Energy Storage in the Distribution Grid

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Preface

This is a Master‘s Thesis by Sven Arild Kjerpeset, graduate at University of Bergen (UIB) and Western Norway University of Applied Sciences (HVL). Sven Arild Kjerpeset graduated the autumn of 2013 with a B.Sc. in Electrical Power Engineering, and is currently employed at Sogn og Fjordane Energi Nett AS (SFE Nett AS) as a project engineer. This Master‘s Thesis is a part of the Master‘s in Energy Program, which is a collaboration between UIB and HVL. The report is carried out in the autumn/spring semester of 2016/2017.

SFE Nett AS is a Norwegian distribution system operator, and the main challenges in Electrical Power Engineering are related to issues surrounding poor grid quality and capacity problems in the low voltage distribution grid. The theme of choice of this thesis was chosen with the collaboration between SFE and HVL, and it serves the purpose of addressing these issues using distributed energy storage, which might delay the need for grid reinvestments.The thesis is written with regards to the reader as someone with a basic understanding of electrical systems and distribution grids.

Acknowledgment

After two and a half years of balancing family life, work life and studies, this Master's Thesis is the culmination of my time as a student within Electrical Power Engineering.

First and foremost, I wish to thank my partner in life, Cathrine Eikevoll, for allowing me to pursue this dream of mine. This could not have been done without your supportive and tolerant being.

And my sincerest gratitude goes to my supervisors Emil Cimpan and Knut Øvsthus for your helpful guidance and inspiring talks that made this report possible. Your inputs and suggestions have been invaluable, and lifted the quality of this report to the level that it deserves.

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Thank you to my parents and parents in law for stepping in and solving the logistical challenges that we've experienced on numerous occasions the last year.

And lastly, but not least, a huge thanks to SFE Nett AS, especially to Atle Isaksen and Asgeir Aase for believing in me, and giving me the opportunity to evolve professionally in a way that I hope will give value back to the company. Also thanks to Ole-Gaute Hovstad for the interesting discussions and your out-of-the-box thinking, and thank you so much to all of my colleges at SFE Nett who has helped me along the way.

This report is dedicated to my daughter, Pia.

Florø, 2017

Sven Arild Kjerpeset

Summary

The implementation of distributed energy storage will play a vital role in the Smart Grid of the future, which is the merging of IT and the electrical power grid. With the increasing penetration of distributed energy generation (DEG), like wind and solar, the power grid is changing from a vertically integrated structure to a more dynamic bidirectional system. This system is often referred to as the Energy Cloud with reference to the Internet as a system based on distributed resources feeding into one common platform.

Due to the intermittent nature of DEG, the system relies on large centralized energy producers to maintain steady and secure energy supply. However, by the implementation of distributed energy storage (DES), a variety of services are introduced that permit further increase of DEG penetration.

As well as changes in energy generation, the introduction of high intensity loads are pushing the grid to its limits. The number of electric vehicles (EV), induction based cooking tops and direct water heaters are increasing and often occurs at times of peak load and forces the grid equipment to work above tolerance limits which may create high temperatures, premature ageing or in worst case failure.

Traditional methods for handling equipment capacity issues have been to reinforce the grid so that peak load is kept within equipment limits. With high intensity loads, this method would result in a grid that is underutilized in off peak periods, which is most of the day. This is not cost effective, and a socio-economical sub optimal solution.

In this report, the research targets peak shaving as a service provided by an Li-Ion battery storage located in the distribution grid, with the purpose of achieving increased flexibility that may prevent grid under-utilization and delay the need for grid reinforcements. In order for this solution to be economically viable, and able to compete with traditional grid reinforcement methods, dimensioning strategies are proposed to find the ideal balance between initial investment cost and service time.

With seasonal changes and the subsequent variable energy consumption, the average required battery capacity on an annual basis is used as reference when sizing the battery storage. The dimensioning strategies proposed involve the design of an energy storage that accommodates the average required battery capacity within given depth-of-discharge limits, and the use of buffer capacity to accommodate the energy requirements in times of higher load.

The energy consumption data available shows that the number of days that require more and less than the energy consumption average are similar, thus counteracting each other and giving a storage size that is ideally sized with the desired level of depth-of-discharge on an annual basis.

To validate the sizing strategies, a simulation model is built using MATLAB Simulink, that incorporates energy consumption data from SFE Smart Valley together with a dynamic Li-Ion battery block from the Simscape library.

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List of Abbreviations

AMS	Advanced Metering System
DEG	Distributed Energy Generation
DES	Distributed Energy Storage
DoD	Depth of Discharge
DSO	Distributed System Operator
EV	Electric Vehicles
FASIT	Faults and Outages in the Power System
HVL	Western Norway University of Applied Sciences
Li-Ion	Lithium Ion
Na-S	Sodium Sulfur
Ni-Cd	Nickel Cadmium
NVE	Norwegian Water Resources and Energy Directorate
SFE Nett	Sogn og Fjordane Energi Nett
SoC	State of Charge
TSO	Transmission System Operator
UIB	University of Bergen
UPS	Uninterrupted Power Supply
VEE	Validation, Estimation and Modification

Chapter 1

Introduction

1.1 An Introduction to the Smart Grid Concept

"*Smart Grid is an electricity network that can efficiently integrate the behavior and actions of all users connected to it in order to ensure an economically efficient, sustainable power system with low losses and high levels of quality and security of supply and safety*" [8]

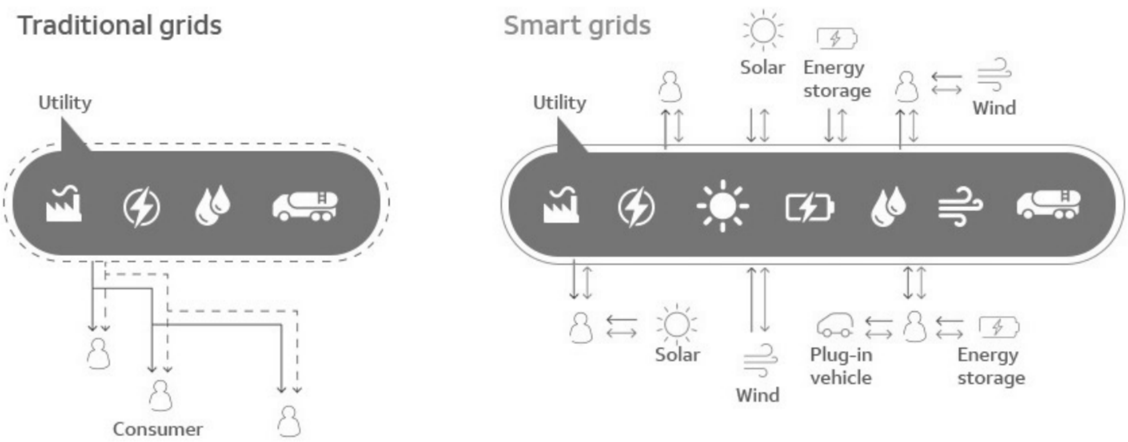


Figure 1.1: Traditional Grids vs. Smart Grids [1]

The definitions of the Smart Grid concept are many, but in short it is the power grid of the future. It is the merging of the energy system and the internet, where IT will be integrated at all levels of the power grid. This will enable the possibility of a continuous flow of information between all contributors connected to the Smart Grid.

In contrary to the traditional grid with a vertically integrated architecture and a one way power flow, the Smart Grid will be bidirectional, supporting a much higher penetration of DEG feeding into the system. Some authors refer to this system as the "Energy Cloud", with reference to the internet architecture with multiple sources feeding into one common platform.

The national roll-out of the AMS-meters is an important step towards preparing the Norwegian distribution grid for the Smart Grid of the future. SFE Smart Valley is a live demo lab in Hyen, Sogn og Fjordane, and subject for the early implementation and testing of AMS-meters. This area gives valuable insight to the energy consumption behaviour in the village of Hyen, and serves the purpose of being the source of data for this report.

1.2 Energy Storage in the Power Grid

A key player in the Smart Grid is energy storage. Due to the intermittent nature of wind and solar energy, the increasing penetration of DEG creates a need for flexibility. In order to fully utilize DEG, the implementation of energy storage systems are needed. This can offer different services that can both increase the consumption of locally produced energy, but also offer a variety of grid supporting services.

To determine the value of energy storage in the grid it is necessary to answer three key questions:

- What services can energy storage provide?
- Where can energy storage provide these services?
- What costs are associated with energy storage, and can this compete with traditional reinforcement methods?

1.2.1 Energy Storage Services

In 2015, The Rocky Mountain Institute conducted a meta-study of existing estimates of grid and customer values, which resulted in a number of general services at three different levels - the transmission grid, the distribution grid and behind the meter (consumers) [2, p.6]. Figure 1.2 shows a graphical representation of 13 different services that storage can provide.

This report will address the use of peak shaving service according to Table 1.2, by placing a storage in the low voltage distribution grid between the substation and the DSO/customer meter interface.

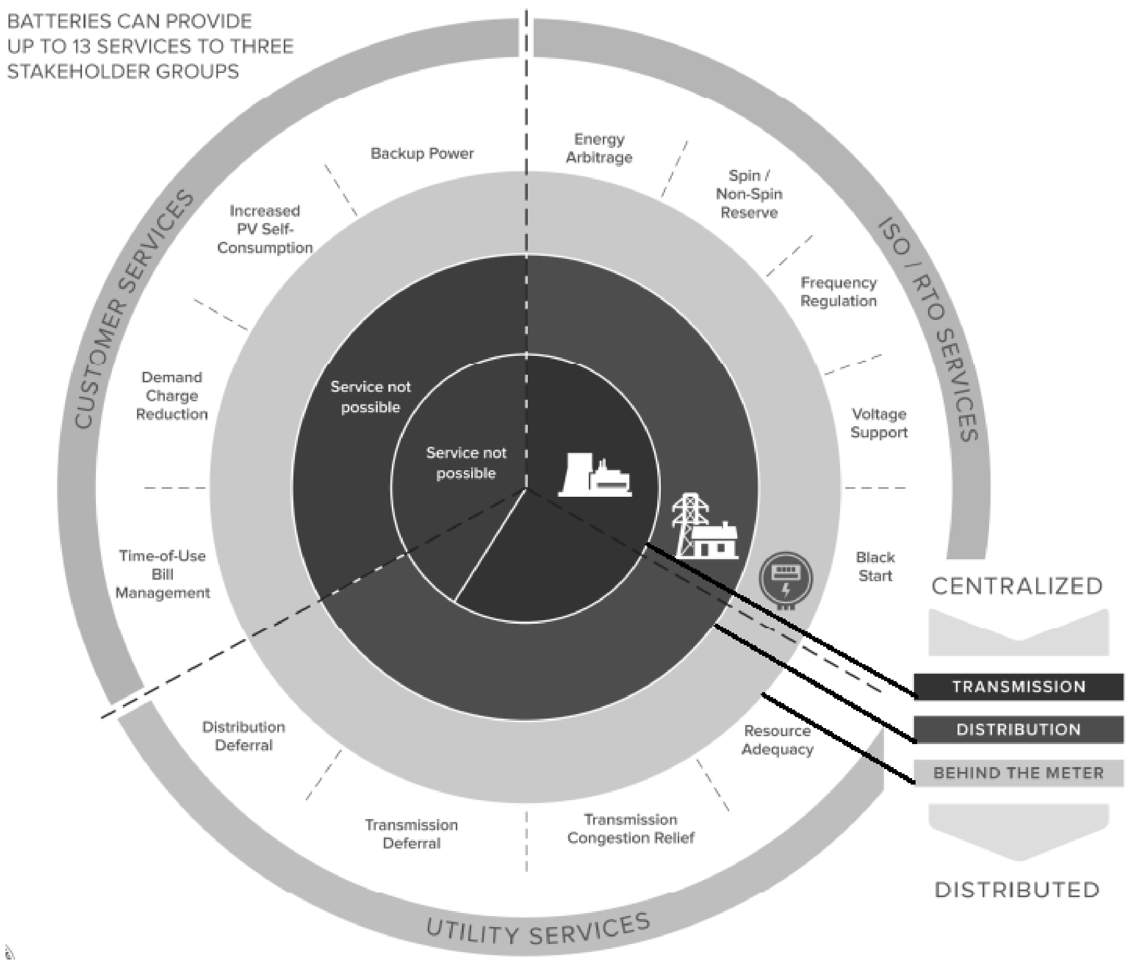


Figure 1.2: DES Services [2, p.6]

ISO/RTO Services	
Spinning reserves	Grid connected energy capacity, online and able to support the grid in an event such a grid outage.
Voltage Support	Voltage regulation to keep grid voltage within acceptable limits in all parts of the grid.
Black Start	Grid outage requires assets that are able to restore operation and bringing the grid back online.
Frequency Regulation	Load support to decrease the impact load variations have on the frequency of the grid.
Energy Arbitrage	The purchase of energy when the energy price is low, and sale of energy back into the market when the price is higher.

Table 1.1: ISO/RTO Storage Services

Utility Services	
Resource Adequacy	Taking advantage of the modularity of batteries to enable incremental increase in grid capacity, reducing the risk of over-investments.
Transmission/ Distribution Deferral	Postponing or reducing the need for grid reinforcements to meet the demands of increasing load in certain regions.
Congestion Relief	Energy storage can be installed in places of the grid that is congested to support the grid in periods of high load. This is also known as peak shaving.

Table 1.2: Utility Storage Services

Customer Services	
Increased PV Self Consumption	With the combination of storage and PV, the amount of locally produced energy is increased.
Time Shift Service	In cases with time differentiated pricing, electricity can be purchased in periods of low cost and used in periods of high cost, reducing the customer bill.
Demand Charge Reduction	In cases of power based tariffs, a local form of peak shaving can be used to reduce peak load at the customer, and effectively reducing the customer bill.
Backup Power	The grid operator may purchase storage energy from the customer for backup power during grid failure.

Table 1.3: Customer Storage Services

1.2.2 Peak Shaving Service

As part of relieving load congestion in an area, using storage for peak shaving service will help reduce the stress on the grid in periods of high load. Using this method, an energy storage close to the demand can be used to relieve the grid locally, in stead of introducing traditional grid reinforcements that in turn will result in a grid that is underutilized for most of the time. The principle is illustrated in Figure 1.3 which shows a varying load where a battery discharges in times of high load, and recharges in periods of low load, resulting in a more steady demand so that the load seen from the power grid is constant.

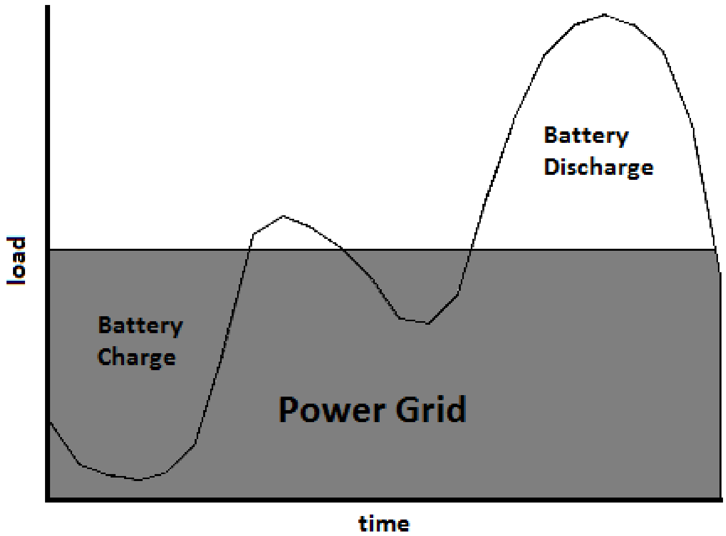


Figure 1.3: Peak Shaving

1.2.3 Storage Location

The number of possible services that a battery storage can provide, increase as the location is moved further downstream the power line. Services located at transmission grid level represents centralized storage services, whereas storage located closer to the customer represents distributed energy storage. Services located at distribution grid level can be of both centralized and distributed character.

DES in the Distribution Grid

Traditionally, studies regarding grid connected storage has been focused on either large centralized storage systems, or storage located at the customer's site, behind the meter. Not much work have been done to cover the storage services that may be provided by putting the storage between these two extremities. The storage system analysed in this report is therefore situated at the transformer substation, in the low voltage section of the distribution grid. This type of storage may be characterized as distributed energy storage.

1.2.4 Energy Storage Capacity and Traditional Reinforcement Methods

The cost of energy storage is closely related to the size and storage capacity. The use of DES for peak shaving service in the distribution grid serves as an alternative to traditional grid reinforcement methods, which include the upgrade or replacement of existing grid equipment. DES will be as a supplement to the existing equipment, with the possibility of delaying the need for grid equipment upgrade.

As the placement of DES in this report is close to the transformer substation, peak shaving service is provided to relieve the transformer is times of high load, and work as a supplement to the transformer. This report therefore focus the cost of transformer upgrade and the possibility of delaying the need to upgrade this to a larger size with increased capacity. The energy storage capacity must be kept at a minimum in order to keep the costs down for this to be an attractive solution.

1.2.5 Storage Legislations

Legislative issues connected to energy storage is not of focus in this report, but a brief introduction is given to shed light in today's status. The emergence of DES is an example of technological advancements, which regulatory changes struggle to keep pace with. New markets are opening up, which create new business models with focus on DES and DEG. Grid customers are also changing in terms of environmental awareness and a desire to utilize these new business models.

Some also problematize a scenario where the distribution grid operator (DSO) uses storage as part of their infrastructure, as the charging and discharging process would emulate a form of energy arbitrage. This will in turn violate regulations stating that a DSO are to distribute energy, but not engage in activities connected to the purchase and sales of energy.

The DSO is somewhat stuck in the middle between a changing market and a changing customer. The DSO is a monopolist and thereby heavily regulated, and due to lagging in regulatory changes, the use of DES in the distribution grid is not possible as of today.

Work is being done, both in the U.S. and the EU to solve this issue by incorporating the necessary changes in the regulatory framework. The EU has gathered a collection of regulation changes referred to as the "Winter Package", which will be implemented in the EU and Norway in the coming years. This is presented in a consultation response by The Norwegian Water Resources and Energy Directorate (NVE) [9].

1.3 Status and Research Interests

Storage on the grid is a fairly established topic, but until recently this has been focused around centralized storage in the form of hydroelectric storage, thermal storage, compressed air and large scale battery systems [10, p.11] [11]. Distributed energy storage however is a topic that has come into play in the later years. As the market is opening up due to technological advancements, more and more studies are conducted on this topic, and a recent study performed by the Swedish company Power Circle shows that small battery packs can act as a buffer and shave off the biggest load peaks. The results are quite interesting and shows that a 9 kWh battery pack installed after at the customer site in a villa is enough to reduce the peak power consumption from the grid by 40% [12, p.34]. This shows that it is possible to reduce peak load on the grid with relatively small energy storage units. Since this study is concentrated on behind-meter-storage, it relies heavily on the engagement of individual grid customers. Seen from a DSO‘s point of view, behind-meter-storage is regarded as indirect grid control. The need for direct grid control is great, which can be fulfilled by placing the storage somewhere in front of the meter.

The University of Texas has an on site test lab environment known as Pecan Street with live testing and evaluation of DEG and DES together with real life residential load from over 700 homes [13]. A simulation model has been built using MATLAB Simulink, simulating this residential area that incorporates load profiles from all homes together with a modelled version of the grid to see how these factors interact. Although the working principles for the distribution grid in the U.S. and Norway are similar, the voltage levels, frequency and general topology of the grid differs extensively. In addition to the differences in grid layout, customer behaviour and load profiles differ as well, making it necessary to build new models suitable to address Norwegian conditions.

A Norwegian study from NTNU conducted in 2013 [14] looked at the use of storage together with Norwegian load profiles. This study uses MATLAB to simulate the storage, and general load profiles gathered from a library. This study does not include actual load profile measurements or the grid characteristics in its calculations, which are necessary to increase model accuracy.

1.4 Aim

Based on field data containing energy consumption and information about Norwegian customer behaviour as basis, the aim of this report is to assess key factors that play a part in determining the feasibility of using distributed energy storage for peak shaving service in the Norwegian distribution grid. For this solution to be an alternative to the traditional grid reinforcements, which include increasing the size of transformers, cables and lines, cost is an crucial factor. An optimal storage sizing strategy is therefore proposed and verified by using computer modelling.

1.5 Problem Description

The purpose of this assignment is to question whether the implementation of DES is an adequate strategy to increase grid utilization reduce the cost or delay the need for grid reinforcements.

1.6 Objectives

The main objectives of this report are:

1. Determine the storage technologies suitable for peak shaving service in the distribution grid.

2. Determine the required size of storage needed to perform peak shaving service, and propose an optimal sizing strategy that balances initial investment cost and service time.

3. Validate the sizing strategy by building a simulation model and running simulations using imported consumption data from SFE Smart Valley.

1.6.1 Limitations

This report will not address the following subjects.

- Control systems and measurement requirements.

- Protection and selectivity coordination.

- Distributed energy generation, wind and solar.

- Consumer flexibility

- In depth battery management system.

- The battery performance in relation to temperature dependency.

1.7 Structure

The report will have the following structure.

Table 1.4: Report structure

Chapter	**Chapter Content**
1 Background	An introduction to the Smart Grid concept and distributed storage.
2 Method	The methodology used in this report.
3 Theory	DES technologies, battery modelling principles, battery sizing.
4 Data	Data description and evaluation. Dimensioning strategy.
5 Results	Presentation of the model and results from the simulations.
6 Discussion	Analysis and evaluation.
7 Conclusions	Conclusions, further research.

Chapter 2

Method

The need for electrical power for residential housing, industry and business may be categorized as the need for instantaneous power and the need for energy. The instantaneous power represents the power needed the instance an appliance is switched on, causing an increased load current and stress on the power grid. The instantaneous power varies throughout the day, following a profile that is characteristic for each type of load. The need for energy can be shifted in time, to compensate for load fluctuations.

The energy demand within a defined time interval is calculated as the integral of the instantaneous power. The energy demand varies at different time scales, from an annual variation to a daily variation.

- Annual variation is due to seasonal changes in temperature and weather. In Norway, electrical heating constitute a great part of the base load, thus there is an increased load in the winter months compared to the summer months.

- The daily variation follows the activities of the consumer, where the demand is higher during the day and low during the night.

The concept of peak shaving is to control the load profile to achieve a stable energy consumption from the power grid over a given time period. This is achieved by shifting the peak energy consumption to periods of low consumption. Since the power requested by the consumer fluctuates, energy must be pre-stored locally in order to support the peak load. In this study, a battery provides power in times of high load and thus reduce the load on the power grid. During low load, the battery recharges and thus effectively shifting the energy need so that a mean consumption is achieved over a defined time interval. The consumer observes no changes, but seen from the power grid the consumer has a stable, mean consumption, thus eliminating variations that stresses the grid.

In this study peak shaving is used with focus on smoothing the daily variations. This solution requires a smaller energy storage compared to what is required in order to smooth for example the annual peaks. A possible extension of the DES theme is to investigate the use of several DES-units collaborating to reduce yearly variations, but that is beyond the scope of this thesis.

However, due to seasonal changes, the yearly variation must be taken into consideration when determining the ideal capacity of the battery. A battery capacity adequate for the winter consumption may prove to be greatly oversized compared to the summer consumption, which is not cost effective. An optimal sizing strategy is therefore proposed, using the annual consumption average.

The battery capacity strategy is validated by a simulation model. The model that is built is an idealized model that calculates the mean energy consumption over a 24-hour period. The basis of the model construction is that the daily consumption is known. Thus the model is regarded as a reference point. The model is a planning tool, a necessary first step for simulating battery dynamics. A natural continuation of this work is to build a live model that incorporates prediction principles and machine learning, but that is beyond the scope of this thesis.

2.1 Approach

The work in the report can be divided into the following four sections.

- Energy Storage Technology Assessment
- Consumption Data Analysis and Storage Dimensioning Strategy
- Simulation and Validation
- Analysis

2.1.1 Energy Storage Technology Assessment

A literature survey is conducted to determine the proper storage technology suitable for peak shaving service in the low voltage distribution grid. Traditionally, energy storage in the Norwegian power grid has been in the form of hydroelectric storage. However, this approach is too demanding for DES. Therefore, more compact solutions are investigated focusing on battery solutions. The basic principles of battery dynamics and modelling are assessed, and a control strategy that enables peak shaving is proposed.

The choice of energy storage technology relies on a solution that is of both technical and economic character, and is based on 6 criteria:

1. Specific power
2. Specific energy
3. Operating range
4. Charging rate
5. Cost
6. Lifetime

Technical Assessment

In criteria 1-4 the technical characteristics and dynamic properties of the technology is addressed. *Specific energy* determines the required size and weight of the energy storage, as this is a term measured in Wh/kg or Wh/l. This is not a determining factor for stationary applications (as compared to mobile applications), but is still something that can tip the technology of choice in its favour.

Specific power is measured in W/kg and determines the ability to handle heavy loads and the need for high power output. Performing peak shaving is of high relevance for DES, as the peak load subjected to the substation transformer can be tens of kWs above of the base load.

Operating range is a term that describes the DES technology's sensitivity to temperature variations, and the ideal operating temperature varies for the different technologies. This is expected to be of minor issue, as the DES enclosure may be constructed with temperature regulation so that ideal operating temperatures are maintained in most cases.

Charging rate determines the speed of which the DES technology can accept charge. Load peaks may occur multiple times a day, where the DES must recharge in periods of low load. To achieve the required state of charge (SoC) to maintain its ability to perform peak shaving service, fast charging capabilities are necessary.

Economical Assessment

The storage technology chosen for this purpose must also be of low cost, so that it can compete with traditional grid reinforcement methods. Criteria 5 and 6 addresses the considerations needed to be taken into account when performing an economical assessment of the DES technology.

Cost reflects the initial investment cost determined by a cost unit per capacity often referred to as $/kWh, for the selected technology, as well as the necessary casing, temperature regulation, safety circuits and charging system. Necessary planning cost and installation costs must also be taken into consideration.

Lifetime is expected to be lower than equipment used for traditional reinforcements. DES cycle life is determined by the inherent properties of each technology, but can also be controlled by ensuring optimal operating conditions within those assessed in criteria 1-4. High cycle life means that the battery cells lasts longer before they are obsolete, and is crucial to reduce the frequency of battery cell replacements, and thereby the total cost of the system.

The rate of capacity degradation that occurs at each cycle, is determined by the depth of discharge (DoD).

2.1.2 Consumption Data Analysis and Storage Dimensioning Strategy

The source of data in this study is energy consumption data from 45 households collected from a live demo lab in Hyen, Sogn og Fjordane. The data is with an hourly resolution and is collected over the period of one year, stretching from November 2015 to November 2016. This period is analysed to derive a suitable dimensioning strategy to accommodate the seasonal variations throughout the year. A negative correlation between temperature and energy consumption is presented, with peak load occurring during winter with low temperatures.

An average required battery capacity on an annual basis of 135.7kWh is set as reference for the battery storage dimensioning strategy. Two scenarios with different DoD is simulated:

- DoD of 60%. The energy storage is dimensioned so that the average required battery capacity makes out 60% of the total battery capacity. 40% of the battery capacity serves as a buffer. 51% of the days require an energy storage that is within the this limit, while 49% of the days require more, making use of the buffer. Since the number of days above and below the limit are similar, these will cancel each other out and give a total annual DoD of 60%.
- DoD of 45%. The energy storage is dimensioned so that the average required battery capacity makes out 45% of the total battery capacity. 55% of the battery is set as buffer. This solution gives a battery with higher buffer capacity which increases the initial investment costs compared to the 60% DoD strategy. However, this solution also reduces battery degradation, giving a higher number of cycles before a certain performance threshold is met.

To uncover battery performance, four extreme cases are simulated for each DoD scenario:

- Low load: Consumption data for week 30 is used to simulate a low load scenario.
- High load: Consumption data for week 1 is used to simulate a high load scenario.
- Low battery capacity requirements: Consumption data for week 6 is used to simulate a low battery capacity requirements scenario.
- High battery capacity requirements: Consumption data for week 48, 50, 52 and 53 is used to simulate high battery capacity requirements scenarios. These four weeks contain days where case 1 with 60% DoD gives insufficient battery capacity.

2.1.3 Simulation and Validation

A simulation model containing the battery's response to varying load is built using MATLAB Simulink. Consumption data from the 45 households are imported from excel and used as reference to control the charge and discharge currents of a battery block containing the dynamics of a Li-Ion battery. Two experiments are conducted to validate the model together with the battery block:

- Pulse discharge test: In order to validate the voltage [V] and capacity [Ah] settings, a pulse discharge test is conducted to calculate the battery parameters. A controlled current source is connected to the battery terminals with a 1C discharge current for a 15 minute interval. The dynamic voltage response is measured and used to manually calculate the battery parameters, which is then compared with the values given by the battery block.

- Full discharge tests: Using the same set up as above, three full discharge tests are conducted to validate the discharge current amplitude given by the consumption data reference. The battery is subjected to 0.5C, 1C and 2C discharge currents, giving a full discharge of 2h, 1h and 0.5h, respectively.

Using the results from the pulse discharge test, the required battery capacity of each DoD-scenario is set as input in the battery block. The four extreme cases of high/low load and high/low required battery capacity are simulated using consumption data from the weeks listed under Battery Storage Dimensioning Strategy as reference with a similar set-up as in the full discharge tests.

The charge/discharge currents are calculated from the consumption data with nominal battery voltage of $U_{batt} = 725.2V$, which is derived from the pulse discharge test. In the dataset, energy consumption is given every hour. P_{load} is set as the average power for each 1-hour period and used as reference for battery charge/discharge currents. This means that the model generate charge/discharge currents that are constant for each 1-hour period. This is not ideal, as instantaneous values require higher resolution to be accurate, but due to restrictions in the source materials, this is not available for this study. As the main purpose of the simulation model is to validate the battery dimensioning strategy, energy consumption is of focus. Charge/discharge currents with constant amplitude for a 1-hour period is an adequate approximation as this will give the correct energy consumption subjected to the battery.

This means that peak discharge currents will not be simulated. The Li-Ion technology tolerates discharge currents of 5-20C, something that is not likely to occur in the cases that are simulated, and can therefore be ignored.

2.1.4 Analysis

The working principles of the model is assessed, as well as the results from the dimensioning strategies.

Battery performance from the two DoD-scenarios are discussed to suggest an optimal dimensioning strategy. A brief economical assessment is conducted and compared to traditional grid reinforcement methods. For this, a scenario regarding an upgrade from a 100kVA to a 200kVA transformer is assessed.

Due to grid equipment standardization in the power grid business, this scenario represents a threshold where the cost of transformer upgrade is especially high, increasing the probability of the economical validity of the use of DES as an alternative.

Chapter 3

Theory

This chapter addresses the different technologies used for energy storage in the power grid today, and point at which is most suitable for peak shaving service in the distribution grid. Battery modelling is also explained, as well as the basic principles for peak shaving, and the methodology used to simulate this.

3.1 Storage Technologies

The most common form of storage in the power system is hydroelectric storage. Various other large scale storage as thermal storage and compressed air storage also exists, but these, together with hydroelectric storage represents large centralized units with low response time compared to smaller storage solutions.

DES represents a smaller and more responsive type of storage, capable of providing power system support to the grid. This study focuses on DES in the distribution grid, preferably the low voltage section, where more flexible and modular solutions are preferable. Technologies suitable for DES need to have low response time, and examples of this is super capacitors, hydrogen fuel cells, flywheels and batteries. The focus of this report is on batteries.

3.2 Batteries

In the power system, batteries are a common form of storage technology. With batteries being modular, they are flexible, come in a variety of sizes and require little work to be installed. There are two main types of batteries, primary (non rechargeable) and secondary (rechargeable) batteries. As the batteries used for power system support need to be recharged, this section will concentrate on secondary batteries.

Advancements within battery research is ongoing, most of which regarding lithium-based systems, both energy density and cost. An increasing demand for high energy storage for mobile applications is a driving force for this development. This has moved the development in two directions [15]:

- Consumer batteries: Consumer applications use batteries of small size and cost.
- Industrial batteries: Industrial applications demand reliability and heavy load capabilities, but are less mobile and more costly.

3.2.1 Battery Technologies

For power system applications, industrial batteries are needed. The industrial battery market is made up of four battery families; lead-, nickel-, sodium-, and lithium-based batteries [16, p.7].

Lead Acid Based Batteries

Commonly known for its use in the auto-mobile industry, but are also deployed for stationary purposes like emergency power supply, improving power quality, uninterrupted power supply (UPS), and together with wind and solar power [3, p.3]. Minute time-scale medium duration grid service category.

Advantage: Robust and low cost. Mature technology.

Disadvantage: Short cycle life, low energy density.

Nickel Based Batteries

This technology offer good performance with extreme ambient temperatures and is well suited for a wide range of demanding applications. Larger ventilated wet cell Ni-Cd batteries are still used for standby power, UPS and emergency lighting [3, p.5].

Advantage: High performance in high and low temperatures.

Disadvantage: High cost, cadmium is a toxic heavy metal.

Sodium Based Batteries

Na-S use solid or molten salt as the electrolyte. This type of batteries have been used in both the auto-mobile industry and for space applications. In recent years the use has been concentrated around stationary usage, such as energy grid storage together with wind and solar energy, rating at the MW scale [16, p.10].

Advantage: High energy density and efficiency.

Disadvantage: High cost and high operating temperature due to its molten salt principle.

Lithium Based Batteries

Li-ion batteries are dominating the market today, especially within mobile applications, but also within the stationary segment. The reason for this is that battery cost are declining, as well as longevity and environmental issues that also are in its favour. Since 2010, the use of Li-Ion batteries has increased, and as of 2015 about 100MW are operating as power system support [3, p.4]. This accounts for 75% of the total installed grid-level energy storage. [17]. Of new energy storage installations in 2015, this technology accounted for 96% [18, p.5].

Advantage: Declining cost, and increasing energy density.

Disadvantage: Very temperature sensitive, not susceptible to overcharging.

3.2.2 Battery Specifications

Figure 3.1 shows the types of secondary batteries that are applicable for power system applications like peak shaving service. Batteries of different chemical compositions have different characteristics, but there are also differences between batteries of the same chemistry. These differences are represented by a span of values.

	Lead Acid	Li-Ion	Ni-Cd	Na-S
Specific Energy (Wh/kg)	30 - 50	75-200	50-75	150 - 240
Specific Power (W/kg)	75-300	150-315	150-300	150-230
Charging Rate (C)	1/20	5-20	5	1/8
Lifetime (cycles)	500-1000	1000 -10 000	2000-2500	2500
Lifetime (years)	5-15	5-15	10-20	10-15
Cost ($/kWh)	200-400	230-2500	800-1500	300-500
Operating range °C	-20 - 50	0 - 45	0 - 45	300-350

Figure 3.1: Battery Technologies [3, p.6]

Specific Energy

Long runtime is achieved with high specific energy. This expresses energy density, and determines the size (Wh/l) and weight (Wh/kg) of the battery. In EVs it is preferable with high specific energy as this will increase vehicle range and reduce the weight. For stationary power system support however, battery size and weight is usually not as important, but in some cases the reduction in volume may be preferable if available storage area is limited.

The upper row in Figure 3.1 shows that Li-Ion and Na-S batteries are at the higher end of the scale when it comes to specific energy, while Ni-Cd and Lead Acid score low on this requirement. For stationary applications, this is not crucial.

Specific Power

With heavy loads, the ability to deliver high specific power (W/kg) is preferable. In most EVs, range is more important than high power output, although some high performance vehicles are designed with the ability of fast acceleration in mind, which require the battery to produce high power output. For power system applications, heavy loads can be expected, and as weight and space limitations are not as big of an issue, high specific power is preferable when designing the storage system.

Lead Acid, Li-ion and Ni-Cd batteries show to be good choices when high specific power is in focus, see Figure 3.1.

Charging/Discharging Rate

Charging and discharging are generally divided into two categories; slow charge/discharge that take several hours, and fast charge/discharge that refers to a rate of one to two hours [19, p.1-3]. The latter is of interest in the case of peak shaving service, as load peaks can happen multiple times a day.

C-rate is the rate of charge/discharging current relative to the battery capacity. As batteries come in a wide range of sizes and storage capacities, C-rate is a measure that normalizes the charge/discharge rates and creates a common reference for batteries of different capacity. A charge/discharge rate of 1C means that the battery will be fully charged/discharged in 1 hour. For a battery of 100 Ah, a 1C charge/discharge current will be 100A. 5C will be 500A, and C/2 will be 50A [20, p.131].

The limiting factor for high-rate charging/discharging current is the internal resistance of the cell R. Power loss is given by $P = I^2 \cdot R$ and is manifested in the form of heat dissipation and temperature increase within the cell. If a battery is subjected to a charging/discharging rate beyond that of which is recommended, this may cause damage or premature ageing of the battery cells. The internal resistance of Li-Ion and Ni-Cd batteries are lower than the other technologies displayed in Figure 3.1, and the best choice when it comes to high rate charge and discharge.

Lifetime

The total life time of the battery depends on a number of factors, with these being depth of discharge (DoD), charge/discharge rate, temperature and the choice of materials in the battery construction. Battery lifetime is often specified by the manufacturer as cycle life which is the number of charge/discharge cycles the battery may experience before a certain performance threshold is reached. The cycle life is estimated for specific conditions of the factors above.

High cycle life means that the battery cells last longer before they are obsolete, and is crucial to reduce the frequency of battery cell replacements and thereby the total cost of the system. The majority of secondary batteries lasts between 500 to 2500 cycles, with lead acid scoring at the lower end of the scale with a maximum of 1000 cycles.

However, the number of effective cycles that are possible to extract from the battery depends highly on the use, for example how deep discharge is allowed for each cycle. DoD is defined as a the amount of energy extracted from the battery compared to the total capacity. When designing a stationary battery for power system support, one solution can be to compensate for the capacity loss by including additional storage capacity, more than the original requirements. This creates a buffer for the battery to deteriorate, and also reduces the DoD which in turn also prolongs battery life.

In order to minimize the initial costs associated with battery storage, optimizing battery capacity is important. By sizing up the battery capacity, the DoD gets reduced, effectively increasing battery lifetime which reduces the need and cost for future battery cell replacements. However, increasing the size of the battery also drives up the initial investment costs.

Ni-Cd batteries have the longest lifetime in years, but Li-Ion batteries can achieve a higher number of cycles, see Figure 3.1.

A study from 2016 [4, p.7] looks at battery degradation of Li-Ion batteries at various charge and discharge bandwidths. Figure 3.2 shows the results from the dynamic stress tests performed in this study, and the smallest capacity loss and longest lifetime is achieved with a maximum state of charge (SoC) limit of 75% and a minimum SoC limit of 65%, giving a DoD of 10%. However, this means that 90% of the battery capacity sits idle, which is not cost effective. The highest capacity utilization of the tests is with an 100-25% SoC (75% DoD), but this yields the shortest life span. The results show that the middle ground with 75-25% SoC (50% DoD) and 85-25% SoC (60% DoD), balances battery utilization and lifetime with 88% and 84% of the total capacity remaining after 5000 cycles, respectively. With the battery performing one cycle per day, this is 13.7 years.

A study done by the Pacific Northwest National Laboratory (PNNL) in 2010, determined the ideal trade-off between life time and battery size [21, p.5.3-5.4]. In this study, effective DoD is set to various levels in a 5 to 95 % range in 11 different cases, with the necessary storage capacity and corresponding life cycle at each level.

In the 11 cases that are discussed, the results show that a DoD between 40% and 50% keep the costs at a minimum.

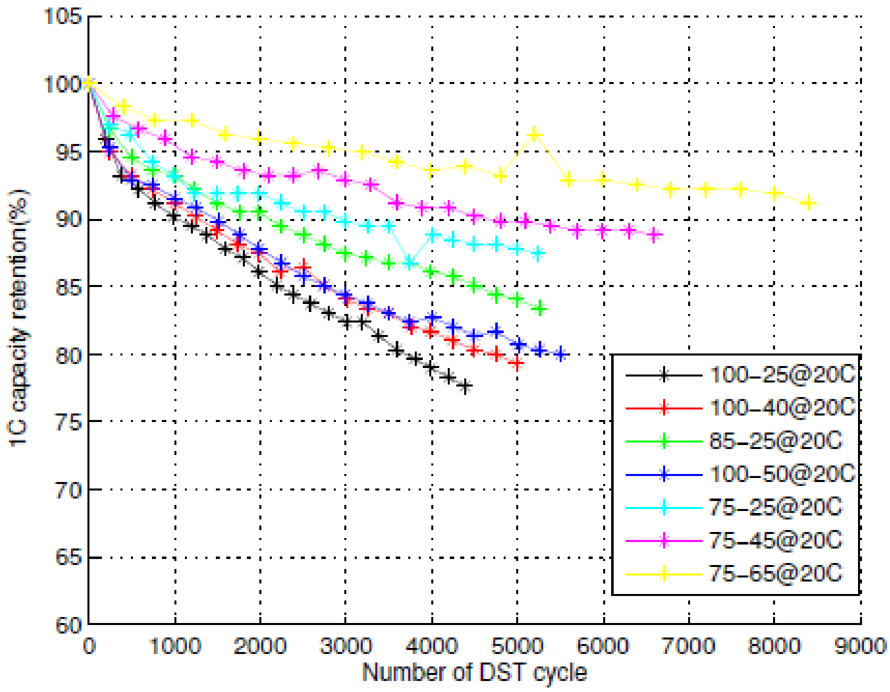


Figure 3.2: The results from dynamic stress tests [4, p.7]

Cost

For energy storage to compete with traditional grid reinforcements on cost, it is desirable to use a technology with a low cost per Wh. Due to the growth of EVs, the cost of Li-ion batteries has been falling rapidly. Since 2010, the average EV battery pack price has fallen 80% from $1,000 per kWh, to $227 per kWh in 2016 [22, p.10] . This correlates with a study done by Bjørn Nykvist and Måns Nilsson of the Stockholm Environment Institute in 2015 where it is estimated that the Li-ion battery industry as a whole is experiencing an annual cost reduction of 14 %, and predicts a battery cost around $230 per kWh in 2017-2018 [23, p.329-330].

Lead Acid and Li-ion batteries are currently the technologies with lowest cost. Li-ion battery pack cost is expected to fall below $100 per kWh between 2025 and 2030 [24, p. 15].

Operating Range

Electrochemical reactions are temperature dependent by nature, and high operating temperature reduces cycle life [20, p. 167]. Lower operating temperature may increase cycle life, but this will in turn reduce battery performance. The temperature effect may be reduced by keeping the batteries in an insulated casing that is temperature regulated.

The climate at the western parts of Norway includes mild winters and wet summers, so in this case extreme temperatures are not expected, but temperature regulation is still required.

In most battery technologies, the charging process is more sensitive to extreme temperatures than discharging. Figure 3.1 shows the temperature that enables safe charging for each technology.

The most resilient technology are Lead Acid. These batteries have the ability to accept charge for temperatures below zero degrees Celsius. Li-Ion and Ni-Cd batteries do not allow charging below zero temperatures. Li-Ion batteries does not allow fast charging for temperatures below 5 °C [20, p.149].

The Na-S battery use molten salt as the electrolyte, which requires high operating temperatures. With temperature between 300 to 350 °C, this may prove impractical for intermittent operation like peak shaving service.

Battery Technology Summary

The selection of suitable battery technology cannot be based on cost alone. In addition to cost per kWh, it is necessary to look at cost per cycle, longevity and frequency of replacements.

Although Li-Ion is dominating the market today, other battery technologies are also suitable for power system support. Lead Acid batteries are a low cost and resilient battery technology with better low temperature charging capabilities than Li-Ion batteries [25, p.13]. For stationary purposes, lead acid batteries have been frequently used, however, for duties with occasional discharges. The lack of fast charging capabilities makes it difficult to use this technology for peak shaving service.

The charging rate of the Ni-Cd battery is good, as well as specific power and lifetime, aspects of which is important for peak shaving services. But due to environmental concerns this battery technology is expected to be phased out because of its heavy metal constituent, cadmium [20, p.44].

The Na-S battery scores well on all aspects except charging rate and operating range. The lack of fast charging capabilities and the extreme operating range (300-350$°C$), means this battery technology is not suitable for peak shaving service in the distribution grid.

The Li-ion battery have high scores on specific energy, specific power, charging rate, lifetime and cost. The operating range is not as good as Lead Acid, and will not accept charge in below zero temperatures. This makes it necessary to equip the battery storage with adequate housing and temperature regulation in order to ensure correct operating temperatures. Safety is also a concern that needs to be addressed, as this battery is sensitive to overcharging. This can cause damage to the battery that can lead to failure and fire. A properly designed charging system is necessary to prevent this and is a key issue of its success. All in all, the Li-ion battery proves to be the best choice for peak shaving service in the distribution grid.

3.3 Battery Modelling

Batteries are non linear in their behaviour, and it is very important to know their dynamic response to control them effectively. There are three commonly used models for batteries: the simplified electrochemical model, the neural network model and the equivalent circuit model [5, p.583].

- The simplified electrochemical model describes the inner reactions of the battery using mathematics. However, this method are not sufficient at addressing the non-linear characteristics of the battery performance.
- The neural network model uses the weight of neurons in stead of state variables. The accuracy of this method could reach 3% under certain conditions, but the usability of this method have shown to be somewhat limited.
- The equivalent circuit model uses an ideal voltage source together with resistors and capacitors to mimic the dynamic properties of a battery. This method provides simulations with high level of accuracy.

3.3.1 The Equivalent Circuit Model

In 2013 a study performed by Ahmad Rahmoun, Helmut Biechl and Argo Rosin at Tallinn University of Technology shows that the equivalent circuit diagram have an analogue behaviour to the actual electrochemical impedance of the battery [26, p.36].

The Thevenin Model

This circuit gives open circuit voltage over the terminals when no current is flowing. It is mainly composed of three parts: an open circuit voltage U_{oc}, an internal resistance and a RC-element in series. R_0 represents the internal resistance that gives the instantaneous voltage drop - the instantaneous response of the system. The RC element consists of the polarization resistance R_{th} and the equivalent capacitance C_1 that creates the dynamic behaviour and transient response during charging and discharging. U_{th} and I_{th} is the voltage and outflow current associated with C_{th}. Figure 3.3 shows the circuit and equation 3.1, and expresses the dynamic behaviour of the model.

$$\begin{cases} \dot{U}_{th} = -\dfrac{U_{th}}{R_{th}C_{th}} + \dfrac{I_L}{C_{th}} \\ U_L = U_{oc} - Uth - I_L R_0 \end{cases} \tag{3.1}$$

R_0 represents the internal resistance that gives the instantaneous voltage drop - the instantaneous response of the system. R_{th} and C_{th} makes up the RC-element that creates the dynamic behaviour and delayed response of the system. More RC-elements may be added to increase model accuracy. Parasitic losses (self discharge) may be represented with a capacitor to ground, but this is ignored as this is very small in Li-ion batteries.

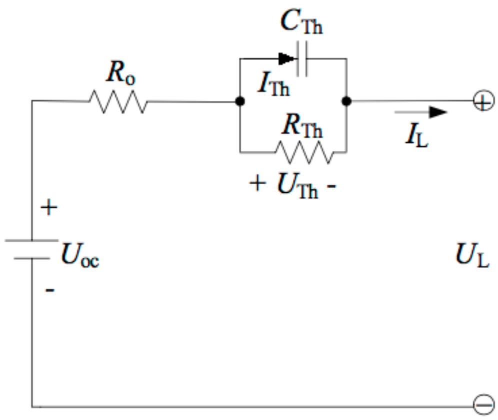


Figure 3.3: Thevenin Equivalent Circuit [5, 585]

Figure 3.4 shows how these components reacts to a pulse discharge and create the instantaneous and delayed response of the battery and resulting open circuit voltage. The instantaneous response is given by R_0, and the dynamic response is given by R_{th} and C_{th}.

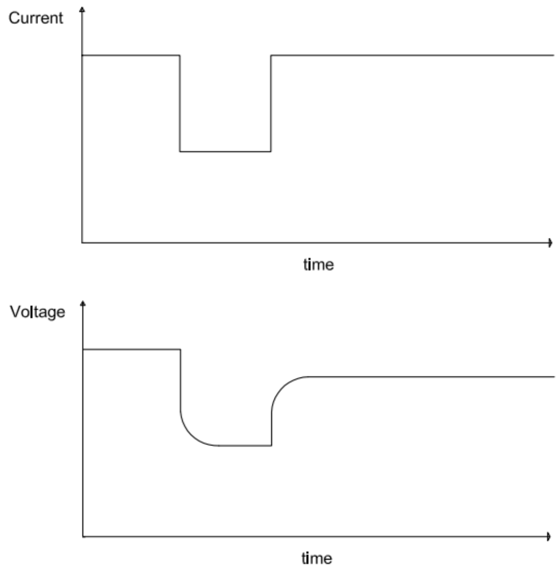


Figure 3.4: The dynamic voltage response of the battery to a pulse discharge.

3.3.2 The Simscape Battery Block

Figure 3.5: Simscape Battery Block

The SimPowerSystem battery cell block used un the simulations is made up of an equivalent circuit [27, 1-87] populated using a method called Parameter Estimation that is a combination between Simulink and MATLAB optimization functions.

The Thevenin model containing one RC-element are sufficient in most battery simulations.

The battery block is able to mimic a the dynamic behaviour with the use of values from the manufacturer's discharge curve of the battery being modelled. A paper by Olivier Tremblay and Louis-A. Dessaint has validated the use of this block for battery simulations and concludes: "In conclusion, this paper demonstrates that the new SimPowerSystems battery model allows for an adequate representation of a battery's real behaviour based on only three points on the battery manufacturers discharge curve. " [28, p.10]

3.4 Load Profiles

The design of a peak shaving energy storage requires knowledge about load profile characteristics, and which types of loads that are suitable for this service.

FASIT is a Norwegian standardization system which concerns faults and outages in the power system. In this standard, a set of general load profiles are defined that give the energy consumption for different load types [29]. These are general load profiles that are intended to illustrate the different load characteristics, and are not corrected for seasonal changes.

FASIT has defined different load profiles, including industry, office buildings, schools, caring homes, farms and residential housing. As peak shaving service requires loads that generate distinct peaks, farms and residential housing proves to be the types loads that are best suitable. An overview of the other load profiles with comments is available i Appendix 8.2. Figure 3.6 shows the residential loads show two distinct peaks both in the weekdays and weekends, with the morning peak appearing later, and being less distinct in the weekends.

The characteristics two peak load profile of residential loads, make these suitable for DES and peak shaving service.

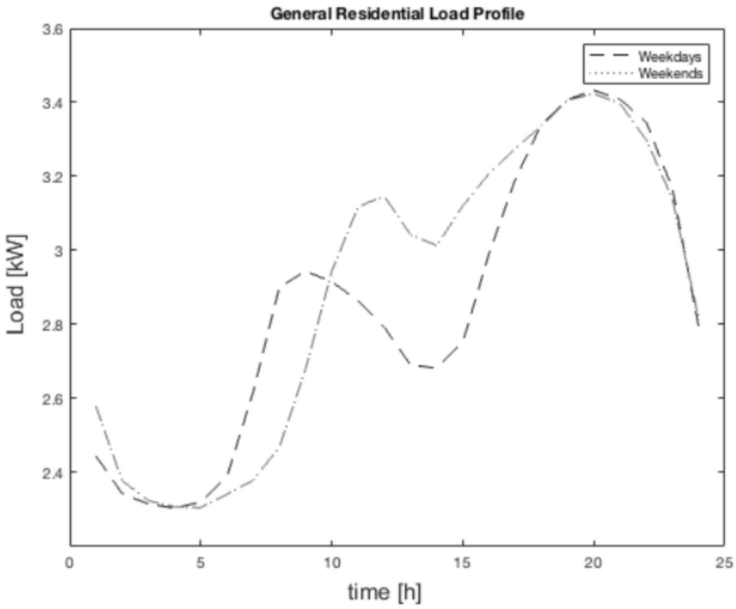


Figure 3.6: General Load Profile Residential.

3.5 Peak Shaving

By introducing energy storage to the power grid, the ability to reduce load peaks becomes available. The battery can be set to discharge above a certain load limit, relieving the transformer at times of high load. The battery can also be set to charge when the load is below this limit, effectively shifting the consumption to a period of lower consumption. In the course of a day, the total amount of energy through the transformer is the same, but without the variable nature of the load curve.

Figure 3.7 shows the values of the weekday load curve for general residential consumption from Figure 3.6, with the characteristic two-peak pattern of low load during the night, a smaller peak in the morning and a major peak in the evening. Hour 1 contain the energy consumed in the period 00:00 to 01:00, hour 2 contain the energy consumed from 01:00 to 02:00 etc. In this example, the lowest consumption occurs between 03:00 and 04:00 with 2.30kWh. The morning peak occurs between 08:00 and 09:00 with an energy consumption of 2.94kWh, and peak load occurs between 19:00 and 20:00 with an energy consumption of 3.43kWh. This is a an average load of 2.85kW.

time [h]	E_{load} [kWh/h]
1	2.44
2	2.34
3	2.32
4	2.30
5	2.32
6	2.39
7	2.62
8	2.90
9	2.94
10	2.92
11	2.87
12	2.79
13	2.69
14	2.68
15	2.75
16	2.99
17	3.19
18	3.34
19	3.41
20	3.43
21	3.41
22	3.35
23	3.17
24	2.79

Figure 3.7: 24 values of energy consumption per hour from the the general residential load profile.

	E_{load} [kWh/h]
min	2.30
max	3.43
average	2.85

Figure 3.8: Minumum, maximum and average values per hour from the general residential consumption.

Figure 3.9 shows the load variation during the day. The dark grey area illustrates the energy consumed by the load in a period of 24 hours.

By introducing a battery to this system, the periods of high consumption can be shifted to periods of low consumption. The average load $P_{avg} = 2.85kW$ is set as limit for battery charge and discharge. Figure 3.10 illustrates how the battery flattens the load curve. The light grey area above P_{avg} illustrates the energy provided by the battery, supporting the transformer using peak shaving service. In the dark grey area below P_{avg} the battery is charging, increasing the energy needed from the transformer in times of low load.

Figure 3.11, shows the battery peak shaving service together with the general residential load curve. The transformer is subjected to a steady load of $P_{avg} = 2.85kW$, providing power to both the load and battery. The battery discharges to provide energy to the area above P_{avg}.

This process reduces the load variability and Figure 3.12 shows how the load is seen from the transformer. The grey area contains the same energy as in Figure 3.9, but without the variability.

Figure 3.9: General residential daily consumption without peak shaving.

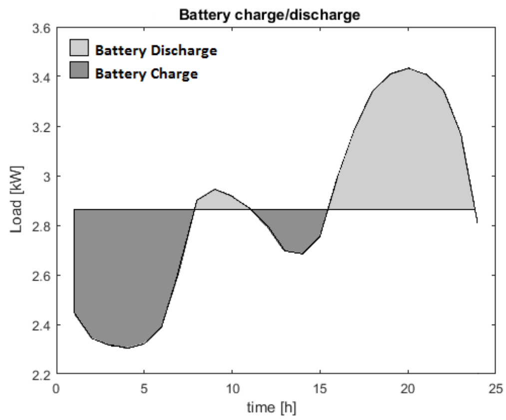


Figure 3.10: Battery providing peak shaving.

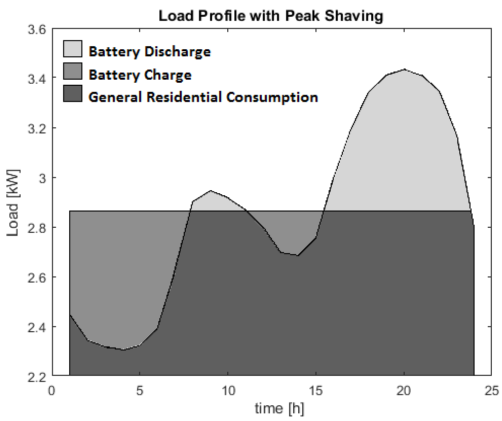


Figure 3.11: General residential load curve with peak shaving.

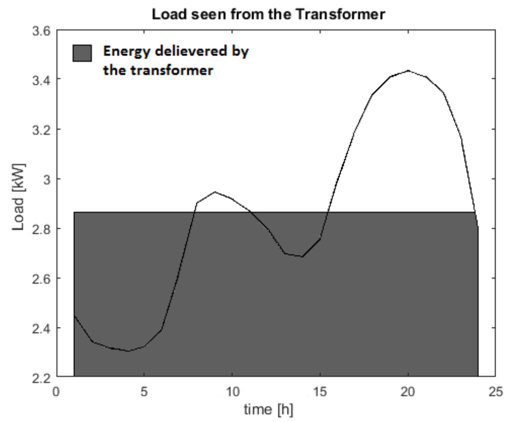


Figure 3.12: Energy consumption seen from the transformer.

3.6 Battery Energy Evaluation

The required energy delivered by the battery E_{batt} is determined by the area between the average energy consumption E_{avg} and the energy consumption E_{load}, see Figure 3.10.

$$E_{batt} = E_{load} - E_{avg} \tag{3.2}$$

This is illustrated by the shaded area above and below the line P_{avg} in Figure 3.10. The table in Figure 3.13 shows the results from Equation 3.2, calculated each hour. Negative values indicate battery charging in the dark grey area below P_{avg}, and positive values indicates battery discharging in the light grey area above P_{avg}. The areas above and below P_{avg} contain the same amount of energy, which become apparent by adding all the values in Figure 3.13 together, which in sum is zero.

time [h]	E_{load} - E_{avg} [kWh/h]
1	-0.40
2	-0.51
3	-0.53
4	-0.54
5	-0.53
6	-0.46
7	-0.23
8	0.05
9	0.10
10	0.07
11	0.02
12	-0.06
13	-0.16
14	-0.17
15	-0.10
16	0.14
17	0.34
18	0.49
19	0.56
20	0.58
21	0.56
22	0.50
23	0.32
24	-0.06

Figure 3.13: The results from equation 3.2, calculated each hour.

In Figure 3.13, hour 1 contain the difference between E_{load} and E_{avg} in the period 00:00 to 01:00, hour 2 contain the difference between E_{load} and E_{avg} between 01:00 to 02:00 etc. Negative values indicate battery charging, and positive values indicate battery discharging.

The battery capacity must be sufficiently sized so that it can accommodate the total energy in the light grey area in Figure 3.10, which can be found by adding the energy delivered by the battery in the form of battery discharge, indicated by the positive values in Figure 3.13.

$$E_{batt_{tot}} = \sum_{t=1}^{24} (E_{load} - E_{avg}) > 0 \tag{3.3}$$

The results from Equation 3.3 is presented in Figure 3.14. These are the periods where the battery discharges, which make up the total needed energy to be discharged by the battery.

time [h]	**(E_{load} - E_{avg})>0 [kWh/h]**
8	0.05
9	0.10
10	0.07
11	0.02
16	0.14
17	0.34
18	0.49
19	0.56
20	0.58
21	0.56
22	0.50
23	0.32
	3.73

Figure 3.14: The results from equation 3.3.

In the case of providing peak shaving service to a day equivalent to the general residential load profile, a total battery capacity of minimum 3.73kWh is needed.

3.7 Simulation Model Principles

The purpose of the simulations is to validate the proposed dimensioning and control strategy of DES in the distribution grid, in close proximity to the substation. The model will process field data from SFE Smart Valley to simulate the battery charge/discharge cycle of the battery storage.

A Norwegian distribution grid consists of high and low voltage cables and lines. In the distribution grid, the high voltage range from 1 kV to 22kV, but mostly lies at 11 or 22kV. Distribution low voltage are 230V, 400V or 690V. Distribution transformer substations are used as the interface between the high voltage and low voltage sections of the grid. Figure 5.1 shows a typical Norwegian distribution grid, together with a DES-system.

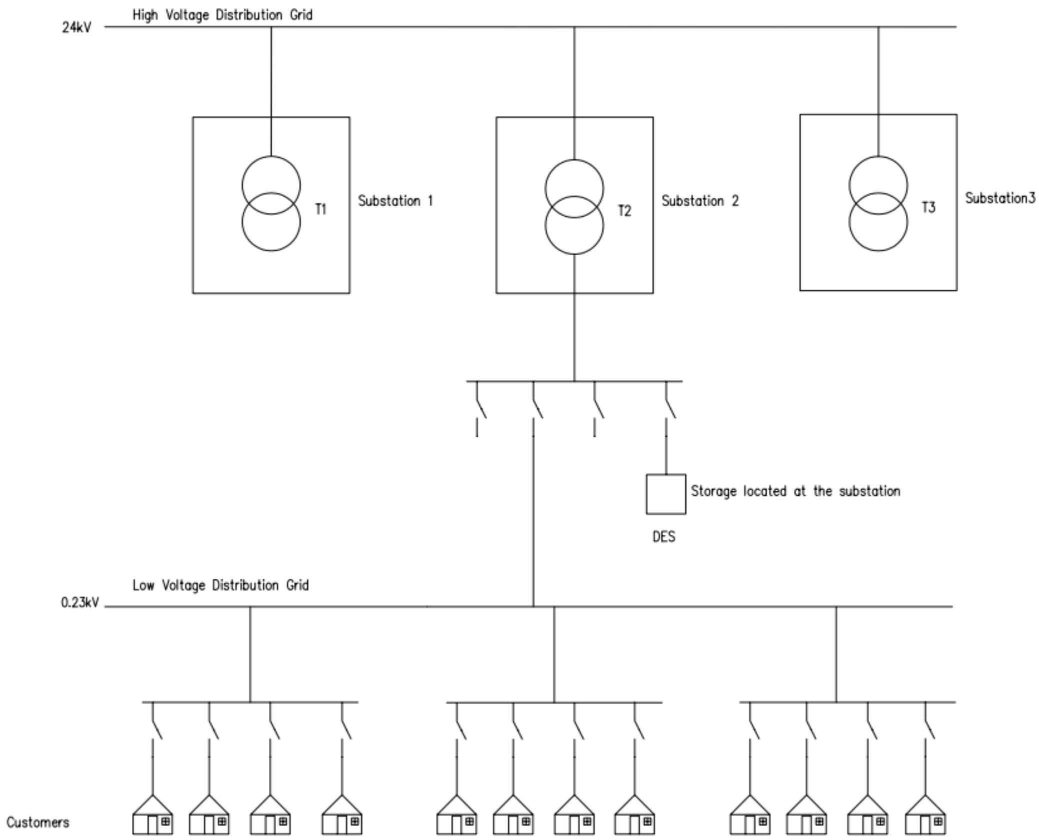


Figure 3.15: The general topology of a Norwegian distribution grid.

The figure shows a 24kV distribution line feeding a substation that transforms the voltage to 230V. This is fed through low voltage distribution lines to the customer. The storage will be placed in the low voltage distribution grid, close to the substation.

3.7.1 Model Architecture

The model simulates the transformer, load and battery in such a way that it mimics the battery/load interrelations, and that the load subjected to the transformer is constant.

A variable load profile is loaded into the model, and the purpose of the battery is to compensate for the variability of the load, so that the load seen from the transformer is constant. The battery will therefore provide support when the load is high (peak shaving), and pull charging current from the transformer in times of low load.

In effect, an ideal sized battery will act in such a way so the the load seen from the transformer is constant.

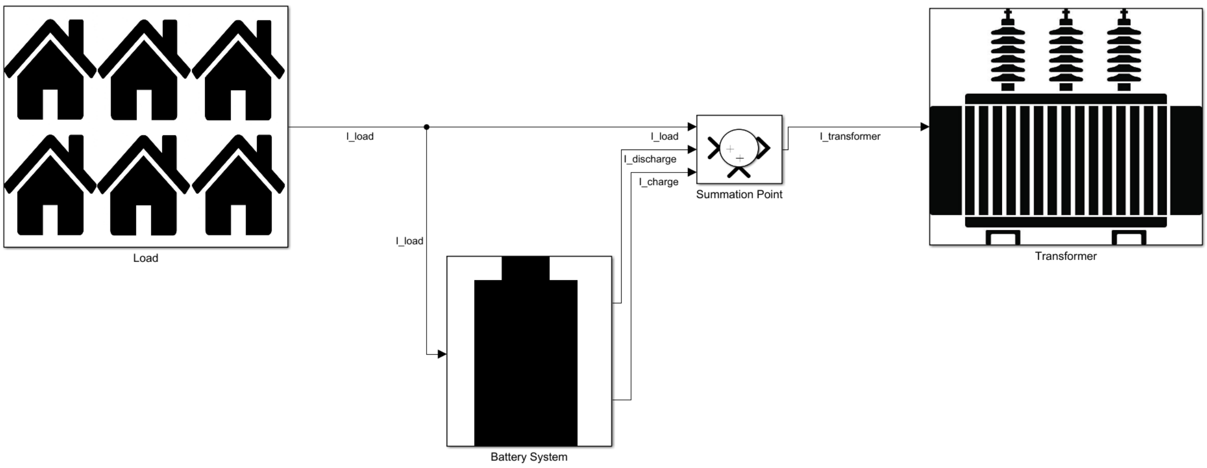


Figure 3.16: A diagram of the of the simulation model.

Figure 3.16 shows all sections of the model - the load section, the battery section, the summation point and the transformer section. In the model, the transformer is not simulated directly. However, the necessary current provided by the transformer is simulated indirectly by determining the necessary battery charging and discharging current. The transformer current $I_{transformer}$ is calculated as the sum of the load current I_{load} and the battery charging/discharging current I_{batt}.

$$I_{transformer} = I_{load} + I_{batt} \tag{3.4}$$

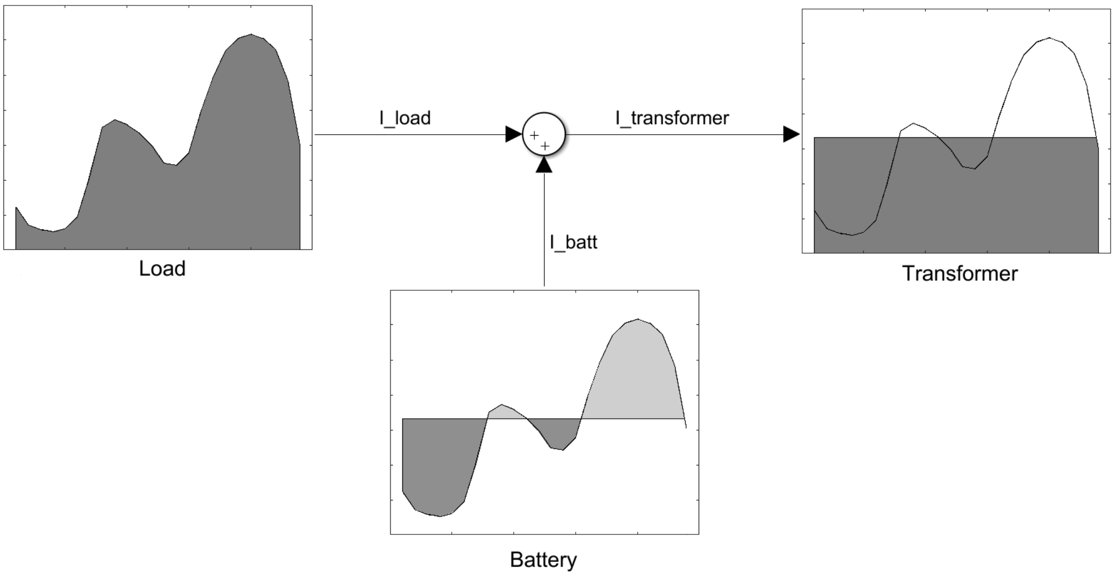


Figure 3.17: $I_{transformer}$ is the sum of I_{load} and I_{batt}

When the battery is charging, I_{batt} is positive, effectively increasing $I_{transformer}$ as the transformer is providing current to both the load and the battery. When the battery is discharging, I_{batt} is negative as the battery is supporting the transformer, effectively reducing $I_{transformer}$.

The following sections describes how the load currents, battery currents and finally the transformer currents are calculated, and how they interact.

3.7.2 The Load

I_{load} is deduced from the consumption curves gathered from Smart Valley. Raw data consumption curves are imported into the model, and made up by the energy consumption per hour at every node in Smart Valley.

Load Power

Due to power being energy per unit time, it is possible to use this correlation to deduce the power.

$$E = P \cdot t \tag{3.5}$$

$$P = \frac{E}{t} \tag{3.6}$$

The load curves from Smart Valley are made up of values collected every hour, meaning that the data is with an hourly resolution. Hence, the data contain information about the power at one hour intervals ($t = 1h$), which is the average power drawn by the load for the duration of one hour.

$$P\bigg|_{t=1h} = \frac{E}{1} \tag{3.7}$$

This principle is used to convert the energy consumption curve at the load (E_{load}) with the unit kWh to a power consumption curve (P_{load}) with the unit kW. With a data resolution of 1h ($t = 1h$), it can therefore be argued that P_{load} can be regarded as proportional to E_{load}.

$$P_{load}\bigg|_{t=1h} \propto E_{load} \tag{3.8}$$

Load Current

Furthermore the power consumption is converted to current using the nominal battery voltage U_{batt}. By using the battery voltage as reference, we ensure that the battery charge/discharge current amplitude calculations are correct. In depth explanations for reference voltage and battery current calculations are explained later in this chapter.

$$I_{load} = \frac{P_{load}}{U_{batt}} \tag{3.9}$$

With U_{batt} being the nominal battery voltage, this value is fixed which leads to I_{load} varying proportional to P_{load}.

$$I_{load}\bigg|_{U_{batt}=U_{nom}} \propto P_{load} \tag{3.10}$$

A 24 h load curve can be displayed in two different ways. Figure 3.18 shows the P_{load} with unit kW, and Figure 3.19 shows the I_{load} with the unit A calculated from P_{load} and U_{nom}.

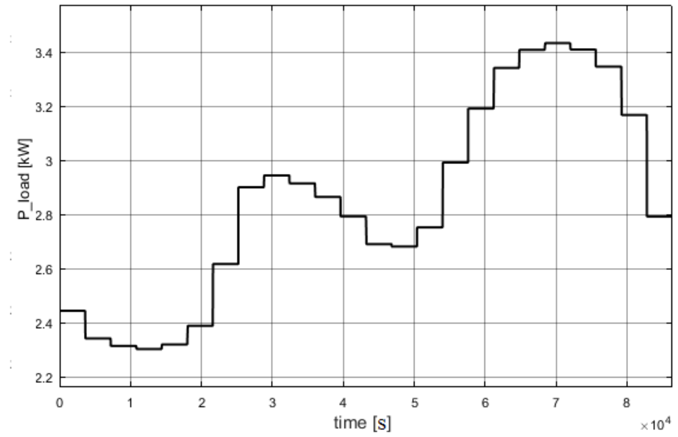


Figure 3.18: General residential load profile before power to current conversion.

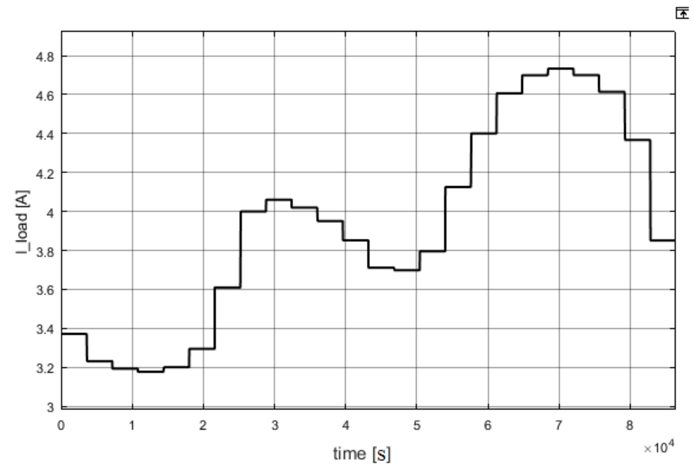


Figure 3.19: General residential load profile after power to current conversion.

3.7.3 The Battery

Battery Current

I_{batt} is made up by two different currents, a negative ($I_{discharge}$) and a positive (I_{charge}) current. I_{charge} is the charging current and is regarded as a positive current, as this gives a positive contribution to $I_{transformer}$, effectively increasing the transformer current. Vice versa, $I_{discharge}$ is regarded as a negative current, as this will aid the transformer and thereby reduce $I_{transformer}$. I_{charge} and $I_{discharge}$ cannot occur simultaneously, with logic embedded in the model to ensure that at least one of the two equals zero. For more details for how this is done, see section 5.2.2. I_{batt} is therefore the collective name for both the charging and discharging current, for which at least one is always zero. The direction of the battery current is determined by whether either the charging or the discharging current is the one currently active.

$$I_{batt} = I_{charge} + I_{discharge} \tag{3.11}$$

Average Current

The logic that controls the amplitude and direction of the battery current is built around the term I_{avg}, see Figure 3.21. This is the average current for one 24 h period. It is desirable to have a model that adapts to the variability of load profiles from day to day. The optimal solution is to use I_{avg} from the same 24 h period that is being simulated, and this is the approach that has been used for the simulations in this report. However, it must be stressed that this is not an approach that is possible in a system with a live battery management system, as this would rely on using historic data to calculate and predict I_{avg} of the given day.

As the purpose of the simulation model is to validate the size of a battery storage, the model is to be regarded as a planning tool. The control logic is therefore built to use the most accurate data, which in this case is I_{avg} from the day being simulated. For a planning tool, this is an adequate approach. More details on how I_{avg} is calculated in the model, see section 5.2.2. Future work will be focused on implementing this planning model into a live battery management system.

I_{avg} serves as the limit for when the battery shall charge or discharge. When I_{load} is above I_{avg}, the battery will discharge to support the transformer. When I_{load} is below I_{avg}, the battery charges. In addition to the current limit, battery SoC-limits are also taken into account, and this is addressed in detail in section 5.2.2.

As whether the amplitude of I_{load} is higher or lower than I_{avg} determines the directions of the battery current, the difference between I_{avg} and I_{load} determines the amplitude of the battery current.

Battery discharge ($I_{load} > I_{avg}$)

$$I_{discharge} = I_{load} - I_{avg} \tag{3.12}$$

Battery charge ($I_{load} < I_{avg}$)

$$I_{charge} = I_{avg} - I_{load} \tag{3.13}$$

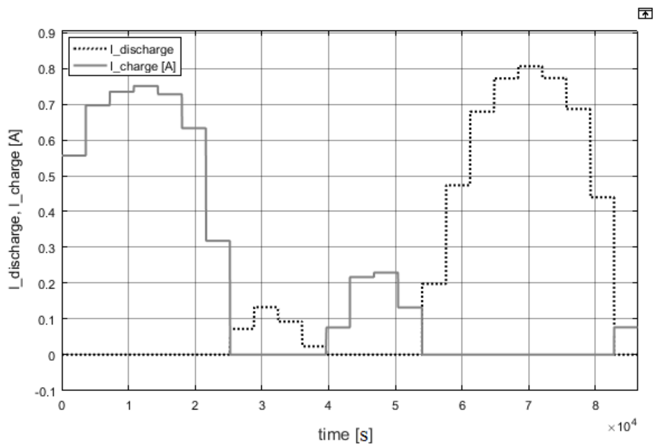


Figure 3.20: Battery discharge and charge current.

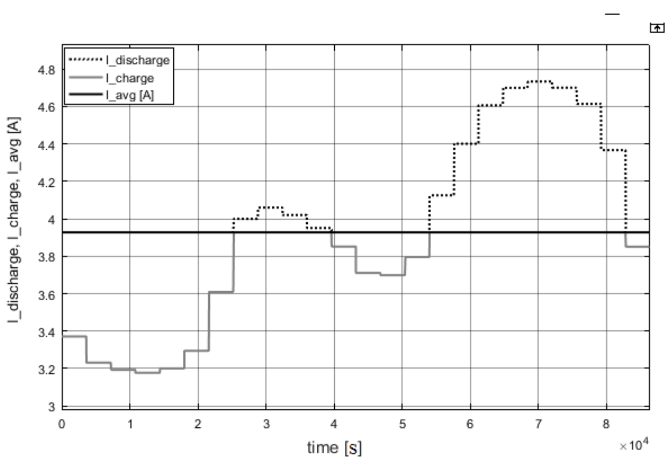


Figure 3.21: Battery discharge and charge current and average load current.

Figure 3.20 shows the amplitude of the charging current (gray) and discharging current (dotted) respectively.

Figure 3.21 displays I_{avg} (black), I_{charge} (grey) and $I_{discharge}$ (dotted). The curve follows the same path as I_{load} (Figure 3.19), and I_{avg} marks the point where the area above and below the line are the same. When I_{load} is below I_{avg}, the battery is charged, pulling current from the transformer indicated by the grey line. A similar process is taking place when I_{load} is above I_{avg}, where the battery is discharging at a rate indicated by the dotted line.

3.7.4 The Transformer

The battery currents reduces and increases the load current so that the transformer current is constant.

- Battery discharge ($I_{load} > I_{avg}$)

$$I_{transformer} = I_{load} + (-I_{batt}) \tag{3.14}$$

- Battery charge ($I_{load} < I_{avg}$)

$$I_{transformer} = I_{load} + I_{batt} \tag{3.15}$$

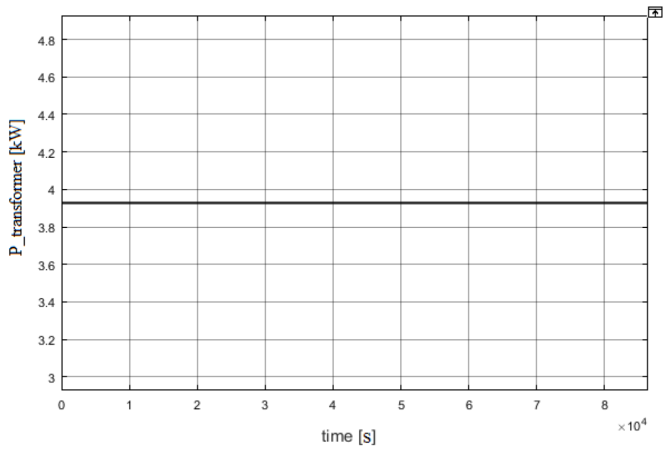


Figure 3.22: Transformer load.

By inserting a properly sized battery in the distribution grid, the variability represented by the consumption curve created by the load from Figure 3.19, can be removed and replaced with a load curve given by I_{avg} in Figure 3.22. The area under these two curves, are the same, but with the aid from the battery, the demand is shifted so that the transformer will not experience major dips or peaks.

Chapter 4

Data Description

This chapter addresses the origin and characteristics of the data set used for the simulations. Trends in seasonal variations are evaluated and a battery storage sizing strategy is proposed.

4.1 Smart Valley

SFE has established a live demo lab in Hyen, Sogn og Fjordane called SFE Smart Valley, for testing, development and pilot activities within Smart Grid systems. This test site was established in 2014 with the early installation of AMS meters. These meters are to be rolled out nationally within the end of 2018.

SFE is the project owner and has collaborated with eSmart Systems and their software Connected Grid which creates a graphical interface for data visualization. Microsoft Azure is used as the cloud service and for data processing.

Roughly 100 metres are installed at the customer and monitors the consumption at an hourly resolution. These metres are divided between 8 substation transformers with sizes varying from 50 - 200 kVA. The site gives access to data such as voltages, currents, active and reactive power. The amount of data is enough to derive load curves from most customers for an entire year.

4.2 Data Basis

The source of data are situated on the west coast of Norway, which is not enough data to cover the geographical differences in electricity consumption for the entire country. However, base load composition and customer behaviour which dictates the load profile on a daily basis is representative for the most of the country. With geographical differences, weather and temperature conditions differ, but this is on an annual basis. This means that the required battery storage size may vary for different parts of the country.

Field recorded data from Smart Valley are collected from two types of sources: AMS meters and substation meters. The data from the AMS meters are collected from 78 nodes, each representing an individual customer connected to the low voltage grid. Data from the substation meters are collected from 4 transformer substations, each representing the interface between the high voltage and low voltage sections of the grid in Smart Valley. Together these data sets contain the load profiles from each node together with the total load at each substation.

4.3 Measuring Instruments and Data Processing

4.3.1 AMS Meters

The AMS meters installed at each customer in Smart Valley are of the type Kamstrup 162M [30]. This is a three phase meter that reports the energy consumption once every hour. Information regarding voltage and currents are measured to calculate the total energy consumption for a period of one hour. The values are transmitted to Connected Grid using both GPRS and radio. Active and reactive power are also measured, but not transmitted. Accuracy class "A", more information about this is Appendix 8.3.

Figure 4.1: Kamstrup Smart Meter

4.4 Data Composition

The AMS meter data set contains measurements from four seasons, stretching from the beginning of winter late 2015 to the end of autumn 2016, with a 1-hour resolution.

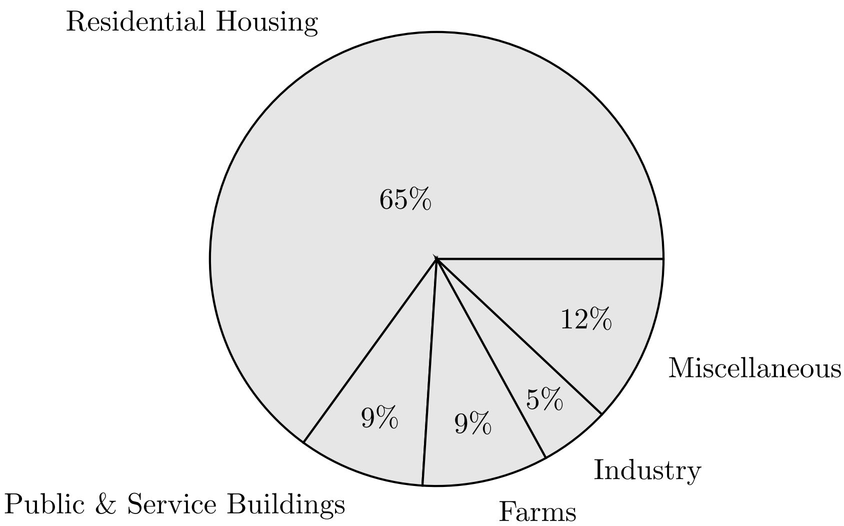
Measurements from the AMS meters are consumed energy (kWh) at each node. This data is collected by the Connected Grid software and aggregated to be presented at the nearest upstream substation, to show the total energy consumption in each transformer circuit. Data from the transformer substation meters include active and apparent power, voltage and current measurements.

Because of holes in transformer substation dataset, these are not used for simulations. However, the data contain information about apparent power, which gives an indication of the power factor and load characteristics. The AMS meter dataset contain complete information about the energy consumption throughout the year and thereby the source of data to be imported into the simulation model.

4.4.1 AMS Data

Each node represent a specific load:

- Residential loads: 43 detached houses, 2 attached houses, and 5 vacation homes.
- Public and service buildings: 5 municipal buildings including a school, kindergarten, retirement homes, fire station and a water purifier facility. In addition we have an office building and a gallery.
- Industry: 8 regular farm houses, a salmon farm, a garage, a gas station and a storage building.
- Miscellaneous: A transmitter base, two municipal lighting nodes, an emergency power node, a fishing hut, a sports club house and four nodes that are unspecified.



As explained in section 3.4, residential housing and farms are of interest because of the similarities of the two-peak pattern load profile. Vacation homes represents a different load profile, and as the dataset only includes 2 vacation homes, this is excluded from the study.

4.4.2 Substation Transformer Data

Smart Valley includes four substations that are connected to the Connected Grid platform.

Instantaneous values (active/apparent power, voltage, current) are measured by the instrument in the substation, while energy consumption are aggregated values collected from the AMS meters at each node connected to the substation. None of the substations contain data from the entire year. Efforts were made to extract substation transformer data for use in this report, but because of a fault in the transmitter module connected to the substations, the author was unable to attain sufficient data to be used for the duration of the assignment. Substation transformer data is therefore not imported into the model, but information regarding power factor is used as reference in calculations.

In the instances where both active and apparent power is present in the data, the relation between them is used to calculate a $cos\phi$ ranging from 0.9 to 0.99. See Section 6.4 of how this is used in calculations.

4.5 Data Presentation and Analysis

In conjunction with the national roll-out of the new AMS meters, Statnett has issued a set of specifications that each DSO needs to follow to ensure proper data validation. These are called VEE - Validation, Estimation and Modification (Validering, Estimering og Endring), and serves as the standard for data to be collected in the national dathub called the Elhub [31].

The VEE-standard states that AMS data are to be collected once every day, and contain consumed energy at each node with an hourly resolution. The AMS meters must also be able to sample data at 15 minutes resolution if needed.

Holidays are regarded as Sundays. Due to the change from winter time to summer time, data string with time-stamp 2016-03-27 03:00 are missing. And vice versa an extra hour is added to the day of October 30th with time-stamp 2016-10-30 25.

Load Profile and Temperature Correlation

In 2015, the company Optimeering performed a study on behalf of NVE, which show that there is a linear correlation between energy consumption and ambient temperature [6, p.13]. The energy consumption can therefore be expected to be higher during the winter months than in warmer periods.

This linear relationship between temperature and energy consumption do indeed materialize in the data collected in Smart Valley. Figure 4.2 shows the load profile for 2016 in Smart Valley, and clearly show a higher load in the winter months than in the summer. Data is collected every hour throughout the year with hour 1 representing the first measurement of 01.01.16, and hour 8600 representing the last measurement of 31.12.16. The missing data from hour 2068 is caused by the shift from wintertime (UTC+1) to summertime (UTC+2) at 03:00 the 27th of March, with time-stamp 2016-03-27 03:00. The hour with missing measurements are not removed from the data presentation, as this would shift the following time series by one hour.

Figure 4.3 shows temperature in the same area for 2016 with the same time scale. The temperature data is collected from the AMS meters in Smart Valley. This figure shows that the temperature increases the first half of the year and peaks during the summer, and drops towards the end of the year. The correlation between temperature

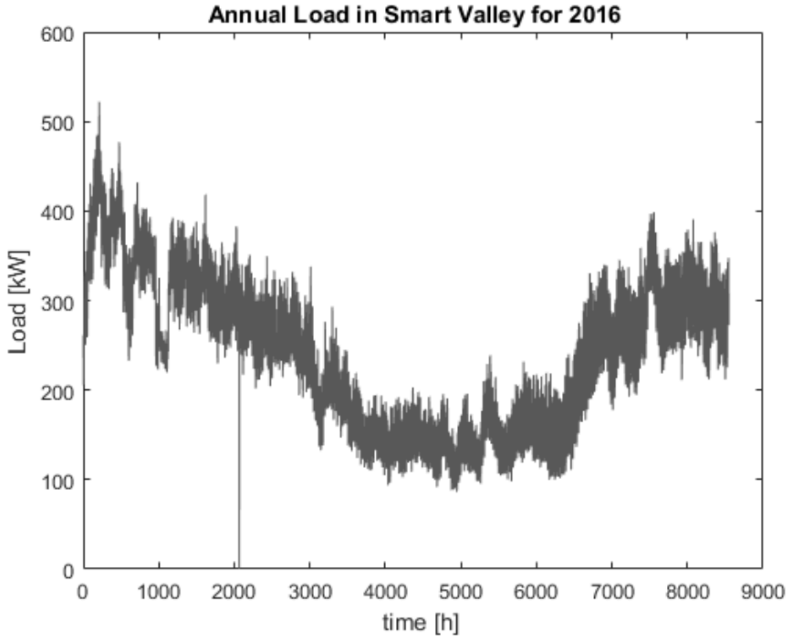


Figure 4.2: Total Electricity Consumption for 2016

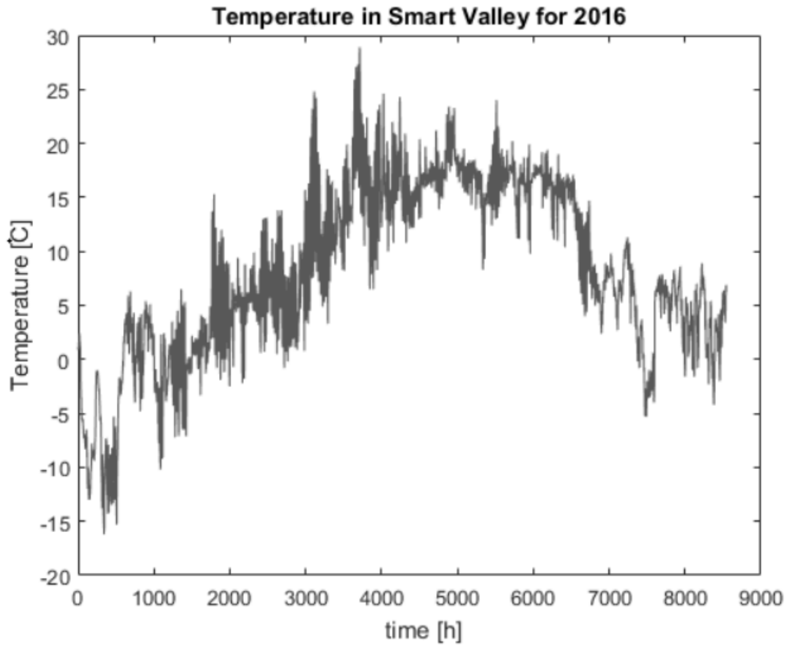


Figure 4.3: Temperature in Smart Valley for 2016

and load show signs of being inversely proportional with an increase in demand as temperature drops, and vice versa. This is apparent both as an overall trend, but also within smaller intervals. As cold periods occur in mid January (500h) and mid October (7500h), electricity consumption peaks, and as temperature rise towards February (1000h) and April (3000h) a load drop appears in the same period.

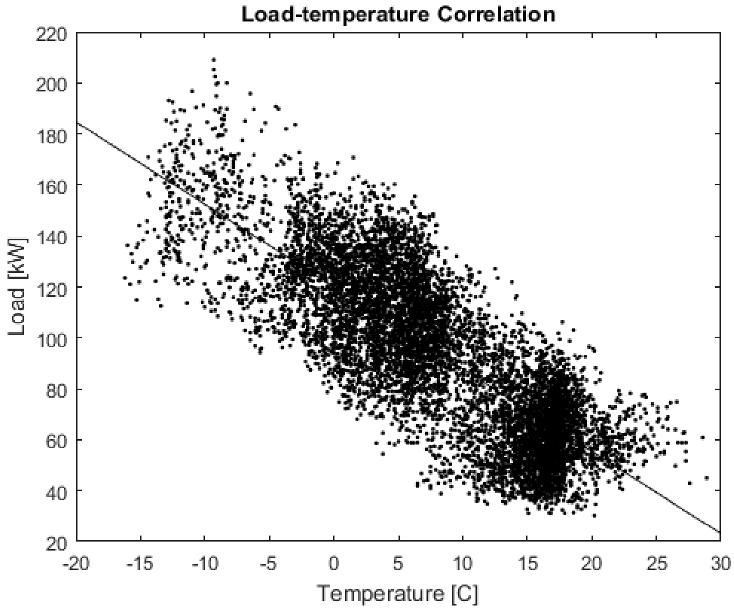


Figure 4.4: Energy consumption plotted as a function of temperature.

Using MATLAB, load is plotted as a function of temperature to derive the correlation between the two. The results show a negative correlation, which is expected. According to [32, p.285], the correlation coefficient is calculated using equation 4.1. The calculations are done in excel, and show a correlation coefficient of r=-0.8. This shows that the correlation between temperature and load presented in the Optimeering study, also presents itself in the data from Smart Valley.

$$r = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2}\sqrt{\sum(y-\bar{y})^2}} = -0.8 \tag{4.1}$$

x = temperature

y = load

Daily Load Variations

The Optimeering study developed a method for calculating a national feed-in profile. This study collected data from DSOs from all parts of Norway. This includes data from large, medium and small sized DSOs. The report show a repeating pattern where the load profile show low consumption during the night and high during the day [6, p.19]. The load profiles show two load peaks during the day, one in the morning (08:00 in weekdays and 10:00 in weekends), and one in the evening (around 21:00). More than 90% of the collected data in that study show that the evening load peak to be higher than the morning peak.

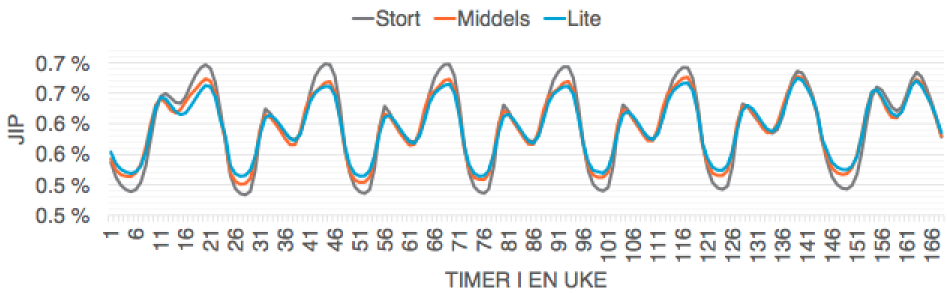


Figure 4.5: Daily variation in energy consumption [6, p.20]

Figure 4.5 is adopted from the report by Optimeer and shows the daily load variation for an average week, for large, medium and small sized DSOs. It shows a two peak pattern every day, as explained above. The study uncovered that the difference between day and night consumption depend on the size of the DSO.

Large sized DSOs tend to have a bigger difference between night and day consumption, something that can partly be explained by the fact that large DSOs typically have bigger apartment houses with central heating, which reduces the need for electricity powered heating. This increases the energy going to lighting and other equipment, which is more present during the day.

SFE with its 24 000 customers is a medium sized DSO, and is represented by the middle line.

4.5.1 The Household Datasets

The 45 households included in this study have different average load that stretches from 0.1kW to above 6kW, with the majority being between 2-3kW in the winter and between 1-2kW in the summer, see Figure 4.6.

The different household loads are determined by the size of the house, customer behaviour and seasonal variation. In order to determine the impact of seasonal variation, it is necessary to look at each customer separately. For most customers, the load is at its highest in the winter months, and at its lowest in the summer months.

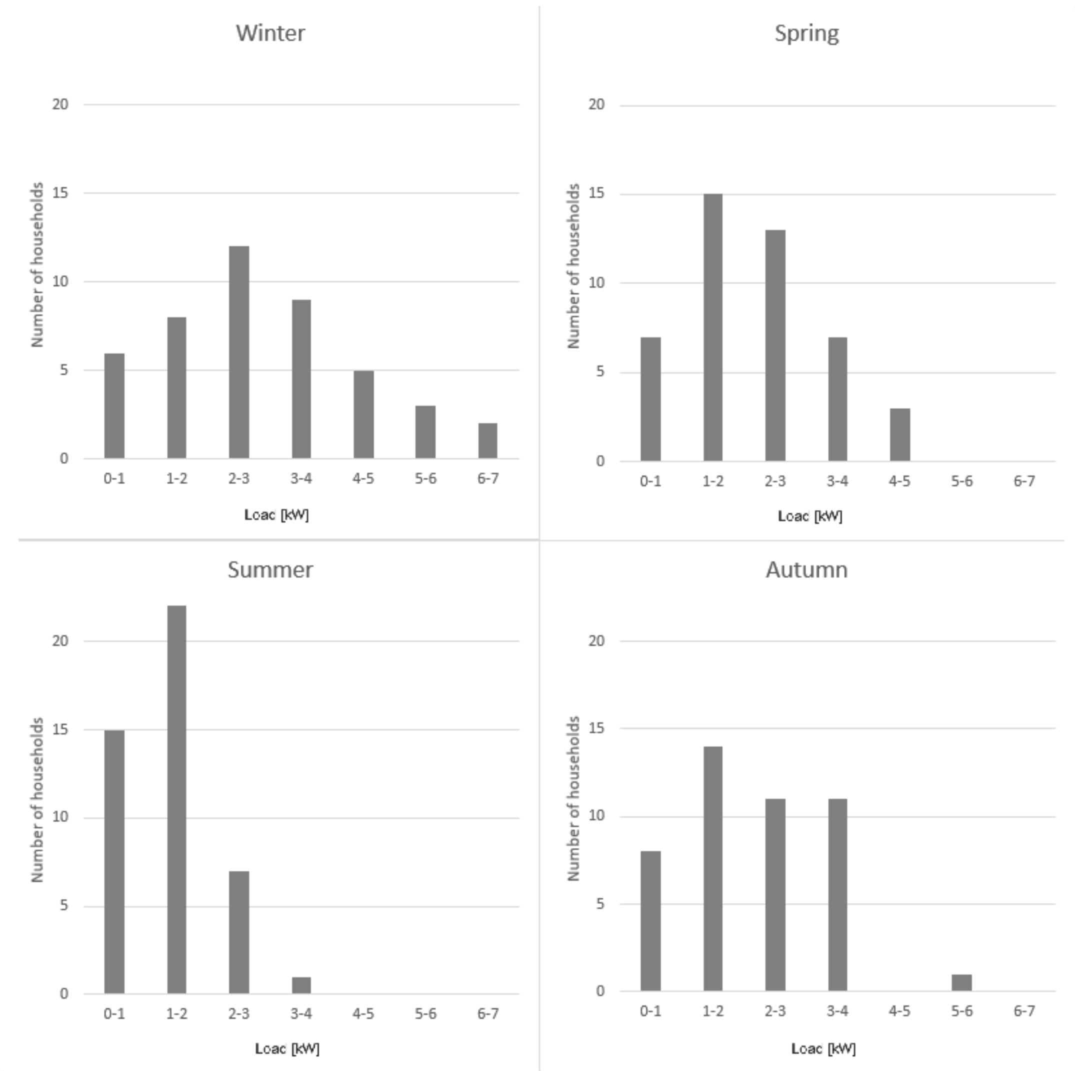


Figure 4.6: Average Household Load

In the Optimeering study, the year is divided into the following periods that define the different seasons [6, p.13]. The same periods are used in this report.

- Winter: week 48-8
- Spring: week 9-20
- Summer: week 21-34
- Autumn: week 35-47

The graphs in figure 4.7 show an example from one of the household data sets with seasonal variation. Data is gathered with an hourly resolution, each with its respective time stamp. This gives 24 samples a day, with time stamp 1 for the first measurement of the day with the load between 00:00 and 01:00, and time stamp 2 with the load between 01:00 and 02:00 etc. For each season, the average of each time-series with the same time stamp is plotted in the graph to represent an average daily consumption for this period.

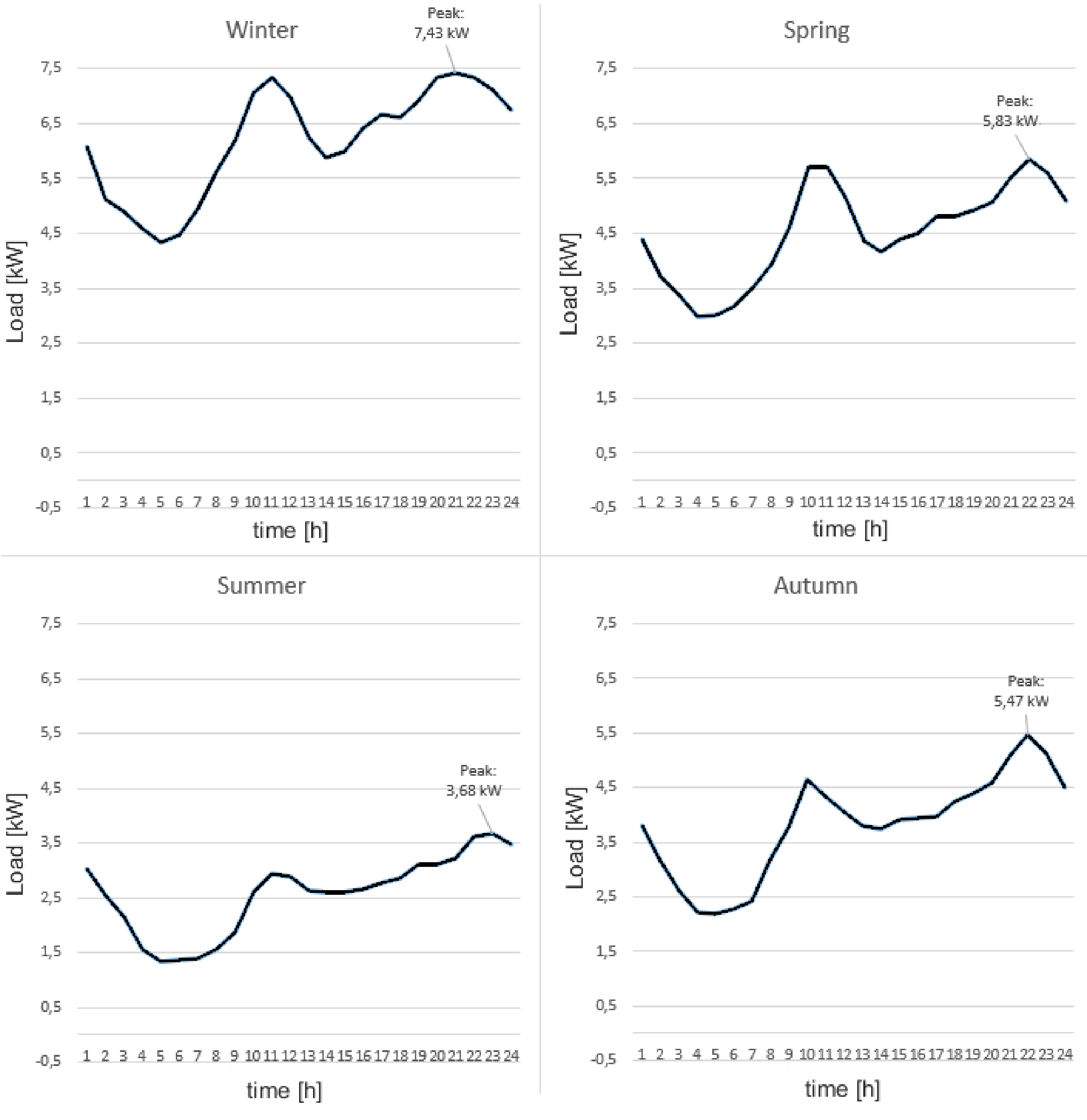


Figure 4.7: Seasonal Variation

For all customers, summer peak load is set as reference, with winter, spring and autumn peaks given as ratios in relation to this. This gives us the possibility of reviewing the seasonal variation for each customer and comparing these regardless of the size of the load itself.

In the example in Figure 4.7, the average spring and autumn peak load is 1.6 and 1.5 times the average summer peak load, respectively, and average winter peak load being a full 2 times the average summer peak. Taking all the 45 household datasets into account, this example represents the seasonal variation on average.

In 51% of the cases, spring peak is higher than the autumn peak, in 31% vice versa, and in 18% of the cases the average peaks of spring and autumn are the same. For all but one customer, the average load peaks are higher in the winter than all of the other seasons. This one customer has very low consumption during the winter, pointing to that the house is left empty during the winter months. With the load being at its highest during the winter months on average, this period is of high interest when determining the size of the storage.

Some extreme cases with very high winter-summer load ratios are also recorded with two customers experiencing 5 and 7 times the summer peak load in the winter. These extreme cases are due to very low initial base load, probably due to vacant houses, or these being left unused for parts of the year. Small changes in these cases may appear very large relative to the initial base load, but not especially large in comparison to other loads in the datasets.

Data Reliability and Uncertainty

The reliability of the measurements is assessed by using complete data from all 78 nodes. The Central Limit Theorem states that the mean winter - summer peak load ratio $\bar{X}$ is approximately normally distributed if the number of values (n) is adequate regardless of the distribution of the data. If the distribution is reasonably symmetric, fewer observations are needed. A rule of thumb is that the average is normally distributed if $n \geq 20$ [32, p.198]. 45 household nodes represents the only load profile group that include a sufficient number of nodes to fulfil this requirement and with certainty can represent load profiles from the inland parts of SFE's power grid. These will therefore be the source of data for the simulations.

As $45 \geq 20$ the mean winter-summer peak load ratio can be calculated by Equation 4.2 with n=45 and X representing each node.

$$\bar{X} = \frac{1}{n}(X_1 + X_2 + ... + X_n) \tag{4.2}$$

The standard deviation (σ) is a measure used to quantify the dispersion of data. Low σ indicating that the data is close to the mean. High σ indicates that the values are far from the mean and spread out of a wide range of values.

Using excel the mean winter-summer ratio for the household dataset is calculated to $\bar{X} = 2.0$. Standard deviation is also calculated using excel to $\sigma = 1.07$.

The peak load winter-summer ratio distribution is plotted using $\bar{X} = 2.0$ and $\sigma = 1.07$ with the normal distribution function in excel, and shown i Figure 4.8.

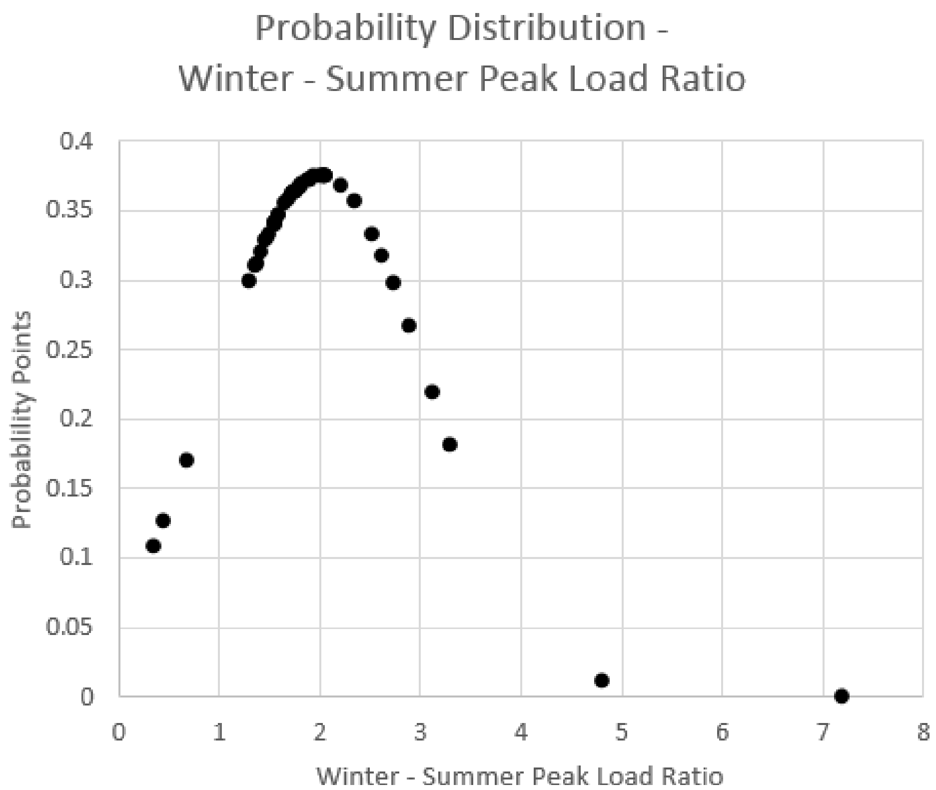


Figure 4.8: Probability Distribution for Winter - Summer peak load ratio

For the data to be normally distributed, 95% of the measurements must be within two standard deviations of the median of 2. This means that a minimum of 42 of the total 45 values is expected to be between is 2 ± 2.014. Only two values are above the limit, which are the customers with the ratio of 5 and 7, giving us 43 values within the 95% confidence interval. In addition, 39 measurements lie within one standard deviation (68% confidence interval), which all together represent a dataset that is normally distributed.

4.5.2 Average Load

A similar relationship between seasonal peak load become apparent by comparing the total average load of all 45 households. Data from each season is collected according to the periods defined in section 4.5.

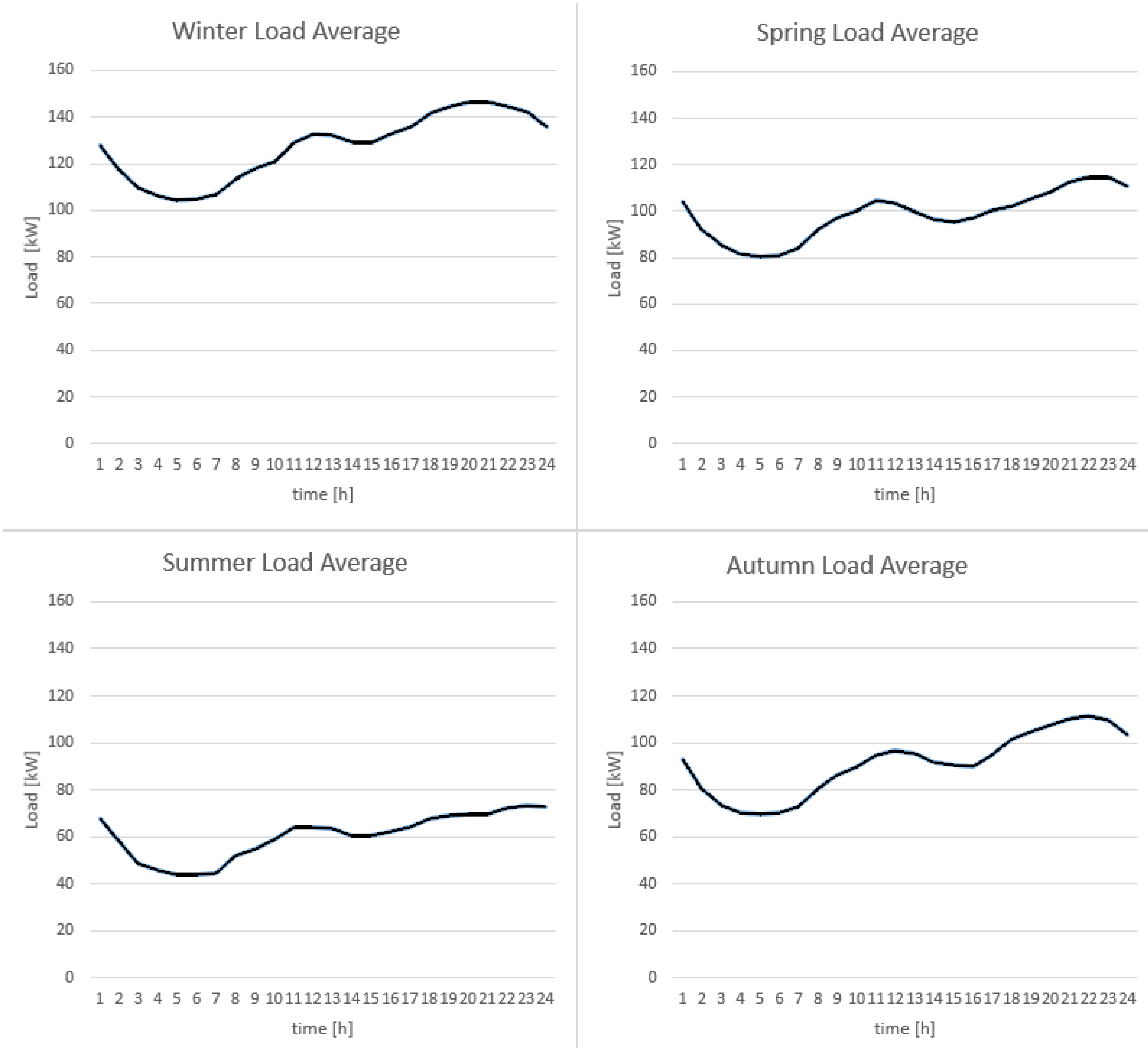


Figure 4.9: Average load for all four seasons

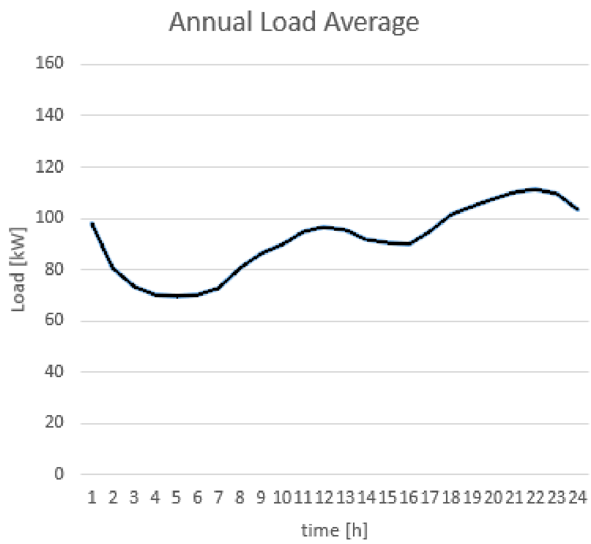


Figure 4.10: Annual load average.

Average Load

	Winter	Spring	Summer	Autumn	Annual
Maximum P_load [kW]	147	114	73	111	111
Minimum P_load [kW]	104	81	44	70	70

Figure 4.11: Maximum and minimum values from the consumption average.

4.5.3 Load Extremities

As explained in section 4.5, periods of low load can be expected during the summer. The ten cases of lowest load all occur in July and August.

Similarly, the ten cases of highest load all occur during the winter, in January.

The highest load in the dataset occurs 09.01.16 with $P_{load} = 209.2kW$. The lowest load occurs 25.07.16 with $P_{load} = 30.3kW$.

Load Extremities

	Maximum	Minumum
Date	09.01.2016	25.07.2016
P_load [kW]	209.2	30.3

Figure 4.12: Maximum and minimum load in the dataset.

4.6 Battery Storage Dimensioning Strategy

4.6.1 Storage Size and Cost

Cost is closely related to storage size, therefore, an ideal capacity must be determined in a way that that balances initial investment cost and life time. As explained in Section 3.2.2, the battery cycle life is dependent of DoD. Low DoD gives high cycle life, but also high initial investment costs. This is due to an increased demand for buffer capacity, which increases the total storage size.

A battery with high DoD requires less buffer capacity, resulting in a battery that utilizes more of its total capacity to provide a service, at a lower initial investment cost. However, high DoD reduces battery cycle life.

Two DoD-scenarios are of focus:

- 60% DoD: In the study from 2016 [4, p.7], the results from a series of dynamic stress tests shows that a DoD of 60% is one of the scenarios that balances battery utilization and life time.

- 45% DoD: In the study from 2010 [21, p.5.3-5.4], the results show that DoD from 40-50% keeps the battery costs at a minimum when comparing initial investment cost and total lifetime cost.

In order to determine the ideal balance between storage size and cost, the energy consumption from the entire year must be taken into account. While the battery must be able to handle peak consumption, measures must be taken to prevent the battery from being over-sized for great parts of the year. With average winter peak consumption being a full 2 times higher than average summer peak consumption, a battery dimensioned for winter consumption may result in a over-sized battery in the summer months.

4.6.2 Required Battery Capacity Evaluation

The battery sizing method presented in section 3.6 is employed for calculating for all 366 days in the dataset, thus giving the required battery capacity for the entire year. Maximum required battery capacity occurs 26.12.15 with $E_{batt} = 288.1kWh$ and minimum needed battery capacity occurs 12.02.16 with $E_{batt} = 30.5kWh$, see Figure 4.13.

As could be expected, the top ten days of required battery capacity all occur during the winter, in November, December and January.

The bottom ten however, do not all occur in the summer months. In fact 7 out the 10 days of the lowest required battery capacity occur in February. This is due to the adaptive battery charge/discharge limit being determined by the average consumption of the day. This means that it is the difference between P_{load} and P_{avg} which determines the needed size of the battery, and not the amplitude of P_{load} per se. During a period of February, the initial base load was high, but with low variability and less distinct peaks compared to the days with higher need for battery capacity.

Of the 366 days in the dataset, the average needed battery capacity is 135.7kWh.

Needed Battery Capacity

	Maximum	Minumum	Annual Average
Date	26.12.2015	12.02.2016	
E_batt [kWh]	288.1	30.5	135.7

Figure 4.13: Maximum, minimum and average battery capacity needed from the total number of 45 households, calculated from the 366 days in the dataset.

In the dataset, there are 179 days that require more than the average battery capacity of 135.7kWh, and 187 days that require less. This means that the dataset contains just about the same number of days above and below the 135.7kWh limit.

Days above and below E_avg

E_batt>135.7kWh	E_batt<135.7kWh
179	187

Figure 4.14: The number of days above and below the average required battery capacity in the dataset.

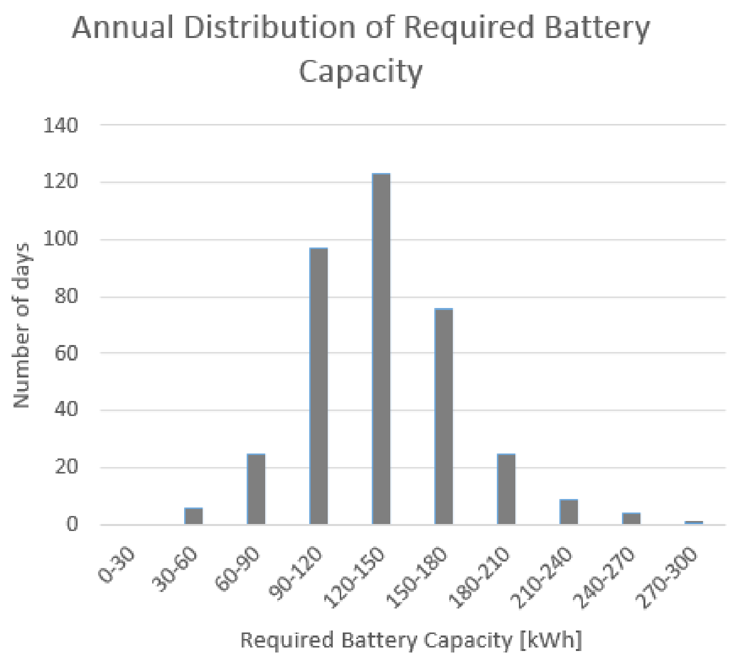


Figure 4.15: The annual distribution of needed battery capacity.

On an annual basis, the required battery capacity is between 90kWh and 180kWh for the majority of the days, and peaks between 120kWh and 150kWh, see Figure 4.15. A closer investigation of the distribution for each season shows that the greatest range of required battery capacity is found in the winter, with the majority from 120-180kWh, see Figure 4.16. The other seasons have a more narrow range.

Required battery capacity during the spring mostly range from 90-150kWh, while the autumn have a majority in the range from 120-180kWh. In the summer, the largest collection of battery capacity requirements range from 90-120kWh.

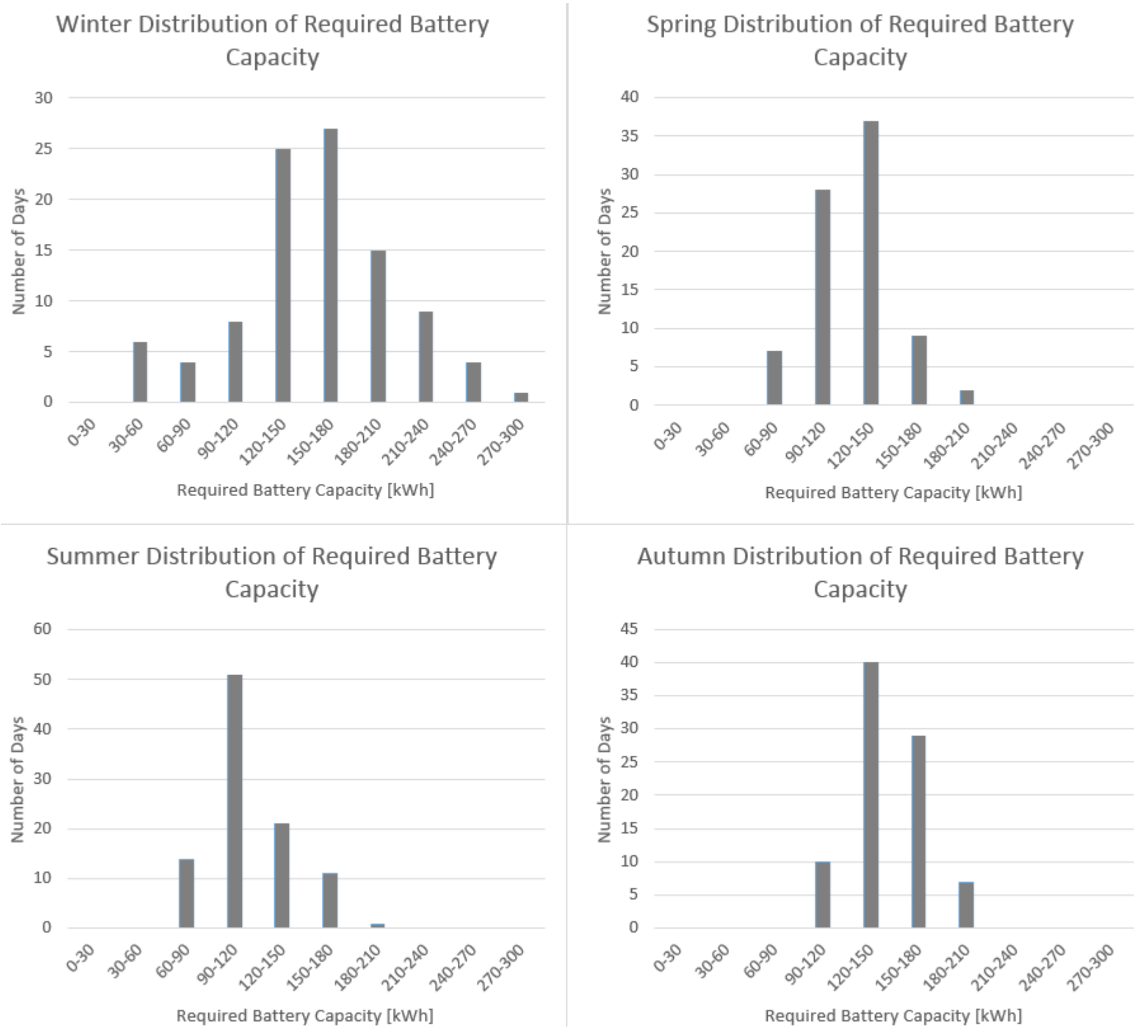


Figure 4.16: The distribution of needed battery capacity for each season.

4.6.3 Average Battery Capacity Requirements as Reference

The hypothesis is that the optimal battery storage sizing strategy is to size the battery according to the average battery capacity requirements on an annual basis of 135.7kWh. The distribution of battery capacity requirements is equally distributed around this point, see Figure 4.14, 4.15 and 4.16. This means that the battery is dimensioned so that the average battery capacity requirements are kept within the desired DoD limit, and taking use of the buffer to accommodate the higher consumption during the winter.

The full range of the battery capacity will be better utilized during the winter, which involves moving past the recommended limits, effectively accelerating battery degradation. However, due to the distribution of required battery capacity, it is expected that periods of low capacity requirements with low battery degradation will counteract the periods of high capacity requirements with high battery degradation, which will lead to an average DoD on an annual basis.

- DoD of 60%. The energy storage is dimensioned so that the average required battery capacity makes out 60% of the total battery capacity. 40% of the battery capacity serves as a buffer. 51% of the days require an energy storage that is within the this limit, while 49% of the days require more, making use of the buffer. Since the number of days above and below the limit are similar, these will cancel each other out and give a total annual DoD of 60%.

- DoD of 45%. The energy storage is dimensioned so that the average required battery capacity makes out 45% of the total battery capacity. 55% of the battery is set as buffer. As with Strategy 1, the number of days above end below the DoD limit are similar, the times of low degradation will cancel out the times of high degradation, giving an annual DoD of 45%. This solution gives a battery with higher buffer capacity which increases the initial investment costs compared to Strategy 1. However, this solution also reduces battery degradation, giving a higher number of cycles before a certain performance threshold is met.

4.6.4 Dimensioning Strategy 1: 60% DoD

A battery with a DoD of 60% will have a 40% buffer with regards to the average required battery capacity of 135.7kWh is given in equation 4.3.

$$E_{batt}|_{60\%DoD} = \frac{E_{batt}|_{annual}}{0.6} = \frac{135.7kWh}{0.6} = 226.2kWh \tag{4.3}$$

With a battery voltage of 725.2V, this translates into battery capacity of 311.9Ah.

$$Q_{batt} = \frac{E_{batt}}{U_{batt}} = \frac{226.2kWh}{725.2V} = 311.9Ah \tag{4.4}$$

4.6.5 Dimensioning Strategy 2: 45% DoD

A battery with a DoD of 45% will have a 55% buffer with regards to the average required battery capacity of 135.7kWh is given in equation 4.5.

$$E_{batt}|_{45\%DoD} = \frac{E_{batt}|_{annual}}{0.45} = \frac{135.7kWh}{0.45} = 301.5kWh \tag{4.5}$$

With a battery voltage of 725.2V, this translates into battery capacity of 415.7Ah.

$$Q_{batt} = \frac{E_{batt}}{U_{batt}} = \frac{301.5kWh}{725.2V} = 415.7Ah \tag{4.6}$$

4.7 Scope of Simulations

Strategy 2 gives a battery capacity that is sufficient to provide the required energy for all 366 days in the dataset. However, by using Strategy 1, battery capacity is expected to be insufficient for 8 days, all situated in the winter. In these 8 cases, the transformer will therefore be subjected to an elevated load for short periods.

Week	Date	$E_{batt}[kWh]$
48	28.11.15	241.0
50	13.12.15	236.2
52	23.12.15	233.2
	24.12.15	242.0
	25.12.15	227.2
	26.12.15	288.1
53	31.12.15	262.7
	03.01.16	251.0

Table 4.1: The distribution of days with needed battery capacity above 226.7kWh, which occurs in week 48, 50, 52 and 53

These 8 days all occur in the winter, during the weeks with number 48, 50, 52 and 53. Four simulations will therefore be done, one for each week, in order to determine the extra load subjected to the transformer due to insufficient battery capacity in these 8 days.

In addition to the four simulations covering the overload cases, three cases covering periods of low load, high load and low battery capacity requirements are also simulated.

In sum, the following cases are to be simulated.

1. Low load: Week 30
2. High load: Week 1
3. Low battery capacity need: Week 6
4. High battery capacity need: Week 48, 50, 52 and 53

Chapter 5

Results

5.1 Simulation Software Evaluation

Software	Cost	Load flow calculations from field data	Battery modelling	Documen-tation	Learning time	Support	User base	Level of proprie-tarism
Open dss	Free	Yes	Yes	Moderate	High	No formal support program	Low	Low
Modelica	Free	Yes	Yes	Moderate	High	No formal support program	Low	Low
Siemens PSS Sinkal	Free (time limited student license)	Yes	Yes	Low	High	Yes	Moderate	High
MATHLAB Simulink	Free (time limited student license)	Yes	Yes	High	Moderate	Yes	High	Moderate

Figure 5.1: Package Characteristics of the Software

Four types of software are evaluated, of which all is considered to be suitable for simulating a battery's dynamic response to varying energy consumption data. Siemens PSS Sinkal's biggest drawback is that it is a proprietary package. At the other end of the scale are Open DSS and Modelica that both offer open source software, but more specialized models and technology need a license. MATLAB Simulink is believed to have the biggest user base and is well documented through manuals and tutorials, and offers a very good support service. This software also requires a license, but it is available at HVL, and it is used for the simulations done in this report.

5.1.1 MATLAB

MATLAB is a mathematical software commonly used by engineers. It is developed by Mathworks and used for plotting functions, data and algorithms, and can solve a whole variety of mathematical problems. It has its own script language that is based on the C programming language.

5.1.2 Simulink

Simulink is also developed by Mathworks and is a graphical programming environment based on the MATLAB software. It uses the programming language of MATLAB and incorporates this into customizable dynamic blocks. These blocks can be linked together to build a dynamic system that can be used for creating models, simulations and analysis.

5.1.3 Simscape

Simscape is built on top of Simulink and MATLAB and can be used to simulate physical systems like mechanical, hydraulic and electrical systems among others. Simscape Power Systems contains component libraries and tools for modelling and analysis og electrical power systems.

5.1.4 Simulation Time

The model is built with the ability to run a seven-day simulation with data at an hourly resolution, i.e. $24 \cdot 7 = 168$ discrete measurements. However, due to the the dynamic response of the battery block, simulation is run in continuous mode.

5.2 Simulation Model Architecture

Figure 3.16 shows a diagram the simulation model, which illustrates the working principle. It is consists of four sections:

1. The Load Section
2. The Battery Section
3. The Summation Point Section
4. The Transformer Section

The simulation model imports the energy consumption curves through the load section and converts this to a load current (I_{load}). This is fed as reference to the battery section that calculates the necessary battery currents ($I_{discharge}/I_{charge}$) to perform peak shaving service. The load current and battery currents are compared in a summation point, which calculates the transformer current ($I_{transformer}$). In the transformer section the transformer current is converted back to power and energy consumption.

With a properly sized battery the variability of the load profile should be smoothed out so that the transformer is subjected to a load profile that contains the same energy, but without the variability.

This is enabled by the logic embedded in the battery section, which calculates the average load from the given day being simulated. This creates a smooth load curve, but with the same area.

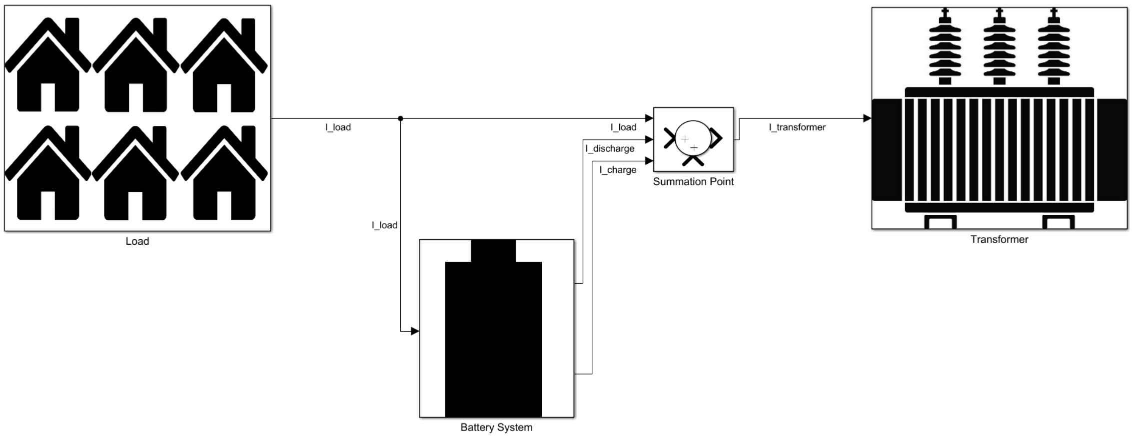


Figure 5.2: A diagram of the of the simulation model.

5.2.1 The Load Section

The first section of the model handles the load profile import. By double clicking the load icon, three outputs becomes available:

- Load Profile [kW]
- Load Profile [W]
- Load Profile [A]

Using the imported load profile, power and current are calculated according to the principles described in section 3.7.2.

The load profiles are imported using switches that triggers on an hourly basis. The model is capable of running simulations for 7 consecutive days. The switches are set to activate its respective value at a given time, to form the load profile.

The data is imported in excel from the Smart Valley database. The switches in the load section are linked to the excel document using different scripts - one script for each simulation.

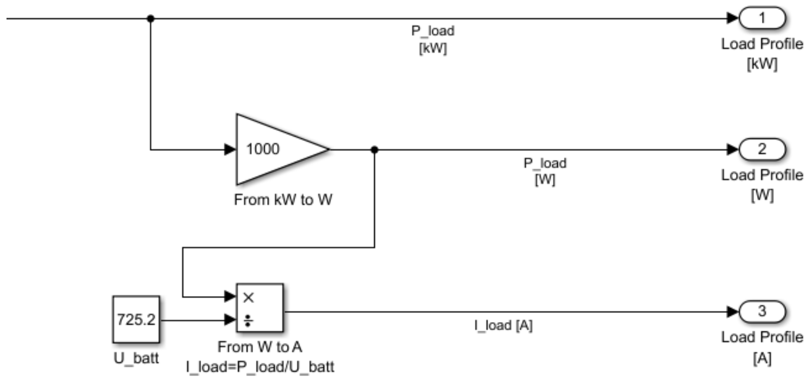


Figure 5.3: Load profile conversions

5.2.2 The Battery Section

Using the load current calculated in the load section as reference, the battery section does the necessary calculations to perform peak shaving. It consists of:

- Average Power Subsystem
- Power to Current Conversion Subsystem
- Battery Control Logic Subsystem
- Battery Dynamic Subsystem

Figure 5.4 shows the battery section, with the average power calculation subsystem that extracts the average power from the load profile, which is converted to current in the power to current subsystem. The logic subsystem controls the battery, and the battery subsystem contains the battery dynamics. The SoC status from the battery subsystem serves as feedback and is connected to the input of the logic subsystem.

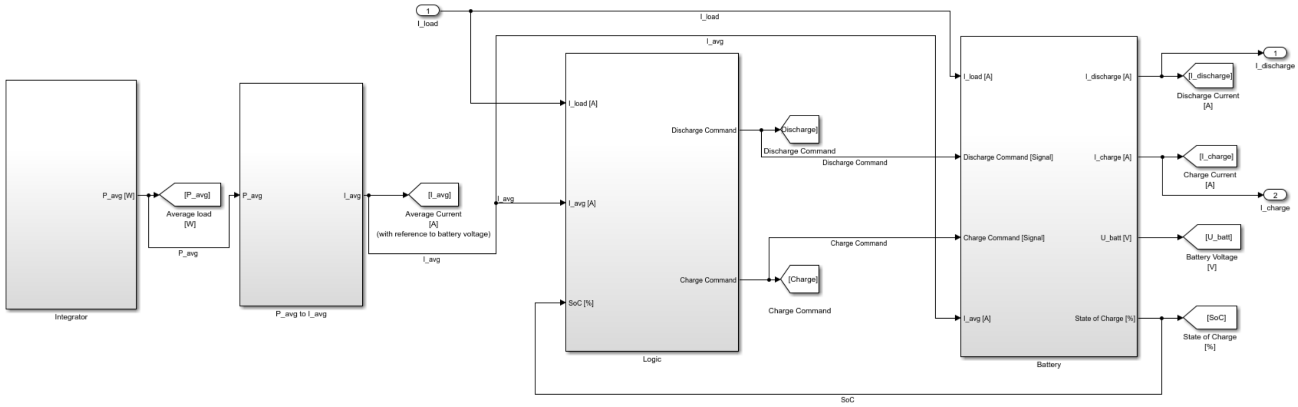


Figure 5.4: The battery section.

Average Power

In addition to the load current input coming from the load section, a secondary input (P_{avg}) is extracted from the excel data sheet. Similar to the load profile import, the use of switches is used to assign the correct P_{avg} to the day of simulation, and the link to the excel document is also determined by the script.

Power to Current Subsystem

The average current is calculated from average power using the nominal battery power as explained in section 3.7.2.

Logic Subsystem

The logic uses three inputs to determine whether the battery will charge or discharge.

- Load current calculated in the load section
- Average current calculated from average power
- SoC calculated in the battery dynamic subsystem, and serves as feedback.

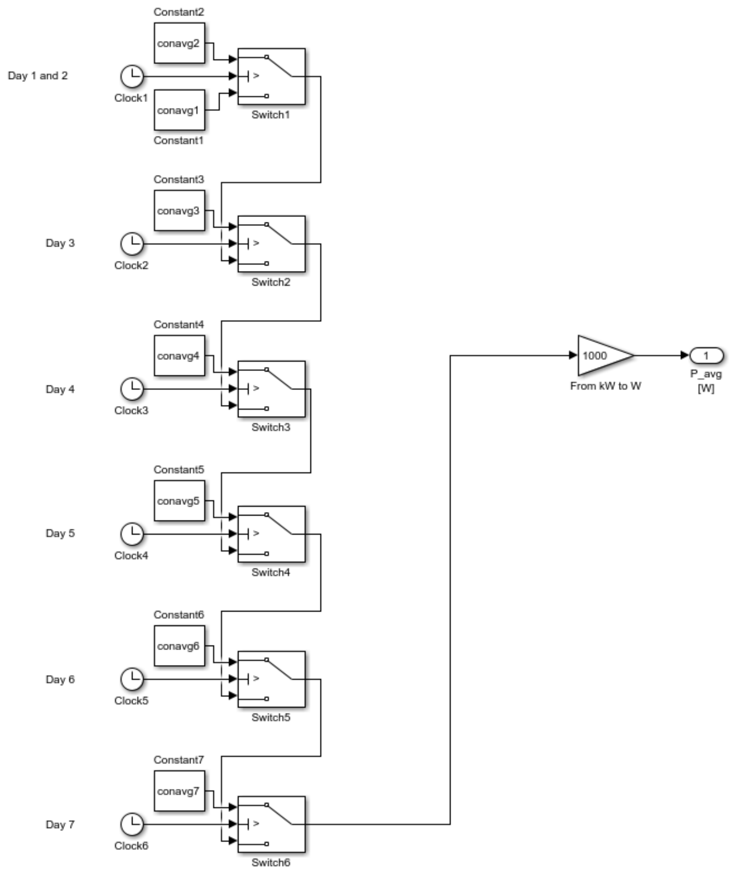


Figure 5.5: The average power subsystem.

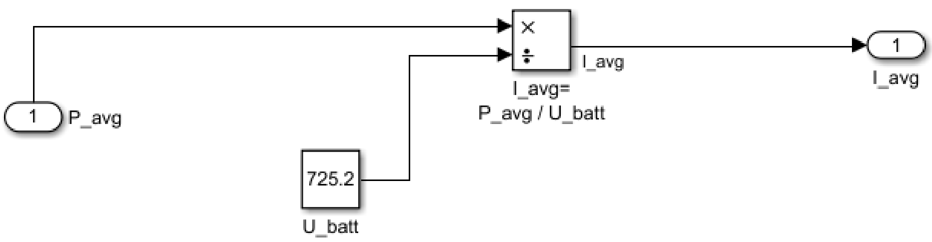


Figure 5.6: The power to current conversion subsystem

Figure 5.7 shows the battery control logic with three inputs, (SoC, I_{load} and I_{avg}) giving the criteria for the two output signals - charge command and discharge command. To explain the battery logic, Strategy 1 - 60% DoD is used as an example.

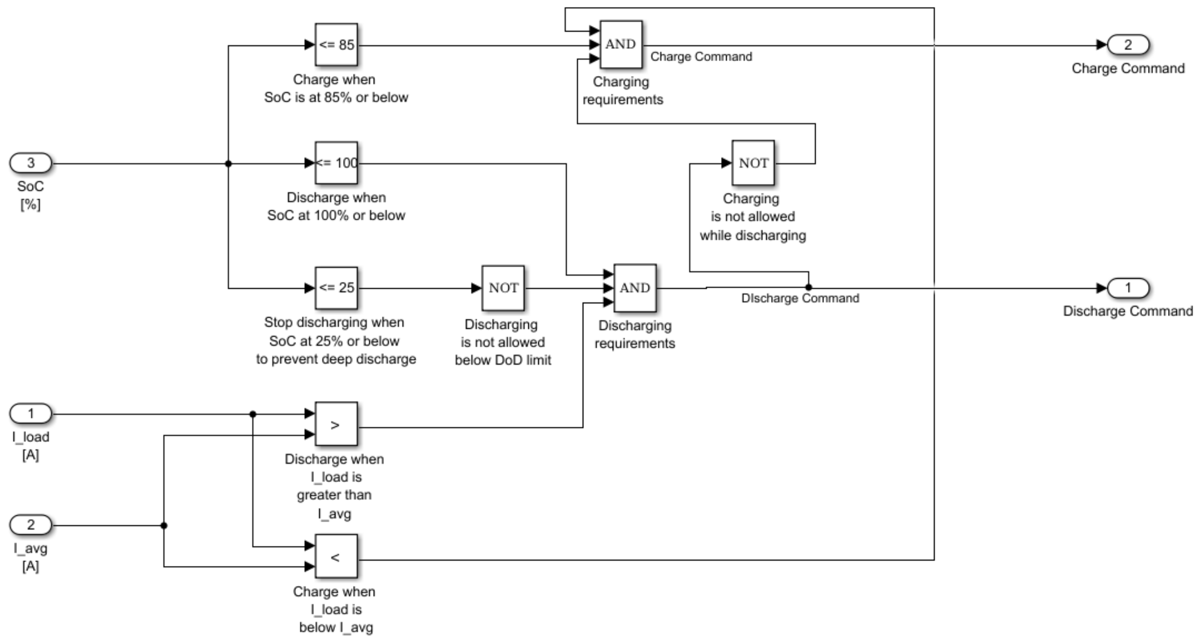


Figure 5.7: The battery control logic subsystem.

<u>Discharge when</u>

- $25\% \geq \text{SoC} \geq 100\%$
  Battery discharge is set to never go below 25% to prevent deep discharge. Upper charge limit is set to 85%, but if the battery charge is to exceed this limit (due to a fault), discharge must still be allowed. Upper discharge limit is therefore set to 100%.

- $I_{load} > I_{avg}$
  Battery discharge is allowed when the load current is greater than the average current for the day of simulation.

When both of the criteria above is fulfilled, a discharge command is activated and sent to the battery dynamics subsystem.

<u>Charge when</u>

- Discharge signal $\neq 1$
  Charging and discharging cannot occur at the same time. If the requirements for battery discharge as mentioned above are active, charging will not begin.

- SoC $\leq 85\%$
  Due to DoD and overcharge limits, charging is set to when SoC is equal to or between 0% and 85%. If SoC should drop below 25%, either due to self-discharge or a fault in the discharge limiter, charging must still be allowed. No lower limit for charging is therefore set. Self-discharge is seldom a problem with Li-ion batteries, but is included here as a precaution.

- $I_{load} \leq I_{avg}$
  Battery charging is allowed when the load current is lower than the average current.

When these three criteria are fulfilled, a battery charge signal is activated and sent to the battery dynamics subsystem.

Battery Dynamics Subsystem

The battery dynamics subsystem has four inputs providing the information needed for battery current calculations, which are used to control two current sources connected to the battery block. There are four outputs coming from both the current sources and the battery block. This subsystem can therefore be said to consists of two main parts:

- Battery current calculations

- Battery block with controlled current sources

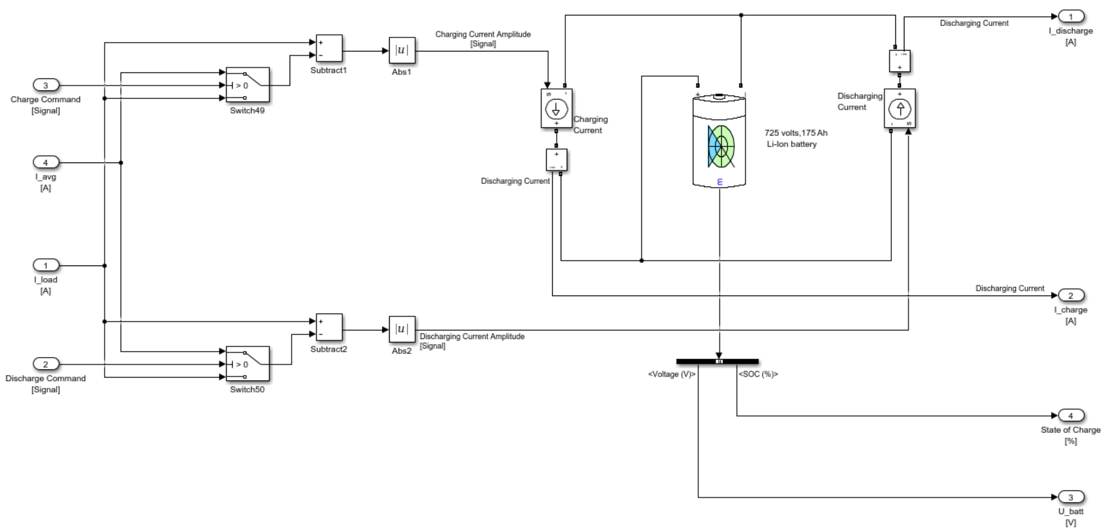


Figure 5.8: The battery dynamics subsystem.

Figure 5.8 shows the battery dynamic subsystem, with four inputs (I_{load}, I_{avg}, charge command and discharge command), battery amplitude calculations, current sources, the battery block and four outputs ($I_{dicharge}$, I_{charge}, SoC and U_{batt}).

The charging and discharging signal coming from the logic subsystem serves as triggers for two switches that is used to calculate the charging and discharging currents. As long as the trigger signal is 0, the switch is in default position, giving current amplitude 0. When the trigger signal is 1, the difference between I_{load} and I_{avg} is calculated and is fed as a current amplitude signal to the controlled current source.

Two current sources are connected to the battery block, simulating the charging and discharging currents, respectively. One current is connected to the positive terminal of the battery block, creating the charging current with the amplitude according to the calculations explained above, charging the battery and increasing SoC.

The second current source is connected to the negative battery terminal acting as the discharging current with an amplitude as explained above, discharging the battery and reducing the battery SoC. Both battery currents are used as outputs and sent to the summation point to calculate the transformer currents.

SoC is also used as output and feedback to the battery control logic subsystem, as well as battery voltage that is used for validation purposes.

The battery current charges and discharges the battery block according to the capacity that is defined in the properties settings, and using the battery dynamics embedded in the battery block, the SoC dynamic is plotted.

5.2.3 The Transformer/Summation Point Section

The transformer current ($I_{transformer}$) is calculated according to the equations 3.14 and 3.15 in section 3.7.4. As $I_{discharge}$ will reduce $I_{transformer}$, this is subtracted from I_{load}. And vice versa, I_{charge} increases $I_{transformer}$ and therefore comes in addition to I_{load}.

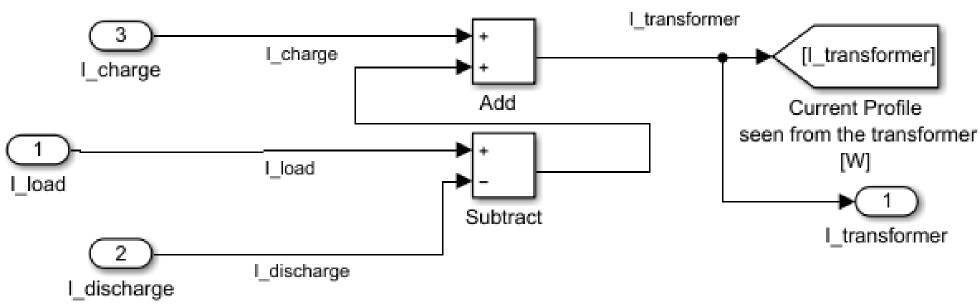


Figure 5.9: The summation point with its three inputs I_{load}, I_{charge} and $I_{discharge}$, which is used to calculate $I_{transformer}$

Furthermore, the transformer current is used to calculate the load and energy consumption subjected to the transformer using the same principles as in the load section and explained with the equations 3.5 - 3.8.

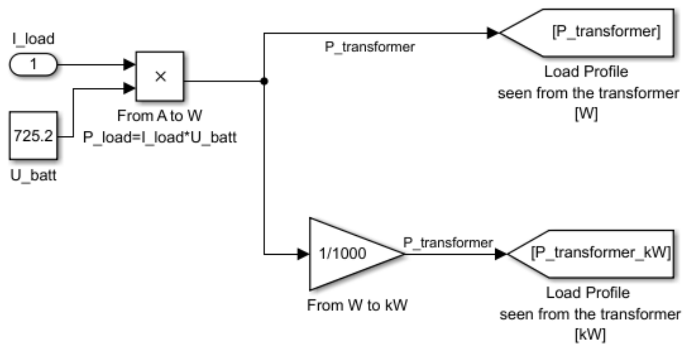


Figure 5.10: The transformer and the calculation of $P_{transformer}$ using $I_{transformer}$ and U_{batt}.

5.3 Battery Block Implementation

In order to implement the working principle of the battery block into the model, two types of experimental tests are conducted. Firstly, the dynamic response is tested using a pulse discharge test. Using the plot from the dynamic response, battery parameters are calculated manually and then compared to the values presented by the battery block.

Secondly, three full discharge tests are conducted to ensure that the correct voltage level and current amplitude are applied in the model, so that the battery block responds according to the desired use, and with the energy capacity needed.

5.3.1 Pulse Discharge Test

Battery Parameters

By conducting a pulse discharge test it is possible to extract the parameter values of a given battery cell. In order to employ the battery block in the simulation model, a pulse discharge test is conducted to a single Li-ion battery cell using the battery block from the Simscape Library. By evaluating the voltage response, it is possible to determine the internal resistance R_0 and the time constant (RC-element) of the battery. The instantaneous voltage response gives us R_0 and the dynamic voltage response gives us R_1 and C_1.

Using the following method, the parameters of a battery equivalent circuit with one time constant is determined. The test is conducted using a controlled current source connected to the battery terminals, creating a discharge current.

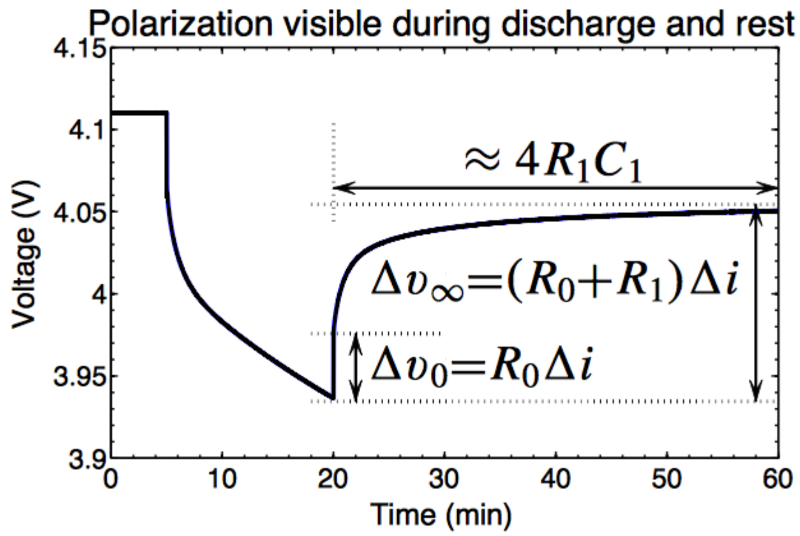


Figure 5.11: An illustration of how it is possible to extract battery parameters from the dynamic response created by a pulse discharge test [7, p.2-10].

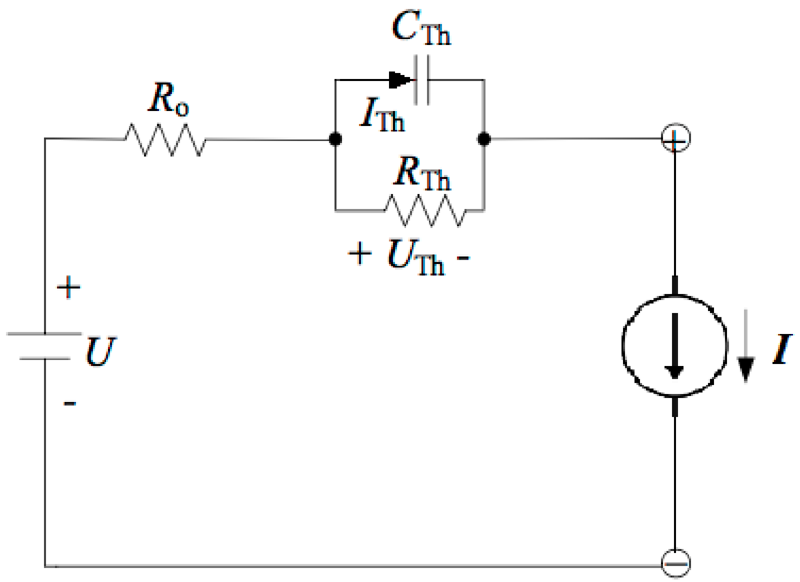


Figure 5.12: Discharge pulse test equivalent circuit with battery parameters and a currents source connected to the battery terminals.

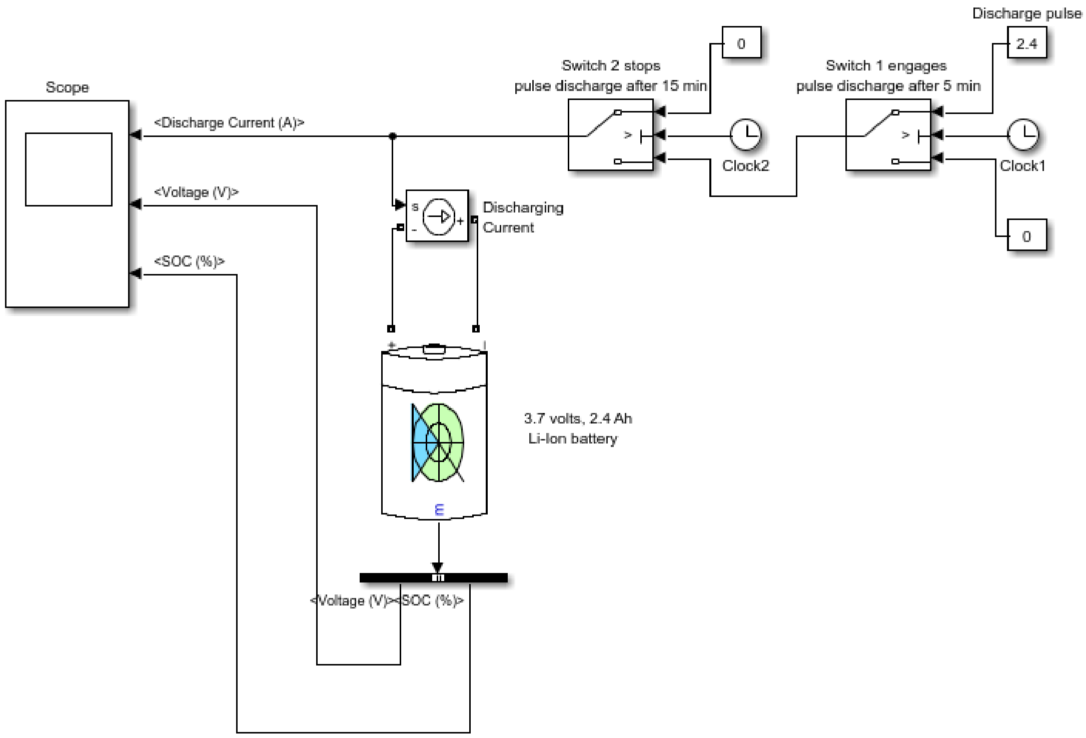


Figure 5.13: Discharge pulse test model set-up with a controlled current source connected to the battery terminals of a 3.7V, 2.4Ah battery cell.

1. **Conduct a pulse test**
   A single Li-Ion cell with Q=2.4Ah and U_{batt}=3.7V is subjected to a 1C discharge current (2.4A) for 15 minutes, in the interval between 5 minutes (300s) and 20 minutes (1500s) after t=0. This reduces the SoC by 25%, the voltage drops to 3.95V during discharge, before returning to 3.99 Voc when the current is removed. Figure 5.14 shows the current step, voltage response and SoC from $t = 0$ to $t = 2000s$.

2. **Calculation of R_0**
   The instantaneous voltage drop is caused by R_0 and can be found at $t = 300s$ and $t = 1500s$. R_0 can be extracted from both of these points. Figure 5.15 shows the current step from 2.4 to 0A at $t = 1500s$. R_0 can be calculated using the following formula.

$$\Delta U_0 = R_0 \cdot \Delta I \tag{5.1}$$

$$R_0 = \frac{\Delta U_0}{\Delta I} = \frac{3.957V - 3.921V)}{2.400A} = 0.015\Omega \tag{5.2}$$

3. **Calculation of R_1**
   From the steady state voltage, R_1 can be deduced.

$$\Delta U_\infty = (R_0 + R_1) \cdot \Delta I \tag{5.3}$$

$$R1 = \frac{\Delta U_\infty}{\Delta I} - R_0 = \frac{3.998V - 3.957V)}{2.400A} - 0.015\Omega = 0.002\Omega \tag{5.4}$$

4. **Calculation of C_1**
   Steady state occurs at $t = 1560s$, which gives $\Delta t = 60s$ from the time of the current step to the voltage has stabilized. The pulse response converges to steady state after 4 time constants, which makes it possible to deduce C1.

$$\Delta t = 4 \cdot R_1 C_1 \tag{5.5}$$

$$C_1 = \frac{\Delta t}{4R_1} = \frac{60s}{4 \cdot 0.002\Omega} = 7.2kF \tag{5.6}$$

This also gives the time constant.

$$\tau = R_1 C_1 = 2 \cdot 10^-3\Omega \cdot 7.2 \cdot 10^3 = 15s \tag{5.7}$$

Battery Pack Wiring

The RC-element parameters are not available in the battery block, but R_0 is displayed in the battery block properties. For a single cell Li-Ion battery cell, the block confirms a value of $R_0 = 0.015\Omega$ with a cell voltage of 3.7V and capacity of 2.4Ah. By wiring the cell in series and parallel the voltage, capacity and inner resistance varies according to the table in Appendix 8.4.

Table 8.12 shows some wirings schemes that achieves different battery capacities. The results are cross checked with battery block calculations and with a data sheets from the battery producer LG Chem [33, p.9].

The first row show the voltage, capacity and inner resistance of a single LiFePO4 cell. LG Chem provides modules of 51.8 V and a capacity of 62.4 Ah. By wiring 14 cells in series, the desired voltage is achieved, and by wiring 26 of these in parallel, the desired capacity is achieved.

A similar approach is used to build the entire battery packs. By combining the modules in different combination of series and parallel, several battery packs are achieved.

Figure 8.13 to 8.17 in Appendix 8.4 shows the change of properties in the battery block as the voltage and capacity is increased.

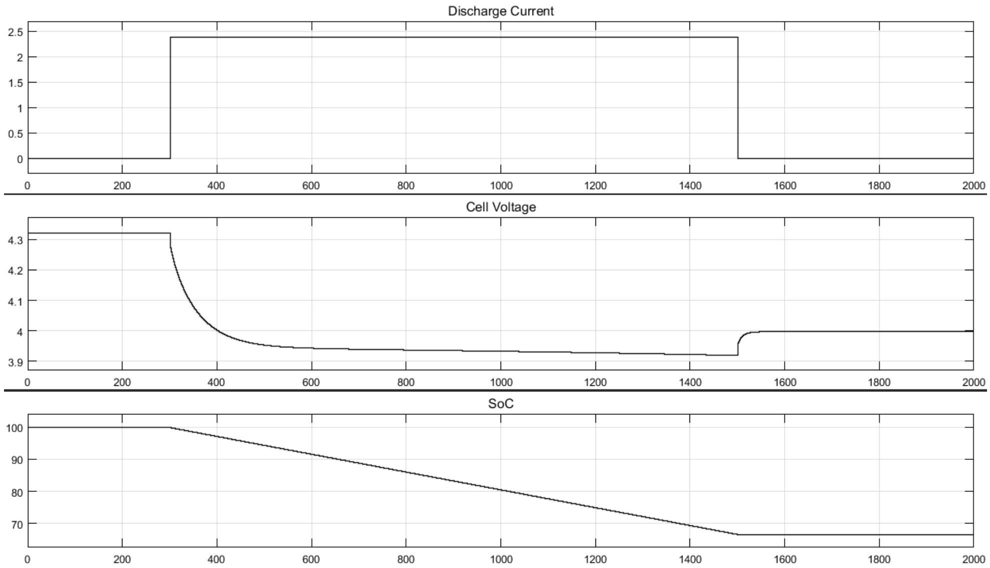


Figure 5.14: Battery cell response for the entire test period of 2000s. At t=300s (5min) the discharge pulse of 2.4A activates and lasts for a duration of 15 minutes and ends at t=1500s. An additional time of 500s is included in the test for steady state to occur.

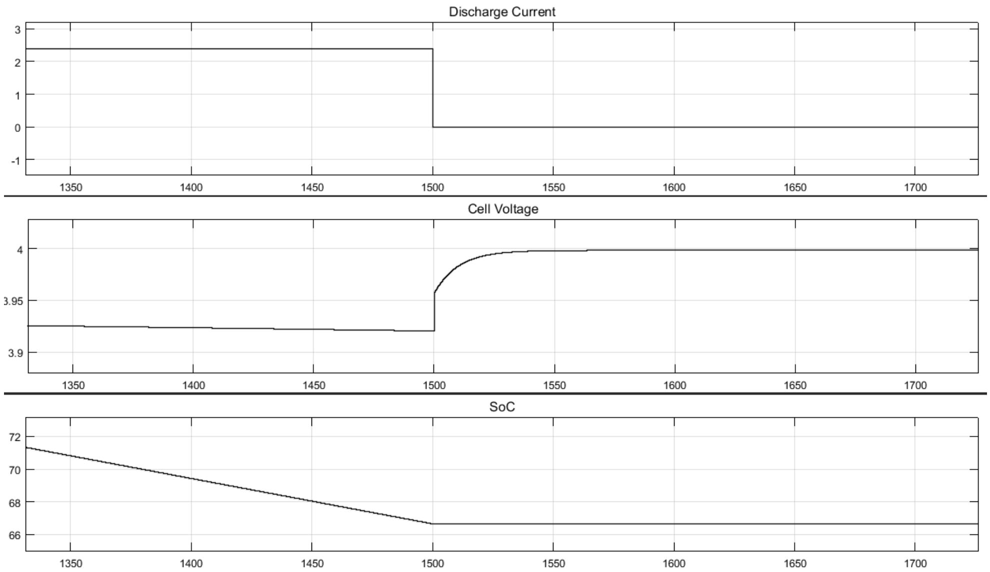


Figure 5.15: Voltage response at t=1500s. By extracting values from this plot it is possible to calculate the battery parameters. R_0 is calculated from the instantaneous response, R_1 and C_1 and τ is calculated from the dynamic response.

5.3.2 Full Discharge Tests

Using battery storage data sheet from LG Chem as a cross reference, a discharge test is conducted using a 196x26 cell combination according to table 8.12, giving an energy content of 45.3kWh with a nominal battery voltage 752.2V and a nominal capacity 62.4Ah.

Figure 5.16 shows the model set-up for the test with a 1C discharge current. The set-up is identical for all discharge tests, with the discharge power ($P_{discharge}$) being the input that is altered to give the different C-rates.

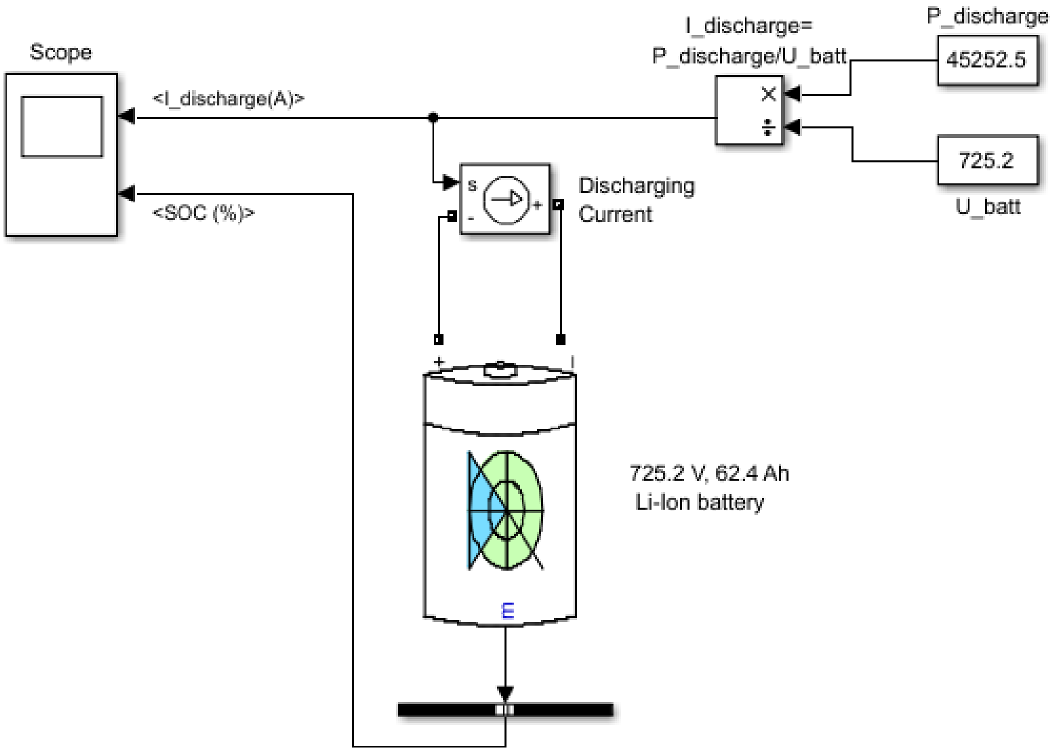


Figure 5.16: Full discharge model set-up with a controlled current source connected to the negative battery terminal. The discharge current amplitude is calculated using the discharge power with nominal battery voltage as reference. Discharge current and SoC is connected to a scope.

Three discharge tests where conducted using discharge currents of 0.5C, 1C and 2C, where a discharge current of 1C is expected to result in a full capacity discharge in 1h. As the simulation model is built using load power curves as input for load current, power is therefore also used as reference in these tests.

0.5C Discharge Current

A discharge current of 0.5C should give a full capacity discharge in 2h. As the rated capacity of the battery in the discharge test is 62.4Ah, a 0.5C discharge current is calculated to 31.2A.

$$I_{discharge} = \frac{Q}{t} = \frac{62.4Ah}{2h} = 31.2A \tag{5.8}$$

With the nominal battery voltage of 725.2V, this discharge current will give a discharge power of 22626.2W.

$$P_{discharge} = U_{batt} \cdot I_{discharge} = 725.2V \cdot 31.2A = 22626.2W \tag{5.9}$$

The results can be seen in figure 5.17, where a 0.5C discharge current ($I_{discharge} = 31.2A$) for a duration of 2h gives a full battery discharge.

1C Discharge Current

A discharge current of 1C should give a full capacity discharge in 1h.

Discharge current:

$$I_{discharge} = \frac{Q}{t} = \frac{62.4Ah}{1h} = 62.4A \tag{5.10}$$

Discharge power:

$$P_{discharge} = U_{batt} \cdot I_{discharge} = 725.2V \cdot 62.4A = 45252.5W \tag{5.11}$$

The results can be seen in figure 5.18, where a 1C discharge current ($I_{discharge} = 62.4$) for a duration of 1h gives a full battery discharge.

2C Discharge Current

A discharge current of 2C should give a full capacity discharge in 0.5h.

Discharge current:

$$I_{discharge} = \frac{Q}{t} = \frac{62.4Ah}{0.5h} = 124.8A \tag{5.12}$$

Discharge power:

$$P_{discharge} = U_{batt} \cdot I_{discharge} = 725.2V \cdot 124.8A = 90505W \tag{5.13}$$

The results can be seen in figure 5.19, where a 2C discharge current ($I_{discharge} = 124.8$) for a duration of 0.5h gives a full battery discharge.

Figure 5.17, 5.18 and 5.19 verifies that the use of the nominal battery voltage as reference when calculating discharge current from the discharge power, gives correct discharge characteristics with the battery block. Tests where also conducted using internal cell voltage as reference, but this proves not to be a valid solution, as this gives increased discharge current with falling voltage, leading to premature battery discharge and under performance by the battery block.

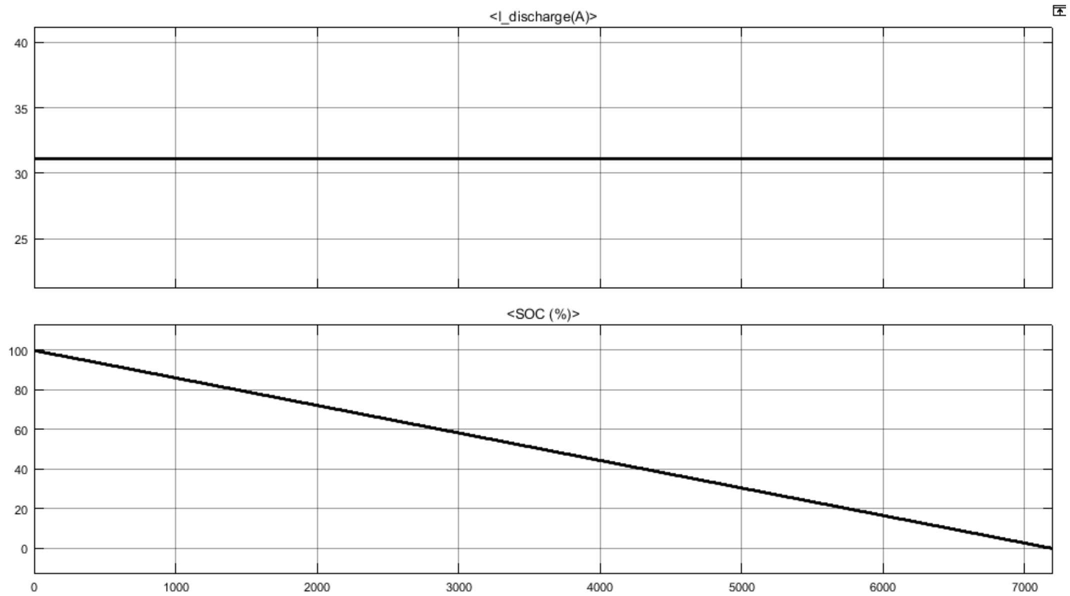


Figure 5.17: Discharge current and SoC at 0.5C. $I_{discharge} = 31.2A$ and SoC drops from 100% to 0% in 7200s (2h).

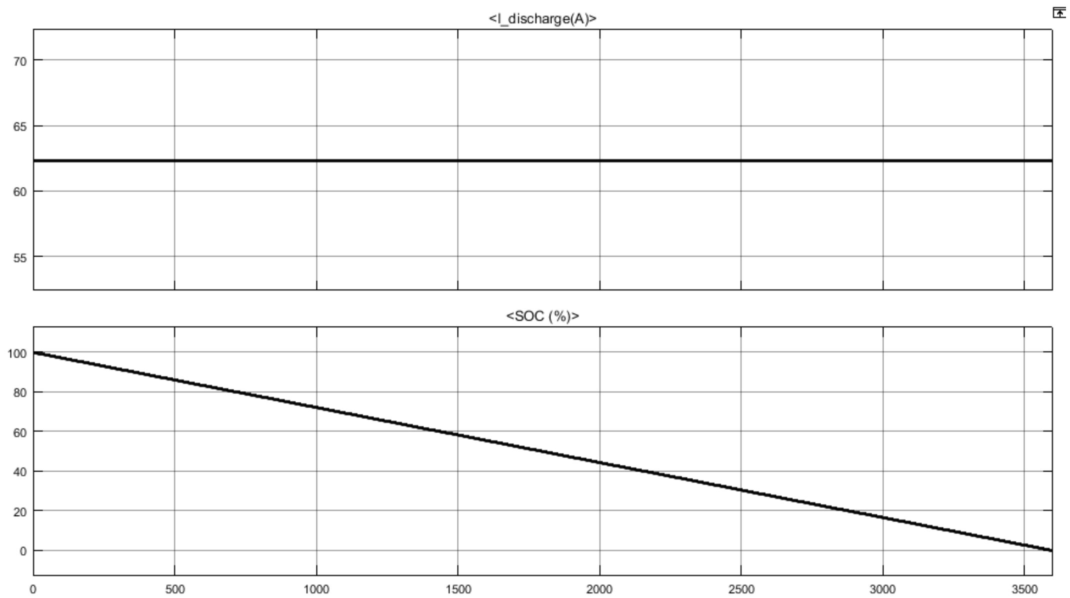


Figure 5.18: Discharge current and SoC at 1C. $I_{discharge} = 62.4A$ and SoC drops from 100% to 0% in 3600s (1h).

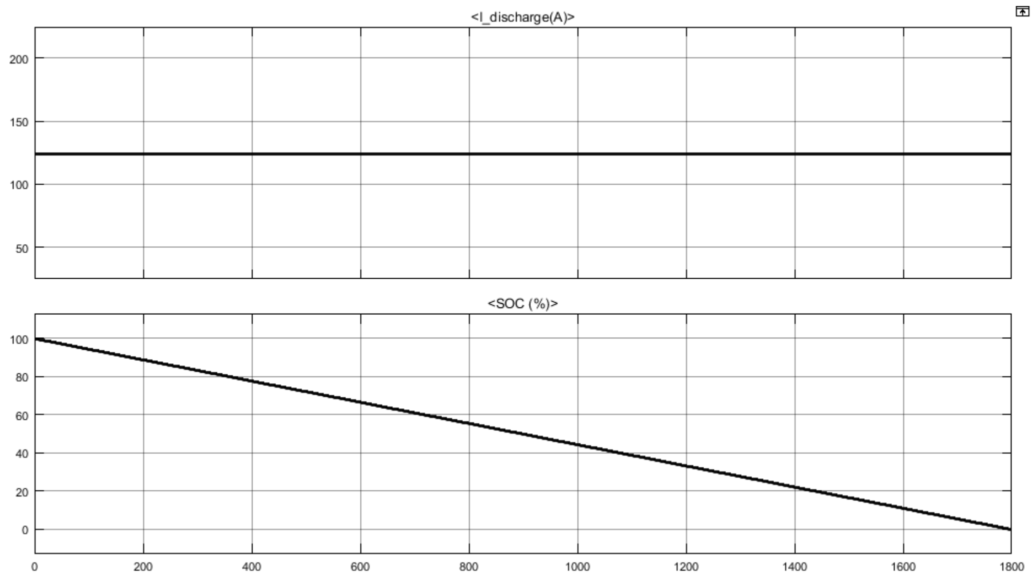


Figure 5.19: Discharge current and SoC at 2C. $I_{discharge}$ = 124.8 and SoC drops from 100% to 0% in 1800s (0.5h).

5.4 Simulations

Four cases are simulated to cover the extremities of the year to validate the battery dimensioning strategies using the annual average consumption as reference.

1. Low load: Week 30
2. High load: Week 1
3. Low battery capacity need: Week 6
4. High battery capacity need: Week 52, 53, 50 and 48

The data used in the following simulations are presented in the tables in figure 5.20, 5.27, 5.34, 5.41, 5.48, 5.55 and 5.62. These tables are load profiles from the 45 households in the Smart Valley dataset. Each table presents the data used in one simulation of seven days, using data with an hourly resolution - 24 measurements a day. The results are presented on the following figures and visualizes the load profile, the battery charge/discharge calculated using the principles explained in section 3.6, the dynamic battery response in SoC and the load seen from the transformer. All scopes show time in seconds on the x-axis.

5.4.1 Case 1 - Low Load

The day of the year with lowest load in the dataset occurs Monday 25.07.2015 at 07:00 of week number 30. The entire week is simulated to achieve a cohesive simulation that includes the transition between the days.

hour	P_load Week 30 [kW]						
	Monday 25.07.2016	Tuesday 26.07.2016	Wednesday 27.07.2016	Thursday 28.07.2016	Friday 29.07.2016	Saturday 30.07.2016	Sunday 31.07.2016
01:00	61.2	56.9	60.9	70.6	83.1	83.7	73.1
02:00	53.8	52.3	59.9	61.7	70.5	68.4	63.2
03:00	38.7	42.5	48.3	49.5	55.2	52.7	60.8
04:00	39.2	37.4	40.7	48.8	51.7	53.6	50.4
05:00	34.6	37.6	38.4	47.5	44.6	48.8	42.6
06:00	34.0	33.3	38.1	44.0	44.3	44.9	43.9
07:00	30.3	37.6	41.8	41.2	44.5	46.9	43.8
08:00	40.4	38.3	41.4	48.6	45.4	52.0	48.9
09:00	43.5	42.0	49.4	53.6	56.2	47.2	50.3
10:00	44.7	47.7	50.6	64.9	63.5	70.8	58.5
11:00	53.2	70.3	70.4	70.2	86.8	88.3	69.3
12:00	61.0	70.7	71.1	78.6	88.8	99.0	66.8
13:00	62.2	71.2	83.7	85.4	94.2	92.6	76.8
14:00	72.2	72.6	82.8	76.8	76.8	74.9	70.7
15:00	72.6	67.8	79.2	72.8	79.9	64.3	69.8
16:00	63.3	65.2	74.0	82.1	84.1	54.7	77.8
17:00	72.6	71.9	81.5	87.6	80.2	66.0	55.3
18:00	68.8	68.7	84.6	98.8	93.0	66.5	61.2
19:00	67.7	69.9	83.7	91.7	82.0	69.0	60.2
20:00	69.2	82.6	77.4	83.9	85.9	92.8	67.0
21:00	73.7	78.9	77.8	82.0	72.3	92.7	72.1
22:00	84.1	74.9	79.4	84.7	77.7	84.5	67.7
23:00	81.9	79.9	81.5	85.4	72.6	74.1	67.1
00:00	68.2	70.8	75.2	87.0	75.8	77.7	70.5

Figure 5.20: P_{load} for week 30. Measurements once every hour for 7 days, Monday 23.11.15 to Sunday 29.11.15.

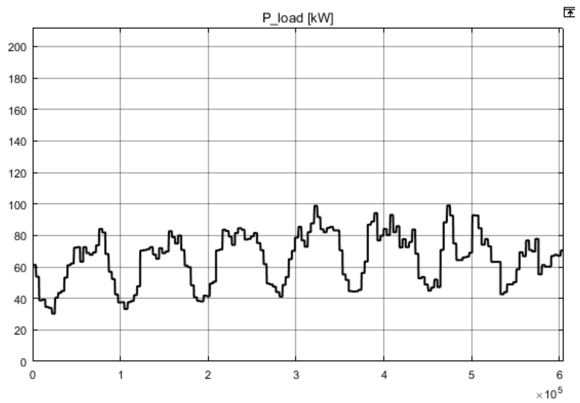


Figure 5.21: P_{load} for week 30.

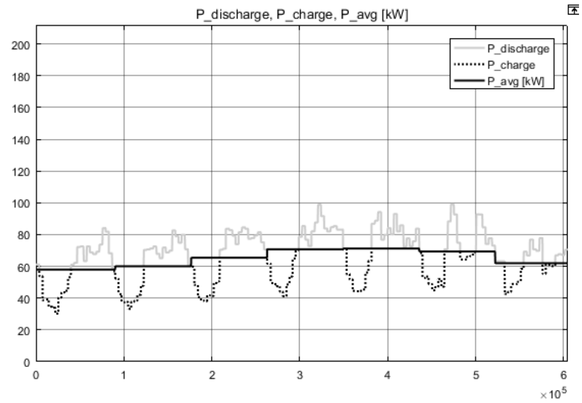


Figure 5.22: Battery discharge and charge in week 30.

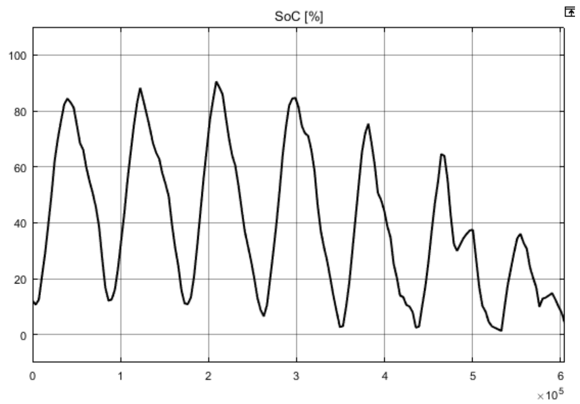


Figure 5.23: Battery SoC for week 30 with 60% DoD.

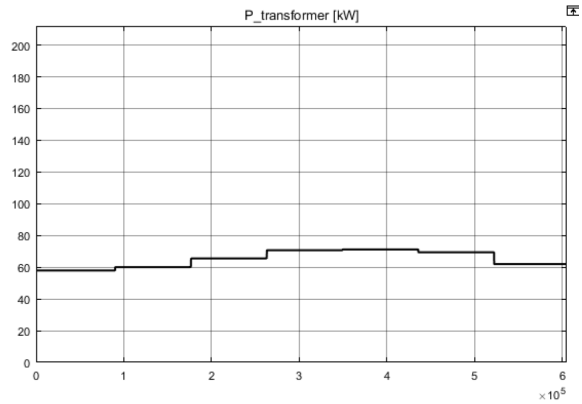


Figure 5.24: $P_{transformer}$ for week 30 with 60% DoD.

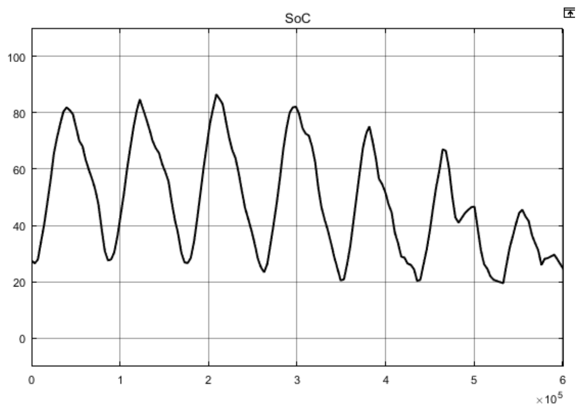


Figure 5.25: Battery SoC for week 30 with 45% DoD.

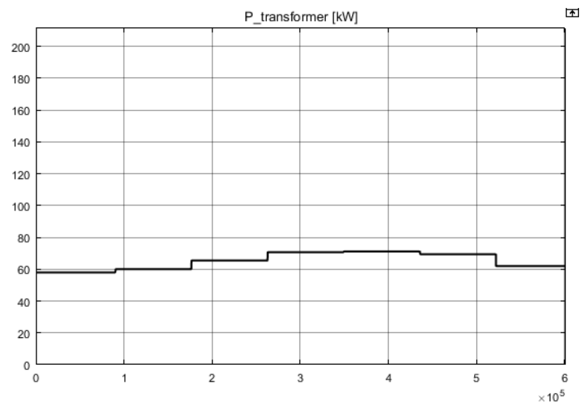


Figure 5.26: $P_{transformer}$ for week 30 with 45% DoD.

5.4.2 Case 2 - High Load

hour	P_load Week 1 [kW]						
	Monday 04.01.2016	Tuesday 05.01.2016	Wednesday 06.01.2016	Thursday 07.01.2016	Friday 08.01.2016	Saturday 09.01.2016	Sunday 10.01.2016
01:00	130.1	157.2	147.9	159.2	161.6	183.9	179.7
02:00	119.5	138.1	128.6	148.5	146.4	174.1	170.7
03:00	114.7	123.6	127.7	140.3	138.4	160.9	158.5
04:00	116.9	119.9	122.2	131.2	134.9	155.5	156.3
05:00	108.2	124.0	121.2	132.0	136.1	155.9	147.9
06:00	113.6	122.9	122.9	133.9	137.1	152.3	147.9
07:00	113.3	119.7	123.3	134.6	141.6	147.1	150.6
08:00	130.4	134.5	129.9	149.9	145.2	154.3	147.7
09:00	131.5	138.7	142.5	153.3	159.5	156.6	151.5
10:00	132.2	143.0	147.2	158.7	155.7	163.7	156.6
11:00	142.2	142.3	152.9	164.9	171.3	182.2	177.5
12:00	147.7	147.1	155.3	161.5	168.1	189.5	185.2
13:00	150.9	151.6	154.3	163.4	168.2	200.0	195.8
14:00	141.7	140.9	144.8	161.4	158.2	190.2	189.7
15:00	140.7	135.8	143.6	154.5	155.7	179.4	181.2
16:00	146.9	142.5	155.0	162.2	155.8	183.1	184.4
17:00	156.6	154.3	159.1	165.6	165.6	188.7	189.9
18:00	148.5	159.6	167.6	167.4	185.7	199.4	190.8
19:00	161.0	165.6	176.0	176.9	185.9	194.9	183.7
20:00	169.3	172.1	188.8	174.5	187.4	209.2	172.8
21:00	171.6	171.8	192.5	176.3	200.0	205.4	162.4
22:00	170.3	173.1	193.2	190.4	189.9	202.5	162.5
23:00	170.8	170.1	185.4	176.2	181.3	181.9	157.0
00:00	170.8	161.2	164.1	166.4	179.6	179.1	151.5

Figure 5.27: P_{load} for week 1. Measurements once every hour for 7 days, Monday 04.01.16 to Sunday 10.01.16.

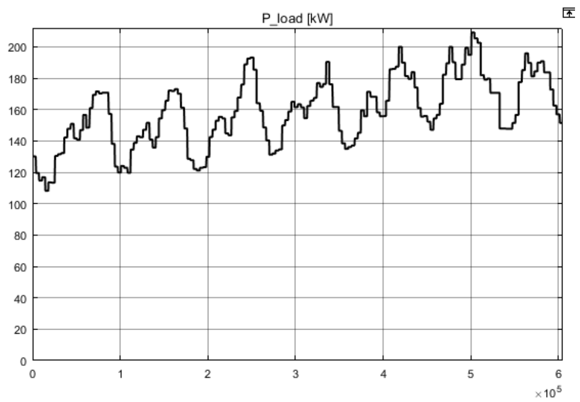


Figure 5.28: P_{load} for week 1.

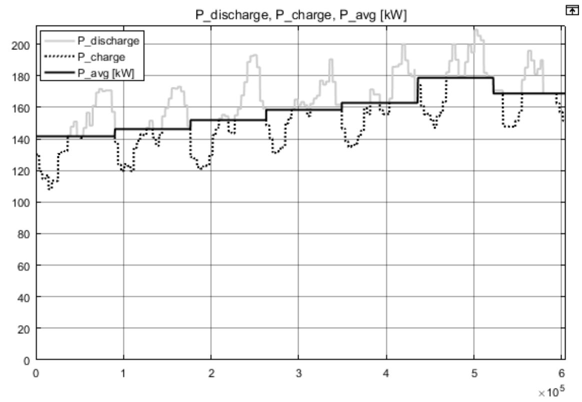


Figure 5.29: Battery discharge and charge in week 1.

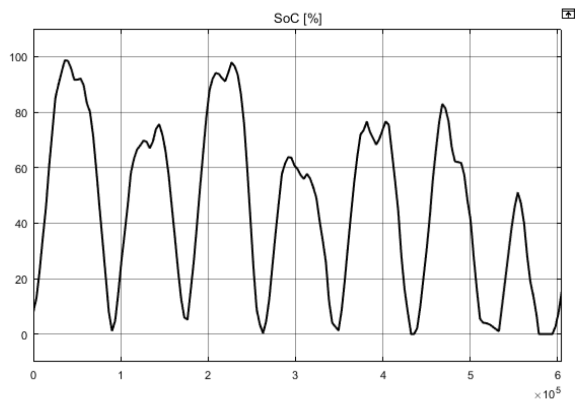


Figure 5.30: Battery SoC for week 1 with 60% DoD.

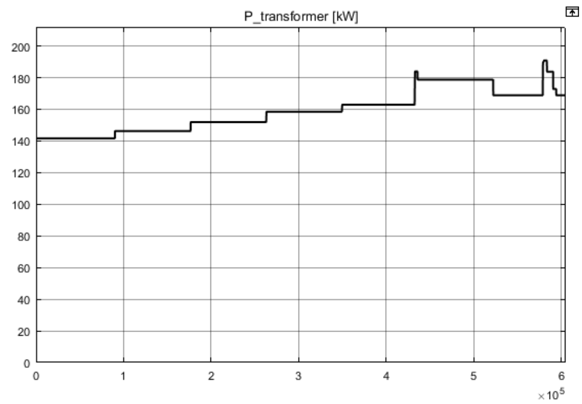


Figure 5.31: $P_{transformer}$ as a result of peak shaving with 60% DoD.

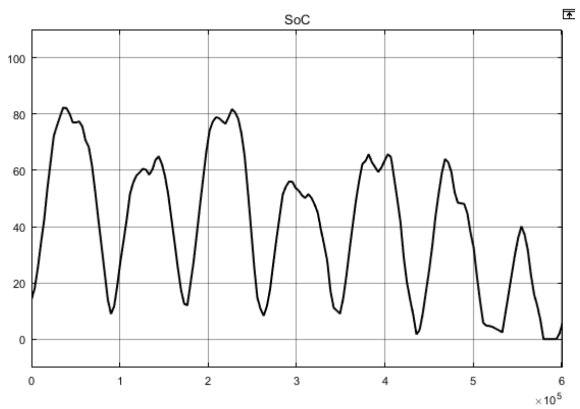


Figure 5.32: Battery SoC for week 1 with 45% DoD.

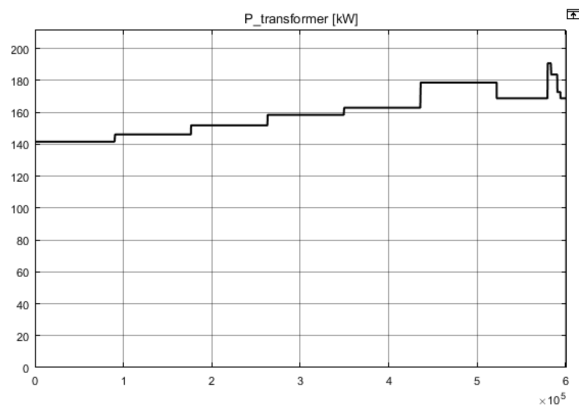


Figure 5.33: $P_{transformer}$ as a result of peak shaving with 45% DoD.

5.4.3 Case 3 - Low Battery Capacity Need

hour	Week 6: P_load [kW]						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
	08.02.2016	09.02.2016	10.02.2016	11.02.2016	12.02.2016	13.02.2016	14.02.2016
01:00	127.6	125.4	130.2	134.9	134.8	124.0	121.2
02:00	120.7	116.7	120.7	125.8	129.0	122.5	120.0
03:00	115.7	112.0	118.9	119.0	127.5	117.3	117.6
04:00	114.0	113.7	115.4	114.5	126.2	119.1	115.9
05:00	110.0	111.9	113.0	110.4	125.9	117.0	114.5
06:00	114.1	111.8	112.7	110.7	123.3	115.8	115.6
07:00	115.8	113.8	114.6	116.3	125.2	115.3	114.4
08:00	122.4	119.7	122.5	126.5	126.6	117.9	114.8
09:00	125.4	123.4	126.4	132.0	129.8	121.4	115.9
10:00	121.8	124.8	128.5	129.2	128.7	122.6	119.1
11:00	129.8	128.3	130.5	135.8	130.6	128.3	127.1
12:00	121.8	125.7	134.6	136.0	133.5	129.0	126.1
13:00	124.6	126.5	133.3	130.5	130.0	125.8	128.3
14:00	125.3	125.3	130.7	126.7	129.8	127.7	127.2
15:00	123.6	124.0	126.0	133.1	125.7	129.0	129.5
16:00	125.7	131.4	136.2	135.3	128.3	125.4	130.6
17:00	128.1	130.8	135.0	139.8	128.7	128.9	128.0
18:00	136.1	138.1	143.4	146.2	131.4	128.9	125.1
19:00	138.7	136.7	145.3	147.0	134.6	130.5	127.1
20:00	142.3	143.4	146.5	148.7	136.1	132.9	126.8
21:00	141.0	146.2	149.2	152.2	132.2	129.7	123.4
22:00	143.4	139.8	148.6	155.0	132.9	127.5	122.9
23:00	133.8	138.5	148.6	149.4	129.4	125.8	123.8
00:00	131.7	136.3	138.3	140.9	129.0	123.2	121.6

Figure 5.34: P_{load} for week 6. Measurements once every hour for 7 days, Monday 08.02.16 to Sunday 14.02.16.

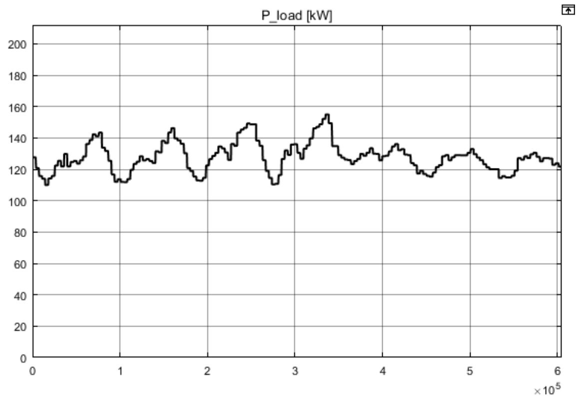


Figure 5.35: P_{load} for week 6.

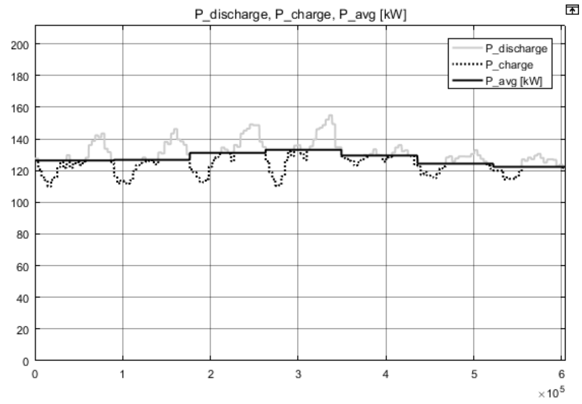


Figure 5.36: Battery discharge and charge for week 6.

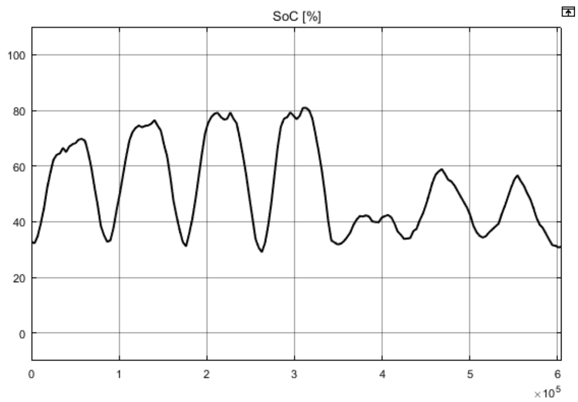


Figure 5.37: Battery SoC for week 6 with 60% DoD.

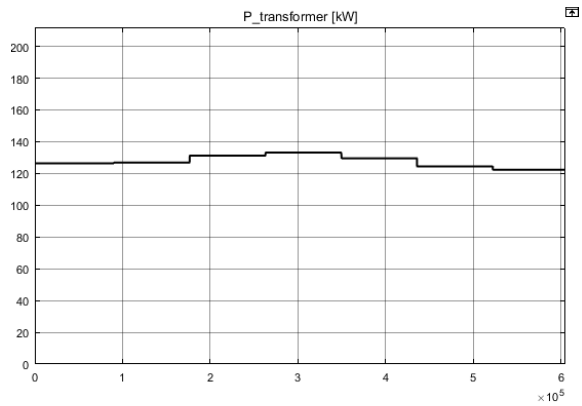


Figure 5.38: $P_{transformer}$ for week 6 with 60% DoD

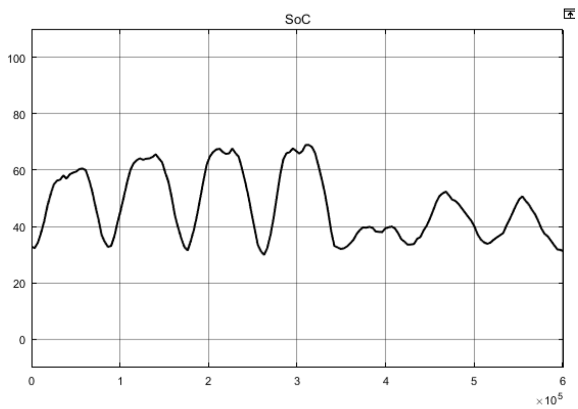


Figure 5.39: Battery SoC for week 6 with 45% DoD.

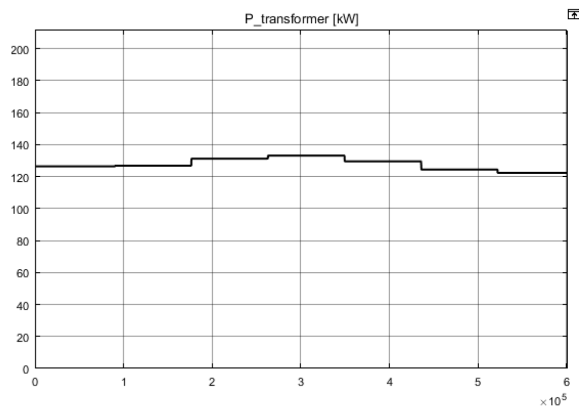


Figure 5.40: $P_{transformer}$ for week 6 with 45% DoD

5.4.4 Case 4.1 - High Battery Capacity Requirements - Week 52

hour	P_load Week 52 [kW]						
	Monday 21.12.2015	Tuesday 22.12.2015	Wednesday 23.12.2015	Thursday 24.12.2015	Friday 25.12.2015	Saturday 26.12.2015	Sunday 27.12.2015
01:00	93.3	111.6	114.0	133.9	119.6	117.7	132.6
02:00	84.5	92.7	102.8	117.2	106.2	112.3	130.2
03:00	79.1	85.3	90.4	105.7	96.6	97.6	120.7
04:00	76.5	80.2	87.8	85.2	93.0	95.7	114.4
05:00	72.3	77.2	82.8	85.5	82.0	94.0	110.4
06:00	76.8	79.9	79.9	95.8	86.6	91.0	115.1
07:00	79.0	84.1	85.4	94.1	91.1	95.1	116.0
08:00	84.6	90.1	88.1	93.3	85.8	102.0	119.3
09:00	88.7	94.9	90.8	91.8	88.9	96.7	122.7
10:00	86.4	108.6	98.2	108.0	93.9	110.1	127.1
11:00	94.9	108.4	121.7	129.1	110.5	129.4	146.0
12:00	107.1	111.7	119.6	152.6	127.8	142.9	141.8
13:00	103.3	108.0	123.4	147.3	135.3	148.4	153.2
14:00	98.8	106.6	120.7	148.6	134.9	158.8	161.6
15:00	109.3	103.8	122.9	142.4	132.4	154.5	157.0
16:00	115.6	102.0	120.0	131.0	142.2	153.4	147.8
17:00	119.9	107.9	130.0	135.5	142.1	156.4	150.5
18:00	128.0	125.9	135.3	149.2	141.1	156.3	146.9
19:00	127.7	127.6	143.7	153.9	131.7	153.1	153.9
20:00	124.8	138.6	138.8	140.2	135.0	149.8	159.8
21:00	131.2	147.8	137.7	146.1	129.5	162.1	158.7
22:00	131.0	132.4	141.4	135.7	126.8	154.4	158.1
23:00	123.5	126.5	143.3	135.9	132.0	149.5	164.0
00:00	119.1	128.7	149.5	125.0	123.2	138.0	149.7

Figure 5.41: P_{load} for week 52. Measurements once every hour for 7 days, Monday 21.12.15 to Sunday 27.12.15.

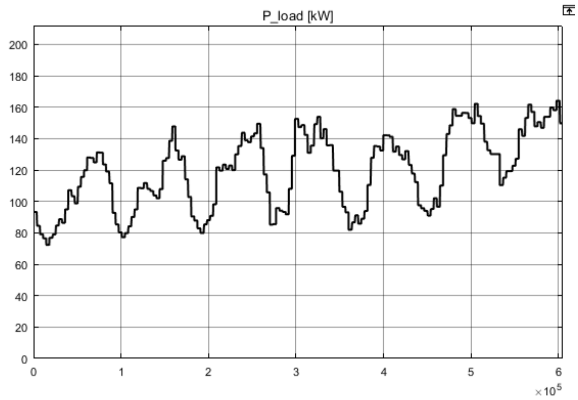


Figure 5.42: P_{load} for week 52.

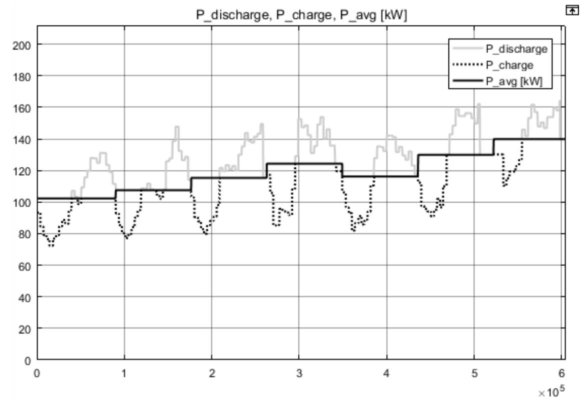


Figure 5.43: Battery discharge and charge in week 52.

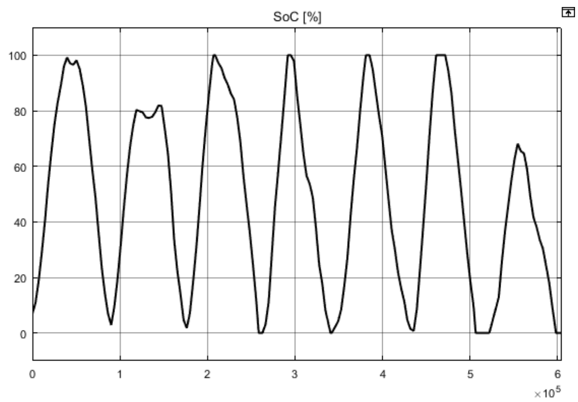


Figure 5.44: Battery SoC for week 52 with 60% DoD.

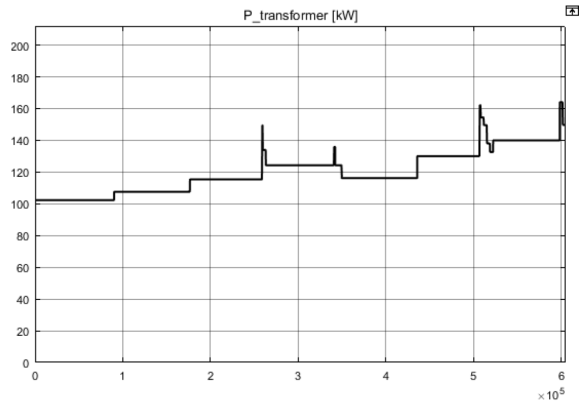


Figure 5.45: $P_{transformer}$ as a result of peak shaving with 60% DoD.

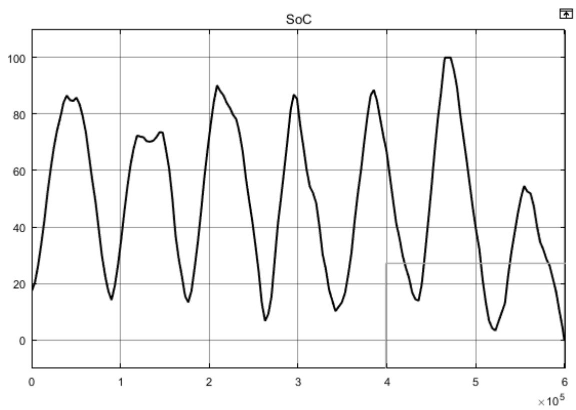


Figure 5.46: Battery SoC for week 52 with 45% DoD.

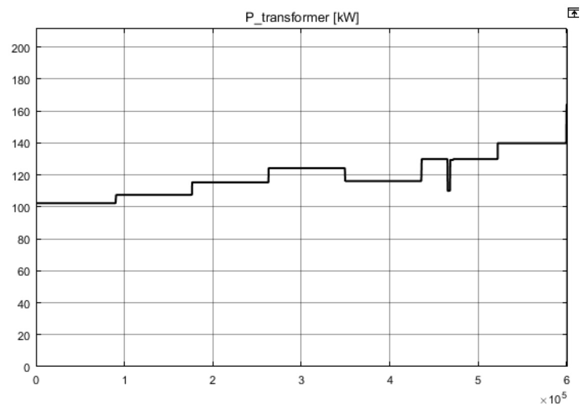


Figure 5.47: $P_{transformer}$ as a result of peak shaving with 45% DoD.

5.4.5 Case 4.2 - High Battery Capacity Requirements - Week 53

hour	Week 53: P_load [kW]						
	Monday 28.12.2015	Tuesday 29.12.2015	Wednesday 30.12.2015	Thursday 31.12.2015	Friday 01.01.2016	Saturday 02.01.2016	Sunday 03.01.2016
01:00	144.7	131.6	123.7	113.9	112.0	111.8	126.5
02:00	125.4	122.7	112.1	101.0	106.4	103.8	114.7
03:00	123.4	119.2	102.5	88.2	98.8	95.8	110.4
04:00	126.1	103.6	97.5	83.2	91.6	98.0	95.9
05:00	124.9	104.0	97.5	84.7	79.6	93.4	94.4
06:00	121.1	103.9	91.9	84.0	75.2	93.0	95.5
07:00	117.5	103.3	92.8	83.1	80.8	95.7	100.8
08:00	120.9	103.9	95.1	86.0	89.1	99.8	104.3
09:00	127.6	108.9	94.0	87.6	83.2	93.1	103.9
10:00	126.8	113.8	99.0	94.8	91.7	99.2	107.1
11:00	137.7	120.3	111.2	108.0	98.3	125.4	114.4
12:00	163.5	134.1	120.8	130.6	113.2	129.2	138.2
13:00	143.7	127.6	120.2	134.9	122.1	139.6	150.6
14:00	156.3	122.5	115.9	126.7	122.8	124.4	149.0
15:00	147.0	133.3	123.5	134.3	131.8	131.4	149.3
16:00	148.6	127.4	126.6	134.1	134.9	144.7	139.4
17:00	156.2	134.2	124.8	144.9	142.0	131.7	142.7
18:00	153.4	132.6	141.2	148.3	133.5	149.7	144.2
19:00	167.2	137.4	144.5	155.8	125.3	139.7	154.9
20:00	161.3	136.8	145.3	145.3	125.3	132.3	162.3
21:00	147.2	136.4	124.1	147.4	127.8	132.0	160.9
22:00	136.4	131.3	102.2	130.3	124.8	130.8	155.4
23:00	149.8	129.5	139.2	121.3	131.6	132.8	142.6
00:00	140.3	121.8	122.7	118.0	123.2	128.1	138.4

Figure 5.48: P_{load} for week 53. Measurements once every hour for 7 days, Monday 28.12.15 to Sunday 03.01.16.

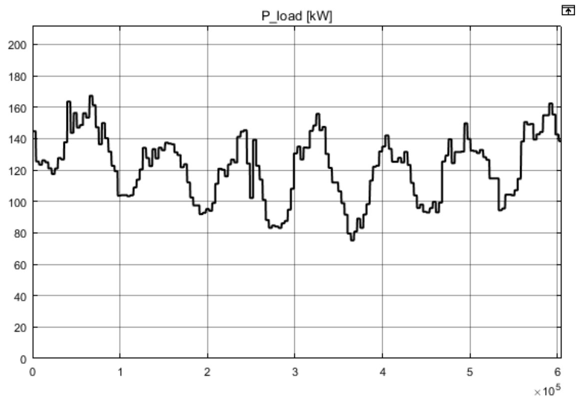


Figure 5.49: P_{load} for week 53.

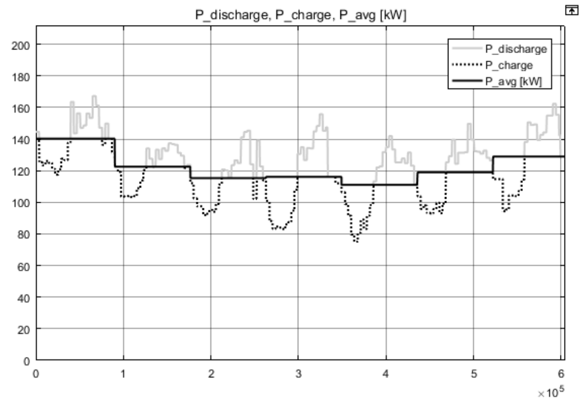


Figure 5.50: Battery discharge and charge for week 53.

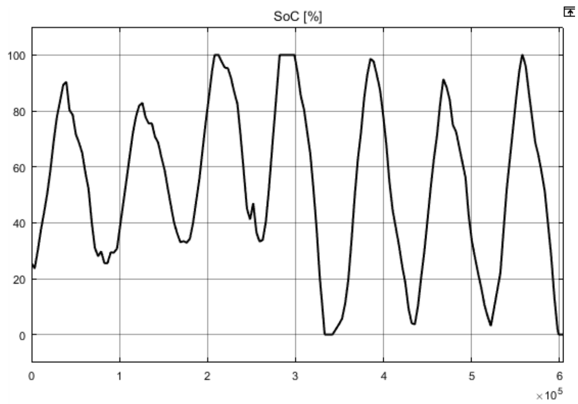


Figure 5.51: Battery SoC for week 53 with 60% DoD.

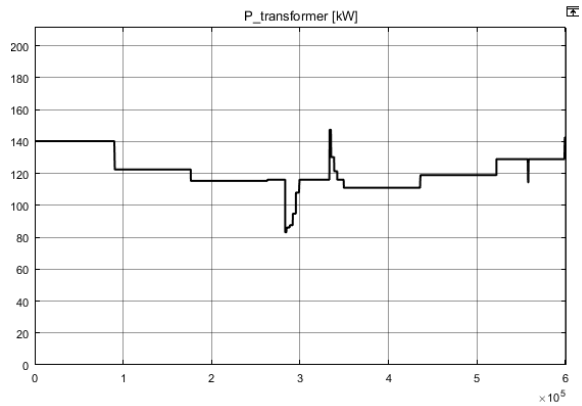


Figure 5.52: $P_{transformer}$ as a result of peak shaving with 45% DoD.

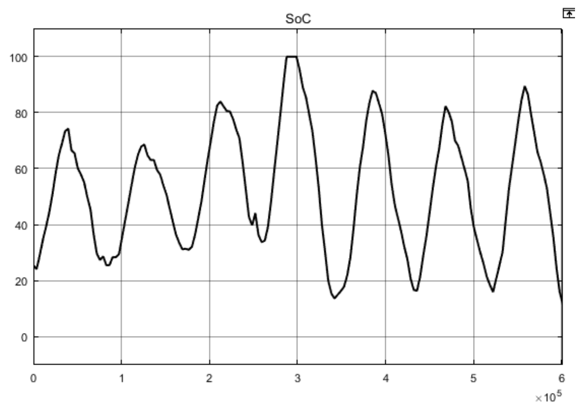


Figure 5.53: Battery SoC for week 53 with 45% DoD.

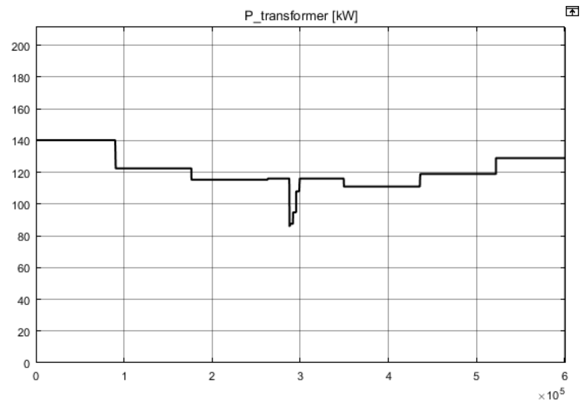


Figure 5.54: $P_{transformer}$ as a result of peak shaving with 45% DoD.

5.4.6 Case 4.3 - High Battery Capacity Requirements - Week 50

hour	P_load Week 50 [kW]						
	Monday 07.12.2015	Tuesday 08.12.2015	Wednesday 09.12.2015	Thursday 10.12.2015	Friday 11.12.2015	Saturday 12.12.2015	Sunday 13.12.2015
01:00	109.3	115.6	103.5	118.9	114.0	119.3	123.4
02:00	90.2	99.9	85.3	102.6	100.4	109.3	110.9
03:00	86.4	84.7	84.2	92.3	95.9	100.3	97.7
04:00	84.0	91.6	87.9	89.4	85.6	98.5	97.3
05:00	78.2	93.3	78.9	83.5	87.6	93.3	94.1
06:00	84.7	96.9	79.7	85.4	91.4	90.5	99.5
07:00	86.9	102.9	81.2	88.2	93.1	93.2	95.1
08:00	101.4	107.1	95.6	103.5	103.0	94.1	96.1
09:00	97.7	102.5	111.9	111.8	111.0	98.9	103.8
10:00	106.7	101.8	108.6	102.9	111.6	108.2	105.4
11:00	114.9	103.6	110.1	105.6	114.8	126.6	120.4
12:00	118.0	110.8	106.0	108.8	114.1	130.9	124.7
13:00	114.2	107.9	107.9	105.5	109.4	141.1	143.0
14:00	105.8	107.2	110.5	103.7	107.1	123.5	134.7
15:00	112.7	107.3	113.0	110.9	107.6	119.3	142.9
16:00	114.4	108.7	119.2	111.1	110.5	135.1	151.2
17:00	126.6	114.1	128.8	111.2	123.7	122.1	152.3
18:00	137.1	116.7	139.8	130.5	126.5	128.0	154.4
19:00	145.4	127.6	141.7	137.5	126.2	135.9	148.2
20:00	141.9	130.4	140.1	138.3	132.8	130.3	154.0
21:00	125.2	131.7	144.0	140.2	140.4	125.0	147.3
22:00	130.0	125.9	139.8	143.6	139.1	121.7	138.7
23:00	122.2	119.2	148.3	136.4	136.0	132.4	142.7
00:00	119.1	117.4	127.5	132.6	126.5	128.2	131.3

Figure 5.55: P_{load} for week 50. Measurements once every hour for 7 days, Monday 07.12.15 to Sunday 13.12.15.

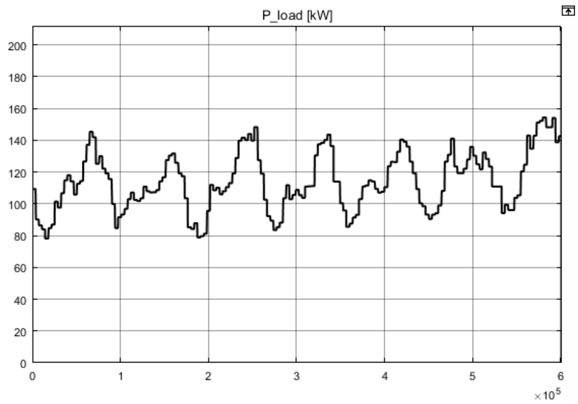


Figure 5.56: P_{load} for week 50.

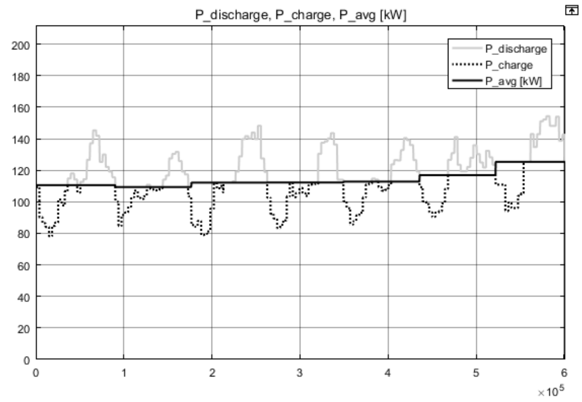


Figure 5.57: Battery discharge and charge for week 50.

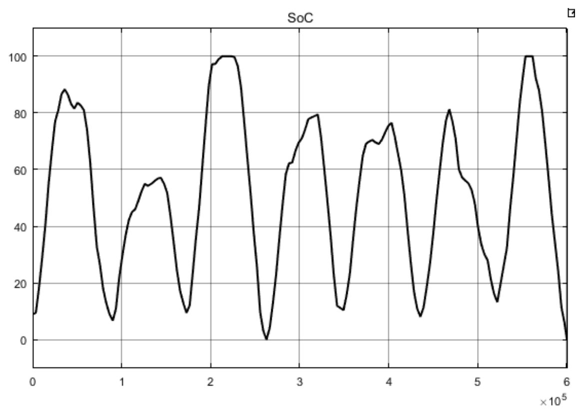


Figure 5.58: Battery SoC for week 50 with 60% DoD.

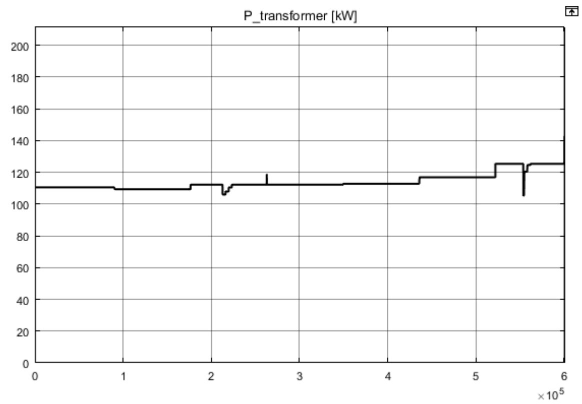


Figure 5.59: $P_{transformer}$ as a result of peak shaving with 60% DoD.

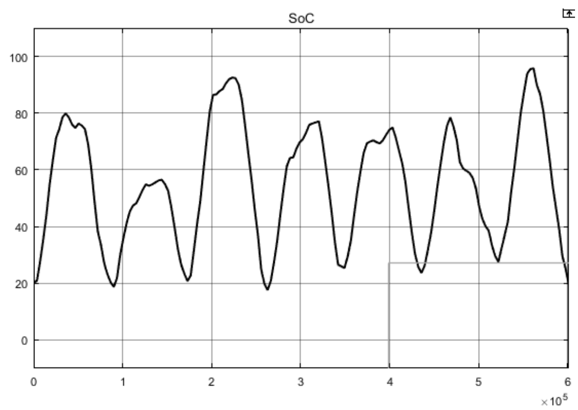


Figure 5.60: Battery SoC for week 50 with 45% DoD.

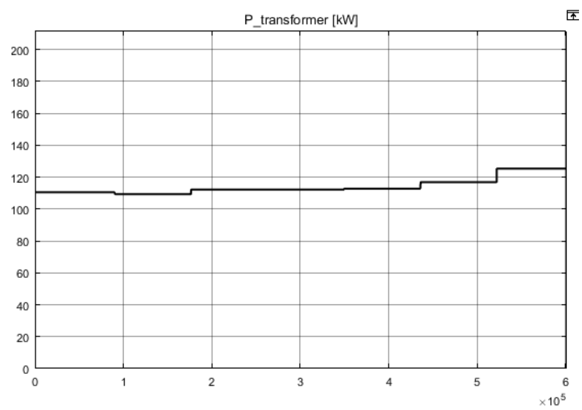


Figure 5.61: $P_{transformer}$ as a result of peak shaving with 45% DoD.

5.4.7 Case 4.4 - High Battery Capacity Requirements - Week 48

hour	Week 48: P_load [kW]						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
	23.11.2015	24.11.2015	25.11.2015	26.11.2015	27.11.2015	28.11.2015	29.11.2015
01:00	119.3	101.6	108.0	113.1	103.2	101.3	120.9
02:00	108.4	96.3	97.2	97.3	87.1	96.1	108.4
03:00	100.2	81.7	87.4	94.4	85.7	82.6	97.3
04:00	89.7	85.1	76.9	92.0	81.7	81.3	87.1
05:00	92.8	80.5	82.8	89.1	76.6	77.3	85.0
06:00	94.6	84.7	84.3	88.5	76.6	78.9	89.1
07:00	94.0	82.4	85.5	90.7	78.1	83.7	88.8
08:00	109.7	93.4	99.3	104.7	89.2	89.3	88.2
09:00	107.7	101.9	100.3	107.4	88.1	98.5	96.2
10:00	121.3	100.2	109.4	103.7	98.7	103.1	105.9
11:00	119.4	104.0	119.6	107.1	98.6	110.1	122.2
12:00	126.7	114.7	111.6	111.0	106.2	126.9	128.2
13:00	110.4	105.3	113.8	110.1	99.9	131.4	132.9
14:00	109.3	98.4	112.1	100.8	96.5	134.7	143.0
15:00	117.3	103.0	107.4	107.9	95.8	135.6	146.6
16:00	111.5	104.3	106.8	109.3	103.2	136.7	149.9
17:00	126.2	112.8	110.8	116.5	108.9	129.5	136.7
18:00	128.8	115.3	119.2	117.6	116.9	131.7	128.0
19:00	127.3	114.8	123.1	120.6	120.5	132.6	135.3
20:00	129.6	130.4	126.2	134.2	120.9	127.7	134.2
21:00	128.1	133.2	135.7	142.6	115.3	140.8	131.7
22:00	123.1	122.8	132.5	137.1	116.7	133.8	127.1
23:00	123.3	123.1	134.0	125.3	117.7	126.0	125.2
00:00	114.5	116.4	125.9	121.5	109.6	122.9	114.0

Figure 5.62: P_{load} for week 48. Measurements once every hour for 7 days, Monday 23.11.15 to Sunday 29.11.15.

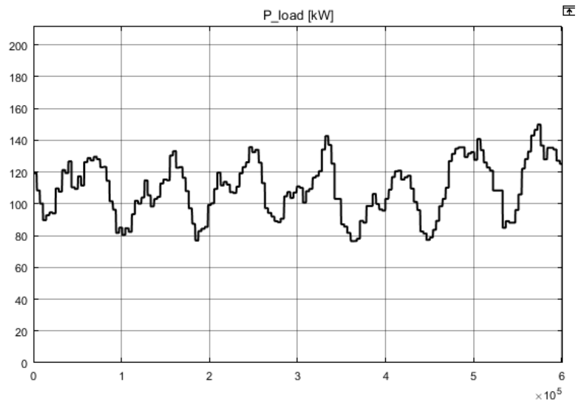


Figure 5.63: P_{load} for week 48.

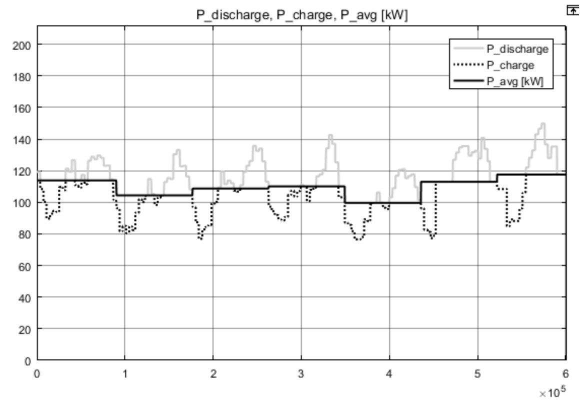


Figure 5.64: Battery discharge and charge in week 48.

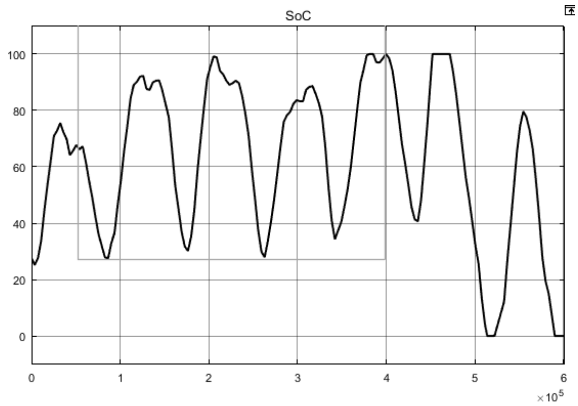


Figure 5.65: Battery SoC for week 48 with 60% DoD.

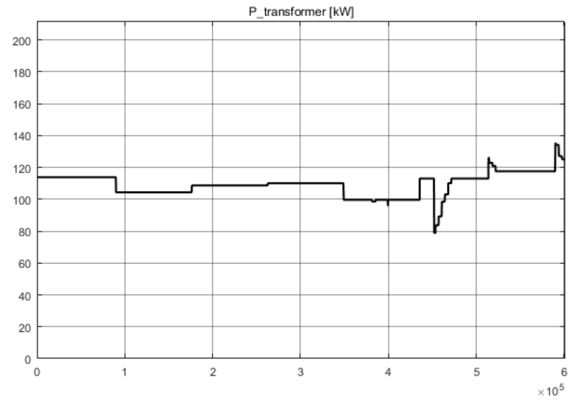


Figure 5.66: $P_{transformer}$ as a result of peak shaving with 60% DoD.

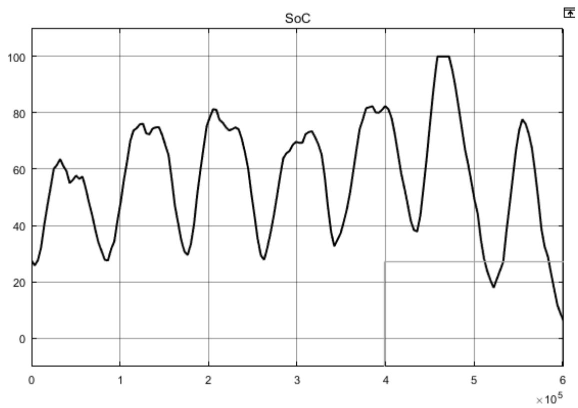


Figure 5.67: Battery SoC for week 48 with 45% DoD.

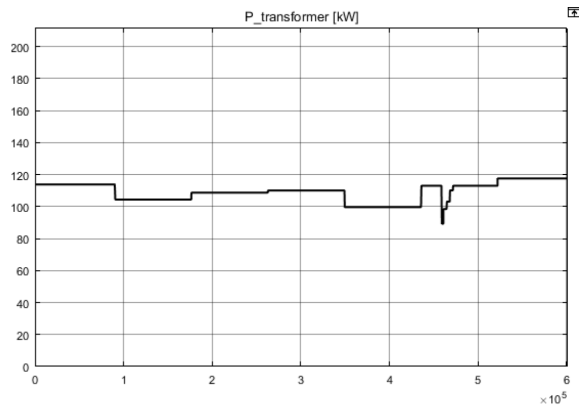


Figure 5.68: $P_{transformer}$ as a result of peak shaving with 45% DoD.

Chapter 6

Discussion

6.1 Simulation Model

To validate the battery storage dimensioning strategy, a simulation model is built using MATLAB Simulink. Due to restrictions in the source material from Smart Valley, instantaneous values are not included in the simulations. In stead, the average power during an 1-hour interval from the energy consumption data is used. As explained in Section 2.1.3 this gives an accurate result when calculating charge and discharge currents as this gives correct energy consumption when subjected to the battery block.

However, in this way it is not possible to detect instantaneous values that may surpass battery tolerance limits. The method of deriving average power from the consumption data will not detect the load fluctuations and actual instantaneous load peaks that occur within each 1-hour interval. According to Figure 3.1 the Li-Ion battery technology is capable of sustaining charge/discharge from 5-10C. For the two dimensioning strategies simulated, this will translate into 1.13 - 2.26MW for Strategy 1 and 1.5 - 3.0MW for Strategy 2, see Section 3.2.2 for details on how this is calculated.

Within the 45 households that is the source of data for the simulations, it is highly unlikely that a load peak of this magnitude will occur. The collection of loads in the simulation will be connected to a 100kVA, 200kVA or 315kVA transformer, which is protected by fuses that will shut down the transformer circuit if such a load were to occur. Transformer substations in the distribution grid range from 50-2000kVA, so loads of this magnitude may occur in transformer circuits connected to 1200kVA and 2000kVA transformers. However, this will also require a larger storage, which in turn will tolerate higher load peaks.

The model is built with the ability to define SoC-limits, but this setting is not used in the simulations for this report. The reason for this is that is sets fixed limits for the entire period of simulation. Since the eventual dimensioning strategies involve making use of the buffer capacity in times of high load, the recommended SoC-limits are surpassed multiple times, making it impractical in use.

From the simulation results, on four occasions full battery discharge (SoC=0%), occurs, even though the needed battery capacity of the day is within the total battery capacity. This is due to insufficient charging time, which points towards a need to enhance the battery control logic in the simulation model. A possible continuation of this, is to create an adaptable battery management system that uses predictive elements and machine learning to maintain the desired SoC. This was not done for this report as it was regarded as to time consuming.

The model is built with a maximum simulation period of seven days, a time series of 168 samples. For future simulations, longer simulation periods may be of interest. Due to limitations in the current design of the consumption import architecture, the load section will require restructuring using another approach to enable an expansion to allow longer simulation periods.

6.2 Dimensioning Strategy

To propose the dimensioning strategies used in the simulations, an analysis of the data from Smart Valley is conducted. The data shows signs of a decoupling between high load and required battery capacity. It is not necessarily the days with the highest load that yields the highest needed battery capacity. The day of highest energy consumption per hour occurs on 09.01.16 between 19:00 and 20:00 with 209.2kWh. However, the needed battery capacity of this day is 188kWh, which is 83% of the total battery capacity. 29.12.15 is the day in the data set with the highest needed battery capacity with 288kWh, with a maximum energy consumption per hour of 162kWh occurring between 19:00 and 20:00. This is not to say that the decoupling between high load and high battery capacity requirements is absolute, as the top ten days with highest needed battery capacity, all occur in the winter months. Two dimensioning strategies are simulated with reference to the annual required battery capacity of 135.7kWh:

- Strategy 1: A battery storage dimensioned so that the annual required battery capacity is covered by a 60% DoD limit. This requires a total battery capacity of 226.2kWh.
- Strategy 2: A battery storage dimensioned so that the annual required battery capacity is covered by a 45% DoD limit. This requires a total battery capacity of 301.5kWh.

Strategy 1 requires a lower total battery capacity than Strategy 2. This means that the initial investment costs are higher, but also causes an increase in battery degradation which reduces cycle life.

Four cases are simulated to cover the extremities of the year

- Case 1: Low load
- Case 2: High load
- Case 3: Low battery capacity requirements
- Case 4: High battery capacity requirements

6.2.1 Strategy 1 - 60% DoD

This strategy gives a higher battery utilization, but the battery capacity shows to be insufficient for some days of the year. Calculations done before the simulations suggests that insufficient battery capacity is to occur 8 times in the weeks 48, 50, 52 and 53 as described in Table 4.1. As expected, the simulations show that the battery SoC reaches 0% during these 8 days, but this also occur at four additional days. Initially, these four days require less than the total battery capacity, but due to insufficient charging time the battery was not able to attain enough charge to accommodate the energy needed. This occurs on Sunday in week 48 (Figure 5.65), Sunday in week 52 (Figure 5.44), Friday and Sunday in week 1 (Figure 5.31). The effect of an SoC of 0% is an elevated transformer load, which appear the days mentioned above, see Figure 5.31, 5.45, 5.51, 5.59 and 5.66.

In week 30, the case with low load also show signs of reaching SoC of 0%. This indicates that the need for a more intelligent battery management system is needed to assure proper control logic.

6.2.2 Strategy 2 - 45% DoD

Dimensioning strategy 2 involves dimensioning the battery storage with a 45% DoD on an annual consumption average. This means that the battery requires 55% of the total capacity as buffer, pushing the total capacity to 301.5kWh. This is 5% more than the day with the highest required battery capacity of 288kWh, occurring on Saturday of week 52. This means that insufficient battery capacity should not occur in any of the simulations. However, at the end of week 52, SoC reaches 0% (Figure 5.44), creating an elevated transformer load (Figure 5.45). Again, this is caused by insufficient charging time, something that may be prevented with a more dynamic charging and discharging control system.

6.2.3 Battery Performance

The foundation of the dimensioning strategies is that the times of high battery capacity requirements is to be provided for by the buffer capacity. The use of buffer capacity will accelerate battery degradation, but the days of low battery capacity requirements will counteract this for the course of the year.

Case 3 - Low Battery Capacity Requirements

Week 6: Required Battery Capacity	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
date	08.02.2016	09.02.2016	10.02.2016	11.02.2016	12.02.2016	13.02.2016	14.02.2016
E_batt [kWh]	88.5	101.1	115.7	123.2	30.5	52.2	55.2
DoD - Strategy 1 [%]	39.1	44.6	51.0	54.3	13.5	23.0	24.3
DoD - Strategy 2 [%]	29.4	33.5	38.4	40.9	10.1	17.3	18.3

Figure 6.1: Needed battery capacity in week 6.

- *Strategy 1*: For this week, the 60% DoD limit is met for all days of the week, with an average DoD of 35.7%. Battery SoC varies between 80% and 30% in the beginning of the week, and between 60% and 30% for the rest of the week, see Figure 5.37. The recommended SoC limits of 85-25% is therefore met.
- *Strategy 2*: The 45% DoD limit is met all days of the week, with an average DoD of 26.8%. Battery SoC varies between 70% and 30% in the beginning of the week, and between 50% and 30% for the rest of the week. The recommended SoC limits of 70-45% is therefore met.

Case 4 - High Battery Capacity Requirements

Week 52: Required Battery Capacity	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
date	21.12.2015	22.12.2015	23.12.2015	24.12.2015	25.12.2015	26.12.2015	27.12.2015
E_batt [kWh]	212.8	185.9	233.2	242.0	227.2	288.1	190.4
DoD - Strategy 1 [%]	93.9	82.0	102.9	106.7	100.2	127.1	84.0
DoD - Strategy 2 [%]	70.6	61.6	77.3	80.3	75.3	95.6	63.2

Figure 6.2: Needed battery capacity in week 52.

- *Strategy 1*: For this week, the 60% DoD limit is surpassed all days of the week, with an average DoD of 99.5%. Battery SoC varies between 0% and 100% several times a week, and the recommended SoC limits of 85-25% is surpassed for all of the days, see Figure 5.44. The battery is depleted multiple times this week. 0% SoC is reached on Wednesday - Sunday. Battery depletion occurs on Sunday due to insufficient charging time.
- *Strategy 2*: 45% DoD limit is surpassed all days of the week, with an average DoD of 74.8%. Battery SoC varies between 15% and 90% for most of the week, and the

recommended SoC limits of 70-45% is surpassed all of the days, see Figure 5.46. According to the calculations, battery depletion is not to happen with a 45% DoD. However, this also occurs on day seven as a result of insufficient charging time.

Battery Performance Evaluation

This Case 3 and 4 shows two extremities of the year. Case 4 representing a week of high battery capacity requirements, on average exceeding the desired DoD limit with 66%. Case 3 representing a week of low battery capacity requirements, on average has a DoD 60% below the desired DoD limit. This shows that a week of low battery capacity requirements may counteract the effect a week of high requirements may have on battery degradation.

6.3 Initial Investments Costs and Life Time

Using the numbers from 2016 [22, p.10], the cost for Li-Ion batteries were at 227$/kWh. Using a factor of 1.5 to include the cost for the enclosure and inverter the two strategies ends up with the following costs:

6.3.1 Strategy 1

$$Cost_{S1} = 227.0\frac{\$}{kWh} \cdot 226.2kWh \cdot 1.5 = \$77021.1 \tag{6.1}$$

With the current exchange rate between $ and NOK of 8.1, this translates into 623 870.9 NOK.

According to the study from 2016 [4, p.7], see Figure 3.2, the battery degradation with a DoD of 60% will result in a battery performance of 84% of the original capacity after 5000 cycles. Over a ten year period, counting one cycle per day this is 3650 cycles, of which 87% of the total battery capacity remain.

$$E_{batt_{10y}} = 0.87 \cdot 226.20kWh = 196.79kWh \tag{6.2}$$

Using the consumption data from 2015/2016, insufficient battery capacity is expected to occur 23 of the total 366 days of the dataset after 3650 cycles. This means that after ten years, the battery will accommodate the energy requirements of 93.7% of the days of the year.

6.3.2 Strategy 2

$$Cost_{S1} = 227.0\frac{\$}{kWh} \cdot 301.5kWh \cdot 1.5 = \$102660.8 \tag{6.3}$$

With the current exchange rate between $ and NOK of 8.1, this translates into 831 552. 1 NOK.

A DoD scenario of 45% is not included in the results from the study from 2016 [4, p.7], but 50% DoD and 30% DoD are presented. The results from a 45% DoD is expected to be between these two, ending on a battery performance of around 88% of the original battery capacity after 5000 cycles and around 90% after 3650 cycles (10 years).

$$E_{batt_{10y}} = 0.9 \cdot 301.5kWh = 271.4kWh \tag{6.4}$$

This gives a remaining capacity of 271.4kWh from the original 301.5kWh. Using the consumption data from 2015/2016, insufficient battery capacity is expected to occur at 1 of the total 366 days of the dataset. This means that after ten years, the battery still will accommodate the energy requirements of 99.7% of the days of the year.

This means that by choosing strategy 2 in stead of strategy 1, the initial investment is 33.6% higher, giving a solution that accommodates 6% more of the days.

6.3.3 Evaluation

Of the two dimensioning strategies, the 45% DoD scenario is the only strategy that can provide all of the days in the dataset with enough energy. However, this ability start to decline pretty rapidly. According to Figure 3.2, the most rapid decline in battery performance occur during the first few hundred cycles. Following Strategy 2, the total battery capacity is dimensioned with a 5% over-capacity relative to the day of maximum battery capacity requirements. Following the path of 50% DoD and 30% DoD, the 95% capacity mark is reached after 1000 and 700 cycles, respectively. If we assume a 45% DoD scenario to be somewhere in between, this threshold can be expected to be reached within the first 2-3 years. Assuming that maximum load stays the same year after year, something in which calls for the need for more years of data to confirm.

If a battery where to be dimensioned so that it is able to accommodate the maximum required battery capacity in the dataset of 288.1kWh after ten years of operation, following the 45% DoD principle, 288.1kWh must equate to 90% of the original installed capacity.

$$E_{batt} = \frac{288.1kWh}{0.9} = 320.1kWh \tag{6.5}$$

This is a total battery capacity of 320.1kWh. Relative to the annual battery requirement average, this would be equate to a 42.3% DoD. This means that if it should be desirable with a battery that is able to accommodate peak load after 10 years, an ideal dimensioning strategy may be to design the battery with 42% DoD with reference to the annual battery requirement average. However, this will push up the battery costs even further.

6.4 Economical Validity of DES in the Distribution Grid

Due to the poor quality of instantaneous values in the dataset, it is difficult to use this data to make a comparison with actual overload cases in the distribution grid. However, approximations are made to give an indication that makes it possible to compare the results from the dimensioning strategies and the economics of grid upgrade.

In order to uncover the economical validity of the use of DES as an alternative to traditional grid reinforcement methods, an upgrade from a 100kVA to 200kVA transformer is investigated.

This upgrade is disproportionally higher than other transformer upgrades, increasing the probability of DES as an alternative. The reason for this is that grid equipment in the power grid business is standardized, and at some thresholds an upgrade leads to the need to change surrounding equipment as well.

A 100kVA transformer in the Norwegian distribution grid is often placed on a pole-mounted platform. The upgrade from a 100kVA transformer to a 200kVA transformer leads to the need for dismantling the platform, and the establishment of a ground mounted substation. The costs related to this kind of project usually ends at around 400 000NOK, see Figure 8.25 in the Appendix 8.6 for calculations.

To use the results from the simulations, it is necessary to scale the results to make them comparable. Two types of overload cases are addressed:

- Transformer overload of 10%
- Transformer overload of 50%

The maximum hourly consumption from the dataset is 209.2kWh, which translates into an average power of 209.2kW for this 1-hour interval. As explained in Section 4.4.2, $cos\phi$ in the dataset varies from 0.9 to 0.99. There is no information about $cos\phi$ at the time of the highest load. By using the median contribution of reactive power in the dataset with a $cos\phi$ of 0.95, the apparent load is given by:

$$S = \frac{P}{cos\phi} = \frac{209.2kW}{0.95} = 220.2kVA \tag{6.6}$$

This result is multiplied with a reduction factor to create a reference for the different overload scenarios. The following calculations shows the approach used to determine the values in Figure 6.3. The example that follows are for a 10% overload case using dimensioning strategy 1 - 60% DoD.

6.4.1 Calculation Example

A 10% overload case means that the 100kVA transformer is subjected to a load of 110kVA. This means that the dataset needs to be reduced with a reduction factor of 0.5 to form a 10% overload scenario.

$$S_{max_{OL110\%}} = 220.2kVA \cdot 0.5 = 110.1kVA \tag{6.7}$$

As the total load and energy consumption is reduced by a factor of 0.5, the same reduction factor is used on the battery capacity requirements.

$$E_{batt_{OL110\%}} = 226.2kWh \cdot 0.5 \approx 113.1kWh \tag{6.8}$$

An additional factor of 1.5 is used to account for battery enclosure and inverter/battery management system. Using the numbers from 2016 [22, p.10], this means a battery cost of:

$$cost_{batt} = 227.0\frac{\$}{kWh} \cdot 113.1kWh \cdot 8.1\frac{NOK}{\$} \cdot 1.5 = 311935.5NOK \qquad (6.9)$$

To account for planning and labour, an additional 50 000 NOK is added.

DoD [%]	Overload [%]	Reduction Factor	E_batt [kWh]	Battery Cost [NOK]	Planning and Labour Cost	Total Cost [NOK]	Transformer Upgrade [%]
60	10	0.5	113.1	311 936	50 000	361 936	90.5
60	50	0.7	158.3	436 599	50 000	486 599	121.6
45	10	0.5	150.8	415 914	50 000	465 914	116.5
45	50	0.7	211.1	582 224	50 000	632 224	158.1

Figure 6.3: Battery cost compared to transformer upgrade

As expected, the dimensioning strategy with lowest battery cost is Strategy 1 - 60% DoD. As this strategy gives a battery capacity which is insufficient some days of the year, elevated transformer load can be expected for short periods. However, since the transformer peak load is reduced for the rest of the year, increased longevity is expected. In this report, the amount of expected increase of transformer life time is not assessed.

Of the cases included in Figure 6.3, only one case turns out to be less costly than a traditional transformer upgrade. At 10% overload with 60% DoD, the total cost of the storage system is 90.5% of the cost of a transformer upgrade. In the other cases, battery cost exceed the cost of transformer upgrade.

As the battery cost decline, this is a solution that will become more attractive with time, which is necessary, as the calculations above are done using a scenario which is especially expensive. In other transformer upgrade cases, the costs lie around 50 000-100 000NOK, which in much less costly. As explained in Section 3.2.2, battery costs are expected to drop below 100$/kWh within few years, which will cut the cost with more than half.

This report has focused on peak shaving as a service provided by the battery, but other services like voltage support, frequency stabilization and grid outage support will increase the total value of the storage system. This has not been addressed in this report, but may be a useful topic to pursue in order to determine the total value of storage in the distribution grid.

Today's battery cost makes it difficult for DES to compete with traditional grid reinforcement methods. However, emerging research such as conducted in this work, lowers continuously the gap between traditional grid reinforcement methods and DES, thus leading to more efficient and cost effective DES strategies.

Chapter 7

Conclusion

7.1 Conclusion

This report has focused on the use of DES in the distribution grid providing peak shaving service to reduce load peaks and subsequently delay the need for grid reinforcements. Two energy storage dimensioning strategies are proposed and simulated with the use of a simulation model.

The seasonal variation in energy consumption is addressed by using the annual consumption average as reference, with various use of buffer capacity to provide energy in times of high load. Both strategies prove to generate a battery storage at a cost that cannot compete with traditional reinforcement methods in the distribution grid today. The cost for battery storage are declining, so this may be an alternative in the future.

Immature regulatory framework within this topic also hinders wide spread utilization of this technology. Work is being done to incorporate the necessary changes in the regulatory framework that enable the use of this technology, but it will take years before this is ready. Both the necessary regulatory changes must be done, as well as a continuous decrease in battery cost, before we will see widespread use of DES in the distribution grid.

7.2 Future work

In order to fully determine that this approach is an adequate strategy, more data should be addressed. With the roll-out of an increasing number of AMS-meters, the available data will increase, effectively providing more data for further research. Multiple years of data from different areas and customer compositions are necessary to fully determine the optimal battery storage sizing strategy.

For this report a simulation model has been built to incorporate battery dynamics to validate the battery sizing strategy. This model is to be regarded as a basic starting point for battery dynamic simulations, and can be incorporated in larger models that both investigates the use in three phase systems, but also more in depth control strategies and battery management systems.

A natural continuation of the model is to incorporate predictive elements and machine learning to enhance the battery control logic.

Especially the latter is of great interest, and serves as the focus point of distinction between the different battery system providers. The battery chemistry in commercially available products is well known, and the industry is heading in a direction of mass production of battery modules, with standardized voltage and energy capacity levels. This gives little room for increasing battery performance with regards to battery chemistry and construction. The main part that differentiates battery system manufacturers today is the battery management system, with efficient and intelligent control of the battery.

The model may be expanded to include several DES-units, collaborating on a larger scale. This may involve peak shaving on a larger time scale, or the use of other services like frequency regulation or voltage support.

Chapter 8

Appendix

8.1 Battery Technologies

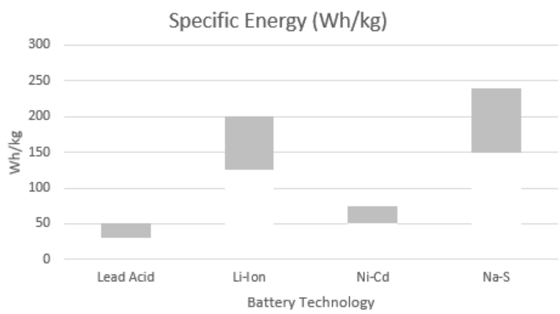


Figure 8.1: Specific Energy

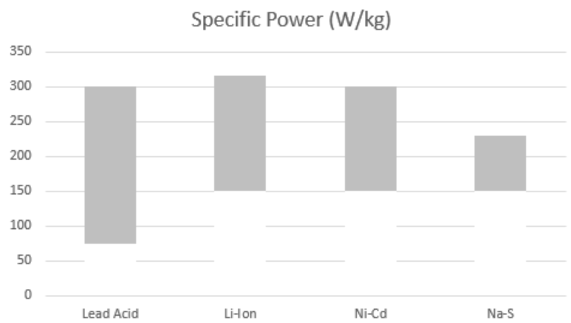


Figure 8.2: Specific Power

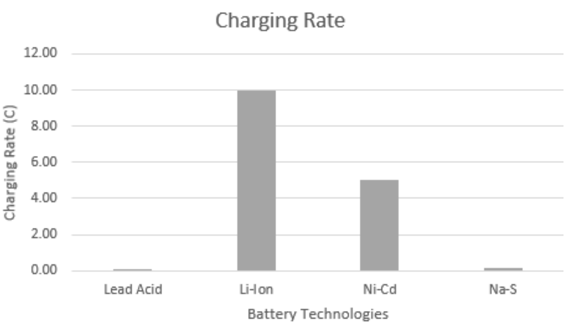


Figure 8.3: Charging Rate

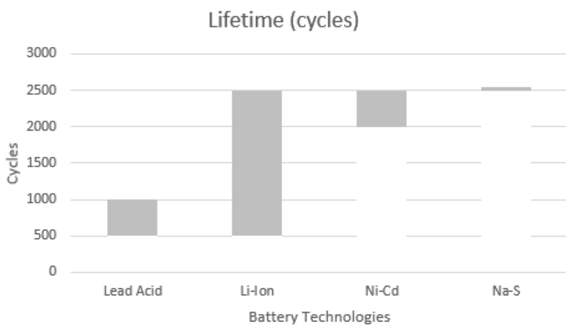


Figure 8.4: Lifetime given as number of cycles

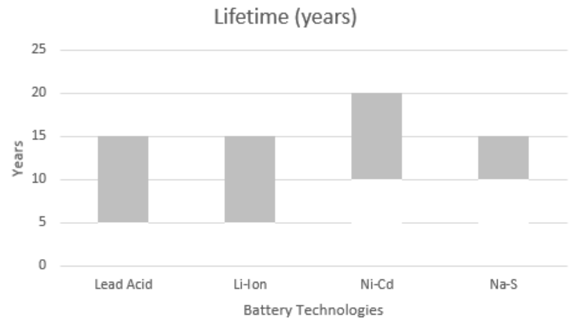


Figure 8.5: Lifetime given as number of years

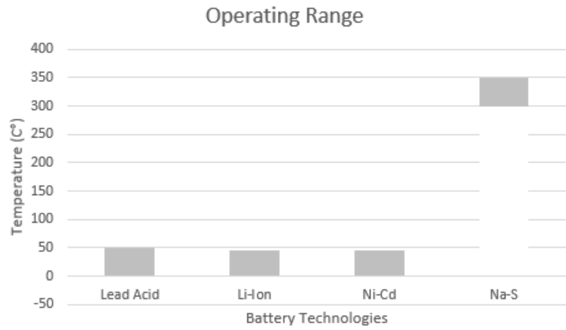


Figure 8.6: Operating Range

8.2 General Load Profiles

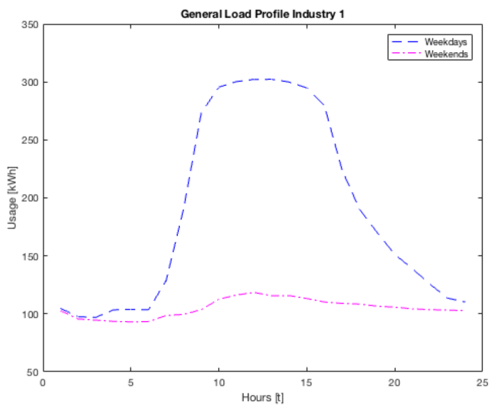


Figure 8.7: General Load Profile Industry 1

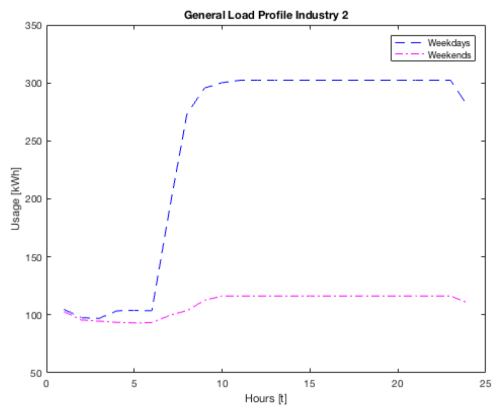


Figure 8.8: General Load Profile Industry 2

Figure 8.7 and 8.8 show stable consumption in the weekdays and a significant reduction in the weekends. No prominent load peaks are present, which makes industrial load profiles not well suitable for DES designed for peak shaving service. An overload problem will in these cases be solved with a transformer upgrade.

Schools and caring homes are illustrated in figure 8.9 and 8.10 and create load peaks around midday, which would make these suitable subjects in cases where they share transformer with other loads, but this is seldom the case. These are buildings with high loads, which often requires its own substation. An overload scenario will in these cases be solved using a transformer upgrade.

The load profile for offices and services in Figure 8.11 follow the same pattern as "Industry 1" with a steady level of consumption in the daytime during working hours. The load profile of public and service buildings are to some extent the inverse of normal households. This is where people come to work, so most of the consumption is between

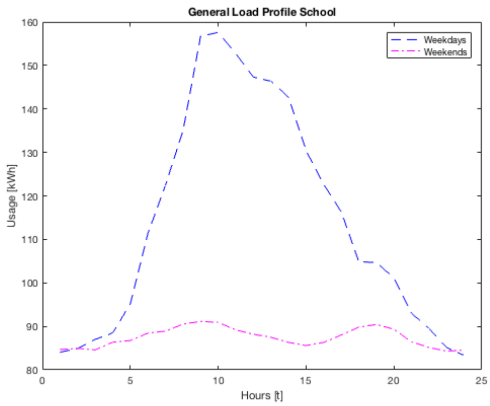


Figure 8.9: General Load Profile School.

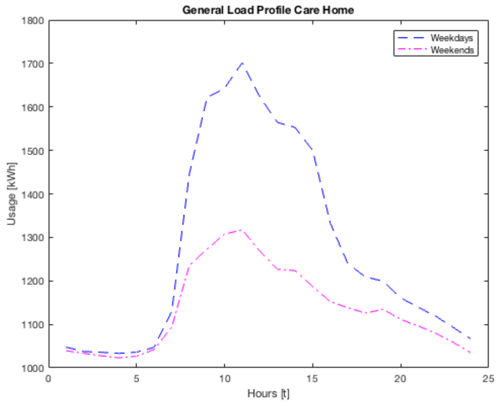


Figure 8.10: General Load Profile Care Home

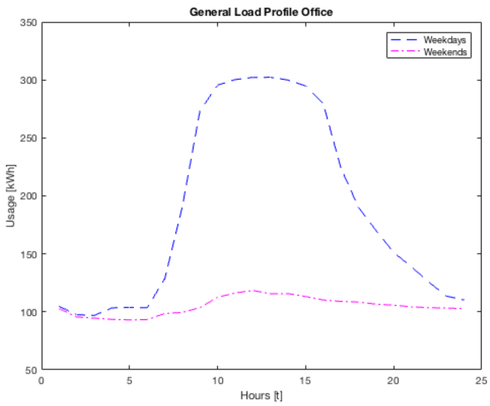


Figure 8.11: General Load Profile Offices and Services.

08:00 and 17:00. There are no distinct peaks, but an even level of energy consumption throughout the day, with low consumption in the evening and night.

8.3 AMS Meters Accuracy Class

Table 8.1 is collected from *Foreskrift om krav til elektrisitetsmålere* [34].

Table 8.1: Accuracy

	Class
I_{st}	$\leq 0.05 \cdot I_{tr}$
I_{min}	$\leq 0.05 \cdot I_{tr}$
I_{max}	$\geq 50 \cdot I_{tr}$
Voltage	$0.9 \cdot U_n \leq U \leq 1.1 \cdot U_n$
Frequency	$0.98 \cdot f_n \leq f \leq 1.02 \cdot f_n$

8.4 Battery Block Properties

Number of cells in series	**Number of paralell wirings**	**Voltage [U]**	**Capacity [Ah]**	**R0 [mΩ]**	**Energy [kWh]**
1	0	2.7	2.4	15.4	6.48·10^(-3)
14	0	51.8	2.4	215.6	0.12
14	26	51.8	62.4	8.3	3.2
Number of modules in series					
14	0	725.2	62.4	116.1	45.30
14	2	725.2	124.8	58.0	90.50
14	5	752.2	312.6	29.0	301.3

Figure 8.12: Battery Pack Wiring Schemes

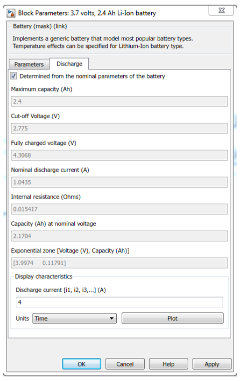


Figure 8.13: Battery block properties for line 1 in table 6.3: $R_0 = 0.015$

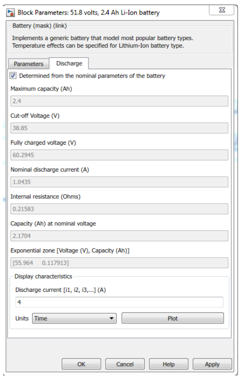


Figure 8.14: Battery block properties for line 2 in table 6.3: $R_0 = 0.215$

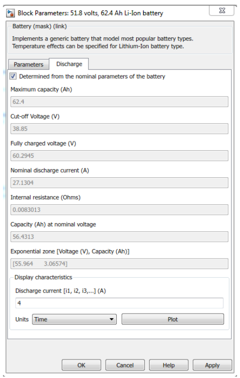


Figure 8.15: Battery block properties for line 3 in table 6.3: $R_0 = 0.0083$

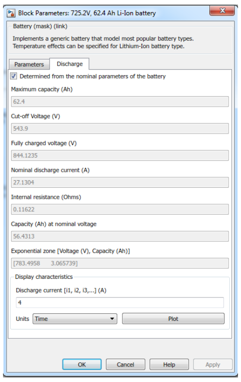


Figure 8.16: Battery block properties for line 4 in table 6.3: $R_0 = 0.116$

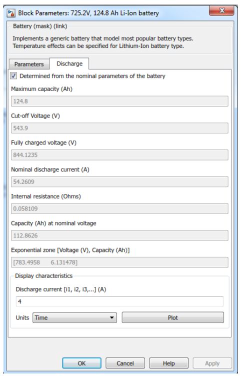


Figure 8.17: Battery block properties for line 5 in table 6.3: $R_0 = 0.058$

8.5 Simulations

Week 30: Required Battery Capacity

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
date	25.07.2015	26.07.2015	27.07.2015	28.07.2015	29.07.2015	30.07.2015	31.07.2015
E_batt [kWh]	167.3	174.7	185.5	177.4	164.9	167.4	106.0
DoD - Strategy 1 [%]	73.8	77.1	81.8	78.2	72.7	73.9	46.8
DoD - Strategy 2 [%]	55.5	58.0	61.5	58.8	54.7	55.5	35.2

Figure 8.18: Required battery capacity in week 30.

Week 1: Required Battery Capacity

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
date	04.01.2016	05.01.2016	06.01.2016	07.01.2016	08.01.2016	09.01.2016	10.01.2016
E_batt [kWh]	206.8	175.2	221.2	148.0	191.2	188.2	175.6
DoD - Strategy 1 [%]	91.2	77.3	97.6	65.3	84.3	83.0	77.4
DoD - Strategy 2 [%]	68.6	58.1	73.4	49.1	63.4	62.4	58.2

Figure 8.19: Required battery capacity in week 1.

Week 6: Required Battery Capacity

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
date	08.02.2016	09.02.2016	10.02.2016	11.02.2016	12.02.2016	13.02.2016	14.02.2016
E_batt [kWh]	88.5	101.1	115.7	123.2	30.5	52.2	55.2
DoD - Strategy 1 [%]	39.1	44.6	51.0	54.3	13.5	23.0	24.3
DoD - Strategy 2 [%]	29.4	33.5	38.4	40.9	10.1	17.3	18.3

Figure 8.20: Required battery capacity in week 6.

Week 52: Required Battery Capacity

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
date	21.12.2015	22.12.2015	23.12.2015	24.12.2015	25.12.2015	26.12.2015	27.12.2015
E_batt [kWh]	212.8	185.9	233.2	242.0	227.2	288.1	190.4
DoD - Strategy 1 [%]	93.9	82.0	102.9	106.7	100.2	127.1	84.0
DoD - Strategy 2 [%]	70.6	61.6	77.3	80.3	75.3	95.6	63.2

Figure 8.21: Required battery capacity in week 52.

Week 53: Required Battery Capacity

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
date	28.12.2015	29.12.2015	30.12.2015	31.12.2015	01.01.2016	02.01.2016	03.01.2016
E_batt [kWh]	155.5	122.3	173.1	262.7	215.7	206.2	251.0
DoD - Strategy 1 [%]	68.6	53.9	76.4	115.9	95.2	90.9	110.7
DoD - Strategy 2 [%]	51.6	40.6	57.4	87.1	71.6	68.4	83.2

Figure 8.22: Required battery capacity in week 53.

Week 50: Required Battery Capacity

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
date	07.12.2015	08.12.2015	09.12.2015	10.12.2015	11.12.2015	12.12.2015	13.12.2015
E_batt [kWh]	184.6	115.7	219.9	179.9	152.9	165.8	236.2
DoD - Strategy 1 [%]	81.4	51.0	97.0	79.3	67.5	73.1	104.2
DoD - Strategy 2 [%]	61.2	38.4	72.9	59.7	50.7	55.0	78.3

Figure 8.23: Required battery capacity in week 50.

Week 48: Required Battery Capacity

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
date	23.11.2015	24.11.2015	25.11.2015	26.11.2015	27.11.2015	28.11.2015	29.11.2015
E_batt [kWh]	124.4	144.5	160.2	138.4	143.1	241.0	215.8
DoD - Strategy 1 [%]	54.9	63.7	70.7	61.1	63.1	106.3	95.2
DoD - Strategy 2 [%]	41.3	47.9	53.1	45.9	47.5	79.9	71.6

Figure 8.24: Required battery capacity in week 48.

8.6 Transformer Upgrade Cost

The costs listed in Figure 8.25 are collected from SFE Nett's internal system, and include the costs related to an upgrade from a 100kVA transformer to a 200kVA transformer.

Planning Cost [NOK]	Labour Cost [NOK]	External Cost [NOK]	Installation Equipment Cost [NOK]	Total Cost [NOK]
60 000	140 000	25 000	175 000	400 000

Figure 8.25: Costs related to transformer upgrade.

Chapter 9

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