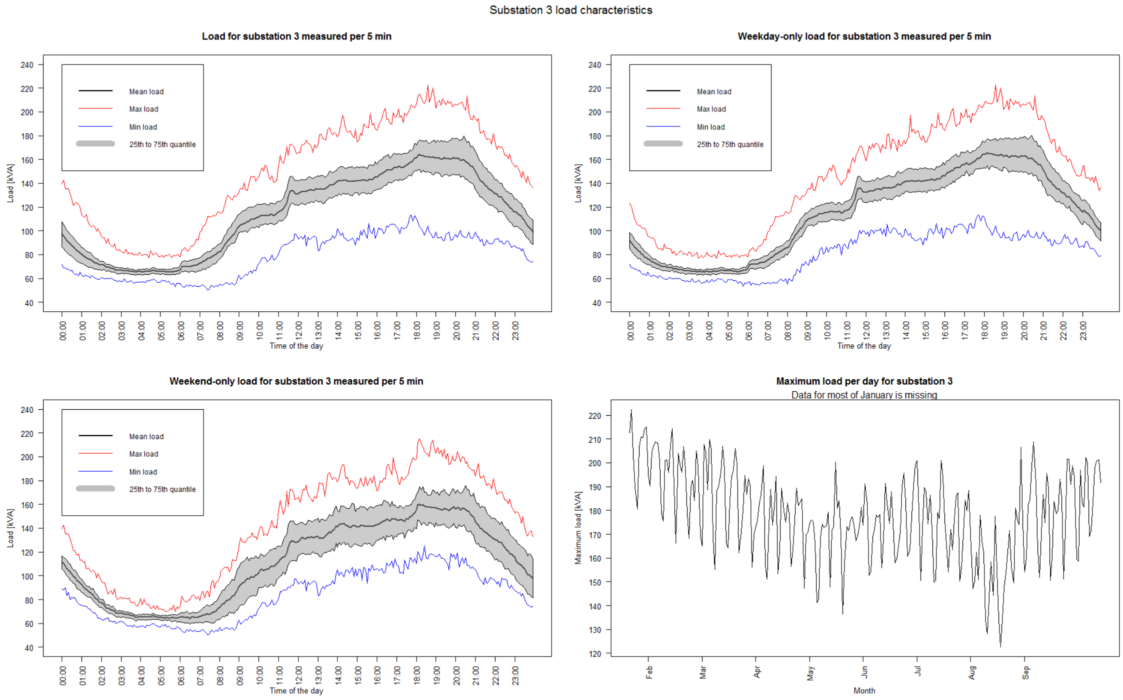

Figure 3.9: Load characteristics for substation 3 (66 residential and 32 non-residential connections) measured per 5 min for 01-01-2016 till 01-10-2016

A number of characteristics of the load of substation 3 need further explanation. The first aspect that stands out is the abrupt increase around 06:00. It is not likely that this increase is caused by one of the residential connections, as the previous neighbourhoods (with a high share of residential connections) did not show this increase. Moreover, the height of this increase (approximately 3.5 kW) combined with the regular occurrence indicate that this peak is not caused by a household. After locating this substation (the exact location can not be shared due to privacy reasons) it became clear that there are two bakeries and a post office in this neighbourhood, which is a more likely explanation for this abrupt increase 06:00.

Hereafter, the load steadily grows till 09:00, which suits the expected behaviour of a neighbourhood with both residential and non-residential connections. The households cause the first part of the growth and then the non-residential connections cause the second part of the growth (from 08:00 onwards). The combination of residential connections and non-residential connections causes the load to slowly increase from 09:00 till 18:00, with another abrupt increase around 11:15. This increase is caused by the presence of multiple catering industries in this neighbourhood.

Designing a storage unit for this neighbourhood is visualized in figure 3.10 and shows a significant different design, namely a lower peak height but a higher peak duration. For this neighbourhood, the storage mechanism would cover the peak load from approximately 13:00 till 21:30. The peak duration is 510 minutes or 8.5 hours. The peak height is 43.0 kVA. This results, with a power factor of 0.97, in a storage power of 41.7 kW and capacity of 355 kWh. A storage unit with these characteristics will not cover the small peak indicated by the green oval, for the same reason as in neighbourhood 2.

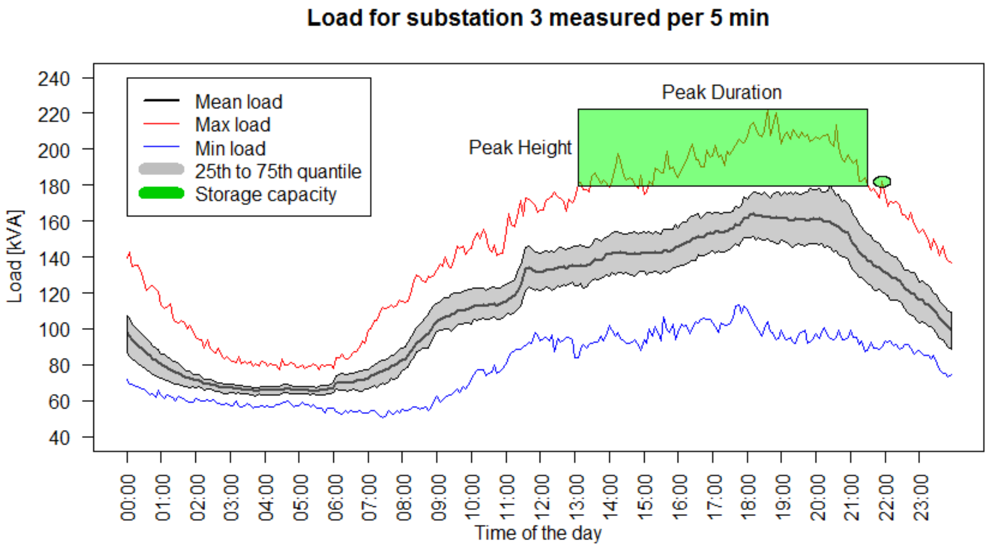

Figure 3.10: Load characteristics for all days of substation 3 (66 residential connections, 32 non-residential) with indication for the capacity of the storage

The fourth neighbourhood has the same amount of non-residential connections as the third neighbourhood, but only 11 residential connections. This creates a different behaviour from the third neighbourhood. The top-left graph in figure 3.11 shows the load characteristics for all days of the week, which has a large spread. This spread, as can be seen in the top-right and bottom-left graph, is caused by the difference between weekdays and weekend. During weekdays, the load starts to increase around 06:00 and increases till 09:00. Then it remains approximately constant till 16:00, after which it increases to its peak at 17:00. Thereafter, the load decreases, with a change in slope around 18:00. The load during weekends however shows a significantly different behaviour. The load decreases from 06:00 till 09:00, after which it remains constant till 11:00. Then the load increases and decreases again. Then it remains constant till 14:30, when it increasingly grows till 17:00 where the load reaches its peak. After a small 'valley', the load remains at this peak-level till 21:00. Then it slowly decreases. The seasonal effect, visualized in the bottom-right graph in figure 3.11, is hardly visible.

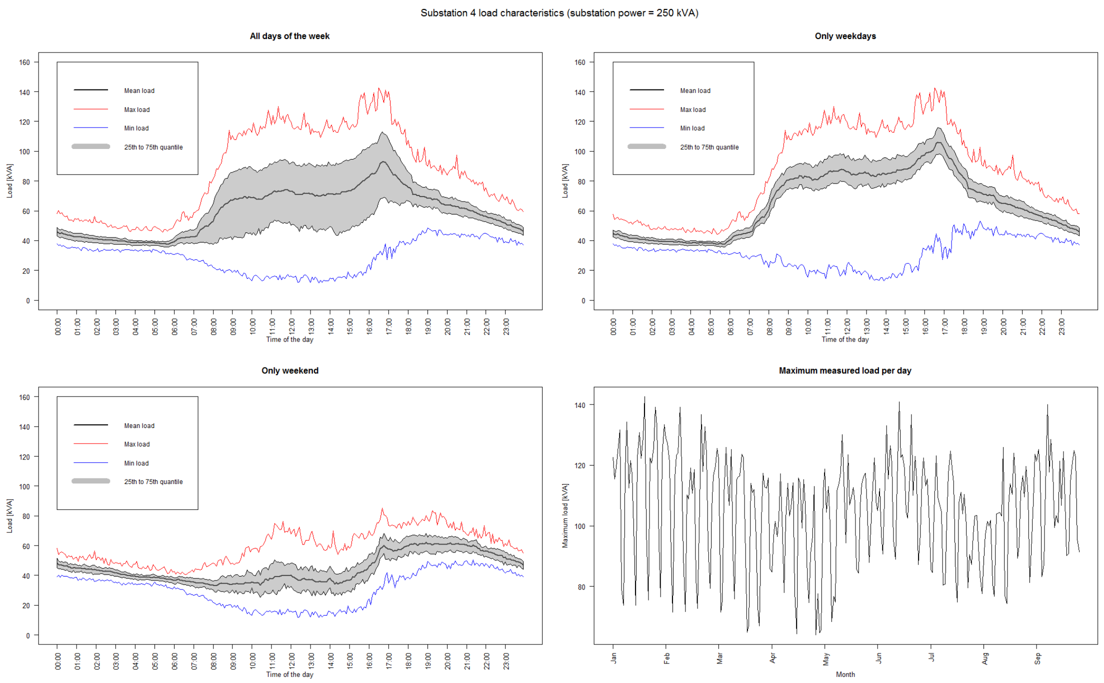

Figure 3.11: Load characteristics for substation 4 (11 residential and 32 non-residential connections) measured per 5 min for 01-01-2016 till 01-10-2016

The peak around 06:00 on weekdays is most likely caused by a non-residential connection starting early. The increase thereafter is a combination of residential connections (households) waking up and non-residential connections starting up. The load, remains constant as the non-residential connections have a constant load during the day. At 17:00, the peak is caused by the residential connections that have their peak there, as visible in neighbourhoods 1 and 2.

The storage capacity for neighbourhood 4 is visualized in figure 3.12. In this neighbourhood, the peak duration is 500 minutes or 8.3 hours. The peak height is 29.6 kVA. The power factor is approximately 0.98, which results in a storage unit with a power of 29.0 kW and a capacity of 242 kWh.

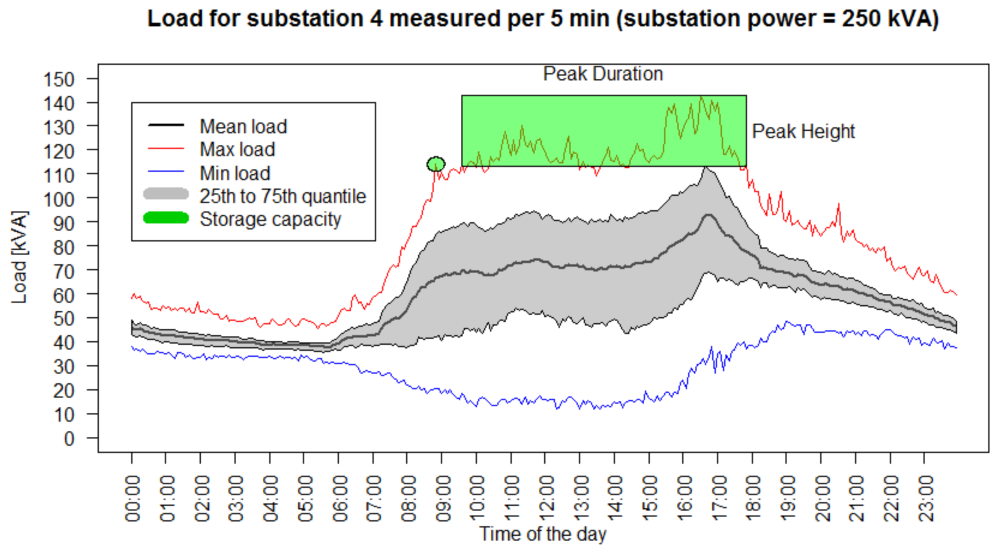

Figure 3.12: Load characteristics for all days of substation 4 (11 residential and 32 non-residential connections) with indication for the capacity of the storage

Figure 3.13 shows the load characteristics for substation 5, which has 15 non-residential connections and 1 residential connection. This was the most suitable dataset available for testing the characteristics of only non-residential connections.

In the top-left graph of figure 3.13, the load of all days of the week for substation 5 is visualized. This load remains constant during the night untill 05:00. Then the load decreases slightly. Around 07:00, the load starts to increase untill 09:00, after which it remains constant till 17:00, besides a small drop around 12:30. From 17:00, the load decreases untill 23:00. For all days of the week, the load has a large spread. Looking at the top-right graph, it is visible that the spread is significantly smaller for only weekdays. During the weekend (the bottom-left graph), the load is low and fairly constant. The seasonal effect (bottom-right graph) is negligible, but the week-weekend differences are clearly visible.

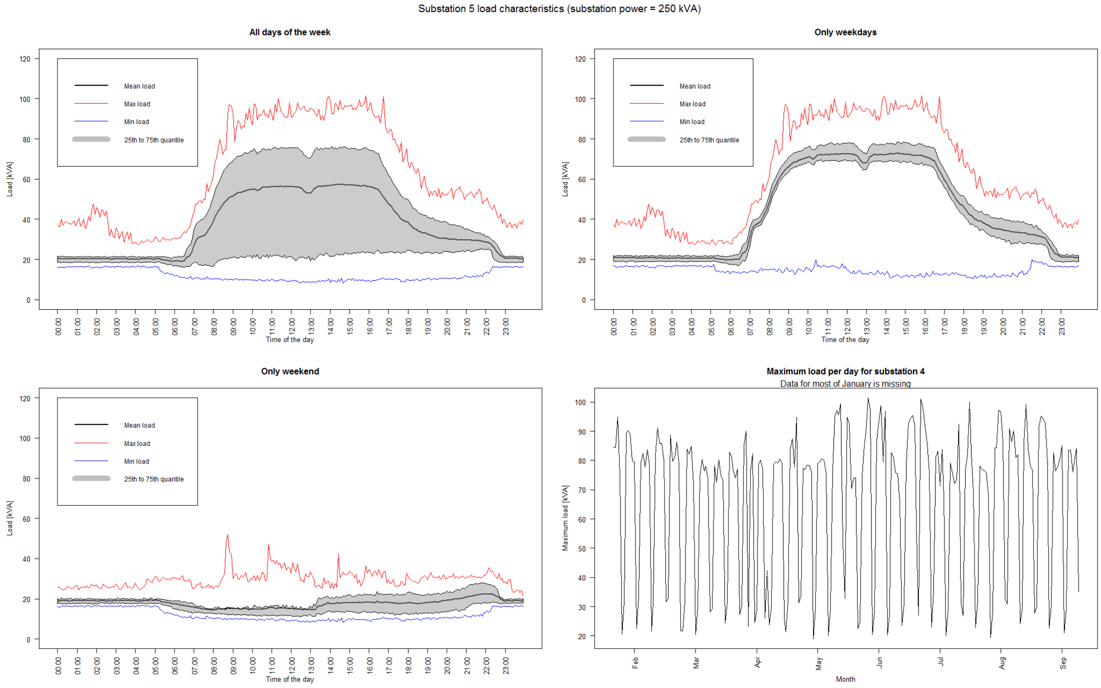

Figure 3.13: Load characteristics for substation 5 (15 non-residential and 1 residential connections) measured per 5 min for 01-01-2016 - 01-10-2016

The load of substation 5 is what can be expected from a neighbourhood with solely non-residential connections (apart from 1 connection). There is a large difference between weekdays and weekend, and even the lunch break at 12:30 is visible. The decrease around 05:00 is most likely caused by solar panels.

The necessary storage capacity for this substation is visualized in figure 3.14. The load characteristics of this substation create a long peak duration, namely 565 minutes or 9.4 hours. The peak height is relatively low, namely 25.1 kVA. Using the power factor for this substation, which is 0.98, the necessary power for the storage unit is 24.6 kW and the capacity is 232 kWh.

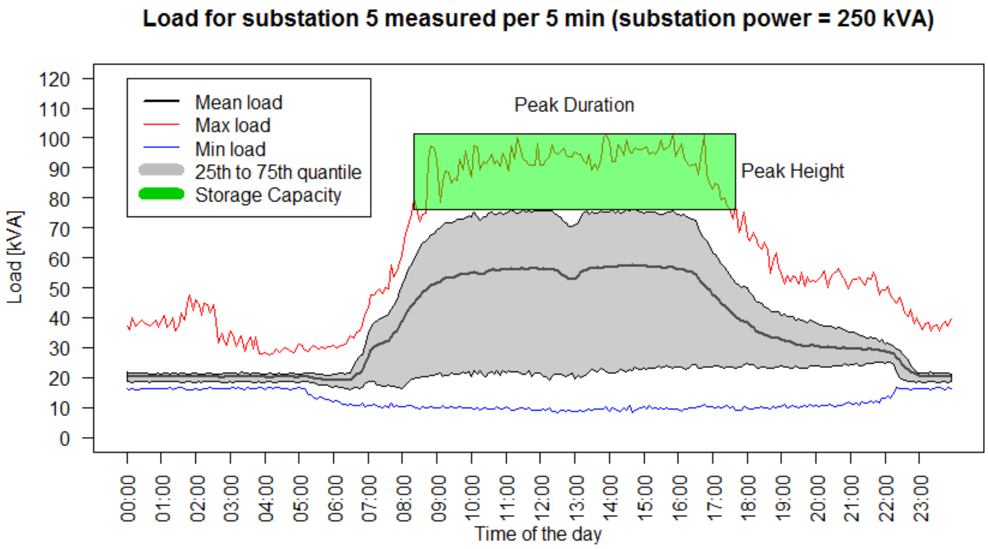

Figure 3.14: Load characteristics for all days of substation 5 (1 residential and 15 non-residential connections) with indication for the capacity of the storage

An overview of the storage units for all the neighbourhoods is visualized in table 3.4. The storage power however does not coincide with the storage powers visualised in the graphs for the five neighbourhoods. The storage powers are all set to 100 kW, as this is the power needed in order to be able to trade on the electricity markets, which is further explained in chapter 4.1. As this power is used in the rest of the research, the necessary power is already incorporated here.

The goal of this paragraph was to determine the duration of peak demand and the effect of the share of residential connections in a neighbourhood on the storage unit needed in that neighbourhood. The results of this analysis are shown in paragraph 3.4. In the first place, it is concluded that there's a large difference in load characteristics between residential and non-residential connections. This difference expresses mostly in the duration of the peak and the absence of seasonal influence. These characteristics implicate that neighbourhoods with lower shares of residential connections are more dependent on the value of deferral for a sufficient business case. Dominantly residential neighbourhoods have more opportunity to create additional value due to less usage by the DSO.

Neighbourhood	Residential connections	Peak Duration & height	Storage power & capacity	Seasonal influence
1	100%	4.8 h 72.1 kVA	100 (71.4) kW 340 kWh	Yes
2	99%	5 h 58.2 kVA	100 (57.6) kW 288 kWh	Yes
3	67%	8.5 h 43.0 kVA	100 (41.7) kW 355 kWh	No
4	26%	8.3 h 29.6 kVA	100 (29.0) kW 242 kWh	No
5	6%	9.4 h 25.1 kVA	100 (24.6) kW 232 kWh	No

Table 3.4: Storage design per neighbourhood. The storage power has two values: 100 kW necessary for trading on the electricity markets and between brackets the necessary power for lowering peak demand.

3.3 Postponement value by storage units

In order to determine the value of postponing grid investments, the growth rate needs to be incorporated as well (as is showed in formula 3.2). Stedin DSO has developed scenarios for the peak growth rate from 2016 till 2050, for four different area types (ranging from rural to urban). As mentioned before, they also possess a dataset containing the current peak load for all their substations, expresses in the percentage of the capacity of that substation. This dataset is used to visualize their need for an alternative for the investment in new substations (e.g. a new transformer in an existing station), as many of their substations are expected to reach the point of maximum capacity in the same year. The scenarios developed by Stedin are used to calculate the postponement in years for the five used neighbourhoods of the previous paragraph. Thereafter, the postponement time is used to calculate the value of deferral of investment by the local storage units.

3.3.1 Postponement time

In figure 3.15, the current peak load and expected peak load for 2025 are visualized in histograms. The current peak load dates from 2016, and shows a strong centering between 0.5 and 0.75. Stedin has 9054 substations in their network, and 45% of them currently have a peak load between 50% and 75% of their capacity. In 2025, most of these substations will reach their maximum capacity. The histograms shows a peak between 1.0 and 1.1, meaning that a large number of substations have a peak load of 100%-110% of their capacity and need to be replaced. The amount of substations that has to be replaced by 2025 is quite large compared to other years, namely 20%. So, in 2025, one out of every five substations has to be replaced. The average amount of substations that have to be replaced per year in the period 2016-2030 is 6.5% per year. Therefore, when substations that are expected to have insufficient capacity in 2025 can be assisted by a storage unit, the investments in new substations can be spread over a longer period.

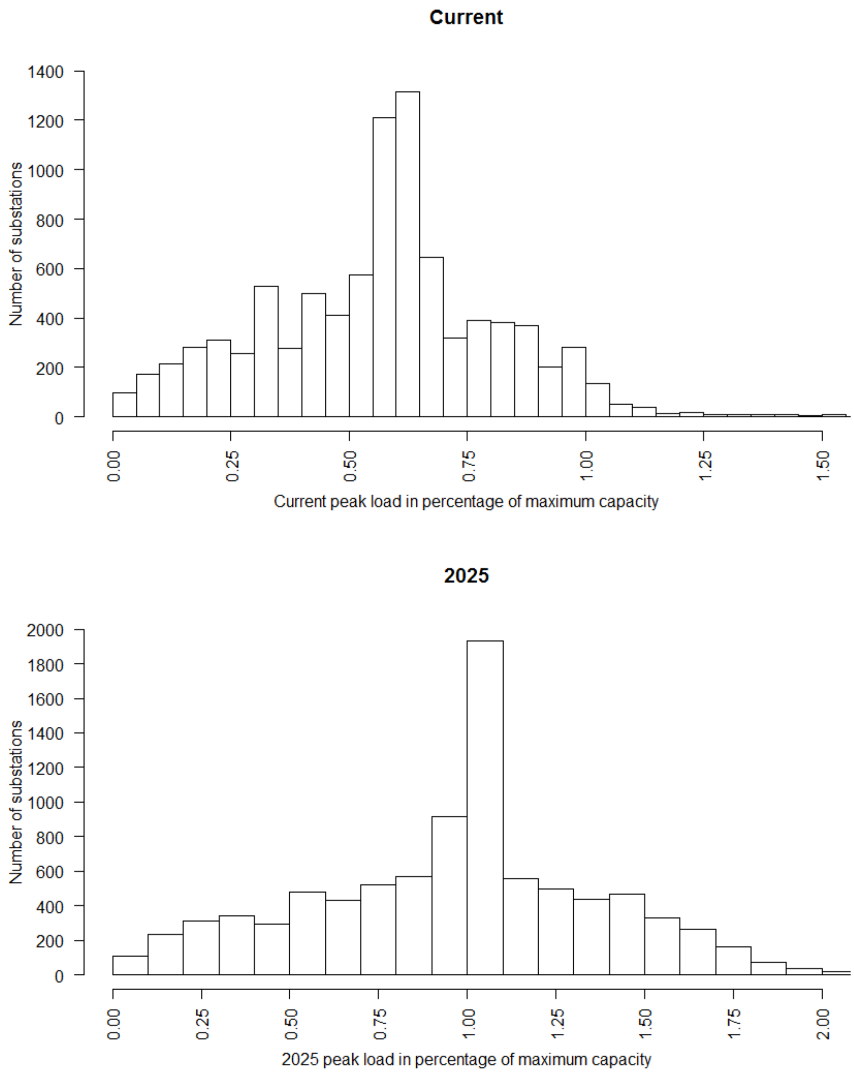

Figure 3.15: Histograms of current and 2025 peak load for all substations controlled by Stedin

Stedin uses four scenarios, each for a different area type. These area types however don't indicate the ratio of residential versus non-residential connections, which means it is not possible to determine which area type is suitable for which of the five neighbourhoods analysed in this research. Therefore, all four scenarios are used to estimate a range for the postponement time for the five neighbourhoods as defined in this chapter. This creates an estimate for when the load in these neighbourhoods reaches the substation's capacity. The results are shown in table 3.5. Columns 2 and 3 indicate the year in which the substation reaches its maximum capacity, excluding and including storage. The fourth column gives the range for the years of deferral. The deferral time is equal to the difference between the year to reach maximum capacity and the year to reach maximum capacity with storage installed. In the calculation of this difference the year-values that are used are within the same scenario.

Nbh	Current peak load	Year to reach maximum capacity	Year to reach maximum capacity with storage	Deferral time [yrs]
1	0.75	2022-2023	2026	3-4
2	0.75	2022-2023	2027-2028	4-5
3	0.74	2022-2023	2025-2026	2-3
4	0.57	2026	2028-2031	2-5
5	0.41	2029-2032	2033-2039	3-7

Table 3.5: Effect of storage on year to replace substation (Nbh = Neighbourhood)

3.3.2 Valuation of deferral of investment

Comparing low-voltage electrical energy storage with replacement of transformers in substations is not a matter of comparing investment costs as such of both alternatives, as storage facilities do not replace the full function of the transformers, but are meant to lengthen the lifetime of the substation by creating extra peak capacity. Moreover, the storage units offer opportunities outside peak hours to generate additional value(s), for example by trading on the electricity market.
The goal of this paragraph however is to determine the value solely of deferral of investments in new transformers in substations. For the calculation of this value the NPV methods is used as introduced at the beginning of this chapter.

For replacement of a transformer in an existing substation the Asset Management department at Stedin has estimated the costs at €40.000. As we are talking of replacement by larger transformers, the costs of replacement are estimated at €50.000.

Determination of the discount rate is a discussion in itself. In a commercial environment investors will argue that the discount rate should equal the expected rate of return on capital and could easily be in the range of 10% to 15%. For a DSO this would not be appropriate, but the discount rate should at least represent the average cost of capital for the company and should indicate how much value an investment or project adds to the company. For this research the discount rate is therefore set at a range between 5% to 10%. Based on the deferral times as calculate in paragraph 3.3.1., the estimated investments and the discussed discount rates the savings are calculated and presented in table 3.6 for the different neighbourhoods.

Discount rate →	5%	5%	7,5%	7,5%	10%	10%
Deferral →	Low	High	Low	High	Low	High
Neighbourhood↓	€	€	€	€	€	€
1	6808	8865	9752	12.560	12.434	15.849
2	8865	10.824	12.560	15.172	15.849	18.954
3	4649	6808	6733	9752	8678	12.434
4	4649	10824	6733	15.172	8678	18.954
5	6808	14.466	9752	19.862	12.434	24.342

Table 3.6: Savings per neighbourhood for different interest rates

As the power and capacity of storage for the different neighbourhoods differ, also the costs of the storage differs. The costs of the storage units are calculated based on Ippolito et al., and are €280 per kWh and €266 per kW (Ippolito et al, 2014). The results are shown in table 3.7 next to the possible savings for the same neighborhoods. As battery techniques are at the moment an important area of research worldwide, it is expected that prices for storage per kWh will go down considerably in the near future, like for solar cells or wind energy in the last decade. Nykvist and Nilsson researched the price trends in battery prices and the expected price trends in both scientific research as industry reports (Nykvist and Nilsson, 2015). They report battery prices only per kWh, whereas Ippolito et al. report both per kWh and per kW. Therefore, the ratio of 2014 price level and 2025 level reported by Nykvist and Nilsson is used to indicate expected price developments of batteries. The research of Nykvist and Nilsson show an average price in 2014 of €383 and an average price in 2025 of €214, meaning a decrease of 45% (Nykvist and Nilsson, 2015). This decrease is taken into account in the conclusion and recommendations.

The lifetime of the storage units is based on a Tesla Powerwall, which has a guaranteed lifetime of ten years. Assuming a lifetime of a battery of ten years, the batteries can be used in two different neighbourhoods within their lifetime. This means that for neighbourhoods one to four, the value can be doubled. For neighbourhood 5, this line of reasoning can't be accepted, as the doubling of the maximum deferral period (and therefore the maximum savings) exceeds the ten-year mark. The maximum possible savings are shown in table 3.7.

Neighbourhood	Max. savings[€]	Costs[€]
1	31.698	121.800
2	37.907	107.240
3	24.868	126.000
4	37.907	94.360
5	24.342	91.560

Table 3.7: Savings and costs per neighbourhood

Table 3.7 clearly shows that the savings by investment deferral are significantly lower than the costs of a storage unit capable of deferring these investments. An additional benefit is therefore necessary in order to come to a positive business case. Neighbourhood 1 and 2 seem to be most suitable for generating an additional benefit, as they have a relatively short peak duration (see table 3.4) and a clear seasonal pattern.

3.4 Conclusion

The goal of this chapter is to determine the value of local storage units when used for deferral of investments. The first conclusion is that local storage can be best placed in a substation, as this ground is already owned by the DSO and it causes no nuisance for consumers.

The type of neighbourhood most suitable for local storage units is a neighbourhood with a high share of residential connections. These neighbourhoods namely show a clear peak in the demand during the day around 18:00 till 20:00, but also have a clear seasonal effect. This seasonal effect creates the possibility to use the storage unit for other means as well and therefore generate a second value. The peak duration in the five neighbourhoods, with connections ranging from 100% residential to almost 100% non-residential, varies from 4.8 hours to 9.4 hours. The peak height respectively varies from 72 kVA to 25 kVA.

The current peak load in most neighbourhoods in the network operated by Stedin is approximately 50% to 75% of the substations' capacity. The growth scenarios from Stedin indicate that these substations therefore have sufficient capacity till 2025. At that time, most of the existing substations have to be replaced. Installing storage to support the transformer in the substation can defer the investment needed for the replacement by 3 to 7 years.

The savings by deferring the investment needed for replacement are in the order of magnitude of €24.000 to €38.000. The storage unit needed to defer this investment costs around €100.000. This leads to the conclusion that there is no feasible business case at this moment for installing a storage unit solely for deferring network investments. Additional benefits are required to come to a more feasible business case. This benefit can be found in selling electricity at times when the DSO has no need for the capacity of the storage unit. Storage units in residential neighbourhoods offer possibilities in this respect.

4 | Trading on electricity markets

In the previous chapter, it became clear that an additional benefit of low-voltage electricity storage is required to achieve a positive business case. The additional benefit for this research is trading, since it appears that the storage is not used constantly for unburdening the transformer in the substation. This chapter gives an answer to the question which markets are accessible for these storage units. First, all the Dutch markets are analysed. This analysis is then used to determine the markets accessible for local electricity storage. Then, the behaviour of the accessible markets is analysed using statistical analysis.

4.1 Overview of Dutch electricity markets

There are six electricity markets in the Netherlands, of which five are covered in this chapter. The sixth market is the Future market, where deals are made to produce or consume electricity a couple years later than the deal-date. Since storage can't hold electricity that long, this market is not relevant and not considered in this research. The other markets are the Day-ahead & Intra-day market, both operated by APX group, and the Primary, Secondary, and Tertiary reserve market, all operated by TenneT.

4.1.1 Day-Ahead market

On the day-ahead market, as the name implies, buyers and suppliers of electricity can place their bids until 12:00 a.m. on the day before delivery. The market is then cleared, based on these bids with technical price limits of -500 €/MWh and +3000 €/MWh. The market is organised by power exchange APX and coupled with markets in northern, western and southern Europe. Market coupling is a method of congestion management which essentially means that the market operator buys electricity in the cheaper market and sells that electricity in the more expensive market (De Vries, 2016).

For trading on the day-ahead and intra-day markets a fee must be paid. This consists of an entrance fee (€5000), membership fee (€28.500), technology fee (€5000) and a fee per MWh. The fee per traded MWh is €0.095 for the intra-day market and €0.07 for the day-ahead market (APX group, 2016). Next to these membership fees, the suppliers of electricity to the market must comply with a number of (technical) specifications.

In the first place, they must be accepted as a balance/program responsible party by TenneT. Second, the minimum duration of a product on the market is one hour. Last, the products on the market are traded in units of 100 kW or a multiple thereof(APX group, 2016(4)).

The amounts traded on the day-ahead market vary from 2800 to 4000 GWh per month (APX group, 2016(1)). The prices vary from 20 to 100 €/MWh, with an average of 45 €/MWh (APX group, 2016(2)). These numbers are based on monthly averages from September 2015 till June 2016.
One could expect the fluctuations in the day-ahead market to increase due to for example higher penetration of renewable energy sources. In order to determine whether there are more fluctuations, a boxplot is shown in figure 4.1. This figure shows per year, for every hour of the day (Day-ahead prices are determined per hour), what the amount of fluctuation is. The red line is drawn at 50 €/MWh. The boxplots in figure 4.1 don't show outliers, meaning that the extreme prices are not visible.

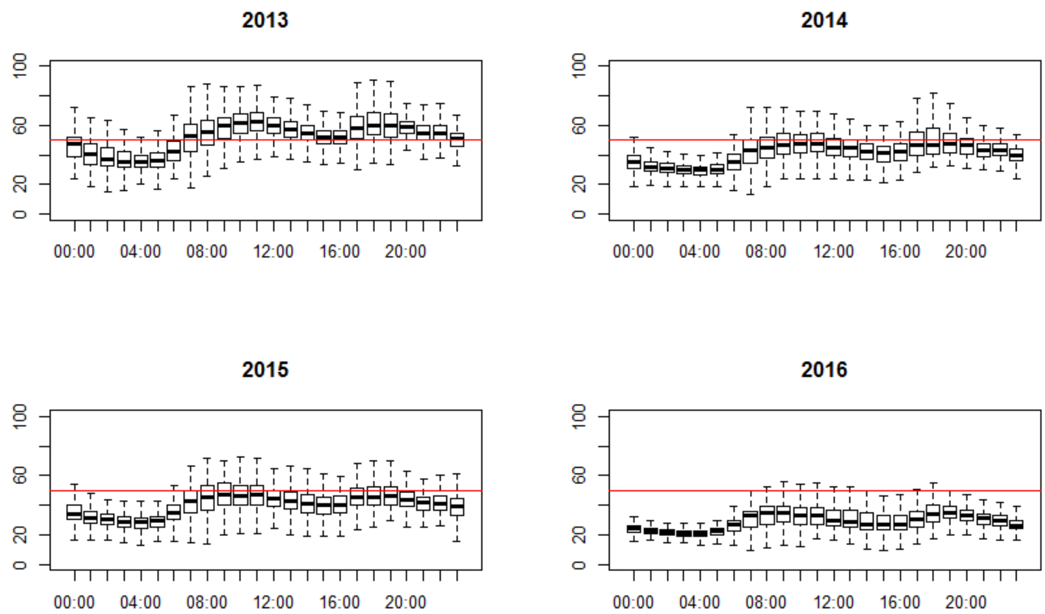

Figure 4.1: Day-Ahead price per hour of the day per year (red line indicates 50 €/MWh)

This graph clearly indicates that the fluctuation and the price of electricity has decreased in the last years. This needs to be taken into account in the conclusions regarding the value of trading with storage units.

4.1.2 Intra-Day market

The intra-day market arranges the final adjustment between the amount of electricity procured and effective demand or between the amount of electricity sold and effective generation. This can be done up to 5 minutes before time of delivery on the APX market. The prerequisites for trading on this market are equal to the prerequisites for trading on the Day-Ahead market.

The amounts traded on the intra-day market vary from 36 to 138 GWh per month. The prices vary from 27 to 51 €/MWh, with an average of 31 €/MWh (APX group, 2016(3)). The amounts traded and price of electricity on this market are clearly lower than on the Day-Ahead market. In conversations with Eneco, it became clear that trading on the Intra-day market is done via bilateral contracts. Since the value of these contracts is very sensitive for competition, they were - obviously - not willing to share their data. For this research it means that this market could not be further investigated.

4.1.3 Primary Reserve market

Despite the two mentioned markets for equalizing supply and demand, there still exists a possibility of imbalances because of power outages or forecast errors. In order to balance supply and demand at all times, the transmission system operator (TSO) uses balancing energy. Three kinds of reserves can be distinguished: primary reserve, secondary reserve, and tertiary reserve (Frontier economics, 2015). The order of activation of the different reserve capacities is shown below.

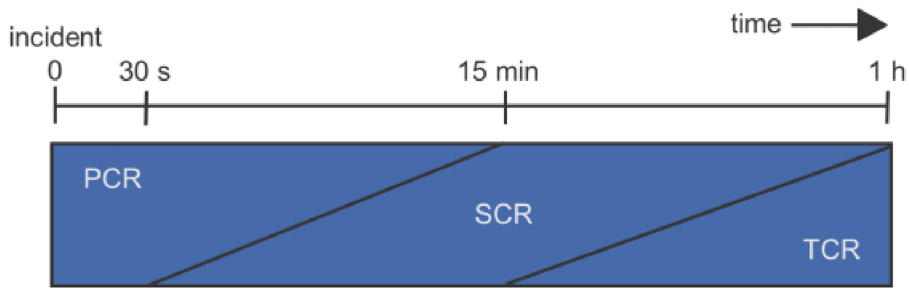

Figure 4.2: Time schedule of activation of reserve capacities (Primary, Secondary, and Tertiary Control Reserve) (Consentec, 2014)

Primary reserve or primary control is automatically used to stabilize frequency disruptions within 30 seconds. The primary control reserve is procured once per week, partly in an auction with the German TSOs and partly in a separate Dutch auction. In total these two auctions provide at least the required 96 MW of primary reserve capacity for the Netherlands (Frontier economics, 2015). The required amount of primary reserve is determined every year by the ENTSO-E (European Network of Transmission System Operators for Electricity). The required amount of primary reserve is in proportion to the amount of production in the control area of the relevant TSO (Transmission System Operator). The minimum bid on the auction is 1 MW and the producing unit needs to be able to be activated by an automated control mechanism, which is operated by TenneT (TenneT, 2013).

The determination of the required amount of primary reserve is done by ENTSO-E on basis of generated electricity in a control area (in this case: the Netherlands) divided by the sum of generated electricity of the control areas in the synchronous area (in this case: regional group continental Europe). The Netherlands is also part of the voluntary regional group northern Europe, which concentrates its efforts on the impacts of high voltage direct current interconnectors, which connect the Dutch market to the English and the Norwegian market (ENTSO-E, 2004).

The reimbursement for primary reserve is based on having capacity ready to be activated, so the payment is per MW and not per MWh. The offers on the auction with other TSOs vary from 1 to 60 MW (average 6 MW), and from 1660 to 6600 €/MW (average 2900 €/MW) (Regelleistung.net, 2016). The offers on the separate Dutch auction vary from 2 to 55 MW (average 7,5 MW), and from 2000 to 5800 €/MW (average 3060 €/MW)(Regelleistung.net, 2016(1)).

4.1.4 Secondary Reserve market

Whereas primary reserve re-establishes the system frequency to a common level for the synchronous area, the secondary reserve or secondary control re-establishes the system frequency to the set-point value (50 Hz)(ENTSO-E, 2004). Suppliers of secondary reserve are called by TenneT to increase supply (or reduce demand) or decrease supply (or increase demand) when the system balance in the Netherlands is over- or under-balanced. It is important to mention that the secondary reserve capacity in the Netherlands consists of "regelvermogen" (control capacity) and "reservevermogen" (reserve capacity). The latter is activated either when TenneT assumes that the first can't cover the demand for secondary control or when TenneT assumes that the first one becomes too expensive. Any producers or consumers larger than 60 MW are obliged to offer any power that they can produce/consume more/less as "reservevermogen" (DTe & TenneT, 2004).

Secondary control consists of automatic generation control, which modifies controllable load up to 15 minutes after an incident using secondary control reserves. The total necessary capacity of the control reserves can be determined using multiple methodologies (specified by ENTSO-E), due to different characteristics and patterns of generation (ENTSO-E, 2004). TenneT does not specify which method they use, but it is likely that they use either the empiric noise management sizing approach or probabilistic risk management sizing approach. The third possible approach is largest generation unit or power feed-in, which determines the size of the control reserve using the assumption and expectation of the largest possible generation incident. Since the secondary control capacity is approximately 400 MW in the Netherlands and the largest plant is more than 1 GW, TenneT probably does not use the third method. The first two methods calculate the secondary control size using respectively the maximum anticipated consumer load and the individual distribution curve of the power imbalance (which includes a number of factors which all relate to generation (capacity)) (ENTSO-E, 2004).

There are a number of requirements for secondary reserve units. In the first place they must be controllable by TenneT's national FrequencyPowerRegulation ("Frequentie VermogensRegeling") and have a minimal size of 4 MW and a maximal size of 200 MW. In addition, it must be adjustable in discrete steps of 1 MW. Next to that, the ramp up and ramp down speed must be at least 7% per minute in order to achieve full deployment within 15 minutes. The last requirement is a reaction speed of 30 seconds (TenneT, 2014). Secondary reserve capacity is traded on a market where TenneT is the only buyer (single buyer market). A part (250 MW) of the need for secondary reserve is covered with yearly contracts with suppliers. This means that these suppliers must have capacity available for secondary control for all PTU's (ProgramTimeUnit, "PTE" in Dutch) in a that year (DTe & TenneT, 2004). The rest of the need for secondary reserve is traded from one week before delivery until 14:45 on the day before delivery. Adjustments can be made until one hour before delivery (TenneT, 2012).

TenneT publishes all the total volume of the secondary control bids and the price of the most expensive bid at 100 MW, 300 MW, 600 MW, and the maximum necessary capacity. TenneT also publishes the "balance delta" with prices, which means the actual used secondary reserve and the price against which it is used. It is unclear whether these data include the 250 MW of yearly contracts. The amount of ramp up power lies between 0 and 500 MW, with an average of 25 MW. The amount of ramp down power lies between 0 and 525 MW, with an average of 27 MW. The ramp up reserve lies between 0 and 125 MW, with an average of 0,12 MW (since it not frequently used). The ramp down reserve lies between 0 and 120 MW, with an average of 0,04 MW. The prices for ramp up power/reserve lie between 0 and 660 €/MWh, with an average of 51. The prices for ramp down power/reserve lies between 92 and -430 €/MWh, with an average of 18 . A negative price means that TenneT pays this Balance Responsible Party (BRP). Both prices can be negative, but the ramp down price is more often negative because that basically means that there's more electricity available on the grid.

4.1.5 Tertiary Reserve market

Tertiary reserve is deployed when the grid frequency is not restored after 15 minutes (Frontier Economics, 2015). Requirements for tertiary reserve are that the time between the call by TenneT and the actual availability must be known (with a maximum of 3 days) (TenneT, 2004). The value of the contracts for tertiary reserve capacity is not published by TenneT. This makes it harder to determine the value for low-voltage electricity storage. That fact, combined with the requirement of being always available for TenneT during the contract period, indicates that this market is not where low-voltage storage units will gain a lot of value.

4.1.6 Summary of markets

In tables 4.1 to 4.3, a comprehensive overview of the analysis of the Dutch electricity markes is given.

Overview Dutch electricity markets - part 1				
Market (Dutch name)	**Time of trading**	**Platform**	**Volumes**	**Prices**
Day-Ahead (Spotmarkt)	Trading untill 12:00 AM on the day before delivery	APX market	2.800 - 4.000 GWh per month	20-100 €/MWh (average 50 €/MWh)
Intra-Day (Spotmarkt)	Trading untill 5 min before delivery	APX market; Elbas market	36 - 138 GWh per month	27-51 €/MWh (average 31 €/MWh)
Primary Reserve (Primaire reserve)	Cleared once per week	TenneT; Regelleistung	102 MW capacity stand-by at all times	1700 to 6600 €/MW/week (average bid 3300 €/MW/week)
Secondary Reserve (Regel- en reserve-vermogen)	Trading from 1 week before delivery until 14:45 on day before delivery	TenneT (Single Buyer market)	Unknown	Ramp-up: 0 -660 €/MWh (av. 51) Ramp-down: -430 - 92 €/MWh (av. 17)
Tertiary Reserve (Noodvermo-gen)	Yearly tender; Quarterly tender	TenneT	350 MW capacity stand-by at all times	Unknown

Table 4.1: Overview of Dutch electricity markets - part 1

Overview Dutch electricity markets - part 2		
Market	**Prerequisites for trading**	**Miscellaneous**
Day-Ahead & Intra-Day	1. Program Responsible Party contract; 2. Minimum duration is 1 hour; 3. Trading in multiples of 100 kW	1. Entrance fee - €5000; 2. Member fee - €28.500; 3. Technology fee - €5000; 4. Day-Ahead - 0.07 €/MWh 5. Intra-Day - 0.095 €/MWh
Primary reserve	1. Instantaneous frequency 49,2 - 50,8 Hz; 2. 50% evenly activated in 15s, and linear increase to 100% activated in 30s; 3. Minimum of 1 MW; only integer values; pooling is possible; symmetric power (both ramp up and ramp down); 4. Minimum control range of 2% of nominal power (with a minimum of 100 kW for a pool-unit);	1. No costs of trading; 2. Development: TenneT is looking into lowering minimum amount of 1 MW to allow smaller parties to join this market, as well as lowering duration of supply from 30 min to 15 min;

Table 4.2: Overview of Dutch electricity markets - part 2

Overview Dutch electricity markets - part 3		
Market	**Prerequisites for trading**	**Miscellaneous**
Secondary reserve	1. Must be controllable by FrequencyPowerRegulation; 2. Continuously adjustable in discrete steps of 1 MW; 3. Ramp up/down speed of at least 7% per minute to achieve full activation in 15 minutes; 4. Reaction speed of 30 seconds; 5. Minimum of 4 MW and maximum of 200 MW;	1. No costs of trading; 2. Contracts for this market are for 1 quarter. Reimbursement for capacity -> value unclear
Tetiary reserve	1. Reserve must be available within 15 minutes; 2. Company supplying reserve must be reachable by phone 24/7; 3. Sufficient metering in order to control supply (5-minute values); 4. Minimum of 20 MW (pooling is possible); 5. Power must be available exclusively for TenneT;	1. No costs of trading 2. Administratively not possible to join both secondary reserve as tertiary reserve

Table 4.3: Overview of Dutch electricity markets - part 3

4.2 Accessible markets

An overview of the analysis of the markets, described in the previous paragraph, can be found in table 4.1, 4.2 and 4.3. From these overviews, the markets accessible for local storage units are determined. Moreover, from these overviews and analysis of prices and amounts, it is concluded that two markets are most suitable for trading.

The first market that is excluded is the tertiary reserve market. Within this research, the trading is an additional value - the first value being decreasing peak load for the DSO. As a tertiary reserve unit must be exclusively available for TenneT, this is can't be combined with creating benefits for the DSO. Moreover, as table 4.3 shows, it is administratively not possible to trade both on this market and the secondary reserve market.

On the secondary reserve market, higher prices can be expected, meaning a higher profit when traded upon with storage (see table 4.1). Also, as the tertiary reserve market consists only of bilateral contracts between suppliers and TenneT, the information that is publicly available is very limited. Therefore, this market will not be analysed further in this research.

The second market that is excluded from further research is the Intra-Day market. The Intra-Day market namely consists mostly of bilateral contracts - again making the amount of public information very limited. Moreover, the Day-Ahead market is likely to have a higher revenue and has higher amounts traded (see table 4.1).

The third market that is excluded is the Primary Reserve market. This market would be accessible with a pool of storage units and have a promising revenue. However this market demands that offered capacity can be used for ramping-up and ramping-down. Moreover, it is unknown beforehand when the offered capacity is claimed by TenneT. This means in the first place that only half of the available capacity can be offered, as the storage units must half-charged at all times. Second, this value is not combinable with lowering peak demand for the DSO.

This leaves two markets for further research: the Day-Ahead market and the secondary reserve market.

One of the prerequisites for being able to trade on the Day-Ahead (and Intra-Day, but this market is already exempted from analysis) market is to trade in 100 kW or multiples of 100 kW. The storage units as designed in chapter 3 (see table 3.4) however have a power of less than 100 kW, making them ineligible for the Day-Ahead market. Therefore, these systems need to be redesigned to 100 kW power output, making them slightly more expensive. The Secondary Reserve market has a minimum power as well, namely 4 MW. On the Secondary Reserve market, in contradiction to the Primary Reserve market, pooling is not mentioned anywhere in the documents provided by TenneT, indicating that this is not allowed on this market. However, in conversations with Jules Energy (Dutch organisation that trades local produced electricity for consumers) it became clear that for receiving a capacity-reimbursement there is a minimum of 4 MW, but for on-the-spot trading on this market is allowed with lower capacities.

4.3 Price trends on Dutch electricity markets

This section describes price trends on Dutch electricity markets. This analysis is ought to serve as input for the design of a trading algorithm, which is done in the next chapter. The markets that are analysed are the markets accessible for local storage units, namely the Day-Ahead market and the Secondary Reserve market. The structure of this section is as follows. First, the Day-Ahead market is analysed and thereafter the Secondary Reserve market. This structure is similar to the point in time at which the traded electricity is activated: first on the Day-Ahead traded electricity (e.g. scheduled) and then the Secondary Reserve (second balancing mechanism). All markets are analysed on short-term basis for the period 18 of July 2015 till 18 of July 2016.

The three markets are analysed using different methods, as they operate differently as well. The Day-Ahead market is analysed using regression analysis, as described in the research framework in chapter 2.1.

The analysis of the Secondary Reserve market has a different character. As batteries in neighbourhoods are not going to have a capacity of 4 MW, the trading on the Secondary Reserve market has to be done on-the-spot. This means that at any minute during the day trading can be done on the Secondary Reserve market. However, as the settlement is done per 15 minutes, the decision to trade or not should be done not per minute but per 15 minutes. The first thing that is analysed is if a time series can be fit to the Secondary Reserve market, as it would be most useful to forecast this market well in advance, since a trade-off between this markets and other markets must be made. If a time series can't be fitted, the forecast error (both load and renewable production) is used to explain the Secondary Reserve market. Last, the relation between the first or first two minutes and the rest of the quarter is checked.

4.3.1 Day-Ahead market

The Day-Ahead market is analysed using regression analysis. However, before the regression analysis is executed, the relation between the explanatory variables and the price is checked, as regression analysis measures linear dependency. The short-term price trends on the Day-Ahead market will be analysed on basis of auto-correlation, correlation with (forecasted) (residual) load, and correlation with renewable energy production. There are also clear relations between the Dutch market and other markets, such as the German market (Mulder, 2013).

The auto-correlation of the Day-Ahead price has been researched before by others. Mohsenian-Rad and Leon-Garcia calculated the correlation of a price with past prices at different days (Mohsenian-Rad, 2010). A clear peak in correlation is visible at 7 days, 14 days, 21 days, and so on. This means that a there's a strong relation between prices on the same day of the week. Also Mulder (Mulder, 2013) shows a correlation between average daily Day-Ahead prices on the Dutch market. Therefore in this research, it seems logical to create an Auto-Correlation Function (ACF) plot of hourly Day-Ahead market prices.

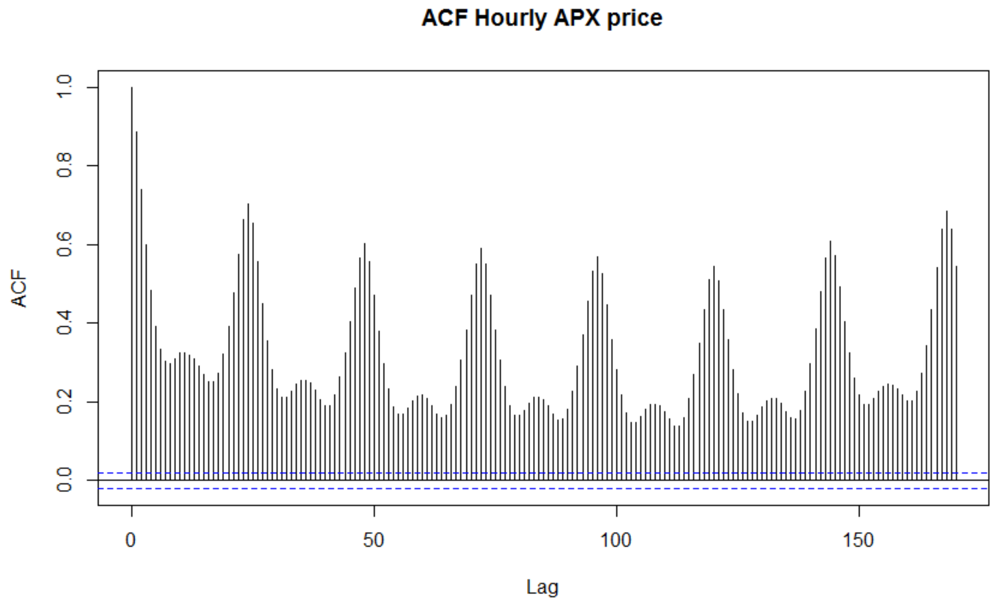

Figure 4.3: ACF plot for hourly APX prices

This figure shows for "lags" 0 till 170 the correlation coefficient for the APX Day-Ahead price. The lag can be interpreted as follows. If the lag is 1, the auto-correlation function tests the correlation between the first and second value, between the second and third value, and so on. If the lag is two, the function tests the correlation between the first and third value, between the second and fourth value, and so on. The results of these tests are then visualised in these plots.
The plots also include a blue horizontal dashed line, in this case very close to the 0.0 value. This line indicates the 95%-significance of the correlation coefficient. If the correlation coefficient is higher than the significance line, the auto-correlation for that lag is significantly non-zero.

From the ACF plots, a number of conclusions can be drawn. A number of peaks are visible. These are located at very low lags (i.e. 0,1,2), and around 24 and multiples of 24. The high correlation coefficient at low lags can be explained that the price on the Day-Ahead market is very similar to the price in the hour(s) before. The most likely explanation for the peaks around 24 and multiples of 24 is that prices each day at the same hour are similar.

Another explanation for high correlation coefficients in the ACF plot is that the correlation coefficients at higher lags are influenced by the high correlation coefficients at lower lags. A solution for this phenomenon is using the Partial Auto-Correlation Function (PACF). The PACF is more suitable to estimate the significant lags (Reinsel et al., 2015). The PACF plot for the Day-Ahead market can be found in figure 4.4.

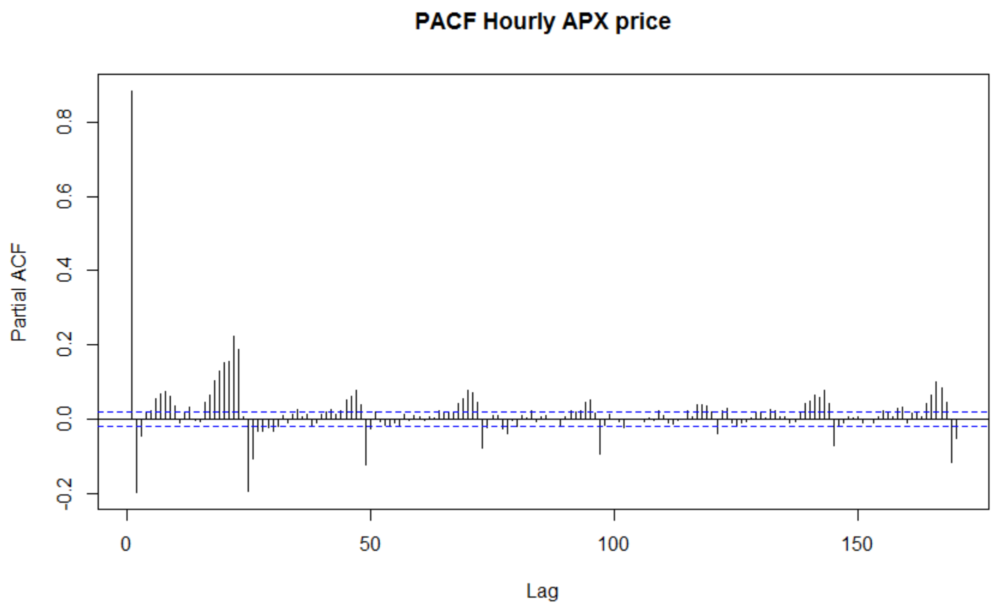

Figure 4.4: PACF plot for hourly APX Day-Ahead prices (no value at lag = 0)

Figure 4.1 shows the adjusted correlation coefficient for lags 1 till 170. The PACF has no value at lag 0. Also in figure 4.4, the blue line indicates the significance of the coefficient. The adjusted correlation coefficient indicates that the only significant values are at lag 1 and multiples of 24. The same explanation as at the ACF can be applied here as well, namely that the price at each day at the same time is similar.

Next to the correlation of Day-Ahead prices with itself, there are also other explanatory variables for the price on the Day-Ahead market. One example of this is the forecasted load, since the trade on the Day-Ahead market takes place on the day before the actual delivery. The relation between the forecasted load and the price on the Day-Ahead market for the period 18-07-2015 till 18-07-2016 is shown below.

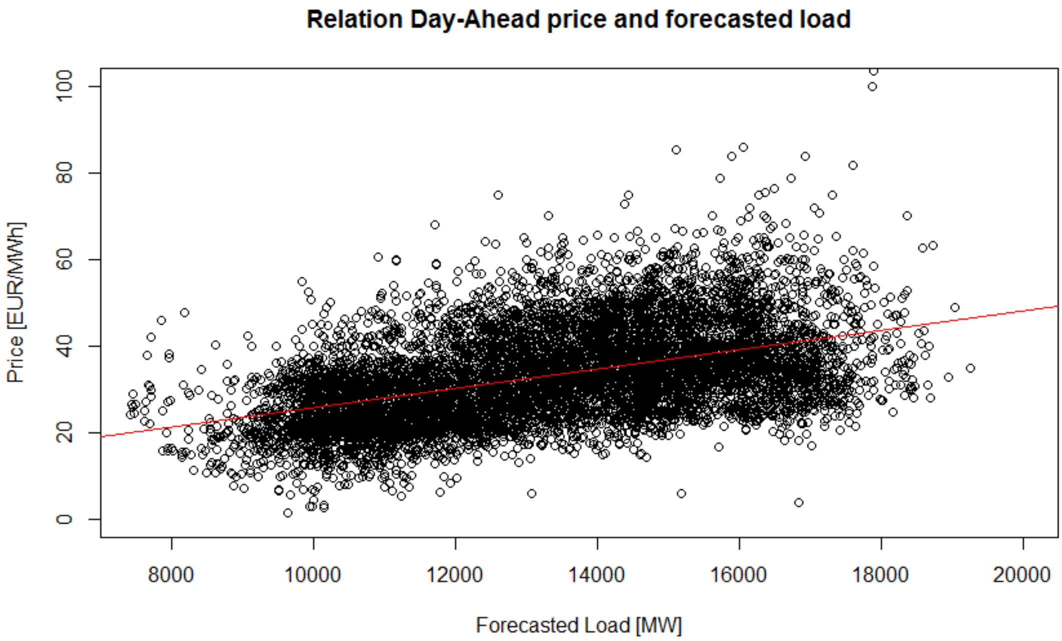

Figure 4.5: Scatterplot of hourly APX Day-Ahead price and forecasted load with regression line

This figure shows the relation between the average load per hour and the price on the Day-Ahead market for that hour. The red line is the regression line. A clear correlation between the forecasted load and the market price is visible. The most logical explanation for this is simple market economics: if the demand is higher, the price goes up. The correlation coefficient is approximately 0.49 with a very low p-value (<2.2e-16).

Another explanatory variable is the residual forecasted load, as the amount of electricity produced by solar panels and wind turbines is likely to influence the price on the market. A higher production by renewables means that less thermal power plants are needed, which can result in a lower price. The relation between the forecasted residual load and the Day-Ahead price is shown in figure 4.6. In this research, residual load is equal to the total load minus the amount of electricity produced by PV panels and on- and offshore wind turbines.

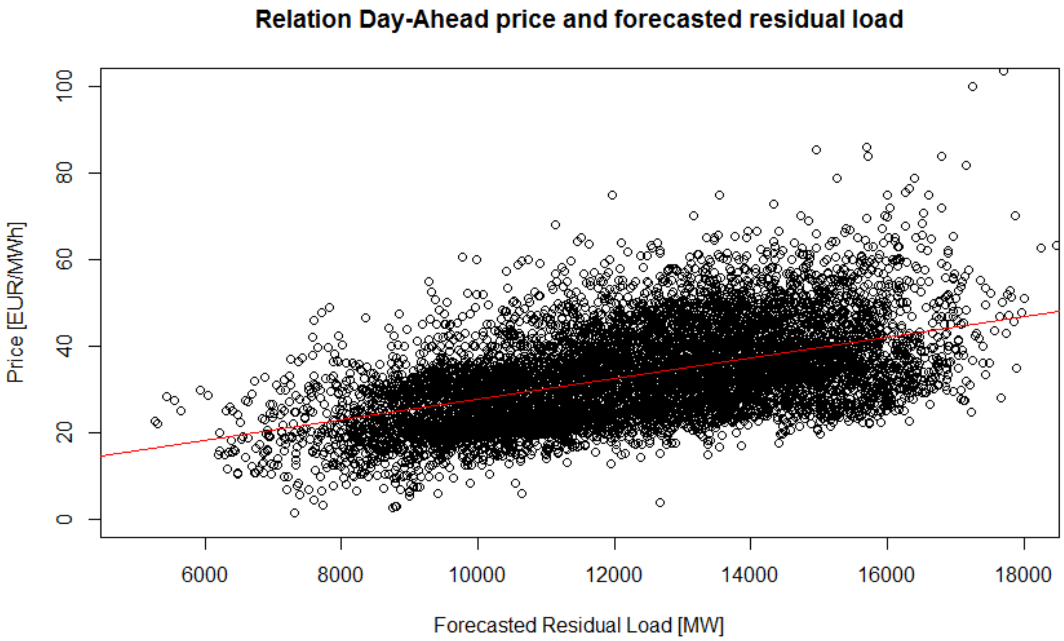

Figure 4.6: Scatterplot of hourly APX Day-Ahead price and forecasted residual load with regression line

Figure 4.6 is very similar to figure 4.5, but the x-axis has shifted around 2000 MW. This is the caused by subtracting the forecasted production by renewables. The correlation coefficient is approximately 0.53 with a very low p-value (<2.2e-16). The correlation between the forecasted residual load and the Day-Ahead market price is higher than the correlation between the forecasted load and this price.

The analyses of the correlation between the Day-Ahead price and forecasted (residual) load is executed with load and production data from ENTSO-E (European Network for TSOs) and market price data from APX group (operator of Day-Ahead market). It could however be that market participants are able to make better forecasts than ENTSO-E and national TSOs. In order to test if this is the case, the relation between the actual (residual) load and the market price is shown below.

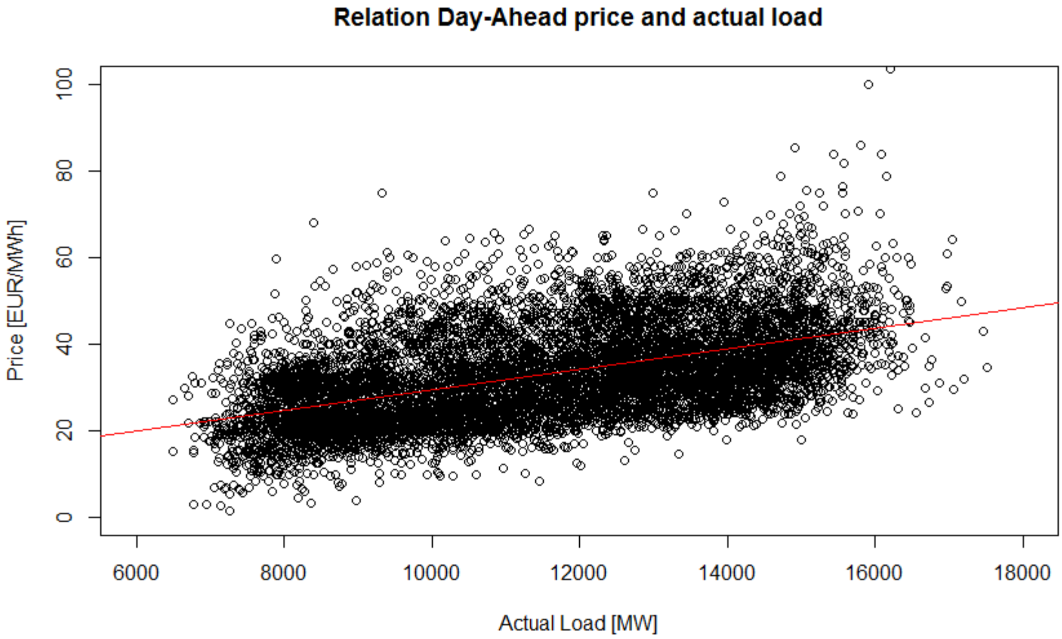

Figure 4.7: Scatterplot of hourly APX Day-Ahead price and actual load with regression line

In this plot the relation between the APX Day-Ahead price and the actual load in the Netherlands is visible. It looks very similar to the relation between the Day-Ahead price and the forecasted load, but the correlation coefficient is slightly lower, namely 0.46. This coefficient differs from the value calculated by Mulder and Scholtens (Mulder, 2013), as they report a correlation coefficient of 0.048. This difference most likely occurs because they use a logarithmic scale to calculate the correlation and because they use a daily average instead of an hourly average.

In figure 4.8 the correlation between the Day-Ahead price and the actual residual load is shown. Residual in this case means the total load minus the production of electricity by PV panels, onshore wind, and offshore wind. The correlation coefficient is 0.53, which is equal to the correlation between the Day-Ahead price and the forecasted load.

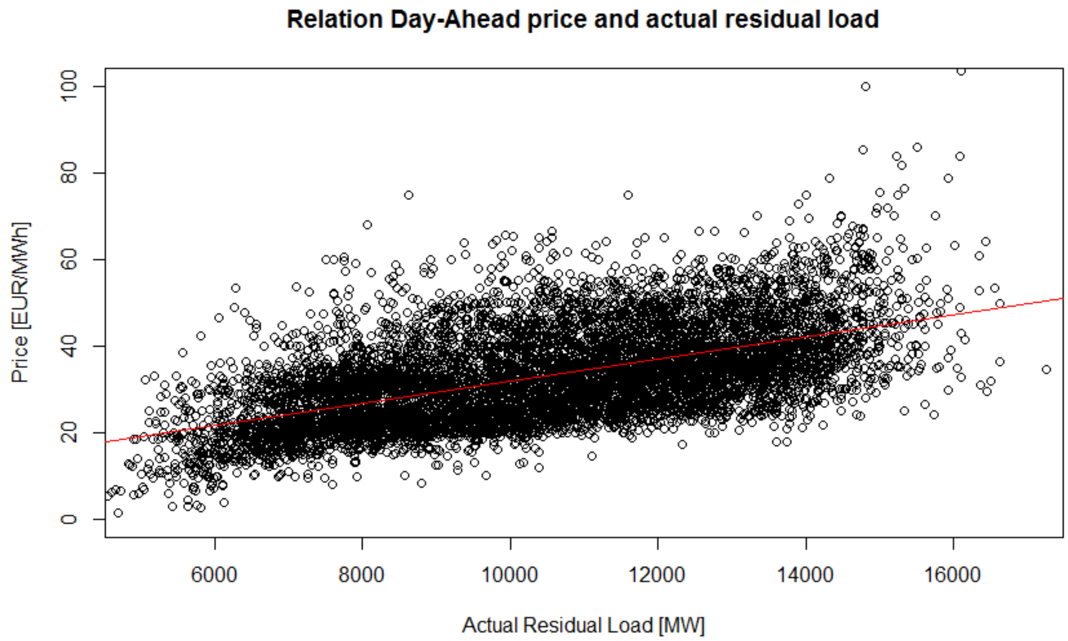

Figure 4.8: Scatterplot of hourly APX Day-Ahead price and actual residual load with regression line

In table 4.4 are some more descriptive statistics to decide which of the correlations can be used as input for the design of the trading algorithm. In the first place, the correlation with the Day-Ahead price is shown. These correlations are mentioned before, but this gives a comprehensive overall view. Next to the correlation, the relative standard error (RSE) is calculated. The relative standard error is the standard error divided by the mean. A lower relative standard error indicates a more precise model. Last, the R squared is shown. This indicator can be interpreted as the amount of variance in the Day-Ahead price that is explained by the regression line.

Input parameter	**Correlation with APX price**	**RSE**	$\mathbf{R^2}$
Forecasted load	0.49	9.45	0.24
Forecasted residual load	0.53	9.22	0.28
Actual load	0.51	9.31	0.26
Actual residual load	0.57	8.90	0.33

Table 4.4: Correlation, Residual standard error, and R squared of different input parameters with the APX Day-Ahead price for 18-07-2015 till 18-07-2016

From this table a number of things become clear. In the first place, the actual (residual) load is more explanatory for the Day-Ahead price than the forecasted (residual) load. This is notable, as the trade on the Day-Ahead market takes place on the day(s) before actual delivery. This means that this trade has to be done on basis of load forecasts. Therefore, one would expect the forecasted (residual) load to be more explanatory.

The second conclusion is that the residual load, either forecasted or actual, is a better indicator than the total load. This makes sense as the intermittent character of renewable production makes it more difficult for parties to bid renewable capacity on the Day-Ahead market.

The next step in the regression analysis is to calculate regression values and to stepwise add explanatory variables to the model. The stepwise-addition of explanatory variables means that each step the variable with the highest significant beta-value is added to the regression model, after which the betas and significances of not (yet) included variables are calculated again. This is repeated till no explanatory variable with significant beta value exists. The explanatory variables that are used in the regression analysis are shown in table 4.5.

Explanatory variable	**Variable type**
Dutch Forecasted Load	Ratio
Dutch Forecasted Residual Load	Ratio
German Forecasted Load	Ratio
German Forecasted Residual Load	Ratio
Month	Ordinal
Day of the week	Ordinal

Table 4.5: Explanatory variables used in the regression analysis

The choice was made to exclude the actual (residual) load, as this value can not be used for forecasting the electricity price, since the actual load value is not known beforehand. The forecasted load however is known beforehand and at the time of bidding. Therefore, this value is more suitable to use as a basis for placing bids on the Day-Ahead market. As can be seen in table 4.5, most variables are ratio-variables. However, month and day of the week are ordinal variables. These variables are not usable in a regression analysis. The months for example are converted to numbers, January being 1, February being 2, etcetera. SPSS considers these numbers as February being twice the value of January, which is nonsense. Therefore, the month values are converted to dichotomous variables. This means that 11 new variables were created, which have either value 1 or 0. The first variable is equal to 1 if the month equals January, and 0 if the month is not January. This is repeated for all months. The same process is done for the different days of the week.

Before the beta values of different explanatory variables can be calculated, it must be checked if these variables are correlated, as they need to be independent in order to continue with the regression analysis. The correlation matrix is shown in figure 4.6. This matrix shows that the Dutch Forecasted Load (DFL) has a high correlation with the Dutch Forecasted Residual Load (DFRL) and the German Forecasted Load (GFL). Therefore, the DFL is not used in the regression analysis, as the use of this explanatory variable is likely to increase the variance of the beta-coefficients by the model, making these coefficients more unstable and more difficult to interpret (Frost, 2013). When DFL is removed, the highest correlation is 0.742, which is low enough to consider adding the remaining variables to the regression model.

Cor matrix	DFL	DFRL	GFL	GFRL	Weekday	Month
DFL	1	,953 (,000)	,810 (,000)	,525 (,000)	,049 (,000)	-,007 (,504)
DFRL	,952 (,000)	1	,742 (,000)	,620 (,000)	,061 (,000)	-,013 (,225)
GFL	,810 (,000)	,742 (,000)	1	,620 (,000)	,098 (,000)	,001 (,949)
GFRL	,525 (,000)	,620 (,000)	,620 (,000)	1	,128 (,000)	-,018 (,102)
Weekday	,049 (,000)	,061 (,000)	,098 (,000)	,128 (,000)	1	-,005 (,609)
Month	-,007 (,504)	-,013 (,225)	,001 (,949)	-,018 (,102)	-,005 (,609)	1

Table 4.6: Correlation (Pearson) matrix for explanatory values. Significance is shown between brackets. D=Dutch, G=German, F=Forecasted, R=Residual, L=Load

The next step is to fit a regression model using the stepwise method. The first model uses the monthly dichotomous variables and the second model uses the weekdays dichotomous variables.

The results of the first model can be found in figure 4.9. As can be seen, 14 variables have been included in the final model, of which 11 monthly indicators. The final model has an R square of 0,655, which means that the explained variance is 66,5%. In table 4.7 the beta-coefficients for the different explanatory variables can be found. The order of the variables in this table is equal to the order in which these variables were added to the regression model.

It is important to notice that these beta-coefficients are the unstandardised. Therefore, coefficients for GFL, GFRL, and DFRL are relatively low compared to the monthly values. The coefficient for the 12th month is processed in the constant.

The last step in the regression analysis is to analyse the residuals of the model, which should ideally approach a normal distribution. These residuals are shown in figure 4.10. The residuals of the fitted model seem to be approximately normally distributed.

Model Summary[o]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	,559[a]	,312	,312	8,98202	,312	3964,983	1	8734	,000
2	,623[b]	,388	,388	8,47399	,076	1079,637	1	8733	,000
3	,667[c]	,445	,445	8,07048	,057	896,092	1	8732	,000
4	,714[d]	,510	,509	7,58518	,065	1154,099	1	8731	,000
5	,748[e]	,559	,559	7,19476	,049	974,272	1	8730	,000
6	,762[f]	,581	,581	7,01164	,022	462,945	1	8729	,000
7	,780[g]	,609	,609	6,77321	,028	626,390	1	8728	,000
8	,789[h]	,622	,622	6,65774	,013	306,371	1	8727	,000
9	,798[i]	,636	,636	6,53464	,014	332,891	1	8726	,000
10	,800[j]	,639	,639	6,50730	,003	74,483	1	8725	,000
11	,802[k]	,644	,644	6,46626	,005	112,106	1	8724	,000
12	,805[l]	,648	,647	6,43090	,004	97,205	1	8723	,000
13	,807[m]	,652	,651	6,39357	,004	103,138	1	8722	,000
14	,810[n]	,655	,655	6,36223	,003	87,160	1	8721	,000

a. Predictors: (Constant), GFL

b. Predictors: (Constant), GFL, MonthV2

c. Predictors: (Constant), GFL, MonthV2, MonthV3

d. Predictors: (Constant), GFL, MonthV2, MonthV3, GFRL

e. Predictors: (Constant), GFL, MonthV2, MonthV3, GFRL, MonthV4

f. Predictors: (Constant), GFL, MonthV2, MonthV3, GFRL, MonthV4, MonthV5

g. Predictors: (Constant), GFL, MonthV2, MonthV3, GFRL, MonthV4, MonthV5, MonthV1

h. Predictors: (Constant), GFL, MonthV2, MonthV3, GFRL, MonthV4, MonthV5, MonthV1, MonthV6

i. Predictors: (Constant), GFL, MonthV2, MonthV3, GFRL, MonthV4, MonthV5, MonthV1, MonthV6, DFRL

j. Predictors: (Constant), GFL, MonthV2, MonthV3, GFRL, MonthV4, MonthV5, MonthV1, MonthV6, DFRL, MonthV10

k. Predictors: (Constant), GFL, MonthV2, MonthV3, GFRL, MonthV4, MonthV5, MonthV1, MonthV6, DFRL, MonthV10, MonthV8

l. Predictors: (Constant), GFL, MonthV2, MonthV3, GFRL, MonthV4, MonthV5, MonthV1, MonthV6, DFRL, MonthV10, MonthV8, MonthV9

m. Predictors: (Constant), GFL, MonthV2, MonthV3, GFRL, MonthV4, MonthV5, MonthV1, MonthV6, DFRL, MonthV10, MonthV8, MonthV9, MonthV11

n. Predictors: (Constant), GFL, MonthV2, MonthV3, GFRL, MonthV4, MonthV5, MonthV1, MonthV6, DFRL, MonthV10, MonthV8, MonthV9, MonthV11, MonthV7

o. Dependent Variable: Price

Figure 4.9: Model summary for the first model, which includes DFRL, GFL, GFRL, and Monthly indicators

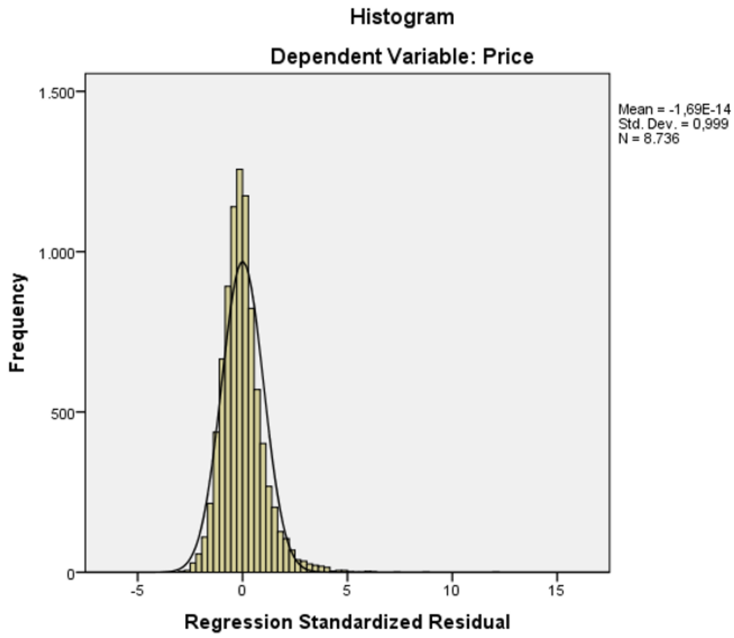

Figure 4.10: Histogram of residuals of the first model, which includes DFRL, GFL, GFRL, and Monthly indicators

The same process is executed for different days of the week. The results are shown on the next page. This immediately shows that the explained variance is significantly lower compared to the model with the montly variables. Therefore, this model is not further analysed, as the model with the monthly variables has a better chance of predicting the correct price on the Day-Ahead market.

Then, the model with monthly variables and weekdays variables are combined, in order to assess if that increases the explained variance. However, this results in an explained variance of 0,66. This is not a large increase compared to the monthly variables only model, but increases the complexity of the trading algorithm. Therefore, the model is limited to the monthly variables and the GFL, GFRL, and DFL. This model is verified and validated in appendix II.

Figure 4.11: Model summary for the second model, which includes DFRL, GFL, GFRL, and Weekday indicators

Model Summary[j]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	,559[a]	,312	,312	8,98202	,312	3964,983	1	8734	,000
2	,612[b]	,374	,374	8,56745	,062	866,709	1	8733	,000
3	,620[c]	,384	,384	8,49856	,010	143,165	1	8732	,000
4	,623[d]	,388	,388	8,47276	,004	54,246	1	8731	,000
5	,624[e]	,389	,389	8,46873	,001	9,312	1	8730	,002
6	,624[f]	,389	,389	8,46501	,001	8,673	1	8729	,003
7	,625[g]	,390	,390	8,45965	,001	12,068	1	8728	,001
8	,625[h]	,391	,391	8,45466	,001	11,314	1	8727	,001
9	,626[i]	,392	,391	8,44820	,001	14,354	1	8726	,000

a. Predictors: (Constant), GFL

b. Predictors: (Constant), GFL, GFRL

c. Predictors: (Constant), GFL, GFRL, DFRL

d. Predictors: (Constant), GFL, GFRL, DFRL, WeekdayV1

e. Predictors: (Constant), GFL, GFRL, DFRL, WeekdayV1, WeekdayV3

f. Predictors: (Constant), GFL, GFRL, DFRL, WeekdayV1, WeekdayV3, WeekdayV4

g. Predictors: (Constant), GFL, GFRL, DFRL, WeekdayV1, WeekdayV3, WeekdayV4, WeekdayV6

h. Predictors: (Constant), GFL, GFRL, DFRL, WeekdayV1, WeekdayV3, WeekdayV4, WeekdayV6, WeekdayV5

i. Predictors: (Constant), GFL, GFRL, DFRL, WeekdayV1, WeekdayV3, WeekdayV4, WeekdayV6, WeekdayV5, WeekdayV2

j. Dependent Variable: Price

The beta-coefficients for the first model, which as the highest explained variance, are shown in table 4.7. This model, as said, has as explanatory variables the German Forecasted Load, the German Forecasted Residual Load, the Dutch Forecasted Residual Load, and indicators for 11 months, with the effect of month 12 processed in the constant. These beta-coefficients are used in the trading algorithm in chapter 5.

Variable	**Beta**	**Variable**	**Beta**
(Constant)	-4,686	MonthV6	-1,067
GFL	0,00032	DFRL	0,00090
MonthV2	-10,336	MonthV10	6,180
MonthV3	-9,178	MonthV8	6,051
GFRL	0,00023	MonthV9	5,322
MonthV4	-7,076	MonthV11	4,526
MonthV5	-3,367	MonthV7	3,071
MonthV1	2,696		

Table 4.7: Unstandardised beta coefficients. All coefficients have a significance of 0,002 or lower.

4.3.2 Secondary Reserve market

The Secondary Reserve market is the second market analysed in this research. The provision of data for the Secondary Reserve market is sufficient to analyse it. Contradictory to the Day-Ahead market, this market needs to be forecasted both in terms of price as in terms of demand. The Secondary Reserve market is analysed using three analyses. The first analysis is, just as for the Day-Ahead market, a regression analysis. However, due to the purpose that this market serves, namely restoring the frequency on the grid when imbalances occur, using the load as an explanatory variable is non-logical. The explanatory variable that is used is the forecast error, both for load as for renewable production, as these forecasts are most likely to cause imbalance that has to be restored by the Secondary Reserve market. The second analysis is to check if the time of the day is a good explanatory variable for the amount and/or price. The third analysis checks to what extent the first value of a quarter is explanatory for the rest of that quarter. The time instant quarter is chosen as the Secondary Reserve market is cleared per quarter.

As said, the factor that is expected to be most explanatory for the amount of imbalance is the height of the forecast error. The forecast error in figure 4.12 is a sum of four factors. The assumption is made that most error in plant production is caused by renewable plants - for the Netherlands that is solar and wind. So, the difference between the total forecast of solar, onshore wind, and offshore wind and the actual production by those production types is calculated. From this amount, the load forecast error (forecasted load minus actual load) is subtracted. The load forecast error is subtracted from the production forecast error, because when the load is higher than forecasted, but the production is also higher than forecasted, this has an equalizing effect. The calculation of the forecast error is visualized in figure 4.12.

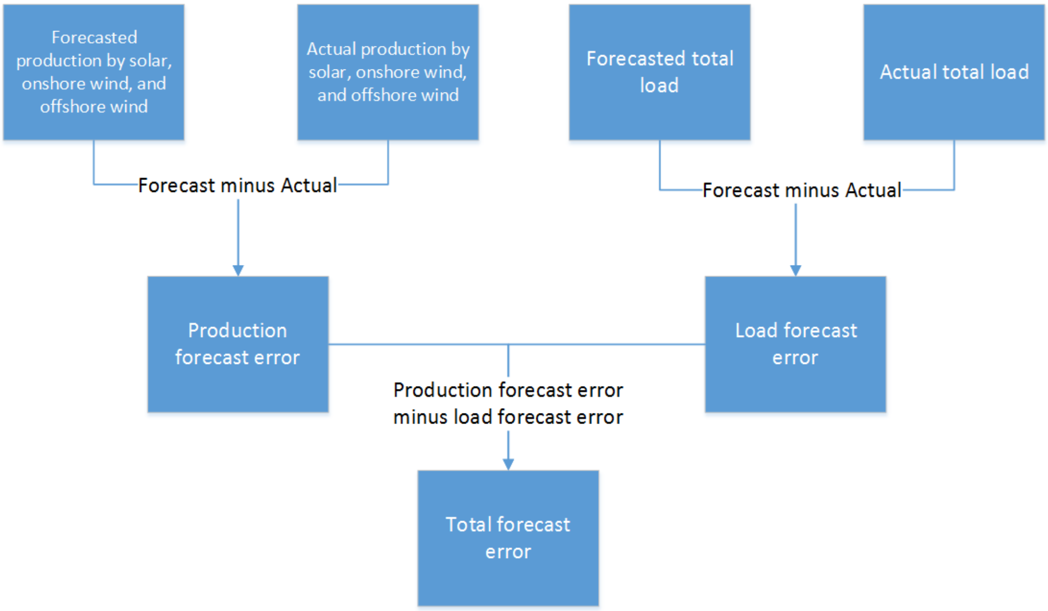

Figure 4.12: Calculation of the forecast error

The total forecast error per quarter is compared to the average amount sold on the Secondary Reserve market and visualized in figure 4.13. A number of observations can be made from this graph. In the first place, there's no real correlation between the forecast error and the amount traded on the Secondary Reserve market. A correlation is namely always linear, and the data points are spread in a circle or star shape. The second observation is that the amount traded on the Secondary Reserve market is usually in the hundreds of megawatts, but the forecast error is in the thousands of megawatts. The last observation is that the forecast error is usually positive, whereas the amount traded on the Secondary Reserve market is more equally distributed between positive and negative.

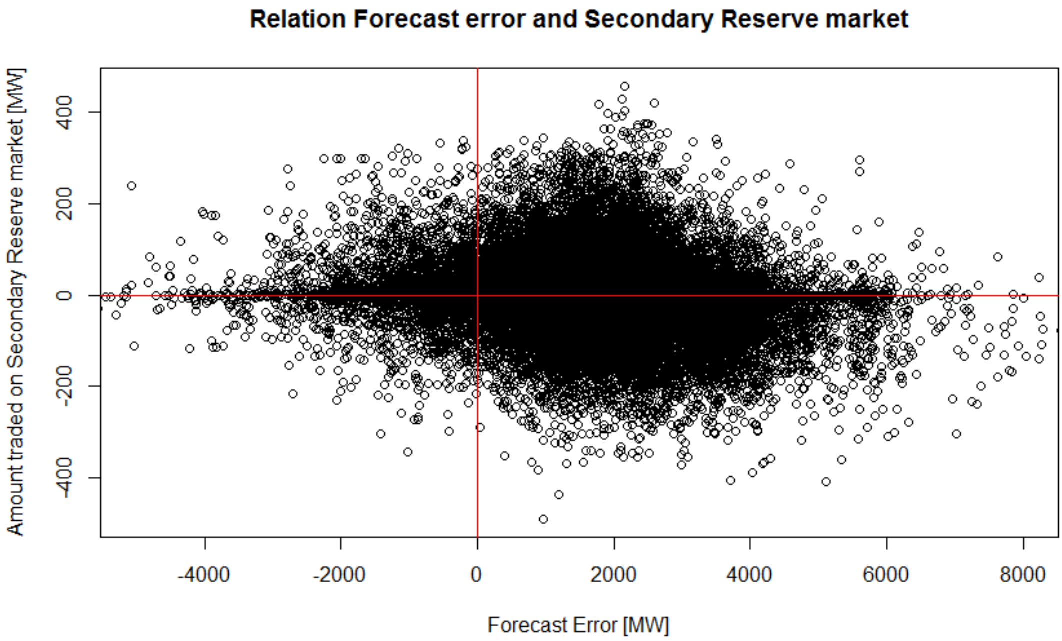

Figure 4.13: Relation between forecast error and amount traded on Secondary Reserve market. Data is for 18-07-2015 till 18-07-2016 and measured per 15 minutes

The first observation, which is that there is no correlation between the forecast error and the demand on the Secondary Reserve market, is valuable to analyse further as this contradicts with the hypothesis that the forecast error creates imbalance. Therefore, the next step is to analyse if the time of the day is relevant for the amount of imbalance.

To check if the time of the day has a relation with the amount traded on the Secondary Reserve market, a graph of the mean amount traded on the Secondary Reserve market per minute of the day is made. This means that for every first minute of every day between 18-07-2015 till 18-07-2016 the mean of the traded amount is calculated. Then the mean of every second minute of every day in the same period and so on. As there are 1440 minutes in one day, there are 1440 means calculated and visualised in figure 4.12.

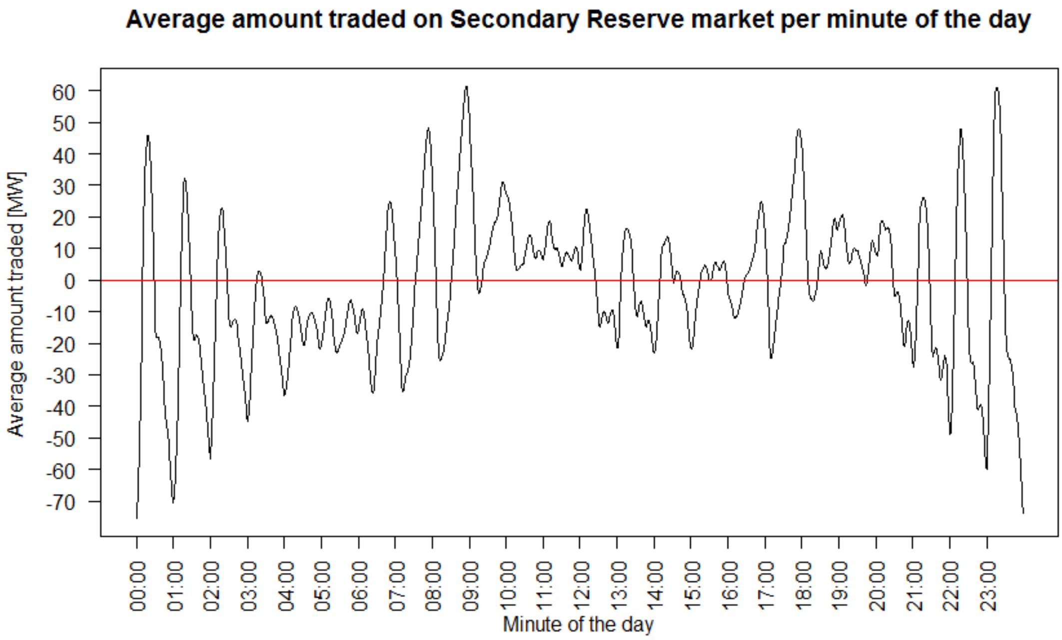

Figure 4.14: Average amount traded on the Secondary Reserve market per minute of the day, for 18-07-2015 - 18-07-2016

Figure 4.14 shows that the amount traded on the Secondary Reserve market is on average mostly not equal to zero. This is not what would be expected of this market. The expectation would be that it is equal to zero for a large number of data points, as the amount of imbalance is caused by unpredictable events with an equal chance of positive or negative imbalance. Moreover, there is a pattern noticeable, especially between 23:00 and 04:00. The pattern is an oscillating behaviour. This is an indication that the time of the day has an influence on the amount traded on the Secondary Reserve market.

The same process as used for the Day-Ahead market is applied for the secondary reserve market. There are 1440 minutes in one day, which means that 1440 variables need to be created that have either value 1 or 0. However, 1440 dummy variables in SPSS is too much for the computational means available during this research. Therefore, the analysis for the influence of the time of the day is done per 15 minutes, as the Secondary Reserve market reimbursement is also done per 15 minutes. This means, as there are 96 quarters in a day, that 95 dichotomous variables are created.

The results of these regression analyses are shown in table 4.9. This table shows that a regression model is not a suitable method for forecasting the Secondary Reserve market, as the explained variance is at maximum 10,2%. Moreover, none of the models incorporate all 95 quarter-variables, which indicates that time of the day is not a suitable explanatory variable in a regression analysis.

Explained variable	**Explanatory variables**	**Explained variance**	**Variables included**
Ramp-up power	Quarters(95) RPFE, LFE, TFE	6,6%	Quarters (64) RPFE, TFE
Ramp-down power	Quarters(95) RPFE, LFE, TFE	7,8%	Quarters (76) RPFE, LFE
Ramping power	Quarters(95) RPFE, LFE, TFE	10,2%	Quarters (67) RPFE, LFE
Ramp-up price	Quarters(95) RPFE, LFE, TFE	8,2%	Quarters (61) RPFE, TFE
Ramp-down price	Quarters(95) RPFE, LFE, TFE	1,8%	Quarters (24) RPFE, TFE

Table 4.8: Overview of explained variance by regression model for different aspects of Secondary Reserve market. RP = Renewable Production, L = Load, T = Total, FE = Forecast Error

As the explained variance in the regression analysis is too low to use for the trading algorithm, another method is necessary to decide whether or not to trade on the Secondary Reserve market. This method is to use quantiles to decide per quarter per day of the week to trade - or not to trade. In the trading algorithm, the forecasted values of the Secondary Reserve market must be compared to the Day-Ahead market, in order to be able to make a decision to bid on which market. This is done for the demand and for the price. For the quantiles, a probability must be chosen. This probability is set at 70%, as this is roughly the same certainty as the regression model used for the Day-Ahead market. The results of this analysis can be found in Appendix II. These values are used for the trading algorithm.

4.4 Conclusion

The goal of this chapter was to give an overview of the Dutch electricity markets, evaluate which of those markets are accessible for local stored electricity, and last, if and how the accessible markets can be forecasted.

There are six Dutch electricity markets. The futures market, traded upon years in advance, is not considered in this research. The other five markets are all designed for a different purpose. The first (meaning the earliest to trade upon) is the Day-Ahead market. As the name implies, trading on this market can be done till 12:00 on the day before delivery. Thereafter, the Intra-Day market is traded upon. On this market, trading can be done till 5 minutes before delivery. The trading on the Intra-Day market takes place mostly via bilateral contracts. After these markets, there are three markets, all operated by TenneT, designed to keep the electricity grid balanced. The Primary Reserve market is cleared once per week, meaning that bidding on this market means being able to supply primary reserve capacity for one week. The primary reserve capacity is designed to maintain an equal frequency throughout continental Europe. There are two auctions to ensure sufficient primary reserve capacity. The first auction is shared with the German TSOs, and the second is a separate Dutch auction. The reimbursement on this market is for having a certain amount of capacity ready at all times during that specific week, but there is no reimbursement for supplied electricity.

If the frequency is not restored automatically or by the primary reserve capacity, the secondary reserve capacity restores the frequency back to 50 Hz. The Secondary Reserve market is operated by TenneT and is only meant for the Netherlands. There are two possibilities to trade on this market. The first is having a contract which obliges a party to offer a certain amount of capacity. These parties receive a reimbursement for that capacity, and for the supplied electricity. The other option is to offer capacity whenever a party wants to. These parties only receive reimbursement for the supplied electricity. The last reserve mechanism in the Netherlands is the tertiary reserve capacity, also referred to as emergency-power. This market is the most non-transparent of all markets. There is no official data known about this market about reimbursements. It is however clear that TenneT claims complete access to the capacity, which makes it impossible to combine with the value for the DSO.

Two of these five markets are analysed further, being the Day-Ahead market and the Secondary Reserve market. The other markets are rejected for trading with storage units and therefore exempted from further analysis. The Intra-Day and Tertiary Reserve market both have insufficient supply of data to analyse trends on these markets, and the other markets showed more potential in terms of expected revenue. The reason for rejecting the Primary Reserve market is that one of the prerequisites states that the offered power is for both ramp-up and ramp-down demand, creating the necessity for storage units to be ready for both types of demand. The impact of this is that only half of the capacity of storage units can be used, as the units should be able to both deliver as store electricity at the same time. This reduction of capacity, combined with the absence of data on demand per week for ramp-up or ramp-down (reimbursement is for offered capacity, not for supplied electricity), leads to the conclusion that this market is not attractive for local storage units.

The Day-Ahead market can be forecasted quite well using a regression model. Explanatory variables in this model are the Dutch forecasted residual load, the German forecasted load, the German forecasted residual load, and a monthly variable to cope with seasonal effects. This model explains 66% of the variance. Using weekdays as an input instead of months has significantly less explained variance (39%), and using weekdays as an addition to the month-model didn't have an increase large enough to consider making the trading algorithm more complex.

The validation of the regression model indicated that the regression model is valid for the purposes of this research. The of the model residuals reflect a normal distribution well. The cross-validation executed for the months July, August, and September 2016 indicated that the regression model forecasts the electricity prices too high. This is an error to be accounted for when designing an algorithm to be used in a real trading environment. The values used to forecast the electricity prices do however still explain 55% of the variance, and have a primarily one-sided bias, meaning that they can still be used for the purpose of this research, namely getting an indication what profit can be made by trading on electricity markets with local electricity storage.

The Secondary Reserve market is attempted to forecast using regression analysis with as explanatory variables the load forecast error, renewable production forecast error, total forecast error, and the time of the day. However, these explanatory variables at best reach 10% explained variance. Therefore, this market is analysed using quantiles per quarter of the day. These values are used for the trading algorithm.

5 | Value of trading with local storage

The previous chapter identified the Day-Ahead market and Secondary Reserve market as being the most suitable markets for trading, using local stored electricity. This chapter takes that information and the forecast formulas/values and transforms them to a trading algorithm. Then, this trading algorithm is tested on the same dataset that was used to determine these forecasting elements. In order to check if the trading algorithm is not only suitable to use for that specific time period (18-07-2015 - 18-07-2016), it is tested on a couple months more. This assesses the value of trading with local storage. The validation of the R-model is done in this chapter, but the verification can be found in Appendix IV.

5.1 Conceptual design of trading algorithm

This paragraph designs the trading algorithm for trading both on the Day-Ahead market and the Secondary Reserve market. This means that a decision has to be made how much capacity to offer on each market, and for what price. This decision becomes more complex by the fact that the DSO has to be able to use the battery as well (see chapter 3, figures 3.5 and 3.7).

The general decision steps that have to be taken are shown in figure 5.1. The first step is to check for ramp-down demand on the Secondary Reserve market. The second step is to check for a negative price for that ramp-down demand. These two steps are incorporated in the algorithm first, because a negative imbalance price means that a party can get paid to supply less electricity, or demand more electricity. In the case of local storage, this means receiving reimbursement for charging the battery. This creates 'double' profit: first receiving reimbursement for charging the battery, storing the electricity for a period of time, and then receiving reimbursement for supplying the electricity.

The next step in the trading algorithm is to use the regression values for the Day-Ahead market and quantile values for the Secondary Reserve market and using those values to compare expected prices on those markets. Obviously, if there is one market with a significantly higher price than the other, all available capacity is bid on this market. If however the prices are within a certain range, it seems wise to spread the available capacity over the markets, as the prices are subject to a certain level of uncertainty.

The last step is to check real-time if there is a negative price on the Secondary Reserve market. As said, negative prices on that market create double profit and it is possible to bid real-time on this market. This is however only possible if there is capacity left from the bids that have already been made.

Step 1	Check for ramp-down demand on SR market
Step 2	Check for negative ramp-down price
Step 3	Compare DA-price, ramp-up price and positive ramp-down price
Step 4	Bid on markets with highest forecasted price
Step 5	On actual time of delivery: check for negative SR prices

Table 5.1: General decisions for trading algorithm. DA=Day-Ahead, SR=Secondary Reserve

The five general steps in table 5.1 are translated into the conceptual scheme of the trading algorithm. This is shown in figure 5.1. The first step of the scheduling algorithm is to check if there are any PTU's expected with ramp-down demand. If so, the next check is if the price is then expected to be negative. If those PTU's exist for the following day, then buying (e.g. charging) is scheduled. As explained, this is the first step of the trading algorithm as these moments cause double profit.
After the scheduling of ramp-down demand, or if no ramp-down demand is needed, the scheme continues with forecasting the rest of the prices: Day-Ahead, and ramp-up, and positive ramp-down prices. Then, using a yet to be determined buy threshold and sell threshold, the amount of PTU's to sell and PTU's to buy are determined. Those thresholds can be used later in this research to experiment with. The next step in the bidding process is to determine the minimum of on one hand the PTU's to buy plus the ramp-down scheduled, multiplied by the efficiency of the system, and on the other hand the PTU's to sell plus the current charge in the battery. This minimum makes sure that the buy (charge) minus the loss due to transforming is equal to the sell (discharge). The minimum is then used to finalize the schedule, working from most profitable to least profitable PTU's (above/below the threshold).

During the day, there are some checks in order to make sure that the schedule can always be followed. It could namely happen that a bid was placed, but that that bid didn't win because it was too high or too low. In this case, no trade takes place.

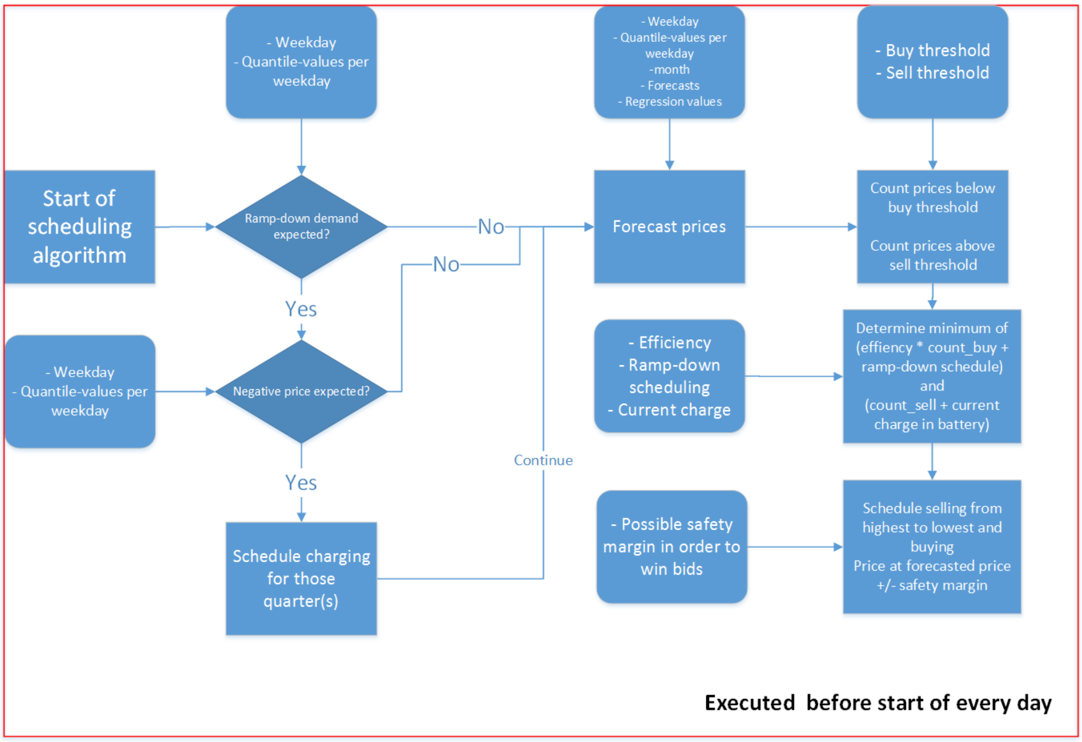

Figure 5.1: Conceptual scheme for the scheduling element of the trading algorithm

5.2 Implementing trading algorithm in R

The conceptual trading algorithm is implemented in R. This paragraph describes the process of this implementation, in terms of input data, variables needed, the time instant chosen, actions per time instant, and output of the model.

The input data and origin is shown in table 5.2. One thing that immediately stands out is that the frequency of the data differs quite a lot. This creates the need for a decision for a time instant to use in the model, and thereby having to transform some variables to another frequency. The units are all based on Megawatt, which makes them easier to use in the model.

Data	**Unit**	**Data frequency**	**Origin**
Day-Ahead market	Price: €/MWh	Per hour	APX/Eneco
Secondary Reserve market	RU-price: €/MWh RU-demand: MW RD-price: €/MWh RD-demand: MW	Per minute	TenneT
Load forecasts (German & Dutch)	MW	Per quarter	ENTSO-E
Renewable production forecasts (solar,wind onshore, wind offshore)	MW	Per quarter	ENTSO-E
Day-Ahead forecasting values	[dmnl]	Irrelevant	This Research
Secondary Reserve forecasting values	[dmnl]	Per weekday per quarter	This research

Table 5.2: Input data for testing the trading algorithm (RU = ramp-up, RD = ramp-down)

The variables created for the model and their use are shown in table 5.3. The table indicates the type of variable and describes the function of the variable. The bid percentage is a constant that is used to adjust the bid from the forecasted market price. This variable is only used for the Day-Ahead market. For buying on this market, the bid is increased by this percentage, to increase the chance of placing a winning bid. For selling on this market, the bid is decreased by this percentage. The buy threshold and sell threshold are variables that indicate the maximum buying price and the minimum selling price. These are typically variables to test the model with. Then there are four variables rewritten at the beginning of each day. These variables are used to indicate for both markets at which quarter that day there will be electricity sold or bought. The decision logic for these variables is described in figure 5.1.

Variable name	Variable type	Description
BidPercentage	Constant	Margin that can be used to adjust the bid from the expected market price in order to increase chance to win bid
BuyThreshold	Constant	Maximum price to buy electricity
Charge	Array(35232)	Charge of the battery per quarter
DAbuyvector	Array(96)	Array rewritten each day when to buy on Day-Ahead market
DAsellvector	Array(96)	Array rewritten each day when to sell on Day-Ahead market
Efficiency	Constant	Battery-system overall efficiency
ForecastMatrix	Matrix (35232x6)	Matrix containing forecasted values for both markets
MonthIndices	Array(12)	Array with the monthly indices for the price-forecast of the DA market
PriceAmountMatrix	Matrix (35232x10)	Matrix containing all real values for both markets
Profit	Array (35232)	Profit made by trading
SellThreshold	Constant	Minimum price to sell electricity
SRbuyvector	Array(96)	Array rewritten each day when to buy on Secondary Reserve market
SRsellvector	Array(96)	Array rewritten each day when to buy on Secondary Reserve market

Table 5.3: Most important variables in the trading model

5.3 Running and testing the algorithm

This paragraph gives an overview of the designs of the experiments that are run with the trading model, and use the outcomes of those experiments to verify the working of the model. There are four constants in the model that can be adjusted: the bid percentage, the buy threshold, the sell threshold, and the efficiency of the battery. This last variable is used as a constant in the model. The experimental set-up for these variables is given in table 5.4. The model is checked on logical outcomes in terms of profit and the charge profile of the battery.

The complete overview of the experiments can be found in Appendix III. The most important results are shown in this paragraph. The first observation from the results of the experiments is that the bid percentage has a strong influence on the amount of bids that are accepted. This also significantly increases the profit made in one year. The

Constant	Low	Medium	High
Bid percentage [%]	0.8	1.0	1.2
Buy threshold [€/MWh]	15	20	30
Sell threshold [€/MWh]	30	35	45

Table 5.4: Design of experiments to run with the model

buy threshold increases the profit made in one year as well, but does not increase the amount of bids per year. The sell threshold hardly has any influence on the profit nor on the accepted bids. The maximum profit that can be made in one year with this trading algorithm is €54.386. With the scenarios tested, the maximum profit occurs when the bid percentage is on 1.2%, and the buy- and sell-threshold on respectively €15/MWh and €30/MWh.

When the three tested constants in the model are all on their lowest value as shown in table 5.4, the model shows a difference in number of trades per month and therefore profit per month. In the months January till June, the number of trades significantly increases and therefore the profit increases. This effect is either caused by the low bid percentage or by the low buy threshold, as increasing the sell threshold has no significant influence on the number of trades executed throughout the year.
Increasing the bid percentage has a strong influence on the behaviour of the model. The higher the bid percentage, the more trades are executed in the year and the more profit is made. In other words, if the bids have more safety margin to increase the chance of being a winning bid, the more trades are indeed winning.
If the buy threshold is increased to medium, the seasonal influence on the number of trades is still present, but less compared to the all-low scenario. When the buy threshold is increased to high, the seasonal influence is hardly present. In other words, if the minimum buying price is high enough, the seasonal influence is decreased and the number of trades throughout the year is increased, generating more profit. This is probably caused by the decision logic, that prioritizes charging the battery using the Secondary Reserve market. On this market, the profit increases during charging due to the negative electricity price. Therefore, if the buy threshold, which is used for positive electricity prices, is increased, there is less electricity bought on the Day-Ahead market and more electricity 'received' via the Secondary Reserve market.
The sell threshold has no influence on the model behaviour compared to the all-low scenario. This indicates that the minimum price for scheduling selling is less influential than the maximum price for scheduling buying for the profit made. This could be explained by the bid percentage. The experiments run for testing the sell threshold all use the same bid percentage, namely the low bid percentage. This percentage decreases the height of the bids on the market. This bid percentage probably reduces the effect of changing the sell threshold, which is why the results are comparable.

5.4 Validation of the model

The validation of the model is aimed at determining that the model reflects the reality of a trader in the Netherlands. This means that the variables used to forecast the prices have to be available at time of trading and that the efficiency losses are representative for a real battery system. The decision logic and trading algorithm itself allow room for improvement, and suggestions to act on these points of attention are included in the conclusion paragraph under recommendations. This paragraph is checking the circumstances created in the model and compares them to a real trading environment.

The first step is to check the constants in the model. The efficiency of the battery system is set at 70%. This is caused by losses in the battery system. First, the alternating current is transformed to direct current, as a battery can only be charged with direct current. Then the electricity is stored for an unknown time, and then the electricity has to be converted to alternating current again to be supplied to the grid. If at each of those steps there is a loss of 10%, the total efficiency comes down to 72.9%, which is rounded to 70% to be safe. The capacity and power of the battery in the model is 10 MWh and 4 MW. As it is not clear in what neighbourhoods trading is most beneficial, an average of all five neighbourhoods was taken. The average capacity installed in the five neighbourhoods in this research is 291 kWh. Assuming 35 neighbourhoods to be equipped with storage units, the total capacity available comes to approximately 10 MWh. All neighbourhoods have a storage unit with a power of 100 kW, which is approximately 35% of their capacity. For the total capacity of the 35 neighbourhoods, this would be 3,5 MW. However, the model has difficulties with using the 0.5 MW, which is why the power was increased to 4 MW. The rest of the constants are part of the trading algorithm and can therefore be used for optimizing the financial result of trading, but are not part of this validation.

The next point of validation is the forecasting element of the algorithm. If the model represents reality well, the input for the forecasted prices should be available at time of bidding. The forecasting of the Day-Ahead market is done on the basis of monthly indicators, and on the Dutch and German load forecasts. These load forecasts are provided by ENTSO-E and are known a week in advance. The trading on the Day-Ahead market can be done till 12:00 AM on the day before delivery. It can be concluded that the load forecasts are available at time of bidding.

The last part of the validation concerns the beta-values. This is where a limitation of the research becomes clear. The beta-values and monthly indicators are calculated for the period 18-07-2015 till 18-07-2016. The trading is done in the same period. Of course, it is not possible for a trader to calculate the beta values of prices yet to come. The beta-values were validated in the validation of the regression analysis, but this remains a limitation. This choice was made in order to have a consistent time frame for which this research presents prices, national load characteristics, and neighbourhood load characteristics. This neighbourhood load dataset is the first constraining factor. The dataset that Stedin made available for this research is from 01-01-2016 till 01-10-2016. The second constraining factor is that since 01-01-2017, Stedin is no longer part of Eneco Group , who provided the data of the Day-Ahead market. Therefore, the time period chosen was the only possible time period for analysing all the data over an almost equal time period.

5.5 Value per neighbourhood

The value of trading is determined in the model for a pool of storage units, but per neighbourhood this value has to be determined. There are four factors to take into account in this determination. First, the seasonal influence that is or is not present in the neighbourhood. Second, the hours per day that the DSO would need the storage unit. Third, the presence of difference between weekdays and weekend. Fourth, the different capacities of storage units per neighbourhood. This is summarized per neighbourhood in table 5.5.

Nbh	**Seasonal influence**	**DSO usage [Hours/day]**	**Weekdays vs weekend**	**DSO usage [%]**
1	Yes	4.75	No	10%
2	Yes	5	No	11%
3	No	8.5	No	71%
4	No	8.3	Yes	49%
5	No	9.4	Yes	55%

Table 5.5: Neighbourhood characteristics used for determination of value of trading; see chapter 3.2 for origin of these characteristics (Nbh = Neighbourhood).

For neighbourhood 1, there is a seasonal influence present. This means that for three months per year, the DSO would need this storage unit for 4.75 hours per day. In the other months, the storage unit can be used completely for trading. In the three months that the DSO needs the storage unit, it is assumed that the hours needed for charging the storage unit is equal to the hours that the DSO needs it. Therefore, in 25% of the year, the storage unit can not be used for 9,5 hours per day, which is 40%. This results in a total usage by the DSO per year of 10%.
For neighbourhood 2, there is also a seasonal influence present. This means that for three months per year, the DSO would need this storage unit for 5 hours per day. The same line of reasoning as for neighbourhood 1 is applied here. Therefore, in 25% of the year, the storage unit can't be used for 10 hours per day, which is 42% of the day. This results in a total usage by the DSO per year of 11%.
For neighbourhood 3, there is no seasonal influence present. There is also no significant difference between weekdays and weekend. Therefore, the DSO would need this battery

every day of the year for 8,5 hours. If the hours for charging are also included, the storage unit can't be used for 17 hours per day. This means that for 71% of the time, the storage unit is needed completely for the DSO.
For neighbourhood 4, there is no seasonal influence present. However, there is a significant difference between weekdays and weekend. This means that the DSO needs the storage unit every weekday of the year, for 8.3 hours per day. Therefore, in 71% of the year, the storage unit can't be used for trading for 16.6 hours per day, which is 69% of the day. This results in a total DSO usage per year of 49%.
Neighbourhood 5 also has no seasonal influence and a significant difference between weekdays and weekend. The DSO would need the storage unit 71% of the year, for 18.8 hours per day, which is 78%. This results in a total DSO usage of 55% per year.

These values are used to calculate the 10 MWh trading value to the values for the individual neighbourhoods. This is visualized in table 5.6. The trading usage is equal to 1 minus the DSO usage. The storage lifetime used throughout this research is 10 years.

Nbh	**Capacity [kWh]**	**Trading availability**	**Value [€/year]**	**Value [€/ storage lifetime]**
1	340	90%	1.664	16.640
2	288	89%	1.394	13.940
3	355	29%	559	5.590
4	242	51%	671	6.710
5	232	45%	567	5.670

Table 5.6: Trading values per year and per storage lifetime for the different neighbourhoods (Nbh = Neighbourhood).

5.6 Conclusion

This chapter described the design of the trading algorithm and the process of implementing the trading algorithm in R in order to test it. The basis of the design comes from chapter 4, which has designed methods to forecast the electricity markets.

With the trading algorithm designed in this research, the profit that can be made with a storage unit of 10 MWh and 4 MW with trading on both the Day-Ahead market and the Secondary Reserve market is calculated at approximately €54.000 per year. The profit is maximized when the thresholds for buying and selling are relatively low, namely respectively €15 and €30. The margin used for adjusting the bid is at 1.2, meaning a 20% deviation from the expected market price in order to have more chance of placing a winning bid. With these settings, the number of trades executed in one year is also higher compared to other model settings. This indicates that the most profit is generated when the number of trades is attempted to be maximized, instead of trying to maximize the profit made per trade.

The trading algorithm is designed as follows. The first step in the algorithm is to check for a negative prices on the Secondary Reserve market, as that provides for a 'double' profit. Then the other prices are forecasted. If the forecasted price is high enough to sell or low enough to buy, bids are placed on the Day-Ahead market. The model then checks if the bids was equal to or higher than the market price for buying electricity, or if the bid was equal to or lower than the market price for selling electricity.
The testing of the trading algorithm indicated that the profit increases when the number of trades per year are maximized, and not when the profit per trade is increased. Therefore, the most profit is made when the thresholds for buying and selling are low, but the safety margin that is used for placing the bids is high. This creates an increase in trades per year and therefore creates an increased profit.

The value of trading per year per neighbourhood ranges from €1.664 in neighbourhood 1 with 100% residential connections to €567 in neighbourhood 5 with 6% residential connections. The difference in trading value between neighbourhoods is caused by the necessary usage by the DSO during peak demand. In residential neighbourhoods, this peak demand has a clear peak during the day and a clear seasonal influence. The neighbourhoods with dominantly residential connections are therefore able to trade 90% of the time. The dominantly non-residential neighbourhoods have a longer peak duration and no seasonal influence, but do have a significant difference between weekdays and weekend. This means that the storage units in those neighbourhoods are available for trading only 50% of the time. The storage unit in neighbourhood 3, with 67% residential connections, is available for trading only 29% of the time. This low availability is caused by a long peak duration, no seasonal influence, and no clear difference between weekdays and weekend.

6 | Conclusions and recommendations

This chapter gives an answer to the research questions. First, the final conclusions of the research are given. Then, the recommendations for DSOs and for further research are discussed. Thereafter, the limitations of this research are given. The last paragraph of this chapter is a discussion on the uncertainties in this research.

6.1 Conclusions

A strong increase in electricity demand is envisaged due to usage of electricity for heating and mobility. This will not only lead to an increase of the overall load on the grid, but also to an increase of peak demand. Stedin, as distribution system operator, expects the substations to be the first elements in the network to have insufficient capacity to cover these increased peak demand. High investments will become necessary to replace transformers in these substations to increase the capacity to required levels. An alternative could be to install storage units that lower the peak demand on the current transformers. By doing so, they can create the possibility to defer investments in new transformers for a certain period of time. This alternative has led to the main research question, being:

"What is the value of low-voltage electrical energy storage for a distribution system operator?"

First investigations into this research question have pointed out that the storage facilities are not constantly required for peak shaving and hence could have an additional value for e.g. trading. Based on these findings three research subquestions are defined, being:

1. **What is the value of low-voltage electrical storage when only used to defer network investments by the DSO?**

2. **On which markets is it possible to trade electricity with low-voltage electricity storage unit?**

3. **What is the value of trading on these markets with low-voltage electricity storage, constrained by the usage by the DSO?**

Before answering the main research question first the three subquestions will be elaborated upon and conclusion will be drawn.

Deferral of investments To determine the value of deferral of investments the deferral time has been estimated. To this end first the existing demand pattern and seasonal influence of five different neighbourhoods have been analysed. Neighbourhoods that vary from 100% residential to nearly 100% non-residential. **From this analysis it can be concluded that the substations in these neighbourhoods run at this moment at 50% to 75% of their maximum capacity and still have spare capacity for future growth in electricity demand**. This conclusion does not only apply to the substations in the five neighbourhoods in this research, but to nearly half (approx. 45%) of the 9000 substations run by Stedin.

Using the growth scenarios as defined by Stedin, it is expected that replacement of transformers has to be done between 2022 and 2023 for the dominantly residential neighbourhoods (1, 2 and 3) in this research and between 2026 and 2032 for the dominantly non-residential neighbourhoods. Based on the existing demand pattern and peak pattern per neighbourhood the deferral time is then calculated using the same growth scenarios. **This leads to the conclusion that the deferral time varies for the different neighbourhoods from 2 years at the lower end to a maximum of 7 years** (see table 6.1). The high value for the non-residential neighbourhood (5) can be explained by the fact that replacement only has to take place between 2029 and 2032, which introduces larger uncertainties within the scenarios used.

Value of low-voltage electricity storage for DSO				
Nbh	**Percentage residential**	**Deferral time**	**Max. Savings**	**Battery costs**
1	100%	3-4 years	€31.698	€121.800
2	99%	4-5 years	€37.907	€107.420
3	67%	2-3 years	€24.868	€126.000
4	26%	2-5 years	€37.907	€94.360
5	6%	3-7 years	€24.342	€91.560

Table 6.1: Value of low-voltage electricity storage for the DSO (Nbh = Neighbourhood).

The deferral time is the basis for the calculation of the value of deferring the investment in new transformers. The costs for such replacement are estimated at €50.000 per substation, as we are talking of replacement by larger transformers. Using the NPV method the calculated values for deferring these investments amount to a maximum of €24.000 to €38.000 (rounded figures). The lower end of the values is significantly lower due to shorter deferral times and lower discount rates. **Regadering subquestion 1, the conclusion can be drawn that the value of deferral of investment is substantial, but lower than the investment costs**. Using storing facilities solely for deferral of network investment does not lead to a positive business case (details per neighbourhood are given in table 6.1.). Other values are required to fill the gap.

Electricity trading markets The second research subquestion is aiming at determining the accessible markets for storage units to get involved in trading on the electricity markets. There are six electricity trading markets in the Netherlands of which four are considered not to be accessible or attractive for trading with local storage capacity.
The first market that can be rejected is the **Future market**, as on this market electricity is traded years in advance which is not relevant for this research. Therefore, this market is not analysed further.
Local storage units comply with the prerequisites for trading on the **Intra-day market**, but trading on this market is mostly done by bilateral contracts, which limits the availability of data. As far as data is available it indicates that prices on this market are comparable with prices on the Day-Ahead market, but that the volume of electricity traded per month is lower. For these reasons this market is not considered further and the focus has been on the Day-Ahead market.
One of the main prerequisites for trading on the **Primary Reserve market** is the minimum power offered of 1 MW. It is however allowed to offer power on this market with a 'pool' of (storage) units. Therefore this market in principle offers opportunities. The reason for rejecting this market is that one of the other prerequisites states that the offered power is for both ramp-up and ramp-down demand, creating the necessity for storage units to be ready for both types of demand. The impact of this is that only

half of the capacity of storage units can be used, as the units should be able to both deliver as store electricity at the same time. This reduction of capacity, combined with the absence of data on demand per week for ramp-up or ramp-down (reimbursement is for offered capacity, not for supplied electricity), leads to the conclusion that this market is not attractive for local storage units.
For the **Tertiary Reserve market** the limiting prerequisite for storage units is that the offered capacity must be available at all times, as this market provides the last available power before the grid goes down. As the business model for this research also consist of a value for the DSO, and TenneT claims exclusiveness over the tertiary reserve capacity, this market is considered inaccessible.

Having rejected four electricity markets leads to the conclusion for research subquestion 2 that out of the six markets two are considered accessible, being the Day-Ahead market and the Secondary Reserve market.

Trading on the **Day-Ahead market** takes place on the day before delivery, a short term and volatile market. The prerequisite for this market is that the minimum power offered is 100kW. This prerequisite has been taken into account in the design of the storage units and the costs in table 6.1 represent the costs of the increased power of the storage units.
The other accessible market is the **Secondary Reserve market**. This market is operated by TenneT with the purpose to balance the grid when imbalance occurs and the primary reserve capacity proves to be insufficient to restore the balance. Trading on the Secondary Reserve market is also possible without a bidding-contract, meaning that a trader can trade at any given time.

Value of trading with local storage units The third research subquestion concerns the value of trading with local storage units. In order to answer this question insight is required in the predictability of the mentioned two accessible markets. The regression model developed for forecasting the electricity prices on the Day-Ahead market include four different explanatory variables. These variables are the Dutch forecasted residual load, the forecasted German load, the German forecasted residual load and monthly indicators for seasonal influences.**From this test is can be concluded that the developed model explains 66% of the variance and is considered accurate enough for the purpose of this research**. The model was also tested with indicators for different weekdays, but the monthly indicators proved to be a better time-component to incorporate in this model.
The Secondary Reserve market is difficult to explain by the variables used in this research. The nature of this market is to balance the grid after an imbalance has occurred. It was assumed that the forecast error would be a good explanatory variable for the volume that is traded on this market. The forecast error however proved to have no clear relationship with the amount traded on this market. Therefore, weekly trends on this

market are used to determine the prices that can be obtained. This is considered a valid approach as bidding on this market is not done on contracts in advance, but traders can accept prices at any given time.

An algorithm was designed for trading on both the Day-Ahead market and the Secondary Reserve market. This algorithm uses the outcome of the regression analysis to forecast the Day-Ahead market, and uses the weekly trends of the Secondary Reserve market. The algorithm is tested in R on real electricity prices in a time span of one year (18-07-2015 till 18-07-2016) using a 10 MWh and 4 MW battery. This capacity and power reflect 35 neighbourhoods being equipped with a storage unit that can be used for trading.

The model is used to calculate the possible trading value for the different neighbourhoods in this research, taking into account the lifetime of the batteries that is set at ten years and the availability of battery capacity after usage of the batteries by the DSO for peak shaving (expressed in a percentage trading availability, see table 6.2). **From these calculations it can be concluded that using storage units for trading on the electricity market does add value to the business case ranging from €5.600 to €16.600** (details per neighbourhood are given in table 6.2). As expected the neighbourhoods with a high share of residential connections have the highest trading values, as load profiles for these neighbourhoods offer the best possibilities for trading, having a clear peak demand during the day and a clear seasonal influence.

Trading value of low-voltage electricity storage			
Nbh	**Percentage Residential**	**Trading availability**	**Trading value [€]**
1	100%	90%	16.640
2	99%	89%	13.940
3	67%	29%	5.590
4	26%	51%	6.710
5	6%	45%	5.670

Table 6.2: Trading values over storage lifetime for the different neighbourhoods (Nbh = Neighbourhood).

Concluding this part of the research it should be kept in mind that DSOs in the Netherlands are, by law, not allowed to enter into production, trading or delivering of electricity. Hence realising the calculated trading value requires a change in law or another solution whereby a related party, that co-operates with the DSO, actually carries out the trading. This legal aspect is not part of this research and is separated from the value determination.

Main research question Answering the main research question requires the determination of the total value that can be obtained by low-voltage electrical energy storage facilities. The combined values that can be obtained are presented in table 6.3.

Combined value of low-voltage electricity storage					
Nbh	**Percentage Residential**	**Max. savings [€]**	**Trading value [€]**	**Total value [€]**	**Costs [€]**
1	100%	31.698	16.640	48.338	121.800
2	99%	37.907	13.940	51.847	107.420
3	67%	24.868	5.590	30.458	126.000
4	26%	37.907	6.710	44.617	94.360
5	6%	24.342	5.670	30.012	91.560

Table 6.3: Trading values per storage lifetime for the different neighbourhoods (Nbh = Neighbourhood).

From this table, it can be concluded that the overall value of low-voltage energy storage is substantial, but does not yet outweigh the costs of these storage units. At best, the benefits cover just below 50% of the investment costs. For other neighbourhoods, this percentage can be even lower. In general, neighbourhoods with a high percentage of residential connections offer the best possibilities to create additional value on the electricity markets because of their load profile and hence offer the best business case.

An important factor to be taken into consideration for the conclusion of this research, as it may influence a future final outcome of the business case, is that this research did not include other possible values of local electricity storage. There are two stakeholders that were not included in this research that can benefit from these storage units.
The first would be the consumers. A trend that is visible in the Netherlands is an increasing production of electricity by consumers, mostly by solar panels. One of the characteristics of solar panels is that they have a peak production during the afternoon, when demand is low, and during the summer months, when overall the consumption of electricity is low (seasonal influence). It can therefore be expected that in the near future the local production of electricity will outgrow the local demand for electricity in the afternoon, starting in the summer months. As soon as this is the case consumers can benefit from local storage if that storage is used to balance production and demand on local scale.
The second stakeholder that can benefit from these storage units is the government (including DSO). The storage units can contribute to this security by delivering system services, as for example the so-called islanding of neighbourhoods. This islanding means that a neighbourhood has sufficient own electricity (production) to be disconnected from the main grid for a couple of hours. Storage units with the size as designed in this re-

search would be able to do so.

Conclusions regarding scientific contribution The scientific contribution of this research lies on one hand in the development of a quantitative methodology for adjusting the design of the storage unit to the load characteristics in a specific neighbourhood. On the other hand, the scientific contribution lies in developing an methodology for combined and related calculation of values created by both deferral of investment and trading on electricity markets. This novel methodology is applicable for other benefits of storage as well.

This research used actual neighbourhood load data to design the storage unit for specific neighbourhoods, as previous research indicated that the different locations of DERs in the grid significantly changes the benefits of those DERs. This research also showed that different locations of storage units have significantly different benefits, using the ratio between residential and non-residential connections in a neighbourhood. It can be concluded that the neighbourhoods used in this research differ in terms of peak height, peak duration, and seasonal influence. The conclusions made regarding these load characteristics of these neighbourhoods can also be used for the determination of other benefits of local storage units, which can be found in figure 2.1.

The second contribution, being combining multiple views in order to determine the monetary value of storage units, showed that it is possible to use a battery for multiple purposes, thereby creating multiple benefits. Supported by the analysis of neighbourhood load profiles, it was shown that the usage by the DSO significantly differs per neighbourhood, ranging from 10% to 71% of the time (see table 5.5). Therefore, the availability for creating additional benefits also differs per neighbourhood. Neighbourhoods with a higher share of residential connections have more availability for additional benefits compared to neighbourhoods with dominantly non-residential connections. Moreover, it was shown that multiple markets in the Netherlands are accessible for local storage units, although the high market concentration reported by the European Commission (2014).

The results of this research are also to be compared to results of other research used to develop the scientific framework for this research. This means that the conclusions of this research can strengthen or contradict conclusions from other research.

Zhang et al. (2010) concluded that the benefits of microgeneration in the grid differed per location (their research considered nodal pricing). Their conclusion is that the biggest microgeneration-capacity should be located at the node with the highest long-term nodal price. This long-term nodal price can be best explained as the extra costs that occur due to earlier need for network reinforcement because of the addition of 1 kW in demand. Their research therefore indicated that microgeneration has the most value at locations in the network where reinforcement is most expensive.

This research is different, as DSOs in the Netherlands don't use the nodal pricing method. However, this research assumed that the reinforcement of the grid is equally expensive for all neighbourhoods. Combining the conclusions of this research with the conclusions of Zhang's research, a DSO in the Netherlands could consider nodal pricing in order to be able to better determine where storage units have the most value. This insight in nodal prices doesn't mean that a DSO has to change the current tariff structure, but is meant for optimizing the value of the storage units.

This research relates to the research towards flexibility steering. Flexibility steering is aimed at stimulating consumers (mostly by price incentives) to use electricity during off-peak hours. Morshed (2016) came to the conclusion that flexibility steering can postpone investments in the grid by up to 2 years. In this research, the postponement comes to 2 to 7 years. However, this research used load growth scenarios developed by Stedin, whereas Morshed's research uses three load scenarios, being 0.35%, 1.5%, and -1% increase per year. These scenarios differ from the growth scenarios used in this thesis and are expected to be the explanation for the difference in deferral time between this thesis and Morshed's research.
Morshed's research also states that "*financial savings are more significant in areas where congestion is occasional and temporary*" (Morshed, 2016). This conclusion can be confirmed be this research by the trading values, which are highest in neighbourhoods with dominantly residential consumers. These neighbourhoods have the shortest peak compared to the other neighbourhoods. Moreover, they also have a clear seasonal influence, which is absent in the other neighbourhoods. Morshed's research also considers these economic aspects, which explains this relation.
However, when the value for the DSO is considered, this research comes to a different conclusion. This research indicates that the value for the DSO is not necessarily related to congestion being occasional and temporary. If only the value of deferred investment is compared to the investment costs of the storage unit, neighbourhoods with dominantly non-residential consumers have the best business case.

6.2 Recommendations

Based on the outcome of this research, a number of recommendations can be made. The first part of the recommendations are for the (Dutch) government and DSOs, and the second part of the recommendations concerns further research.

The first recommendation is to be able to obtain and store data on load profiles in the Netherlands. This research was constrained by the fact that limited data about load profiles in neighbourhoods was available. Currently, only a few neighbourhoods in the Netherlands are equipped with terminals that measure and store data about the load. In other neighbourhoods, Dutch law forbids to do so. This data and neighbourhood characteristics can contribute to optimizing the operations of a DSO, but can also contribute to scientific development. As far as changes in law are required, it should be kept in mind that changing law takes multiple years.

The second recommendation for DSOs is to monitor the prices of batteries and the prices of electricity. At this moment, batteries are still too expensive to use for the purposes as described in this research, but in the future these prices are expected to decrease considerably. DSOs should start monitoring these prices now to get insight in the developments of these prices. Moreover, if a DSO wants to start a pilot with local storage units, a price level of batteries for the start of this pilot should be defined. If the DSO intends to develop local storage as a mean of deferral, a pilot project should be defined and developed for the most beneficial neighbourhoods to gain experience with local low-voltage electricity storage, that can be started as soon as certain conditions are met (e.g. price level batteries). For the value of trading, the current electricity prices are used, but prices could change due to the changes in the electricity sector because of the ongoing transition towards sustainability. Changes in these electricity prices also change the value of trading with storage units.

Further research should focus mainly on two aspects. The first aspect is that there are additional values that can contribute to the business case of local electricity storage. As described before, these additional values can be for consumers and/or for the government. Further research should be aimed at assessing these values and the possibility to combine these additional values with the values presented in this research. For example, one value for consumers can be to store their produced electricity during moment of surplus, so consumers can use this electricity later. However, if the storage unit is completely filled for the expected usage by the DSO for peak demand, it is not possible to store the surplus of locally produced electricity. The additional values for consumers and government could create a more feasible business case. This further research should include the value of local electricity storage in the transition from using both gas and electricity to using only electricity, and in projects such as energy-neutral households ("Nul op de meter").

The second element for further research is the improvement of the decision logic behind the trading algorithm. The decision logic in this research is suitable for trading on the electricity markets, but alternatives for this trading algorithm can be made and tested in order to determine the optimal value of trading with the storage units. There are a two main proposals for modifications of the trading algorithm on the basis of this research. The first modification is to change the priority that is given to either of the two accessible markets. The current algorithm gives priority to the Secondary Reserve market, but the priority could also be divided between the two markets or be given to the Day-Ahead market. The second modification is to change the forecasting method of the markets, especially the Secondary Reserve market. The current trading for the Secondary Reserve market is based on weekly trends, which could be improved by more complex mathematical methods for forecasting.

6.3 Limitations

This research has a number of limitations because of the chosen methods and the assumptions that had to be made. The available data was also a limiting factor for this research, which is already transformed to a recommendation for DSOs (first recommendation in the previous paragraph).

The first limitation of this research concerns the validation of the model for testing the trading algorithm. The current model is trading on the Day-Ahead market in the time period 18-07-2015 till 18-07-2016, which is the same time period for which the regression analysis of the Day-Ahead market was conducted. The outcome of the model could be more valid if the model trades on the Day-Ahead market for a different period than for which the regression analysis is conducted. This choice was made because the available dataset for the load profiles was from 01-01-2016 till 01-10-2016. As the value of trading is constrained by the DSO usage, and the DSO usage is determined by those load profiles, the choice was made to model the trade algorithm in the same time period. The limitations on the validation were reduced by cross-validating the results of the regression analysis for a different time period of three months.

The second limitation of this research concerns the assumption that the load increases over time, but that the load profile remains the same. The load profile could change because of an increase in use of electric vehicles and the upcoming trend to use heat pumps instead of natural gas for heating, but also because of the increasing local production by solar panels. The assumption for constant load profiles was made due to the scope of this research. Determining the development of load profiles in the future are a study in itself. The dataset concerning the load profiles is relatively new to the scientific field, which means that research based on data measured at this level in the electricity system (e.g. neighbourhood level) is not a widely investigated field. Therefore, forecast of the load profiles on neighbourhood level is also not a scientific field that could be used as a basis for this research.

6.4 Discussion on uncertainties

The results of this research are influenced by a number of assumptions that have been made. This paragraph covers the most important assumptions and explains how changes in these assumptions affect the result of this research.

As said, the main conclusion of this research is that the overall value of low-voltage energy storage is substantial, but does not yet outweigh the costs of these storage units. At best, these storage unit cover just below 50% of the investment costs, but projections for future battery prices indicate that by 2025 the battery costs have declined sufficiently for creating a break-even business case. This is an optimistic calculation for the benefits of storage. The values presented in table 6.3 are namely subject to a number of assumptions. These assumptions influence the trading value, the DSO value (and thereby the total value), and the costs. The assumptions that influence the conclusions of this research are visualized in figure 6.1 and are covered in the remainder of this paragraph.

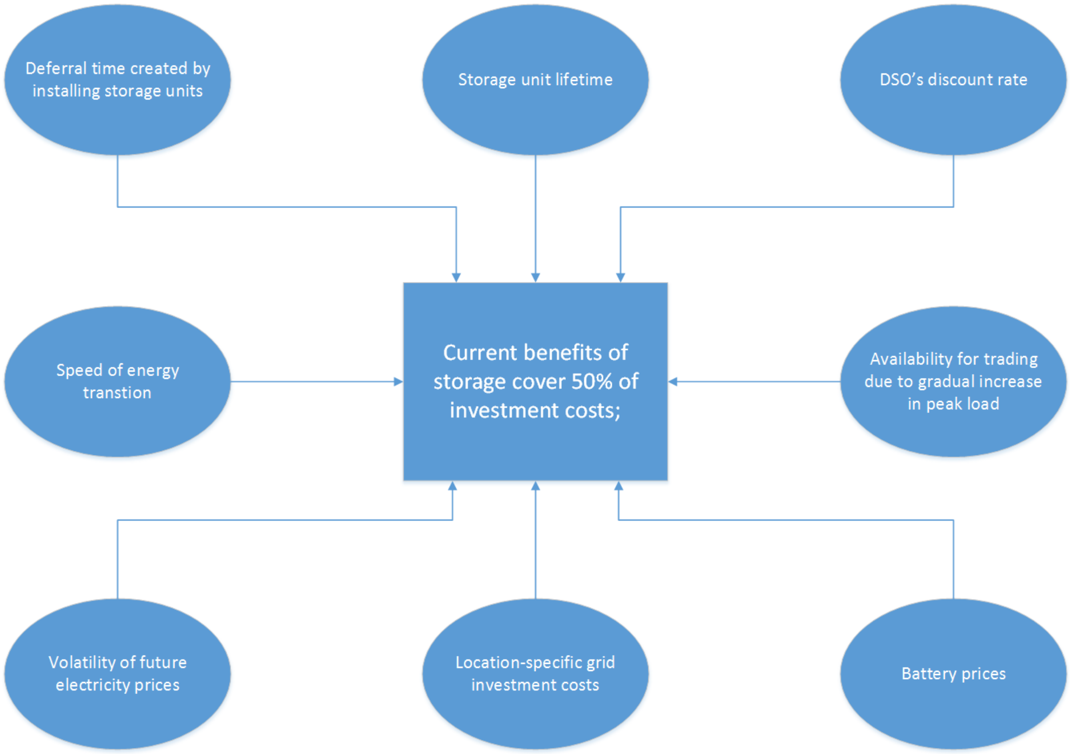

Figure 6.1: Overview of assumptions an their relation with the main conclusion of this research

The DSO values are calculated from the highest possible deferral time. In chapter 3, the range for the deferral times per neighbourhoods is given. The purpose of this research is to investigate if a business case is feasible in the most favourable scenario, which is the reason for reporting the maximum values in this chapter. However, for every year less deferral time, the DSO value decreases with approximately €2.500.

Another assumption is that storage units have a lifetime of ten years, and can consecutively serve two neighbourhoods. This means that the DSO-values for neighbourhoods 1 to 4 are doubled, as the lifetime of the storage unit allows to use that storage unit two times. In neighbourhood 5, this is not feasible, as the highest deferral time in this neighbourhood is already more than half of the storage lifetime, being seven years. If the storage lifetime decreases, the value for the DSO and the trading value both decrease.

The DSO value decreases by 50% if the lifetime of the storage is no longer sufficient to be used two times. For trading, the benefits decrease linearly per year by €500 to €1500. The exact decrease in trading value per neighbourhood can be found in table 5.6.

The DSO values are calculated using the NPV-method, which uses a discount rate. The values presented in table 6.3 are determined with a discount rate of 10%. This discount rate is common in the industry, but one could argue that a DSO has lower discount rates as they are semi-governmental. If the discount rate is lowered to 5%, the value for the DSO decreases. This has a major effect on the value for the DSO, especially since discounting has to be done every year. If the discount rate is decreases from 10% to 5%, the decrease in DSO value over a period of five years would be 21%. Over a period of ten years, the decrease in DSO value because of this lower discount rate is 37%.

One important assumption for the trading value is that the DSO needs the complete power and capacity of the battery from the day the storage unit is installed. In reality, the peak gradually increases, meaning that in the first part of the deferral time the DSO would not need the full capacity and power of the battery. This means that the value of trading could be higher compared to the values shown in table 6.3.

In this research, the assumed grid investments are an average of the complete network operated by Stedin. In reality, grid investments differ per neighbourhood. The higher the grid investments, the more feasible the business case of the storage units. The relation between grid investment costs and DSO benefit is linear, meaning that twice the investment costs lead to twice the benefit for the DSO.

For the calculation of the investment costs the price of the battery is assumed. For the calculation of the costs of the battery, the price level as observed in 2014 is used. As said, the price of batteries is expected to decrease in the coming years, which will make the business case for low-voltage electricity storage more feasible. A significant decrease in battery prices justifies a re-assessment of the business case. Both industry and science envisage a decrease in battery price by 2025 of approximately 50%, which is sufficient to create a feasible business case for neighbourhoods 2 and 4. A decrease in costs of 75% would be sufficient to create a feasible business case for all neighbourhoods.

Future electricity prices influence the trading value of storage units. As storage units have to buy and sell electricity, the absolute height of electricity prices is irrelevant. The volatility of the electricity price however is relevant. The higher the volatility, the higher the difference between buy- and sell-prices, the higher the trading value of the storage units. Volatility is expected to increase due to increased peak demand and local production, which has a positive influence on the business case.

The last aspect to take into account is the speed of the energy transition. The effect of the energy transition can have different effects on the business case of local storage

units. On one hand, the energy transition is characterized by an increase in intermittent renewable energy sources and an increased domestic utilization of electricity. This creates a more volatile production of electricity, and a more volatile demand for electricity. This increases the trading value of the storage units, as the electricity prices can be expected to be more volatile as well.
Another characteristic of the energy transition is the increased domestic production of electricity. If the domestic production in a neighbourhood increases to a level that there's a regular surplus of electricity, the value of storage units for the DSO increases. The storage units can namely be used in that scenario for avoiding having to transport the surplus of electricity to the medium-voltage grid.
However, another trend that is visible is that consumers attempt to be more self-sufficient. A number of companies have responded to this trend by offering domestic electricity storage units. If more households install their own storage units, the benefit for the DSO decreases, as the neighbourhood storage units then become redundant to some extent. It is therefore unsure how the speed of the energy transition influences the business case of the storage units.

Future research should focus on the reduction of mentioned uncertainties to come to more valid estimates of the presented business case.

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8 | Appendix I: Verification and validation of regression analysis

The goal of the verification of the regression analysis is to prove that the executed analysis was done right. This is done by explaining all the steps that have been taken during the analysis, what programs were used, and which transformations of data had to be done. Before the detailed description of the steps is given, it is worth mentioning that every step in the analysis has been checked multiple times for modelling errors. Modelling errors are after all the primary concern of verification. Also, the importing of data in the different computer software has been checked for faults.

The first step was to receive the right data. The data necessary for this analysis were the Day-Ahead price data, the Dutch load forecast, the Dutch renewable production forecast, the German load forecast, and the German renewable production forecast. Table 6.3 indicates where the data was retrieved, what the unit of measurement is, and what the frequency of measurement is. The overview of the datasets in the table indicates that the difference in measurement frequency of the datasets creates the need for re-calculating the four latter variables.

Variable	**Source**	**Measurement unit**	**Measurement frequency**
Day-Ahead price	APX/Eneco	€/MWh	Per hour
Dutch load forecast	ENTSO-E	MW	Per quarter
Dutch renewable production forecast	ENTSO-E	MW	Per quarter
German load forecast	ENTSO-E	MW	Per quarter
German renewable production forecast	ENTSO-E	MW	Per quarter

Table 8.1: Overview of data used for regression analysis

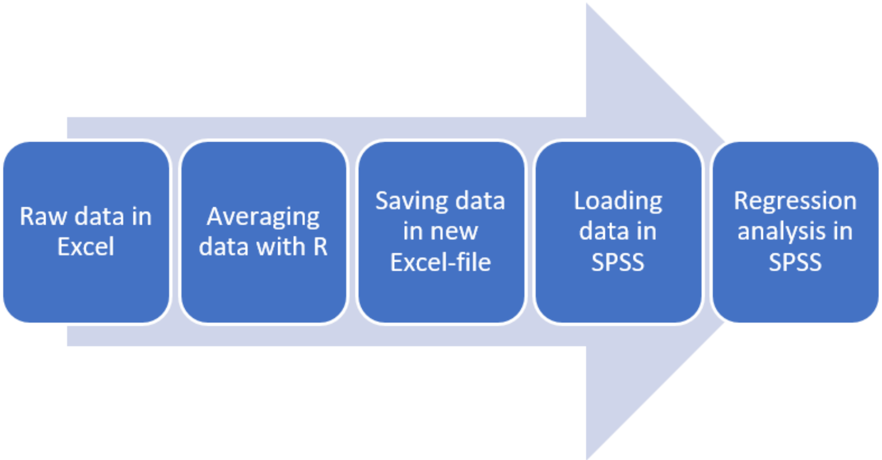

Figure 8.1: Data streams for regression analysis

The second step was to load the data in R. R is an open-source software that is very strong with statistics. In R, the four latter variables in the table above were transformed to hourly averages. This was done by averaging the quarterly values. These values were thereafter stored in a new Excel file and loaded into SPSS from that Excel-file.

In SPSS, executing a regression analysis can be done by the built-in function, found under analyze > regression > linear regression. Under the Plots-interface the histogram and normal probability plot can be selected. The Day-Ahead price is loaded in the dependent variable, and the explanatory variables are loaded in the independent variables. The selected method is Stepwise.

The validation of the regression analysis is aimed at determining that the computerized model (regression model) used for the analysis is representative for the system. The system in this case is the relation between the explanatory variables (4 load variables, 11 month variables) and the price of electricity on the Day-Ahead market. The validation of the model in this research is done using two methods. First, the residuals are analyzed. The residuals are the differences between the forecasted electricity price and the observed electricity price at that time. Ideally, these residuals are normally distributed. Second, the regression model is cross-validated for the period 19-07-2017 âĂŞ 01-10-2016. Ideally, the regression model would be cross-validated for another complete year. However, the dataset of the Day-Ahead prices ends at 01-10-2016. The origin of the data is already confirmed in the table in the verification of the regression analysis.

The analysis of the residuals can be added in the SPSS model fit. The first graph used for this analysis is a histogram of the standardized residuals. The histogram shows that the residuals reflect a normal distribution, with a mean of nearly 0 and a standard

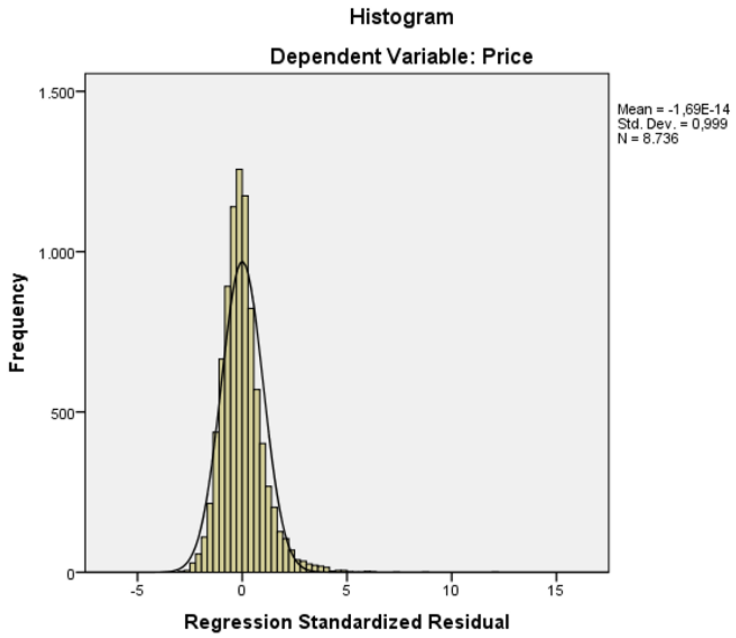

Figure 8.2: Histogram of residuals of regression analysis

deviation of 1,00. The histogram indicates a positive kurtosis and a positive skewness. The kurtosis is the centrality of the peak, which is not further assessed in this research. The skewness however is an indication to be investigated further.

The skewness is further investigated by plotting the forecasted prices against the observed prices. The histogram indicates a positive skewness, meaning that the observed price is expected to be higher than the forecasted price. The graph below shows for all quarters the forecasted price and the observed price. This graph shows a number of outliers. Almost all of these outliers are positive outliers, meaning a higher observed price than forecasted price. These outliers explain the positive skewness indicated by the histogram. The red line in the picture is the 45-degree line, meaning that all values on that line indicate the same forecasted price as the observed price.

The second part of the validation is the cross-validation of the regression-indicators for another time period. As mentioned before, the dataset for the Day-Ahead prices has data until 01-10-2016. Therefore, the beta-values are tested for the data between 19-07-2016 till 01-10-2016. The first step in the cross-validation is to transform the load and renewable production data for both the Netherlands and Germany to hourly averages. Then, the beta-values from the original regression analysis are used to forecast the Day-Ahead prices in the new time period. Last, R is used to calculate the R-squared from the forecasted prices relative to the real prices. This R-squared is 0.55, whereas the

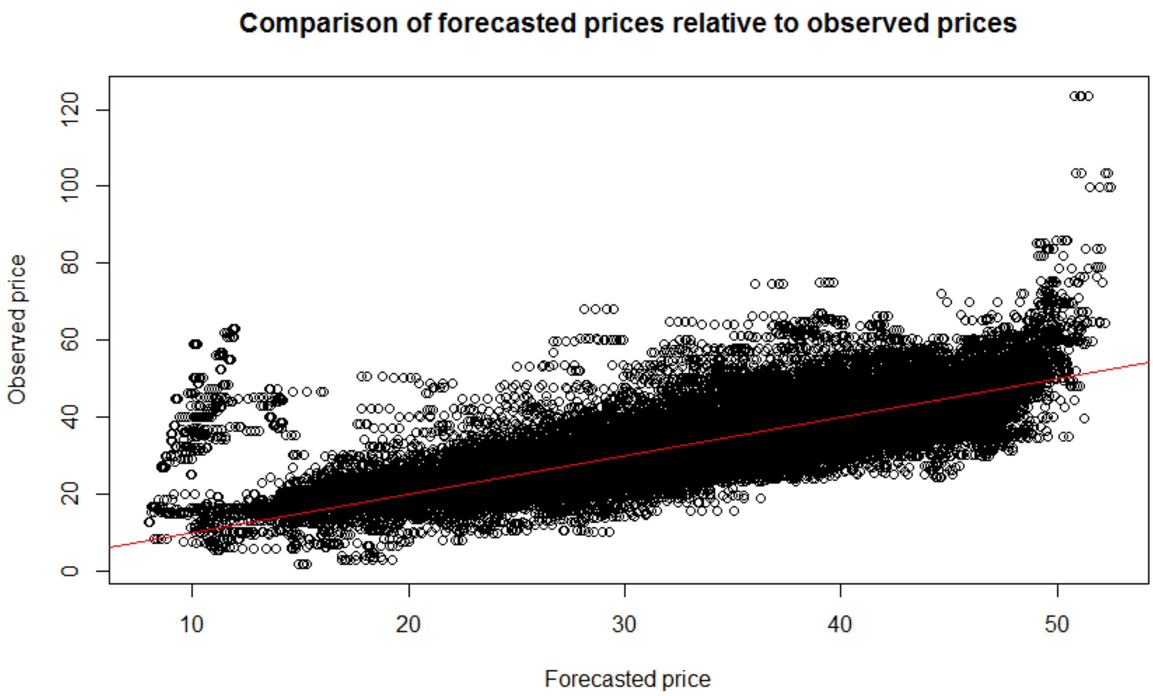

Figure 8.3: Relation between forecasted prices and observed prices. Red line is at x=y

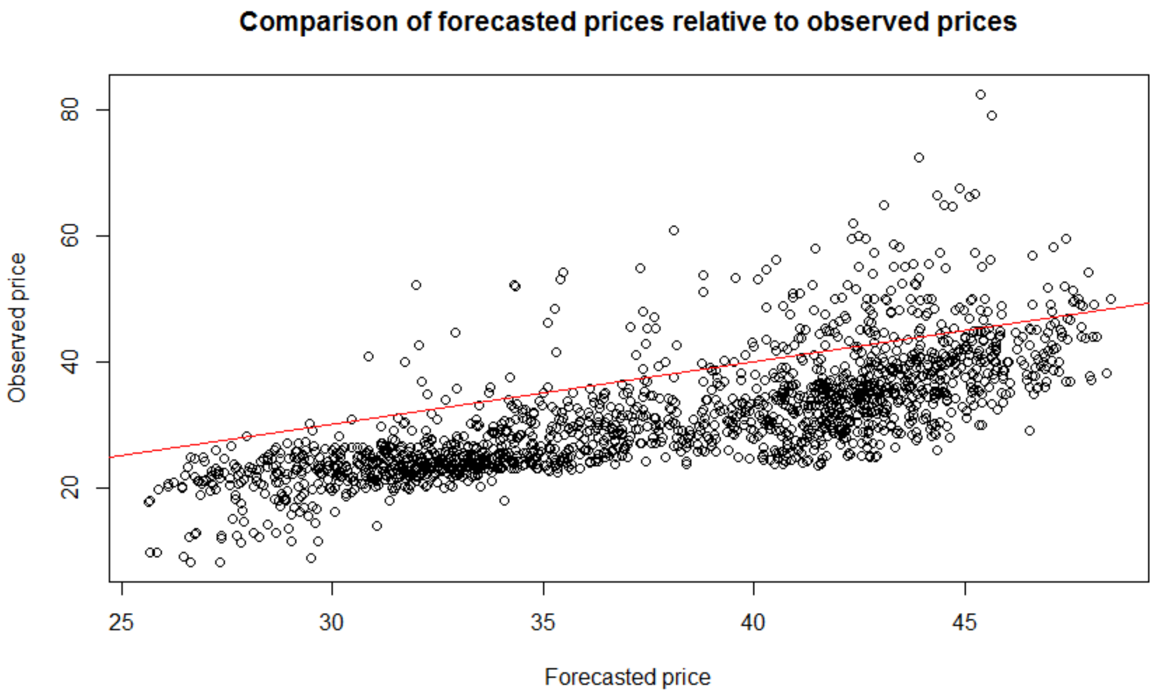

Figure 8.4: Relation between forecasted prices and observed prices for cross-validation. Red line is at x=y

value from the regression analysis was 0.66. The forecasted prices compared to the real prices are visualized below. The red line in the picture is the 45-degree line, meaning that all values on that line indicate the same forecasted price as the real price. As most points are right from the line, it can be concluded that the forecasted prices are often higher than the real price.

The three months used in the cross-validation are July, August, and September. For these three months, the monthly indicators from the original regression analysis were respectively 3.071, 6.051, and 5.322. These values indicate that the electricity price is expected to be higher in these months compared to the average price during the year. These factors are taken into account in the calculation of the forecasted price.

It is concluded that the regression model is valid for the purposes of this research. The model explains 66% of the variance and the residuals reflect a normal distribution well. The cross-validation executed for the months July, August, and September 2016 indicated that the regression model forecasts the electricity prices too high. This is an error to be accounted for when designing an algorithm to be used in a real trading environment. The values used to forecast the electricity prices do however still explain 55% of the variance, and have a primarily one-sided bias, meaning that they can still be used for the purpose of this research, namely getting an indication what profit can be made by trading on electricity markets with local electricity storage.

Appendix II: Values for trading on Secondary Reserve market

In this Appendix, the results of the quantile-analysis of the Secondary Reserve market is presented. First, the calculation method is described, and then per day per quarter the values for amount, ramp up price, and ramp down price are given.

The input for this analysis is the "Balansdelta" for 18-07-2015 till 18-07-2016, downloaded from the TenneT-website. This dataset provides per minute of each day the ramp-up imbalance, ramp-down imbalance, ramp-up price, ramp-down-price and a number of other variables of no interest for this research. The ramp-down imbalance is subtracted from the ramp-up imbalance for the purpose of this research, which is why there is only one 'amount' column in the results.

The total imbalance is then averaged per quarter, as the reimbursement is per quarter as well. However, for the prices, not the averages are taken. The reimbursement for ramp-up is namely the highest price per 15 minutes, and for ramp-down the lowest price per 15 minutes. Then for each quarter of each day, the values are columnized. This creates the possibility to calculate the 70%-quantile, which is shown in figure 10.1. The results of these quantiles can be found in the coming pages.

Calculation method	*Quarter 1*	*Quarter 2*	*Quarter 3*	*Quarter 4*	...	...
Saturday 1	Average of 15 min	Average of 15 min				
Saturday 2	Average of 15 min					
Saturday 3	Average of 15 min					
Saturday 4	Average of 15 min					
...	Average of 15 min	<- 70%-quantile				
...	Average of 15 min					

Figure 8.5: Calculation method for quantile-values

Saturday values							
Quarter	*Amount*	*Ramp up price*	*Ramp down price*	*Quarter*	*Amount*	*Ramp up price*	*Ramp down price*
1	3,91	37,34	21,78	49	41,00	55,21	20,23
2	59,41	46,26	22,57	50	27,52	39,18	21,37
3	4,87	35,24	22,43	51	18,99	35,11	20,57
4	1,75	29,47	22,02	52	2,32	28,37	20,91
5	2,12	34,49	23,15	53	36,96	45,40	20,52
6	17,67	38,32	20,37	54	20,61	40,02	16,31
7	1,31	23,08	20,91	55	15,87	37,22	19,79
8	-1,36	0,00	21,89	56	4,36	30,67	20,04
9	6,28	44,25	22,17	57	12,73	35,53	20,76
10	37,71	35,68	21,51	58	7,71	35,61	19,51
11	2,81	24,36	20,95	59	15,65	36,42	17,86
12	-0,08	0,00	24,33	60	17,29	25,57	19,26
13	-2,32	31,37	22,78	61	-2,25	25,86	23,75
14	5,43	32,02	17,09	62	0,97	29,37	22,08
15	12,11	28,66	16,68	63	0,11	10,30	20,55
16	2,27	24,99	21,88	64	0,85	25,45	23,26
17	0,00	25,90	22,78	65	0,00	26,52	23,20
18	2,40	34,12	20,67	66	0,00	29,06	21,28
19	5,87	28,52	18,65	67	1,17	26,45	20,40
20	8,23	23,83	18,83	68	5,35	35,91	18,79
21	3,25	28,20	19,35	69	3,81	0,00	19,39
22	0,05	24,63	23,05	70	3,49	25,07	26,42
23	0,00	20,88	20,04	71	15,11	34,50	21,15
24	0,19	22,26	20,93	72	58,12	46,18	0,00
25	0,97	8,74	21,23	73	43,68	40,24	21,34
26	0,00	0,00	23,04	74	9,08	31,02	21,73
27	3,56	28,67	17,55	75	22,35	29,76	16,28
28	13,89	35,23	16,26	76	31,72	39,24	6,31
29	0,00	24,20	19,74	77	37,69	52,31	15,93
30	-6,64	0,00	20,27	78	17,32	36,27	20,43
31	0,00	27,57	21,28	79	7,47	27,57	24,61
32	19,36	32,54	18,67	80	19,13	37,99	17,07
33	5,67	24,67	16,77	81	26,33	42,00	22,68
34	0,00	28,97	20,57	82	8,17	30,23	23,72
35	10,13	39,19	22,20	83	2,93	25,71	19,85
36	48,75	41,91	18,55	84	0,59	0,00	21,34
37	16,87	39,26	20,73	85	9,85	40,97	26,02
38	1,32	31,99	18,49	86	8,92	28,52	21,03
39	13,40	38,75	20,24	87	0,00	0,00	21,20
40	58,68	55,56	18,83	88	-0,21	0,00	22,78
41	38,44	43,12	24,51	89	9,60	43,92	21,97
42	8,04	33,07	22,43	90	29,64	44,99	23,12
43	16,05	40,05	19,99	91	3,07	22,65	22,03
44	17,55	38,82	22,37	92	-2,76	0,00	23,11
45	21,64	38,77	22,32	93	11,33	81,28	22,47
46	14,77	36,28	21,10	94	37,57	42,14	20,13
47	25,15	31,63	21,48	95	0,00	20,02	20,56
48	25,69	32,85	20,40	96	0,00	8,45	19,53

Sunday values							
Quarter	*Amount*	*Ramp up price*	*Ramp down price*	*Quarter*	*Amount*	*Ramp up price*	*Ramp down price*
1	15,85	59,96	19,92	49	29,76	41,23	19,05
2	33,08	41,05	24,45	50	12,76	31,79	18,79
3	-4,93	0,00	21,29	51	17,12	25,75	18,46
4	-9,36	0,00	19,11	52	5,63	29,92	20,00
5	6,61	49,31	20,48	53	4,96	36,05	21,54
6	61,28	57,68	15,72	54	3,88	32,11	19,42
7	1,28	24,08	21,06	55	8,03	28,84	15,44
8	-1,47	0,00	22,07	56	9,60	34,36	17,91
9	0,33	38,20	22,97	57	4,36	28,69	20,09
10	31,49	38,95	19,50	58	18,39	36,46	17,17
11	10,47	29,40	20,71	59	16,61	27,38	17,68
12	3,93	26,75	19,30	60	9,08	33,52	15,68
13	12,88	39,55	20,52	61	3,32	31,50	16,93
14	24,44	36,48	16,68	62	2,55	25,31	20,35
15	16,29	26,80	19,87	63	6,59	27,59	19,34
16	-0,37	0,00	21,83	64	4,91	32,93	15,41
17	-0,55	28,17	20,23	65	4,53	26,64	22,06
18	9,15	27,47	17,98	66	1,75	25,62	19,76
19	3,56	26,95	19,46	67	9,35	29,26	21,90
20	4,09	26,33	18,02	68	45,63	38,49	19,78
21	6,61	35,59	19,49	69	8,24	27,09	18,62
22	20,05	31,75	20,72	70	0,51	29,75	23,71
23	6,25	23,53	21,80	71	31,19	43,39	0,00
24	5,44	26,13	11,89	72	84,21	45,57	0,00
25	10,13	27,44	15,10	73	41,49	41,39	19,47
26	5,36	24,87	21,50	74	6,04	34,76	23,58
27	4,24	28,38	20,04	75	15,69	38,69	19,59
28	3,19	25,41	19,94	76	28,71	43,26	20,27
29	5,28	27,13	19,05	77	23,12	38,02	20,87
30	0,40	24,67	20,78	78	20,96	35,85	22,87
31	18,91	32,22	19,99	79	20,65	37,25	23,42
32	41,96	39,06	11,66	80	27,36	39,24	23,82
33	25,97	31,98	18,02	81	56,67	52,99	20,87
34	1,11	27,21	21,27	82	33,80	35,22	23,55
35	23,48	38,92	17,23	83	8,20	26,53	18,38
36	75,15	41,39	0,00	84	11,07	30,01	18,11
37	24,83	30,63	21,47	85	26,01	50,11	19,75
38	0,00	28,90	21,05	86	28,99	39,04	20,70
39	9,16	35,14	20,14	87	3,59	26,80	20,60
40	45,65	38,88	6,47	88	13,51	32,52	18,31
41	44,76	39,12	18,97	89	35,71	50,85	19,46
42	3,03	27,15	20,55	90	49,56	45,04	19,48
43	11,36	34,86	17,46	91	3,32	24,72	20,77
44	26,60	36,56	19,77	92	-3,45	0,00	22,14
45	24,88	35,34	18,38	93	36,85	123,22	22,09
46	0,63	20,13	19,90	94	29,87	40,20	19,37
47	2,92	31,58	21,66	95	0,03	0,00	20,71
48	22,61	39,29	19,11	96	-22,59	0,00	18,76

Monday values							
Quarter	*Amount*	*Ramp up price*	*Ramp down price*	*Quarter*	*Amount*	*Ramp up price*	*Ramp down price*
1	8,67	108,52	21,14	49	35,33	53,16	19,86
2	32,48	37,96	20,39	50	4,17	30,64	24,35
3	-1,07	0,00	22,30	51	1,11	27,45	24,10
4	-19,91	0,00	20,35	52	0,11	24,52	24,14
5	-3,35	41,41	19,77	53	9,79	42,77	21,54
6	15,88	35,22	21,43	54	22,88	42,79	22,65
7	0,00	0,00	20,77	55	10,55	34,61	23,21
8	-2,28	0,00	19,81	56	4,97	33,03	21,90
9	-2,33	34,49	20,78	57	12,31	37,97	24,66
10	6,89	30,72	22,33	58	14,91	43,50	20,97
11	0,45	21,39	21,36	59	12,88	30,71	20,93
12	-0,48	0,00	21,89	60	12,72	26,55	21,54
13	-0,32	27,42	20,63	61	18,88	38,71	20,97
14	0,31	24,75	19,78	62	18,35	38,35	21,46
15	0,00	0,00	20,05	63	19,71	36,49	22,11
16	0,00	0,00	17,71	64	15,12	33,79	23,12
17	0,00	24,98	19,76	65	9,88	33,11	23,92
18	0,00	20,99	18,36	66	8,68	34,86	23,22
19	0,00	0,00	20,88	67	19,43	38,99	20,94
20	-0,08	0,00	21,60	68	44,65	46,22	23,16
21	2,56	36,01	23,28	69	17,64	35,13	23,03
22	-0,24	0,00	22,14	70	17,88	46,42	22,01
23	-0,32	23,38	20,15	71	34,21	40,87	20,22
24	0,00	7,12	19,39	72	47,20	54,54	0,00
25	0,69	36,03	22,38	73	32,33	44,37	22,78
26	0,00	25,43	21,38	74	6,07	34,57	22,51
27	5,95	34,93	22,40	75	11,51	40,46	23,48
28	33,40	39,00	15,70	76	20,08	40,22	20,47
29	12,56	37,46	15,28	77	69,79	64,67	20,10
30	7,31	37,73	19,51	78	27,19	41,34	18,62
31	44,15	56,81	19,92	79	28,25	39,94	20,61
32	108,85	84,97	0,00	80	18,84	43,00	20,92
33	26,25	27,94	23,62	81	33,76	44,96	24,85
34	1,11	41,42	26,37	82	24,07	37,88	21,60
35	42,12	64,10	21,09	83	9,15	25,75	23,32
36	85,89	71,15	0,00	84	13,31	30,04	25,02
37	40,91	43,99	22,41	85	35,85	55,99	20,97
38	6,33	28,45	21,32	86	40,65	45,34	19,99
39	11,92	44,20	24,25	87	5,00	24,11	21,66
40	21,17	44,98	22,59	88	0,00	28,16	25,64
41	64,79	58,13	18,27	89	27,63	150,93	22,78
42	23,55	41,33	20,18	90	96,53	122,62	19,99
43	25,61	41,46	20,61	91	7,15	26,69	20,62
44	14,48	35,33	20,21	92	-0,92	0,00	22,28
45	52,16	45,20	22,75	93	33,49	126,22	18,49
46	22,59	41,47	21,36	94	60,43	47,25	23,05
47	59,83	44,55	24,58	95	2,07	0,00	24,25
48	51,55	41,27	22,59	96	-9,19	0,00	20,37

Tuesday values							
Quarter	*Amount*	*Ramp up price*	*Ramp down price*	*Quarter*	*Amount*	*Ramp up price*	*Ramp down price*
1	-4,07	52,21	20,66	49	53,38	61,08	20,44
2	51,01	47,23	20,12	50	36,59	38,12	22,54
3	1,91	26,65	21,26	51	12,56	27,98	22,58
4	-0,40	0,00	19,49	52	6,43	27,84	23,91
5	7,55	50,21	19,02	53	8,12	47,68	22,14
6	37,26	44,94	18,68	54	20,57	41,08	22,02
7	1,79	25,85	21,70	55	3,66	28,56	23,56
8	0,09	23,81	21,67	56	12,04	31,65	21,11
9	10,92	41,75	22,80	57	32,73	37,63	20,03
10	44,29	36,94	16,73	58	41,03	39,78	0,00
11	0,19	16,89	20,38	59	47,72	40,03	4,05
12	1,45	24,45	23,20	60	43,37	36,32	16,34
13	1,07	32,21	21,90	61	28,68	40,32	21,69
14	14,81	27,72	20,30	62	47,70	41,13	2,73
15	5,35	25,83	22,65	63	56,05	47,24	0,00
16	4,72	26,19	20,75	64	42,07	39,92	19,12
17	0,00	27,77	20,18	65	11,59	34,35	23,06
18	0,69	25,78	20,78	66	1,43	32,51	23,42
19	1,93	25,08	20,20	67	11,49	31,26	16,15
20	9,86	26,52	19,55	68	33,47	38,37	19,02
21	2,41	26,74	21,41	69	11,58	26,56	24,01
22	0,00	12,52	21,01	70	4,97	33,17	24,71
23	0,09	28,62	22,96	71	14,72	35,28	19,56
24	4,43	34,55	20,85	72	45,13	45,51	0,00
25	3,48	33,99	21,73	73	39,98	41,32	21,81
26	-0,84	0,00	21,63	74	9,43	29,92	23,54
27	7,06	33,61	24,30	75	14,53	36,50	21,35
28	43,22	44,75	22,38	76	19,79	36,02	21,49
29	6,25	30,53	19,87	77	19,08	40,42	22,24
30	0,19	28,21	22,56	78	25,76	41,01	20,34
31	20,53	45,67	21,61	79	22,67	40,97	16,62
32	79,51	57,44	0,00	80	35,10	41,66	20,49
33	26,39	38,75	24,02	81	24,71	39,99	21,65
34	2,20	35,92	22,54	82	13,66	36,59	21,80
35	37,37	47,79	20,33	83	4,77	25,27	23,86
36	113,35	72,47	0,00	84	0,00	0,00	23,51
37	46,86	42,05	21,37	85	18,41	53,47	24,78
38	23,35	42,65	22,04	86	31,51	41,05	18,04
39	18,71	37,70	19,86	87	2,27	16,34	22,55
40	45,92	39,78	21,97	88	0,00	0,00	23,58
41	29,62	40,39	20,93	89	7,50	88,38	20,04
42	22,81	41,60	22,62	90	62,71	49,46	21,52
43	22,45	39,70	22,89	91	-0,47	0,00	20,79
44	20,04	36,00	21,04	92	-4,31	0,00	21,88
45	38,78	47,65	22,34	93	1,92	68,59	21,91
46	38,93	39,51	21,09	94	78,88	66,58	21,68
47	43,29	40,55	23,52	95	-11,20	0,00	21,76
48	37,83	36,15	21,84	96	-12,15	0,00	21,80

Wednesday values							
Quarter	*Amount*	*Ramp up price*	*Ramp down price*	*Quarter*	*Amount*	*Ramp up price*	*Ramp down price*
1	-0,02	56,55	20,47	49	24,70	39,92	23,20
2	50,32	48,48	18,68	50	17,29	34,32	23,77
3	6,58	22,07	22,36	51	14,83	30,03	21,15
4	-12,37	0,00	23,05	52	11,07	29,38	19,51
5	13,87	55,58	19,72	53	9,95	36,63	24,13
6	53,77	45,84	21,96	54	11,39	32,93	23,36
7	-0,15	0,00	21,65	55	4,60	29,76	24,07
8	-0,02	0,00	21,58	56	9,29	34,03	20,99
9	-1,88	33,96	22,90	57	30,11	42,19	23,07
10	12,39	33,17	21,72	58	34,20	38,01	22,72
11	-0,70	0,00	23,49	59	10,74	35,32	22,87
12	-2,15	0,00	21,55	60	14,72	38,26	21,06
13	-0,08	31,30	21,59	61	31,82	39,29	22,02
14	2,91	27,68	21,40	62	32,59	43,10	22,79
15	-0,02	15,83	22,83	63	34,99	33,15	21,93
16	-1,07	0,00	21,74	64	35,01	37,96	20,99
17	1,73	27,60	21,25	65	36,05	42,19	20,76
18	6,89	27,34	14,77	66	27,07	34,12	20,96
19	5,24	25,68	18,24	67	48,41	41,71	20,35
20	3,21	26,69	20,72	68	48,13	43,89	22,69
21	3,56	30,73	22,68	69	37,22	32,60	21,63
22	-0,14	28,00	21,51	70	7,99	43,02	24,14
23	3,67	26,68	22,66	71	28,68	46,34	0,00
24	3,61	31,40	22,07	72	58,27	53,17	0,00
25	4,07	27,17	21,18	73	60,21	49,91	21,52
26	-1,23	15,28	23,81	74	14,57	34,71	22,95
27	10,81	34,70	21,04	75	23,38	42,09	20,78
28	40,31	36,51	18,31	76	42,23	46,54	22,19
29	-0,56	24,92	18,31	77	42,85	45,26	21,09
30	-0,31	0,00	22,86	78	5,29	31,11	23,38
31	21,95	42,25	17,77	79	7,40	30,59	23,32
32	85,79	60,42	0,00	80	12,20	29,88	23,12
33	24,98	34,38	23,42	81	31,18	57,17	23,10
34	0,00	0,00	24,31	82	10,43	37,52	22,36
35	12,81	50,13	21,47	83	3,42	26,40	22,83
36	93,91	87,26	8,61	84	2,30	26,33	24,49
37	38,47	47,81	24,86	85	13,79	50,13	22,76
38	8,37	37,01	22,34	86	18,15	43,71	24,36
39	28,51	40,21	23,08	87	0,00	0,00	24,92
40	35,59	43,99	22,02	88	-0,77	26,76	25,05
41	47,15	42,59	24,26	89	8,20	56,73	21,55
42	12,30	33,86	23,65	90	27,85	40,86	18,59
43	36,89	40,12	21,30	91	0,87	15,66	22,01
44	15,70	36,75	23,36	92	-5,91	0,00	24,16
45	23,87	41,69	20,96	93	27,63	114,65	21,38
46	23,81	42,00	19,77	94	81,58	55,03	22,50
47	23,67	33,61	22,75	95	-0,18	0,00	23,31
48	16,12	33,46	27,08	96	-30,93	0,00	20,99

Thursday values							
Quarter	*Amount*	*Ramp up price*	*Ramp down price*	*Quarter*	*Amount*	*Ramp up price*	*Ramp down price*
1	-8,34	68,37	20,69	49	35,88	40,52	21,00
2	72,47	51,20	20,49	50	19,57	34,43	18,99
3	-1,83	15,81	22,79	51	9,27	36,12	21,99
4	-17,76	0,00	22,29	52	13,57	35,43	23,59
5	-9,23	43,36	22,25	53	34,72	51,64	21,33
6	23,75	36,69	20,67	54	48,59	46,13	20,22
7	0,00	0,00	23,41	55	18,31	38,88	23,72
8	-8,97	0,00	20,43	56	23,91	37,62	20,34
9	0,45	35,42	21,96	57	11,12	49,87	22,05
10	25,41	32,34	20,29	58	30,91	44,23	20,30
11	5,19	24,67	21,41	59	56,07	38,82	21,53
12	-0,31	0,00	22,60	60	26,39	40,43	21,17
13	-0,13	26,57	23,69	61	31,31	42,36	21,92
14	10,63	28,65	20,58	62	28,11	34,25	19,02
15	2,95	27,53	20,96	63	37,61	39,73	20,00
16	-0,55	22,56	23,49	64	60,73	39,73	21,02
17	0,27	23,89	22,17	65	21,33	36,50	23,78
18	4,65	28,42	20,21	66	4,05	34,66	22,95
19	1,07	23,34	22,77	67	17,11	41,41	0,00
20	1,74	24,82	21,07	68	44,41	47,04	10,51
21	1,79	26,47	20,62	69	14,21	34,81	22,79
22	4,71	27,82	19,51	70	16,59	39,73	21,70
23	4,30	33,66	21,57	71	27,39	41,43	22,13
24	13,37	34,80	20,24	72	47,51	48,71	5,17
25	10,26	35,27	22,70	73	27,79	46,83	21,87
26	0,00	26,17	21,91	74	6,56	35,63	25,87
27	12,55	39,17	20,81	75	17,75	41,96	21,42
28	25,95	39,72	21,85	76	40,53	47,39	20,84
29	2,45	27,05	23,68	77	29,10	47,90	20,96
30	-1,69	34,86	25,47	78	17,93	35,18	28,20
31	43,87	51,22	20,12	79	21,02	39,99	24,56
32	91,09	55,67	13,03	80	32,42	38,51	22,92
33	44,18	44,60	21,81	81	45,52	50,52	22,25
34	5,17	38,66	24,42	82	42,93	39,67	21,30
35	26,55	61,16	17,76	83	24,60	33,48	21,08
36	84,19	60,40	0,00	84	10,53	34,65	22,17
37	43,16	41,91	24,22	85	32,15	68,72	20,98
38	32,30	44,69	21,52	86	43,11	38,76	23,00
39	46,51	44,26	20,59	87	0,05	0,00	23,23
40	62,11	44,15	18,70	88	-0,55	13,13	24,56
41	43,56	45,96	21,19	89	12,06	53,33	20,92
42	14,51	40,00	22,49	90	47,31	48,38	22,07
43	26,89	43,41	20,82	91	1,31	17,50	19,58
44	47,19	41,62	20,65	92	-1,29	0,00	22,16
45	42,55	47,44	22,57	93	21,50	92,65	22,57
46	34,00	39,67	20,74	94	55,39	47,85	20,67
47	25,84	36,25	15,68	95	0,25	0,00	20,99
48	27,21	41,08	16,14	96	-1,05	0,00	22,53

Friday values							
Quarter	*Amount*	*Ramp up price*	*Ramp down price*	*Quarter*	*Amount*	*Ramp up price*	*Ramp down price*
1	8,18	63,43	23,13	49	30,71	50,22	23,15
2	64,24	42,21	20,77	50	33,00	40,87	21,02
3	3,95	26,54	20,39	51	16,15	34,33	19,61
4	-13,88	0,00	20,12	52	9,09	37,39	20,29
5	1,74	41,99	21,72	53	45,89	51,93	16,24
6	45,09	52,68	21,14	54	42,81	44,61	22,98
7	5,91	27,06	21,44	55	24,89	33,97	23,17
8	-3,65	0,00	21,55	56	14,24	31,22	21,40
9	0,14	38,32	23,09	57	18,79	41,33	18,67
10	25,08	34,56	20,50	58	40,67	41,86	21,28
11	0,58	27,95	20,78	59	17,10	36,01	22,75
12	0,00	25,73	21,72	60	19,06	36,44	22,49
13	2,21	28,45	24,77	61	16,33	38,26	21,38
14	16,69	32,74	20,38	62	11,67	36,53	23,07
15	6,60	27,04	21,64	63	22,00	34,82	21,57
16	0,56	23,70	21,26	64	19,33	36,10	22,67
17	-0,50	24,93	21,93	65	4,37	28,58	25,09
18	1,26	28,45	20,43	66	8,31	27,62	18,13
19	1,41	28,24	21,94	67	17,81	34,54	21,91
20	4,99	30,11	15,28	68	24,89	36,48	23,03
21	13,84	31,61	23,49	69	5,33	27,85	23,12
22	0,00	18,28	22,67	70	5,41	37,90	26,69
23	0,71	29,18	21,92	71	9,29	36,37	22,04
24	11,69	30,38	15,27	72	23,76	45,09	0,00
25	6,35	32,49	23,25	73	37,39	46,49	21,42
26	-0,12	28,09	22,09	74	12,86	30,07	21,01
27	17,79	37,99	21,27	75	15,59	29,24	22,73
28	67,13	43,01	16,29	76	11,50	31,02	24,24
29	16,47	29,26	19,63	77	17,73	36,34	24,01
30	2,05	36,05	22,29	78	16,71	28,57	21,03
31	15,97	41,96	19,48	79	13,61	31,89	23,35
32	68,07	58,72	0,00	80	19,40	30,21	21,98
33	13,57	30,85	18,13	81	23,45	46,03	22,32
34	0,00	36,61	24,22	82	27,40	35,85	21,85
35	40,93	55,73	21,14	83	7,79	27,53	22,53
36	78,41	60,09	0,00	84	1,93	24,02	22,63
37	74,91	51,33	20,96	85	16,09	54,71	22,54
38	34,36	41,32	20,48	86	35,42	40,43	21,09
39	39,05	48,14	20,51	87	0,81	0,00	21,43
40	63,07	52,69	22,84	88	-5,55	27,43	22,21
41	40,79	46,66	21,92	89	9,21	54,47	21,14
42	40,65	45,26	23,08	90	68,27	53,37	25,17
43	46,36	49,34	18,34	91	0,16	15,50	22,76
44	51,30	43,15	19,27	92	-0,08	15,19	23,45
45	53,33	43,25	19,66	93	17,67	123,30	21,04
46	32,54	39,92	18,93	94	74,69	57,07	18,23
47	25,17	39,43	21,72	95	11,11	32,06	22,03
48	27,01	42,55	17,74	96	1,14	28,70	25,56

Appendix III: Testing the model

In this appendix, the results of the tests of the model can be found. There are 9 experiments to be run, which are all shown here. The variables that can be adjusted can be found in table 10.1. The constants are adjusted one by one and not simultaneously.

Constant	**Low**	**Medium**	**High**
Bid percentage	0.8	1.0	1.2
Buy threshold	15	20	30
Sell threshold	30	35	45

Table 8.2: Design of experiments to run with the model

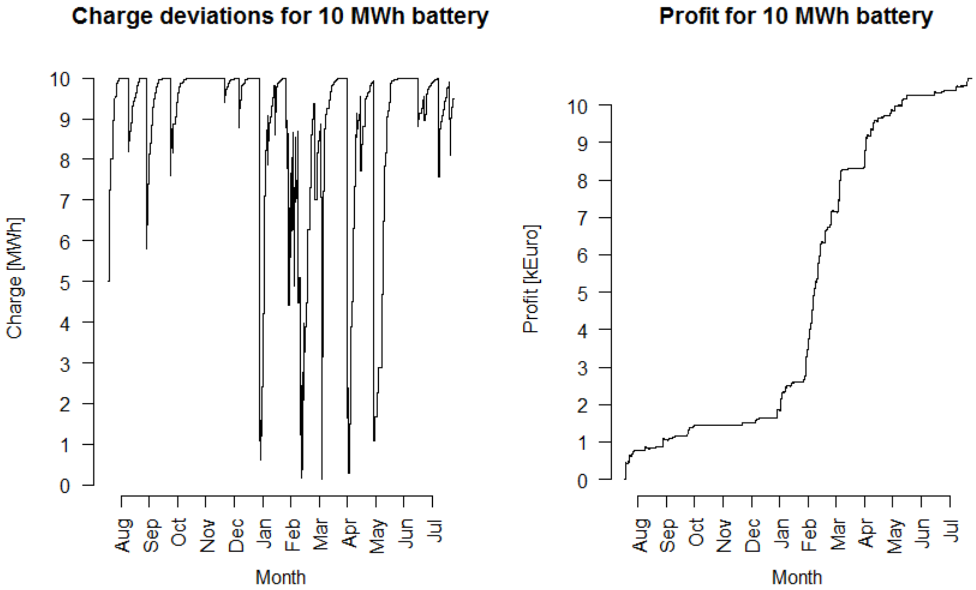

Figure 8.6: Experiment 1: All constants on low

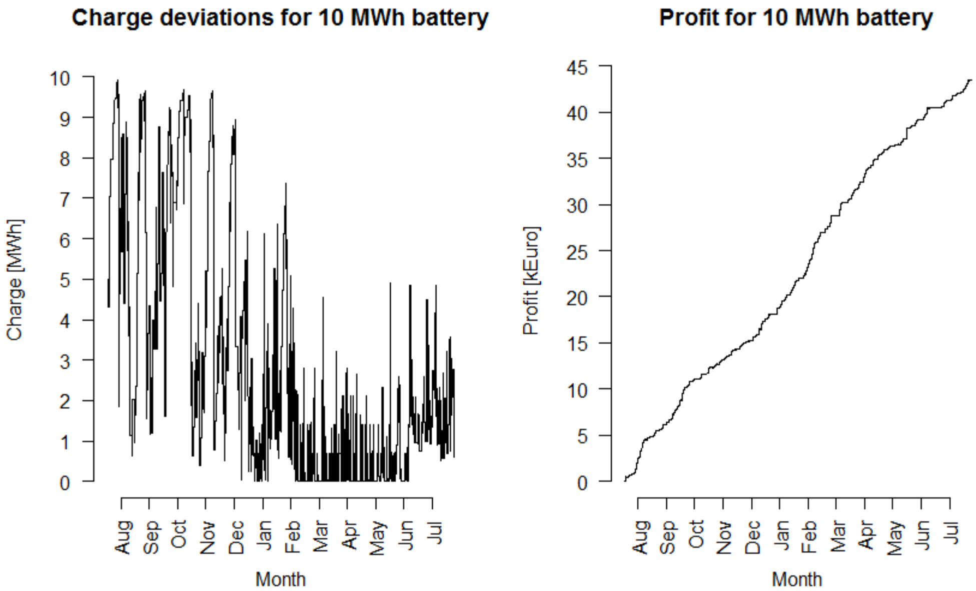

Figure 8.7: Experiment 2: All constants on medium

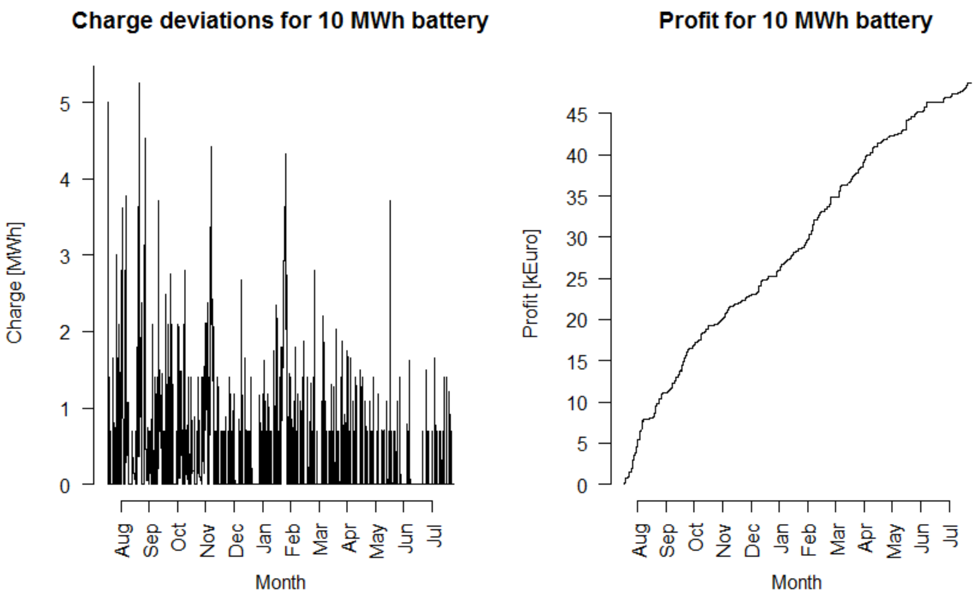

Figure 8.8: Experiment 3: All constants on high

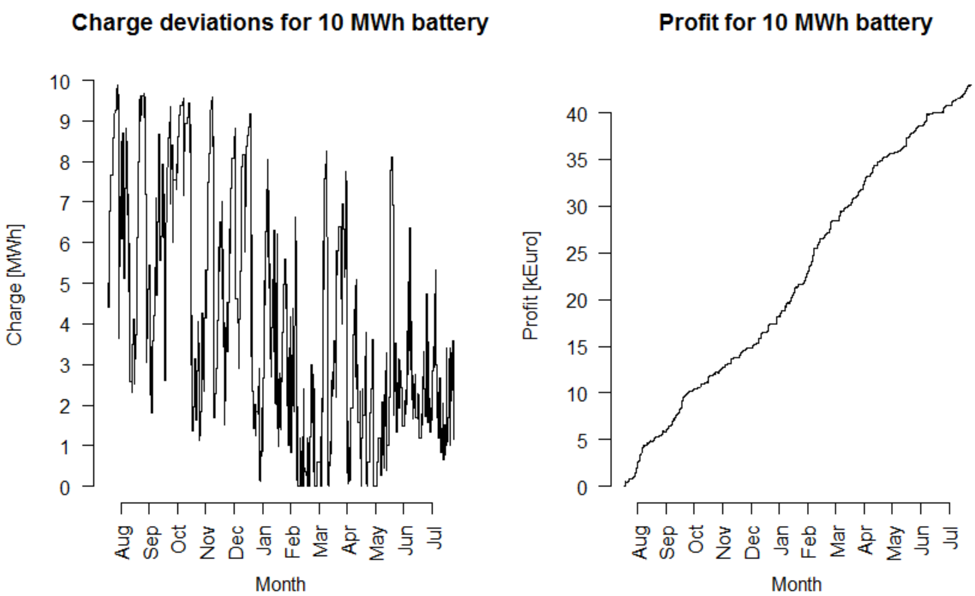

Figure 8.9: Experiment 4: All constants low, Bid percentage on medium

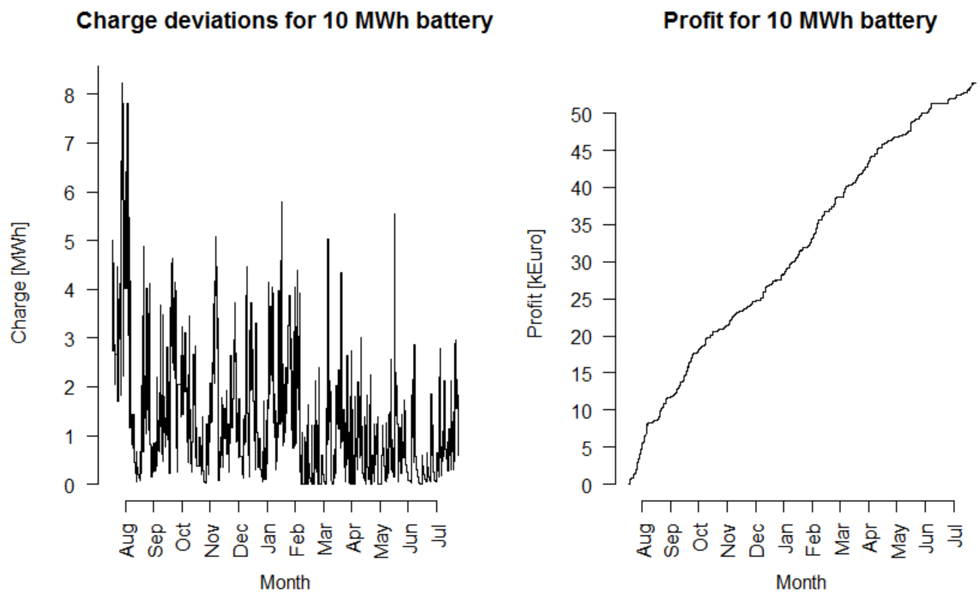

Figure 8.10: Experiment 5: All constant low, Bid percentage on high

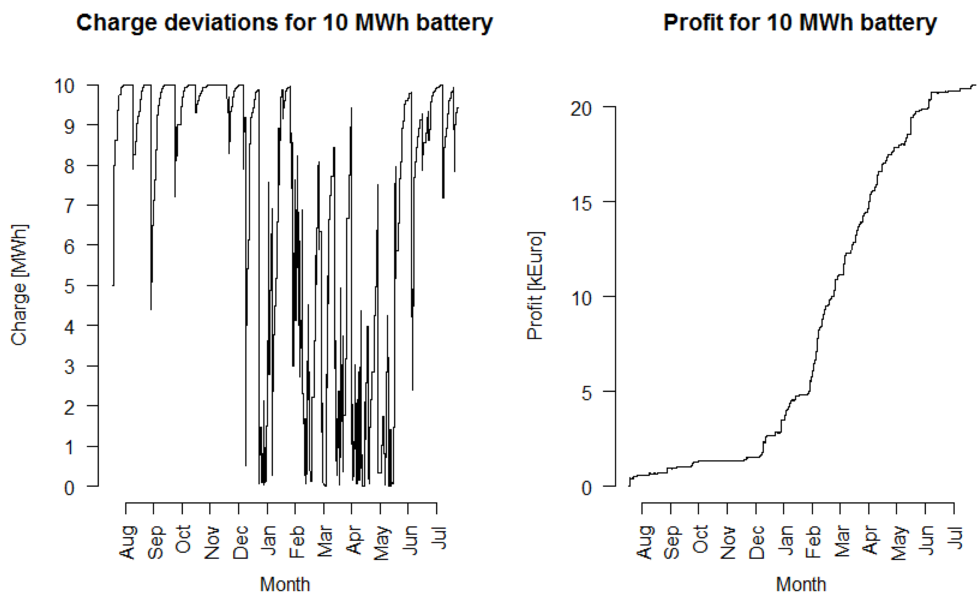

Figure 8.11: Experiment 6: All constants low, Buy threshold on medium

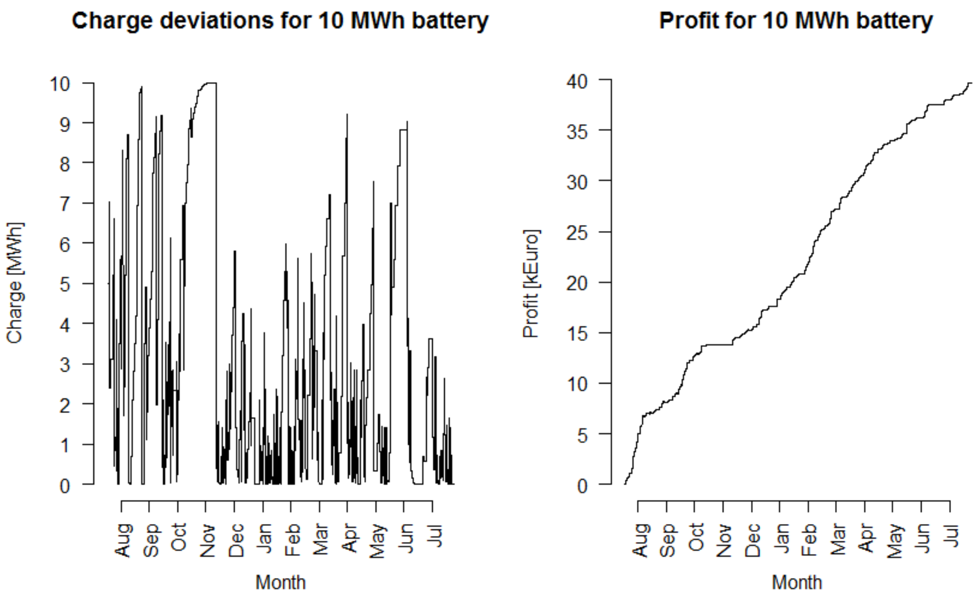

Figure 8.12: Experiment 7: All constant low, Buy threshold on high

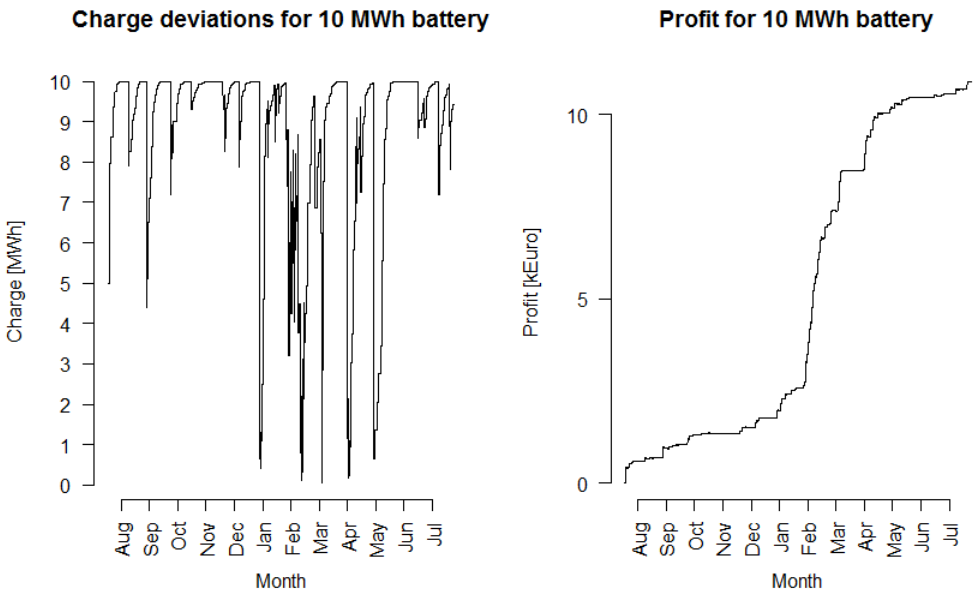

Figure 8.13: Experiment 8: All constants low, Sell threshold on medium

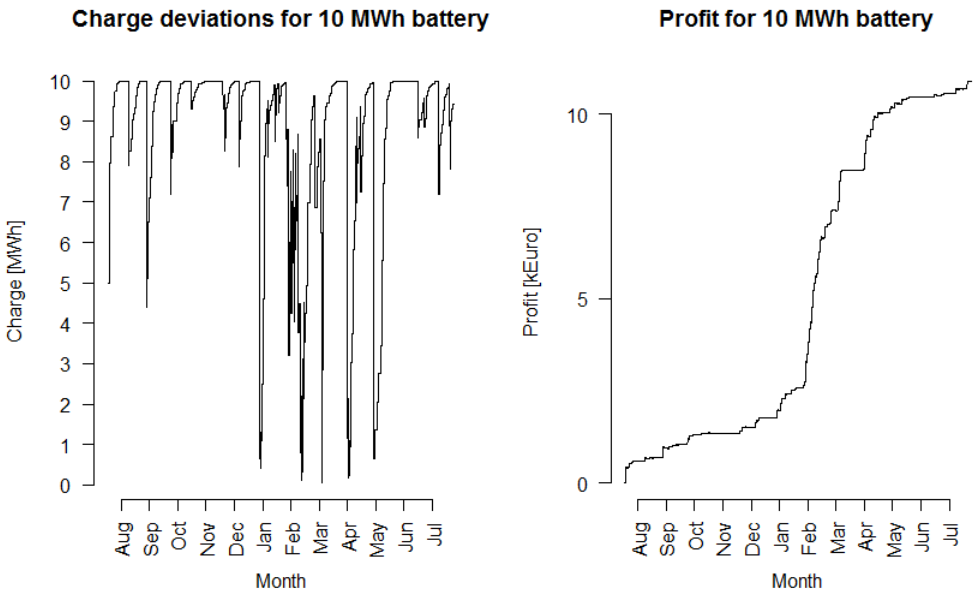

Figure 8.14: Experiment 10: All constant low, Sell threshold on high

Appendix IV: Verification of the R-model

The verification of the R-model for testing the trading algorithm focusses on the implementation of the described decision logic in R. This means that the computerized model (R) has to represent the conceptual model (decision logic) well enough for the purpose of the model. In the R-model in this research, a lot of indices are used to indicate the present day and hour at time in the model during calculation. These indices became complex, and have been check manually if they indeed represented the correct time instant. The rest of the verification is done by assessing one or multiple lines of R-code. The verification process requires that a line of code correctly represents the model formalization.

```
DAbuyvector = array(data = 0, dim = 96) DAsellvector = array(data = 0, dim
= 96) SRbuyvector = array(data = 0, dim = 96) SRsellvector = array(data = 0,
dim = 96)
SellThreshold = 45 BuyThreshold = 30 BidPercentage = 1.2
Efficiency = 0.7 Charge = array(data = NA, dim = 35233) Profit = array(data
= NA, dim = 35233) Charge[1] = 5 Profit[1] = 0 MaxPower = 4 MaxCharge =
10 CountCharge = 0 CountDischarge = 0 CountNothing = 0 ChargeChange =
array(data = rep(0, 35232), dim = 35232)
```

These lines of code simply set the model parameters. A number of them are arrays and a number of them are constants. The efficiency of the battery system is set at 0.7, the initial profit is 0 and initial charge is 5.

```
for (i in 1:367){ # At the beginning of each day: empty the schedules of last day
DAbuyvector = array(data = 0, dim = 96) DAsellvector = array(data = 0, dim
= 96) SRbuyvector = array(data = 0, dim = 96) SRsellvector = array(data = 0,
dim = 96) TradingMinimum = 0 DAtradevector = array(data = 0, dim = 96)
SRtradevector = array(data = 0, dim = 96)
# Check for forecasted negative imbalance if (sum(ForecastMatrix $
SRamount[(((i-1)*96 + 1):(i*96))] < 0) > 0){ for (j in (which(ForecastMatrix $
SRamount[(((i-1)*96 + 1):(i*96))] < 0))){ SRbuyvector[j] = 1 } }
```

The first step is a for-loop. The code runs for 367 days, which explains that the for-loop runs for 367 times. The first step of each day is to empty all the trading-schedules, as each day a new one is formed. Then, as said in the decision logic, the first step is to check for negative imbalance demand. All of the forecasts are in the matrix "ForecastMatrix" and the column "SRamount" holds the forecast for the demand on the Secondary Reserve market. As the matrix is one long matrix with 367 days of 96 quarters of data, each time a new subset of a column of length 96 must be used. This length of 96 represents one day. The "SRbuyvector" is set to 1 when the expected demand on the market is lower than 0, meaning a ramp-down demand.

```
# Check other prices for (j in (which(ForecastMatrix$APXforecast[(((i-1)*96 +
1):(i*96))] > SellThreshold))){ DAsellvector[j] =
ForecastMatrix$APXforecast[((i-1)*96 + j)] }
for (j in (which(ForecastMatrix$APXforecast[(((i-1)*96 + 1):(i*96))] <
BuyThreshold))){ DAbuyvector[j] = ForecastMatrix$APXforecast[((i-1)*96 +
j)] }
for (j in (which(ForecastMatrix$SRupPrice[(((i-1)*96 + 1):(i*96))] >
SellThreshold & ForecastMatrix$SRamount[(((i-1)*96 + 1):(i*96))] > 10))){
SRsellvector[j] = ForecastMatrix$SRupPrice[((i-1)*96 + j)] }
```

After the ramp-down demand, the prices on the other markets are checked. These prices are again checked for the 96 quarters for the i^{th} day. If a price on a market is forecasted to be profitable enough to trade, the relevant quarter is stored in a vector. Profitable enough means above the sell-threshold, or below the buy-threshold.

```
# Next step is to identify the amount of quarters that can be used for trading
TradingMinimum = min((Efficiency * (sum(SRbuyvector[SRbuyvector != 0]) +
sum(DAbuyvector[DAbuyvector != 0]))), (Charge[(i-1)*96 + 1] +
(sum(SRsellvector[SRsellvector != 0]) + sum(DAsellvector [DAsellvector !=
0]))))
```

The next step is to determine the amount of quarters that can be used for trading. On one hand, this is influenced by the amount of electricity that is bought - but this amount is lowered by the round-trip efficiency of the complete battery system (AC âĂŞ DC - Storage - DC - AC). This efficiency namely causes a loss of electricity, resulting in a lower amount that can be sold again. This amount is compared to the amount that can be sold and the minimum of those is determined.

```
# Now that the minimum is known, the buying / selling can be scheduled if
(is.na(TradingMinimum) == FALSE){ for (j in 1:TradingMinimum){
DAtradevector[(which(ForecastMatrix$APXforecast[(((i-1)*96 + 1):(i*96))] ==
sort(ForecastMatrix$APXforecast[(((i-1)*96 + 1):(i*96))], decreasing =
TRUE)[j]))] = -1
SRtradevector[(which(ForecastMatrix$SRupPrice[(((i-1)*96 + 1):(i*96))] ==
sort(ForecastMatrix$SRupPrice[(((i-1)*96 + 1):(i*96))], decreasing =
TRUE)[j]))] = -1
} }
if (is.na(TradingMinimum) == FALSE){ for (j in
1:(1/Efficiency)*TradingMinimum){
DAtradevector[(which(ForecastMatrix$APXforecast[(((i-1)*96 + 1):(i*96))] ==
sort(ForecastMatrix$APXforecast[(((i-1)*96 + 1):(i*96))])[j]))] = 1
SRtradevector[(which(ForecastMatrix$SRupPrice[(((i-1)*96 + 1):(i*96))] ==
sort(ForecastMatrix$SRupPrice[(((i-1)*96 + 1):(i*96))])[j]))] = 1
} }
```

Then, if there is at least 1 quarter for the day to trade upon, the scheduling is executed. This means that for the selling, all the prices are sorted from high to low. The highest price is scheduled first, then the second-highest price, and so on until the maximum amount of quarters to trade upon (determined earlier) is reached. For the buying, the same process is executed. However, the efficiency losses in the battery system need to be accounted for in the process of buying electricity. Therefore, the amount of quarters that the system buys electricity per day is multiplied by the inverse of the efficiency, ensuring the surplus of electricity bought to cope with efficiency losses.

```
for (j in 1:96){ SRtradevector[j] = SRbuyvector[j]
if (DAtradevector[j] != 0 & SRbuyvector[j] == 1){ DAtradevector[j] = 0 } }
```

Then, the buying on the Secondary Reserve market gets priority over all other schedules - as this ensures the maximization of the amount of quarters scheduled for that day to buy electricity when the price is expected to be negative.

```
DayIndex = (i * 96) - 96
for (j in 1:96){
if (SRtradevector[j] > 0 & PriceAmountMatrix$RDD[(DayIndex + j)] > 0 &
PriceAmountMatrix$RDP[(DayIndex + j)] < 0){
ChargeChange[(DayIndex + j)] =
max(min((max(PriceAmountMatrix$RDD[(DayIndex + j)], 0)), MaxPower,
((MaxCharge - Charge[(DayIndex + j)])*1)), 0) Charge[(DayIndex + j + 1)] =
Charge[(DayIndex + j)] + ((ChargeChange[(DayIndex + j)] / 4) * Efficiency)
Profit[(DayIndex + j + 1)] = Profit[(DayIndex + j)] +
((ChargeChange[(DayIndex + j)] / 4) * (-PriceAmountMatrix$RDP[(DayIndex
+ j)])) CountCharge = CountCharge + 1 }
```

Then, the actual trading is done. The "DayIndex" is a variable used to reduce the complexity of the code. Then, a loop is executed for 1 till 96 - because there are 96 quarters in one day. Then, for the Secondary Reserve market, there must be planned for a specific quarter to trade, but the price on the market must also be 'right' (see explanation about buy- and sell-thresholds). This reflects reality as a party can decide per quarter (or actually per minute) to trade on this market or not. Then, the amount traded on this market is limited by the demand on the market, the capacity of the battery, and the maximum power. After this calculation, the charge of the battery and the profit are adjusted accordingly.

```
if (DAtradevector[j] > 0 & ((1 / BidPercentage) *
ForecastMatrix$APXforecast[DayIndex + j] > PriceAmountMatrix$`APX
price`[DayIndex + j])){
ChargeChange[(DayIndex + j)] = max(min(MaxPower, ((MaxCharge -
Charge[(DayIndex + j)])*1)), 0) Charge[(DayIndex + j + 1)] =
Charge[(DayIndex + j)] + ((ChargeChange[(DayIndex + j)] / 4) * Efficiency)
Profit[(DayIndex + j + 1)] = Profit[(DayIndex + j)] +
((ChargeChange[(DayIndex + j)] / 4) * (-PriceAmountMatrix$`APX
price`[(DayIndex + j)])) CountCharge = CountCharge + 1 }
```

On the Day-Ahead market, the buying is slightly different. On this market, the bid has to be low enough in order to win. Therefore, the bid is compared to the actual market price. Also, a "bid percentage" is incorporated that adjusts the bid to increase the chance of winning. After it is determined that the bid has won, the same process as for the other market is done.

```
if (SRtradevector[j] < 0 & PriceAmountMatrix$RUD[(DayIndex + j)] > 0 &
PriceAmountMatrix$RUP[(DayIndex + j)] > SellThreshold) {
ChargeChange[(DayIndex + j)] =
max(min((max(PriceAmountMatrix$RUD[(DayIndex + j)], 0)), MaxPower,
((Charge[(DayIndex + j)])*1)), 0) Charge[(DayIndex + j + 1)] =
Charge[(DayIndex + j)] - ((ChargeChange[(DayIndex + j)] / 4) * Efficiency)
Profit[(DayIndex + j + 1)] = Profit[(DayIndex + j)] +
((ChargeChange[(DayIndex + j)] / 4) * (PriceAmountMatrix$RUP[(DayIndex
+ j)])) CountDischarge = CountDischarge + 1
}
```

For selling on the Secondary Reserve market, the demand on this market is checked, the schedule, and the sell-threshold. If all these are 'right', then electricity is sold on this market. This reflects reality as it can be decided per quarter (or actually per minute) to trade on this market. The process after these checks is the same, except that the battery is emptied instead of filled, and the profit increases.

```
if (DAtradevector[j] < 0 & (BidPercentage *
ForecastMatrix$APXforecast[DayIndex + j] > PriceAmountMatrix$‘APX
price‘[DayIndex + j])){
ChargeChange[(DayIndex + j)] = max(min(MaxPower, ((Charge[(DayIndex +
j)])*1)), 0) Charge[(DayIndex + j + 1)] = Charge[(DayIndex + j)] -
((ChargeChange[(DayIndex + j)] / 4) * Efficiency) Profit[(DayIndex + j + 1)] =
Profit[(DayIndex + j)] + ((ChargeChange[(DayIndex + j)] / 4) *
(PriceAmountMatrix$‘APX price‘[(DayIndex + j)])) CountDischarge =
CountDischarge + 1
}
```

This is the code for selling on the Day-Ahead market. On this market, the bid has to be low enough to win. Therefore, again, there is a "BidPercentage" incorporated to increase the chance of winning the bid. The process thereafter is the same: the battery is emptied and the profit increases.

```
if (DAtradevector[j] == 0 & SRtradevector[j] == 0){ CountNothing =
CountNothing + 1 }
if (is.na(Charge[(DayIndex + j + 1)]) == TRUE){ Charge[(DayIndex + j + 1)]
= Charge[(DayIndex + j)] }
if (is.na(Profit[(DayIndex + j + 1)]) == TRUE){ Profit[(DayIndex + j + 1)] =
Profit[(DayIndex + j)] } } }
```

These last lines of code are present to ensure that the model keeps running and gets no errors. These errors occurred when there was no trading at a given instant. The arrays used for the profit and charge are namely initially filled with NA-values.

The model is unable to cope with NA-values, and therefore, if no trading is done at an instant, the profit and charge are equal to the previous instant.