Smart Grid-Integrated Vessel through a shore power system

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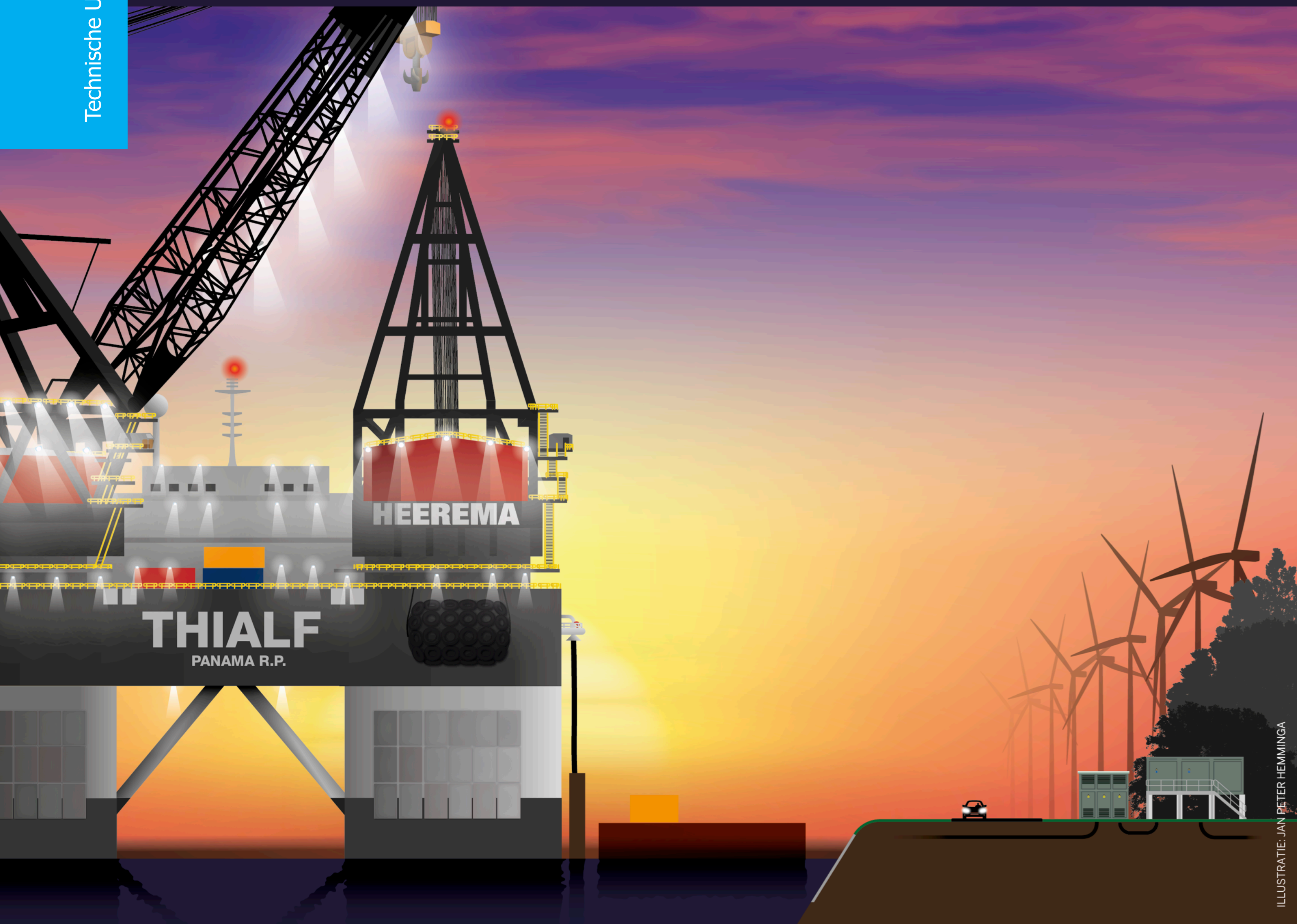

Delft University of Technology

Challenge the future

Smart Grid-Integrated Vessel through a shore power system

by

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Master of Science

In Sustainable Energy Technology

At the Intelligent Electrical Power Grids (IEPG) Group

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Abstract

Battery energy storage systems (BESS) that are integrated with the electricity grid have proven to be a suitable solution for reducing costs by providing flexible demand, but are often uneconomical when used solely for this purpose. Despite the research efforts showing the benefits of an energy-integrated harbor-area smart grid (HASG), the integration of onboard BESS in synergy with shore power connections has not been considered in the literature. Moreover, not from the financial perspective of the vessel owner.

This thesis addresses the integration of onboard BESS with a shore power system. More specifically, by presenting a cost-effective energy management system (EMS) that uses a stochastic approximation to define the charging and discharging decisions based on electricity prices. Additionally, the system takes the uncertainty of wind power production into account and reduces the power strain on the grid. Besides this, the research provides an analysis of the battery parameters that influence the cost-reducing ability of the EMS. As a result, the additional cost reduction presented while at berth may allow for previously uneconomical investments in onboard BESS for SSCV operators.

The wait-and-see (WS) approach was applied to provide an optimal energy scheduling solution with regard to uncertainty in wind power generation. Within the WS, three strategies were applied. By optimally scheduling a 5MWh BESS, the arbitrage, arbitrage + peak shaving, and peak shaving strategies respectively achieved a 1.4%, 15.7%, and 10.2% yearly reduction in electricity costs for the vessel operator during a 100-day stay in port.

Contents

Acknowledgements

While still in my BSc Maritime Engineering program, I had the opportunity to work on the modeling of a peak-shaving algorithm for a hybrid semi-submersible crane vessel. The work I did then inspired me to pursue a degree combining sustainability with electrical-, and maritime engineering. The final phase of obtaining my MSc Degree has been an exciting journey that would not have been possible, or as exciting without many people surrounding me.

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Enjoy reading!

Delft University of Technology — T.C.J. Weenk
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Nomenclature

BESS	Battery-electric Energy Storage System
DG	Diesel Generator
SSCV	Semi Submersible Crane Vessel
PE	Power Electronics
DSO	Distribution Grid Operator
PM	Particulate Matter
EPEX	European Power Exchange
TSO	Transmission System Operator
PV	Photo Voltaics
VGI	Vehicle Grid Integration
EMS	Energy Management System
RET	Renewable Energy Technologies
RES	Renewable Energy Sources
SDG	Sustainable Development Goal
SOC	State-of-Charge
KNMI	Royal Netherlands Meteorological Institute
CAPEX	Capital Expenditure
NPC	Net Present Cost
IRR	Internal Rate of Return
ROI	Return On Investment
DPP	DPP Discounted Payback Period
DAM	Day Ahead Market
FH	Hourly Average Wind Speeds
GO	Guarantee of Origin
STN 330	Hoek van Holland weather station
PDF	Probability Density Function
MF	Membership Function
RA	Risk Averse
OS	Opportunity Seeking
CDF	Cumulative Distribution Function
SAA	Sample Average Approximation
KD	Kantorovich Distance

1 Introduction

1.1. Introduction

Climate change is an urgent issue affecting people worldwide which imposes humankind with the most difficult challenges in recent history. Greenhouse gases (GHG) are emitted as a result of the burning of fossil fuels which results in a global rise in average temperatures. The sectors responsible for the largest emissions of GHGs are the transport, energy, industry, and agriculture sectors. To avoid the most extreme consequences of climate change the Intergovernmental Panel on Climate Change (IPCC) predicts that global temperatures should be limited by 1.5 degrees Celsius compared to pre-industrial levels [1].

Climate policy measures will address energy consumption in addition to the production of renewable energy. New policy measures and the general attitude toward climate change will have a significant impact on the transportation sector which remains heavily reliant on fossil fuels [2]. Shipping plays an essential role in transportation since it is responsible for 90% of global trade and makes up 5% of global GHG emissions [3][4]. Climate regulations set by the Dutch government require the shipping sector to reduce its emissions by 40% in 2030 [5]. To achieve this, ships can reduce emissions in two different places; while being operational offshore or while being moored in port. This research focuses on the vessel's operations in port.

In an effort to reduce the emissions GHG, the IPCC recommends the deployment of renewable energy sources (RES) such as wind energy and solar photovoltaics (PV) [6]. To ensure compliance with the climate agreement, the necessary measures are laid down in both EU and national laws and regulations. On a European level, the Renewable energy directive set up rules to achieve a 32% fraction of energy coming from renewable energy sources (RES) in 2030 [7]. On a national level, the "Klimaat akkoord" from the Dutch government states to have increased the production of renewable energy by 84 TWh by the year 2030 [8]. As a downside, the introduction of RES, has increased to volatility of electricity prices on the market, due to its intermittent nature. Moreover, increased electrification forms another barrier for developing renewable energy project such as shore power, as the grid is increasingly facing congestion problems. As a result, consumers are challenged to develop innovative ways to guard against higher prices [9].

To be more specific, this dissertation aims to develop an optimal method to reduce the costs of electricity for vessel operators during shore power connections. This cost reduction should be achieved while limiting the burden on the grid and increasing the use of locally produced renewable energy. In the end, this will enable the ultimate goal of wide-scale adaptation of battery-equipped vessels and adequate shore power connections by improving the business case for onboard batteries and reducing the grid capacity requirements.

This introductory chapter will go over the following topics. Section 1.1.1 presents the characteristics and limitations of battery-equipped vessels. Subsequently, in section 1.1.2 the trends requirements and limitations with regard to Cold-ironing are explained. Section 1.1.3 presents the opportunities of shore power connected vessels in an energy-integrated port. This leads to the research question of the thesis in section 1.2. Lastly, the thesis outline and motivation are provided in section 1.3.

1.1.1. Hybrid Electric Vessels

Due to current climate policy measures, the shipping sector has started to invest in battery-electric energy storage systems (BESS) in order to meet policy standards and contribute to lower emissions of GHG [10]. Within the world's shipping fleet, onboard BESS are becoming an increasingly common phenomenon as can be seen in Figure 1.1. The prices of BESS are rapidly decreasing due to a year-over-year increase in production volume which is making the investment in such a system more attractive [11]. The interest in these types of vessels will only increase in the future, as policy will become more stringent on tailpipe emissions.

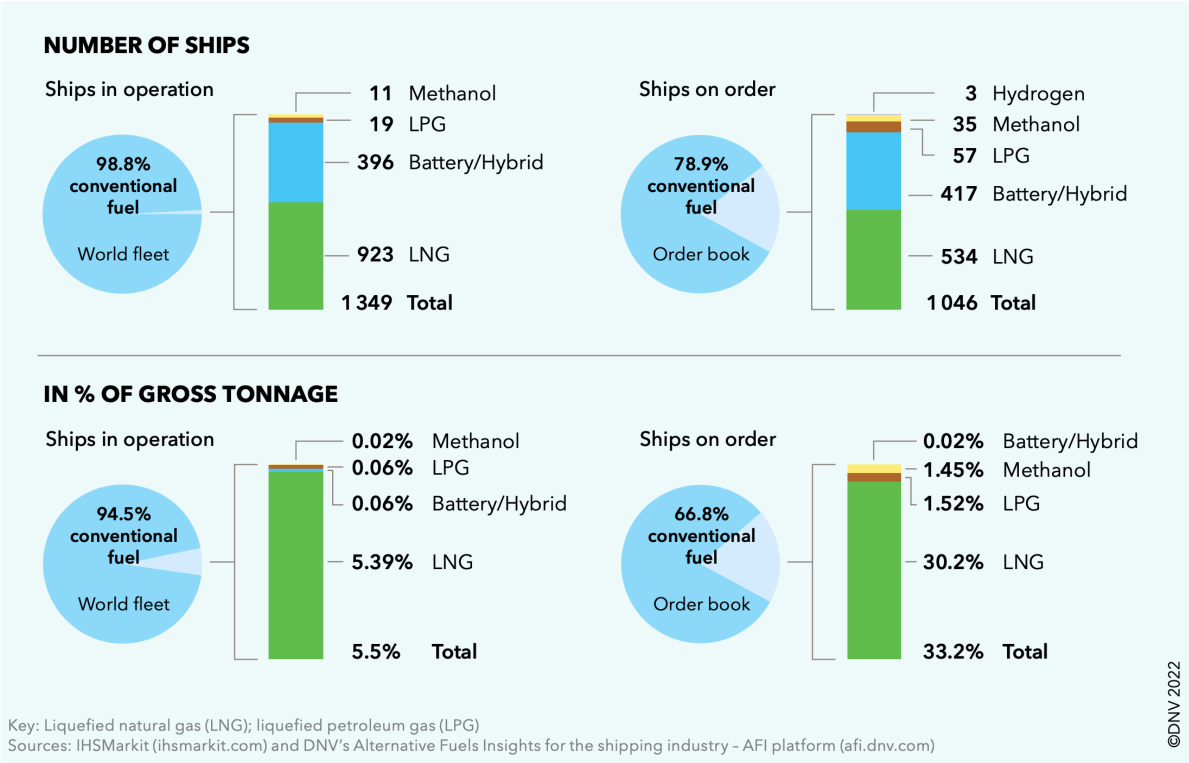

Figure 1.1: Alternative fuel uptake in the world fleet by number of ships and gross tonnage [12]

For small vessels such as ferries, a BESS can be utilized for the full operational profile since these ships have relatively low energy requirements [10]. Besides this, ferries are able to frequently charge during loading and offloading and have a fixed route. Batteries are however not always capable of storing the often vast amounts of energy that a ship requires. For these vessels, there are other use cases for onboard BESS.

Whereas small vessels are able to fully depend on BESS for their energy storage demand, large vessels have introduced BESS for peak shaving-, and for backup-power purposes [11]. Hybrid systems are especially valuable for vessels that operate using dynamic positioning. Using a hybrid system, these ships are able to operate their engines at higher efficiencies and can sometimes even turn off generators. The aforementioned BESS can have a significant impact on reducing fuel consumption by 10-25% depending on the operational profile and with that reduce GHG emissions during their operations [11]. The rising trend in onboard BESS is likely to continue to grow as both company incentives, policy measures and decreasing battery prices keep motivating this sector towards investing in such systems [11].

The incorporation of BESS on ships has been demonstrated to provide a range of benefits. These systems can serve as the primary energy source, backup power supply, or provide peak shaving. Utilization of BESS has been shown to result in significant fuel savings, with reductions of greater than 10% resulting in the reduction of greenhouse gas emissions [13][11]. Besides this, an onboard BESS can also provide power quality issues to ship microgrids [14]. All the benefits that a BESS can provide are however only relevant during the operational sailing profile of the vessel [15]. This poses a financial challenge for a ship operator considering investing in an onboard BESS for hybrid operations especially for Semi Submersible Crane Vessels (SSCV). Since long stays in port of SSCV limit the ability for cost reductions since these are predominantly realized during the offshore operation of the vessel. As a result, SSCV experience an extended return on investment for on-board BESS. In addition to the financial challenge, the non-use of the BESS is a waste of this valuable asset. This is particularly noteworthy when considering that BESS may be able to serve a useful purpose during periods of time when the vessel spends in port. Therefore, it is important to consider the potential for utilizing BESS during these periods in order to avoid this unnecessary waste.

As mentioned, increased RES penetration will likely result in highly variable pricing, and being able to adjust electricity demand accordingly will play an increasingly important role [9]. Furthermore, having existing infrastructure contribute to the electricity grid will increase the utilization of assets and simultaneously provide more financial incentives for adapting vessels with BESS. The synergies between shore power and BESS-equipped vessels should be explored in order for vessel operators and infrastructure to benefit from the onboard high-capacity BESS.

1.1.2. Cold-Ironing Hot Topic

Most large vessels rely on Diesel Generators (DG) to provide auxiliary power for onboard facilities during their stay in port [16]. Although this is still the most commonly used method, there is a growing trend for supplying this power through a shore-side power supply or cold-ironing facility which connects to the ship's grid via a cable [16]. This renders the DG useless and cold, hence it gets the term cold-ironing [16]. Cold-ironing enables ships-at-berth to significantly reduce GHG emissions by providing the vessel with renewable electricity while the ship can continue to be operational [16]. Furthermore, a major benefit of shore power is the elimination of engine noise and emissions of particulate matter (PM)[16].

In addition to the many advantages, there are also disadvantages to using shore power. The necessary infrastructure to facilitate the high power requirements for cold-ironing requires large investment costs for constructing the onboard-, and shore power connection due to the high cost of Power Electronics (PE) [16]. In addition to the ship owner, the port authority may need to invest in a grid-connected storage system in order to mitigate the strain on the grid as a result of the large power requirements of the shore power connection [14]. Adjustments for the high power requirement of ships to the grid can delay the construction of shore power by sometimes years.

Another cost aspect for the vessel operator are electricity tariffs that have a significant impact on the economic viability of cold-ironing. These costs comprise of energy-, and power-related costs. Ships are subject to the day-ahead prices for their energy, which are traded on the European Power Exchange (EPEX) while connected to shore power [17]. During cold-ironing both the average and variability of prices impact the operational costs for the vessel. The price volatility of electricity on the spot market will only keep increasing in the future due to the impact of RES on the behavior of electricity prices [9]. Since RES have near-zero marginal costs they come first in the merit order and push out more operationally expensive forms of electricity production [18]. Although this will result in an overall lower average electricity price, the volatility will increase. Besides the prediction from academic sources, an increase in real-world price volatility can already be observed. The Dutch Transmission System Operator (TSO) Tennet also observed increased volatility from 2019 to 2020 in its yearly overview [19]. In order to utilize most RES and reduce costs, it is therefore essential for ship operators to be able to optimize their energy use according to energy prices.

Grid-related costs consist of transport costs which are based on the maximum power demand during a specified period. While in port, power consumption varies depending on the machinery in use at the time. Lifting loads and moving the cranes results in short peak in power demand of the SSCV. These short peaks, lasting no more than 15 minutes result in increased transport costs for the next month. Locally produced electricity for RES is often available at reduced peak tariffs. The ability to 'shave off' peaks in power demand with BESS, or shifting the peaks to periods with an abundance of renewable energy can result in lower costs of electricity for the vessel operator. Due to the intermittent nature of renewable energy, it is important to consider uncertainty in such an energy scheduling problems.

BESS-equipped vessels and shore power are likely to play a significant role in sustainable developments in the maritime sector. At the same time, the combination of these technologies has the potential to provide financial incentives for investments in onboard BESS through a reduction in electricity costs. Additionally, the battery can act as a buffer during the peak load demand of the vessel, thereby reducing necessary the peak power capacity of the grid. This will improve the construction of new shore power locations in congested ports, while also reducing transport costs for the vessel operator. It is therefore fundamental to understand the synergy between the two technologies and explore the gap in the academic literature which will be described in chapter 2.

1.1.3. Grid Integrated Vessels: Opportunities and challenges

Within the electric mobility sector, many research efforts can be found that aim to increase battery utilization in electric vehicles (EVs). The utilization of the battery is mostly done by providing ancillary services to the grid, this type of utilization is called vehicle grid integration (VGI). Since electric vehicles are only used as a means of transportation for 5% of their lifetime they can be considered more like batteries on wheels than cars [20]. Utilizing the battery in other fields can therefore help reduce the cost of ownership and open new business models[20] [21].

The field of VGI can be divided into two main categories which are distinct because they differ in their power flow to and from the grid. When the car can only determine its charging rate it falls within the category of grid-to-vehicle (G2V) [21]. The ability to provide power to the grid by discharging is called vehicle-to-grid (V2G) [21]. VGI is able to contribute to the reliability of the grid by providing ancillary services such as frequency response in short term as well as load leveling, peak shaving, and demand balancing [20]. By providing such services the vehicle is able to generate revenue for the owner whereby the cost of ownership of the vehicle will be decreased [20]. Within this relatively new market of VGI, the individual EV owner or aggregator can benefit from new business opportunities through renewable energy storage and grid balancing services [20]. The DSO benefits since grid-connected vehicles act as a new resource for ancillary services through power storage and the up and down regulation of power consumption [20]. By doing so, VGI is able to facilitate the necessary flexibility for the penetration of intermittent renewable energy sources as well as provide solutions for problems like grid congestion by delaying or even circumventing the need for grid reinforcements [20].

The potential for ship operators is potentially much higher since the usage profiles for ships are radically different than those of EVs. Compared to EVs, there are many more benefits for vessel-grid integration. First of all, ships have longer times connected to shore power and have a more predictable load. Besides this, the state-of-charge (SOC) and schedule are often known days or months in advance. Furthermore, onboard BESS are equipped with a higher energy and power capacity. Lastly, vessels have the possibility to work in conjunction with other loads in the port as will be discussed in section (2.1). Flexibility is another important aspect ship-to-grid integration can provide.

In an overview of newly built hybrid and fully electric vessels, reference [10] notes that half of all battery-equipped ships currently in use or under construction are ferries. The other 35% are offshore vessels or tugs, the remaining part constitutes cargo- and cruise ships [10]. Ferries are amongst the most obvious ships to be electrified since they require relatively little energy and are able to charge often. Other uses for BESS can be observed in vessels with highly variable loads such as the case for tugs and offshore vessels. Reference [22] shows that even non-variable loads such as container vessels might benefit from an onboard BESS by generating onboard electricity from the main engine shaft take in, utilizing the much more efficient two-stroke main engine instead of the more inefficient auxiliary engine(s). Therefore in a future fleet, most ships can benefit from having BESS on board.

In a future scenario, the large number of electric and hybrid vessels can be aggregated to provide energy flexibility to the port. Estimating the exact energy flexibility that a fully electrified shipping fleet can provide to the electricity grid is difficult to make. A rough estimation for the port of Rotterdam can however be made. To start off an analysis of the number of docked vessels and the respective onboard BESS power and energy capacity. On satellite images from Google Maps, 118 docked vessels were counted in the Rotterdam port area. Assuming that of these vessels roughly 20% were in the process of docking, un-docking, or otherwise not able to be connected to shore power we are left with a selection of 80-100 vessels. From this selection, we assume that all vessels will be equipped with an onboard BESS of 1-5 MWh which is equivalent to the capacity of 12-62 long-range EV battery packs [23]–[26]. When assuming an average SOC of 50% this would amount to a flexibility of 50-2500 MWh. The total wind turbine capacity that is currently installed and under construction in the Port of Rotterdam is 336.1 MW as shown in Table A.1. Under the maximum wind generating conditions, up to 3.5 hours of the total maximum wind energy generated in the port area can be stored with this flexibility. While this future scenario will not be considered in the thesis, studying the synergy between shore power connected vessels and smart vessel grid integration may contribute to bringing this scenario closer.

Many changes are occurring within the landscape of sustainable shipping. The growing number of investments in hybrid- and electric vessels is resulting in an ever-growing fleet of battery-equipped vessels. Additionally, sustainable policies are driving the introduction of cold-ironing connections in ports. The combination of these technologies opens a gap for grid participation for grid-integrated vessels, which itself is a new topic within the scientific literature. While the opportunities for electricity cost reduction appear promising for vessel operators, many questions remain unanswered. The next section will focus on the most important questions.

1.2. Research Objectives

The research objectives are provided in this section. The answers are presented in Chapter 7.

1.2.1. Research Questions

Ships are currently not utilizing the full potential of onboard BESS whilst connected to shore power. As a result of the increasing penetration of RES the electricity market in which ships are operating is moving towards ever-increasing volatility in prices. Furthermore, the electrification of ships poses significant challenges to the capacity of the electricity grid.

The scientific literature describes use cases for BESS in a RES-powered grid and the role of electric vehicles within this system is given as well. Yet the synergy between these two technologies is not well studied. Addressing this by answering the research questions can accelerate the adaptation of onboard BESS and contribute to more efficient and economic use of energy storage assets.

How to develop a cost-effective energy management strategy for a semi-submersible crane vessel (SSCV) to increase the economical benefits for the ship operator which uses cold-ironing service via an on-board BESS?

To be able to formulate an answer to this research question, the analysis must involve different subjects. In that respect, the main research question will be answered through the use of the following sub-questions:

1.2.2. Research sub-questions

1. What **energy management strategies can be performed considering infrastructural constraints** of the shore power connection, the grid, and the BESS?

   The energy management strategy uses the generated wind power scenarios from sub-question 4. This results in a model which is described in chapter 3 based on the case study presented in 5. The results of which a presented in chapter 6.

2. **Which type of support services and participation** in the short-term electricity market **can generate economic benefit to the ship operator** during cold ironing using an onboard BESS?

   This sub-question provides information on the most suitable electricity markets in which vessel operators can offer their battery capacity. The answer to this will be found by means of a literature study of electricity markets in chapter 2.

3. What factors influence the **optimal energy and power specifications for an onboard BESS for Vessel-to-Grid participation**?

   This sub-question will be addressed by a sensitivity analysis of the basic parameters of the battery in chapter 6. Different variations in charge-, discharge rate, and energy capacity will be tested to quantify the optimal battery size.

4. What is a suitable scenario generation method **for generating wind data scenarios from historical data?**

   Scenario generation is a necessity to retain computational tractability for the stochastic programming problem. Yet there are many approaches to generate scenarios. In Chapter 2 these are reviewed. The methods are condensed into 3 viable methods which elaborated upon in chapter 4 and are tested on the wind data to find the most suitable method.

1.3. Thesis outline

1.3.1. Outline

Answering the research questions will be approached by following the flowchart in Figure 1.2. Chapter 2 provides an elaborate overview of the state-of-the-art of vessel-grid-integration, battery energy management strategies and uncertainty approaches in energy scheduling. Chapter 2 will conclude by addressing the gap in the literature and provide a summary on how this thesis will contribute to the scientific literature.

Chapter 3 provides the problem definition in which all necessary equations to come to cost optimal dispatch of an onboard battery are described. This includes a deterministic formulations of the problem, including the objective function and constraints. Chapter 4 describes the chosen approach for energy scheduling in an environment with uncertain wind generation. This includes a stochastic approximation method, to reduce the computational effort. Followed by three scenario reduction approaches within k-means clustering to reduce the number of scenarios and calculate the probability distribution.

The case study is addressed in Chapter 5 in which all the specific elements that make up the system are described. The results for the case study can be found in chapter 6. Finally, the the conclusion and discussion are given in chapter 7.

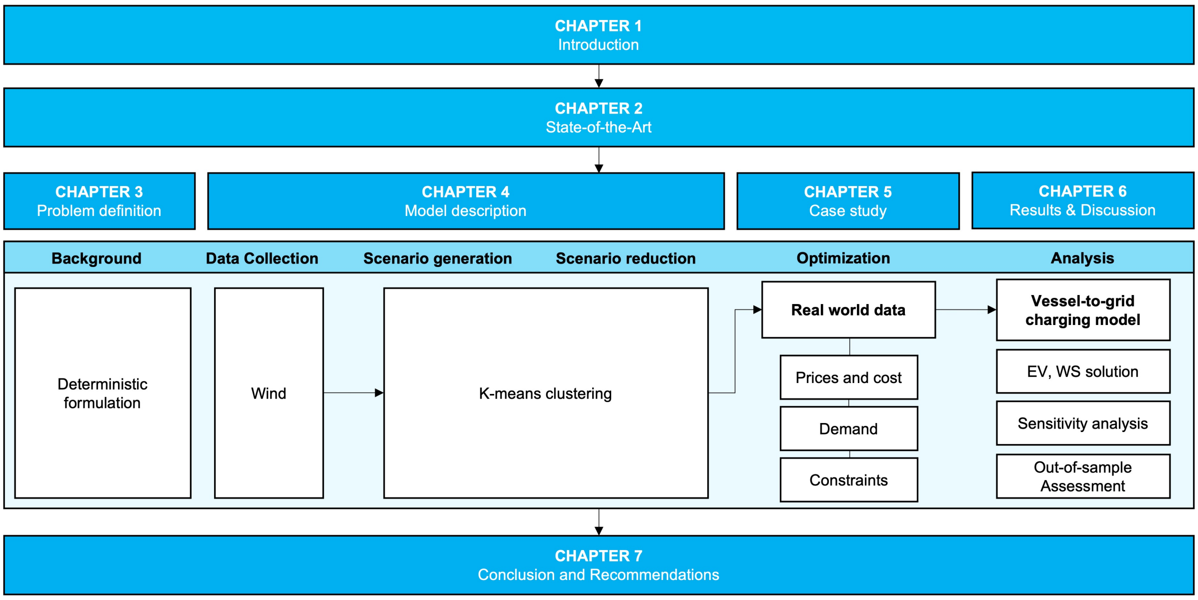

Figure 1.2: Flowchart Methodology

2
State-of-the-Art

The literature review in this chapter aims to provide a theoretical framework for the study of grid-integrated vessels, cost-reducing battery energy management systems, and uncertainty modeling. In particular, the state-of-the-art in these areas will be reviewed, with a focus on identifying gaps in the current literature. Section 2.1 will discuss the latest developments in vessel-grid-integration, while Section 2.2 will focus on energy scheduling models and the markets in which battery energy storage systems (BESS) can be utilized. In Section 2.3, the state-of-the-art in uncertainty handling within energy scheduling models will be reviewed. After identifying the gaps in the literature, Section 2.4 will outline the contributions of this dissertation.

2.1. Vessel-grid-integration

The integration of vessels and power grids is a fairly new concept in the shipping sector. Whereas multiple studies have looked at vehicle-to-grid integration (VGI) in the car sector, fairly little research has been performed on the integration of ships with the electricity grid through cold-ironing. Reference [27] is one of the few studies that explore the battery electric energy storage potential and boat-to-grid integration. Most other studies within the state-of-the-art of cold-ironing focus on smart grids. Smart grids are integrated systems in which different loads and energy producers are able to communicate [16]. The main goal of a smart grid is to improve the efficiency of energy transactions in a cost-effective manner [16][28]. Reference [29] found that improved energy management systems can decrease electricity costs by 20-30%. The ultimate method by which this can be achieved is by improving the balance of electricity supply and demand with the management of smart loads that are able to adjust their demand based on electricity supply [29].

Within smart grids, there are opportunities for ship operators to function as smart loads. As a smart-load vessels are able to contribute to flexibility in the grid, allowing for higher penetration RES [16]. Furthermore, it can also help smooth the demand of the inland grid [16]. Building on the capacity of vessels to function as smart loads, on a system scale; this allows ports to function as electric energy hubs [16]. The main reason for ship operators to adopt this new technology will be the financial incentive that is provided for the ship operator and the infrastructural benefits for the harbor grid. As the European framework described by Directive 2009/72/EC will allow individual electricity consumers to provide demand response based on variable tariffs. While reference [16] presents a possibility for vessels to act as smart load and allowing a port to function as an energy hub, it only presents a framework for how this can be studied. Furthermore, the paper considers only on-shore BESS to enable the possibility for participation in the smart grid.

The Harbour Area Smart Grid (HASG) is a subcategory of smart grids in that it has all the same objectives and functionalities as a smart-grid, but differs in that it concentrates on ports only. The concept of a HASG was first proposed by [30] recognizing that a future scenario with hybrid vessels and all-electric ships (AES) requires a harbor area grid architecture that must be able to facilitate a sufficient power supply for both cold-ironing and the charging of such vessels. The paper presents the use of on-shore BESS that provides ancillary- and balancing services thereby supporting the weak grid and enabling energy arbitrage and peak shaving. Whereas the paper stresses the need for the port to facilitate the growing number of AES and hybrid vessels, the authors do not consider using the onboard BESS of these vessels in the HASG. While the opportunities for energy arbitrage are briefly described, the main focus of the paper is on the grid infrastructure of the port and the benefits of on-shore BESS in a new system architecture. Furthermore, the paper does not touch upon the benefits for the individual vessel operator.

A more in-depth study on the control of a BESS in a HASG is provided by [31]. In this paper, an on-shore battery is used for the reliable operation of the smart grid. The function of the battery is to provide an additional source of power that mitigates the negative effects of peak power demand from shore power connected vessels. This will allow ports with limited electrical infrastructure to provide cold ironing berths without an extensive redevelopment of the current infrastructure. In the newly proposed topology, the economic aspect is only described very generally. It describes the possibility to mitigate the aforementioned investments in electrical infrastructure such as cable and transformers without addressing the costs of grid reinforcements with the use of a battery system in detail. The energy management system described by the paper uses a simple rule-based algorithm, which considers state-of-charge and power demand to control the charge and discharge rates of the on-shore BESS. Other factors such as renewable energy generation, day-ahead prices, uncertainty, or peak demand tariffs are not considered. As presented earlier, the focus of [31] is on the operational advantage of the port's grid as a whole and not on the benefits to the ship owner.

Whereas previous references explored the use of on-shore BESS, reference [32] examines real-time energy control and the positive impact of Plugged-in Electric Vehicles (PEV) in a port. Contrary to on-shore BESS discussed in the aforementioned papers, this more closely resembles the characteristics of onboard batteries. While the paper emphasizes that locally produced wind energy is a very efficient way of providing green electricity to berthed vessels through cold-ironing. Moreover, the authors stress the impact of irregular energy production on the grid and the necessity for methods to control this volatility. Amongst other controllable energy consumers such as reefers, the demand of a PEV park is controlled by a day-ahead scheduling algorithm that bases its decision on a forecast of various parameters such as wind speed, temperature and electricity price. Errors in the forecast are subsequently adjusted by a control loop using real-time power measurements to provide frequency support to the grid. In the paper, PEV contribute to the grid by providing ancillary services to the electrical infrastructure of the port which adds to the relevance of using BESS. However, the proposed approach only considers the added benefits of demand control from a grid conducive system perspective without considering the cost benefits for the providers of this flexibility.

Within the academic literature, a general consensus for the benefits of BESS to the local grid is found. The use of on-shore BESS and PEV technologies are provided as solutions for providing demand response in a supply and demand imbalance as a result of RES. Yet most references do not regard the cost benefits for the individual providers of this flexibility. As most approaches see benefits for a BESS but look at the problem from a system perspective. If mentioned at all, the algorithms used in the papers are relatively simple deterministic ones based on only power supply and demand. Other factors such as prices, renewable energy generation, or uncertainty are not considered.

2.2. Battery energy management strategies

A prerequisite for a viable business case for BESS utilization during shore power connection at berth is the ability to reduce the costs of electricity for the individual vessel operator. As mentioned in Chapter 1 many studies have been performed on energy management systems to reduce electricity costs. Building on the previous section, this chapter will elaborate on these studies, explain their differences, and explore which approach is most relevant to the case study described in Chapter 5. In preparation for determining the most suitable way for a vessel operator to utilize the onboard BESS in a cost-reducing manner, a study was performed on the landscape in which such a system would operate. This included a study on electricity markets in the Netherlands and a study on the type of energy management strategies which can be found in Appendix B and Appendix C of this dissertation. As a result of these studies, behind-the-meter type BESS are seen as the most appropriate method for use in a cost .

Since shore-connected battery-equipped ships are effectively behind-the-meter (BTM) energy storage devices we dive deeper into this subject. The difference between a BTM application and V2G or on-shore BESS is the ability of a BTM system to do self-consumption while staying connected to the grid. In this use case, the battery acts as an energy buffer that can be charged and discharged depending on the objective of the system. In order to look at the potential benefits and gaps in knowledge, the following articles were consulted. This paragraph aims at listing the current state-of-the-art models within the realm of cost-reducing BTM BESS and explores the gap in knowledge within the scientific literature.

The use of BTM systems occurs on a variety of scales. Reference [33] reviews the economic benefits of energy arbitrage for a home-based grid-connected microgrid with self-generation through PV. The paper makes use of a deterministic linear programming method to determine the optimal dispatch for the battery in order to maximize the economic benefits, by taking into account the revenue and investment costs. As a result, the optimal size of the BESS is determined.

Contrary to the smaller domestic load, [34] explores the possibility of generating revenue streams for BESS in industrial applications through offering primary control reserve (PCR), peak shaving, and energy arbitrage in the day ahead- and intraday markets, with the objective to minimize costs for the operator. It uses a linear programming method to find the optimal dispatch of the BESS within these markets with perfect foresight. Hereafter, it analyses the optimal battery size by including investment costs in the model. The use of renewable energy generation is not taken into consideration in this study. Reference [34] also describes a gap in the literature regarding research on the influence of different industrial load profiles. The LP approach used in the aforementioned papers allows for a fast and simple way calculation method to find the optimal value. Where it however lacks in is taking into account the uncertainty surrounding the problem. Where it is relatively simple and fast to calculate an optimal solution with perfect hindsight, making an accurate decision for the future would be impossible.

Uncertain circumstances can however be modeled with alternative modeling methods. Where previously mentioned cases make use of linear programming methods, reference [35] uses a combination of dynamic programming (DP) and mixed-integer linear programming (MILP) for arbitrage and peak shaving. The system regards a smart grid with multiple domestic electricity consumers with renewable generation through wind and PV at various nodes. The main objective is to optimally schedule multiple hubs as to reduce the energy hub's costs. Uncertain behavior of the system is modeled through a Monte-Carlo approach. Furthermore, the number of scenarios is reduced through a fast-forward selection method which allows for a more time-efficient calculation of the optimum.

Yet another approach is used [36] which explores energy arbitrage optimization and looks at individual control of a BESS using a Markov decision process (MDP) for frequency regulation and energy arbitrage. The case study of this paper aims to generate revenue for the battery operator by trading in the frequency response market in combination with energy arbitrage. To make this profitable, it requires the operation in more than one market, allowing the battery operator to 'stack' revenue depending on favorable circumstances in the market. Although the paper mentions the advantages of balancing ability of a BESS, the uncertain nature of RES is not taken into consideration in this research.

Contrary to earlier studies, reference [37] considers external RES. The aim of the research is to reduce energy costs for consumers by dispatching home batteries. This is achieved by optimizing the energy management system such that wind power generation is stored in the home batteries at favorable tariffs for the battery operator. From the perspective of the wind-farm operator, its feed-in is not curtailed thus the co-optimization benefits both parties. Additionally, the optimization includes variable tariffs for electricity allowing the EMS to dispatch the battery without increasing transport costs as a result of increased peak power demand.

Most behind-the-meter applications are utilizing some form of optimization to optimally dispatch the battery. Self-consumption of energy from the battery is a prerequisite for BTM systems, most research papers consider self-generation and consumption from renewable energy generation assets in the system. On an industrial scale, however, these assets are often managed by external parties which changes the business case for self-consumption. Regarding self-consumption, most studies on BTM energy management systems focus on home systems. While reference [34] does explore the benefits of BESS for the load profiles of German small-medium enterprises, the opportunities for the shipping sector remain unexplored. Moreover, the scientific literature mainly focuses on the potential revenue streams from selling electricity back to the grid and utilizing self-generated RE. However, for BTM energy storage the self-consumption loads and constraints imposed by the energy user i.e. the ship are not considered. In this case, the stored electricity is not sold but consumed, the economic benefit can be measured by the price that would otherwise have to be paid by the vessel. This leaves a gap in the scientific literature for energy management strategies of onboard BESS with the load profile of a ship.

2.3. Uncertainty in Energy Scheduling

The focus of this research is to develop an energy management strategy that uses onboard BESS to accomplish a cost reduction for a vessel operator through smart scheduling of a battery. As stated in the introduction, this is a novel method of dispatching a battery that has not been described in the literature. The broader theme of smart energy scheduling is however well described topic, in this section the state-of-the-art of uncertainty within energy scheduling models will be described.

In a future energy system, the energy will increasingly be produced by RES. In some cases, customers are charged different tariffs depending on whether the energy originates from locally produced wind energy, or if it is purchased from the grid. In this first case, the power generation is subject to wind speed patterns. As it is impossible to accurately predict the wind power production in advance, the uncertain nature of wind speed has to be taken into account in the scheduling models. Whereas energy scheduling with perfect hindsight can be described with deterministic programming problems, handling uncertainty is described by stochastic programming.

Stochastic programming can generally be categorized by two types of models, which are coined *wait-and-see* and *here-and-now* models [38]. The first example indicates that a decision was made after the realization of the uncertainty, while in the here-and-now case the decision has to be made without prior knowledge of the uncertain parameters. In either case, the necessary components for these computations are a set of scenarios including their respective probability of occurrence. The method by which these scenarios are selected is described by *scenario generation*.

The review paper of [39] gives general overview and the state-of-the-art of scenario generation methods for integrated energy systems with wind power generation. Amongst others, the most popular scenario generation methods in publications are; Sampling based, ARMA and Clustering based scenario generation. These three sub-classifications are; sampling-based, forecast-based, and optimization-based methods.

Figure 2.1 provides an overview of the various scenario-generation methods that can be applied to stochastic programming. As can be seen, there are many methods one can choose from. From this large set, a selection of three methods - each within a different subcategory - was chosen, to further elaborate on. This was motivated by the fact that the scope of this dissertation should have a generally good working model, rather than finding the perfect scenario generation technique. This being said, a selection of the most popular techniques as described by [39] and highlighted in Figure 2.1 will be discussed in Section 3.

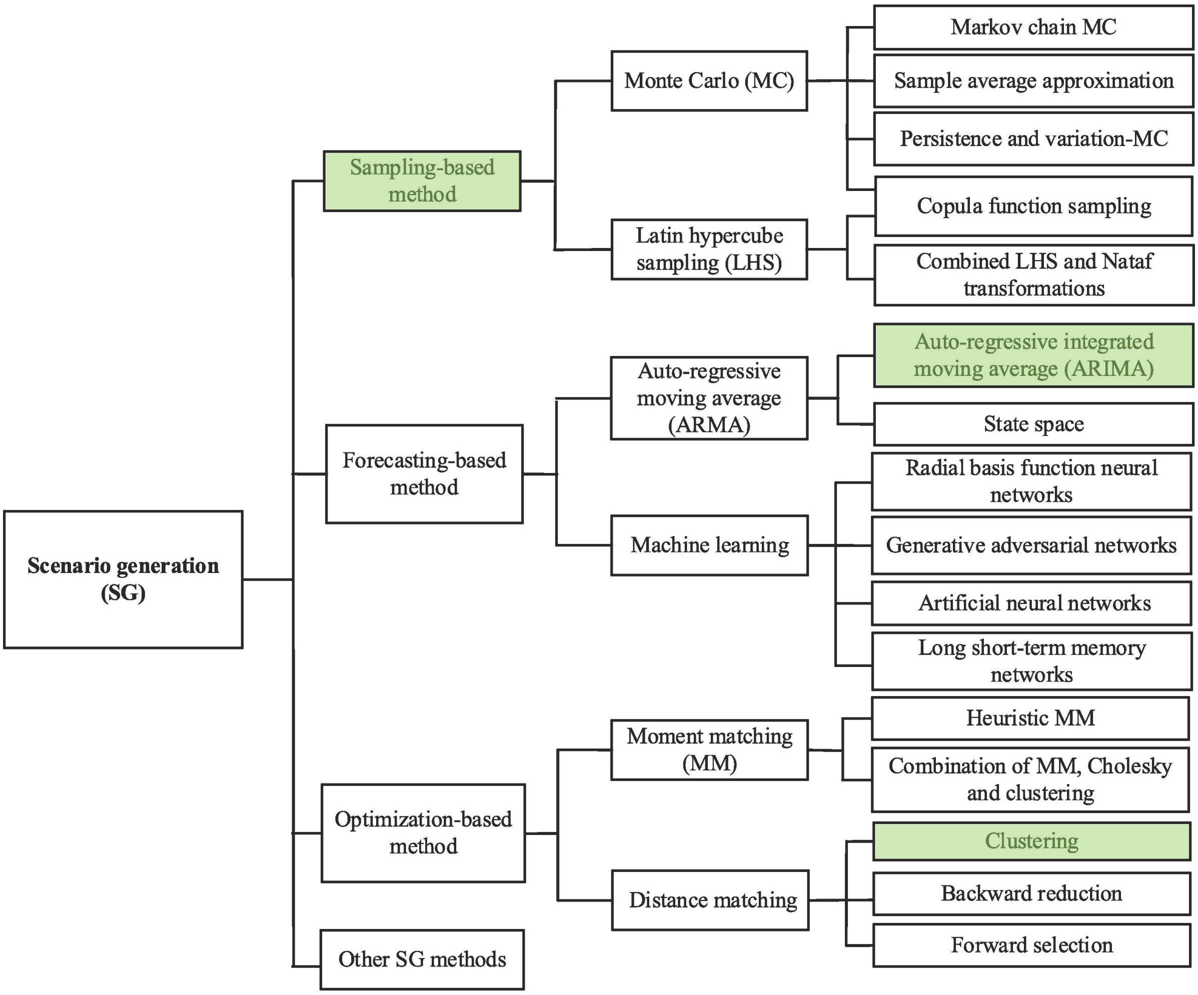

Figure 2.1: Classification of scenario generation methods [39]

Classical selection

A sampling-based scenario generation method typically uses a set of historical data which is analyzed for its uncertainty features. These features are subsequently used to sample data with similar stochastic properties. Monte-Carlo sampling is one of the methods that fall within this subcategory.

The paper of [40] uses a selection of two methods for describing the uncertainty in wind power generation. Historical wind speed data from one year is used to generate scenarios. The paper then describes using the classical selection mechanism based on probabilistic sampling method. In order to maintain the inter-temporal relation between the generated wind speeds it uses another cumulative distribution function (CDF) based on deciles. Using this method, 50 scenarios are generated which are subsequently reduced by a k-means clustering method. This is a distance-based reduction method that clusters based on similar features. The exact method by which k-means clustering is used is not described in the paper.

While the intertemporal relationship and the overall probability distribution were maintained, the method relies on a clustering method to determine the reduced number of clusters and the respective probabilities.

ARIMA

Similar to the previous method, forecast-based scenario generation uses a large set of historical data to replicate the stochastic features of the data to generate a new representative data set with similar uncertain properties. The auto-regressive moving average (ARMA) method is an example of such a prediction model.

In reference [41] an ARIMA scenario generation method is used to generate wind scenarios. The generated scenarios are subsequently reduced by a probability distance based Kantorovich Distance (KD) scenario reduction technique. For the case study 1000 scenarios were generated and reduced to 10 scenarios.

K-means clustering

Whereas previous methods generate synthetic scenarios based on the statistical properties of historical data, another approach is to generate scenarios by selecting historical data. This approach is described by [42]. As mentioned before, the main reason for using scenarios is to represent the distribution of the original data set with a smaller selection thereby reducing the computational burden whilst preserving most of the data related to the original distribution. Historical data can be used as scenarios simply by randomly sampling from a historical data set. This can however result in unrepresentative scenarios, especially when the method is applied to result in a small number of scenarios.

One popular method to reduce the number of historical scenarios that omits the problem of skewed results is by using k-means clustering [39]. K-means clustering can be used to reduce the number of synthetically generated scenarios as well as reducing a historical data set. This final section will focus on the latter approach.

Modellers of uncertainty modelling face a choice when it comes to the scenario generation method. Either a scenario generation method that generates synthetic data based on statistical features of a historical data set can be used, or the modeller chooses to sample from historical data. The use of historical data has several benefits when compared to the synthetic approach. Since we are looking at complex sequences of wind data it is important that the relationship between the data points is realistic. The use of historical data firstly guarantees that intertemporal relationship of data points is accurate, since the scenario actually occurred [42]. Secondly, the actual occurrence of the data sequence can result in a higher level of confidence from the model users perspective, for the same reason that it does not use 'synthetic' data, and the model uses the actual data set provided by the user.

The limitations for using historical data are the limitation to only use sampling and reduction techniques for scenario generation. Whereas other techniques are able to generate large sets of data which can subsequently be reduced to match the original distribution [42]. Moreover, the modeller should take the fact that clustering may also result in a 'synthetic' scenario thus not abiding by the preference of the model user. This can however be avoided by choosing an actual scenario, closest to the cluster center.

Reference [43] analyses the impact of wind power scenario reduction techniques. In the article, the authors show that compared to peak-density and average criterion, k-means performs the best at scenario clustering. The performance was based on statistical quality. Where the k-means method lacks in performance is with regard to the extremes since k-means clustering is more likely to discard the upper-, and lower bound scenarios [43].

Similar to the previous method, reference [44] uses k-means clustering but in this paper it is combined with dynamic time warping (DTW) for building scenario generation framework. In the paper, wind power production from multiple sites with similar time series data are clustered in order to reduce the overall scenario generation calculation. The various scenarios are subsequently used to solve a day-ahead stochastic unit commit problem.

Lastly, reference [45] provides an in depth review of performance of the various clustering methods. It reviews elastic distance functions within the time series clustering framework, such as; dynamic time warping, Barycenter averaging and k-medoids methods. The reviewed three approaches from the open source clustering package for Python, provided in the tslearn.

Considerations of k-means clustering

The k-means clustering methods is a relatively simple clustering method. One of the main advantages in general, is the guarantee of convergence and that it easily scales with large data sets [46]. Since k is manually chosen and dependent on the starting position some variations in results may occur, especially with low numbers of k [46]. Fortunately it is possible to bypass most of these problems by starting with different initial positions for k and by varying the number of cluster centers.

2.4. Research gap

In order to make a contribution to the scientific literature, a gap in the literature should be defined and addressed. Therefore, three fields within the harbor-, energy-, and mobility landscape have been explored in sections 2.1-2.3.

Vessel-to-Grid

Firstly, there is a broadly accepted consensus within the scientific literature about the necessity of BESS in a future grid with a high share of renewable energy sources. Within the field of vehicle-to-grid, there are many studies regarding the grid integration of electric vehicles. Moreover, these studies focus on both the benefits with regard to the electricity grid as well as the vehicle owner. Similar benefits can be expected when battery-equipped vessels are able to provide such flexibility, especially since a large battery capacity on board a vessel and a more reliable operational profile allow for higher utilization of the battery. While grid integration of battery-equipped vessels has been studied[47] and [27], the vessel operator-centered approach when it comes to electricity cost reductions is a novelty in the field.

Smart grids and cold-ironing form the state-of-the-art within future port developments. Within this field research efforts regarding energy management is mainly performed from a system perspective. Reference [16] highlights the impact of flexible loads on the grid in a HASG. Whereas battery electric storage is repeatedly addressed as being able to provide this flexibility in [14], [16], [31] only on-shore BESS is being considered. In applications where onboard batteries are utilized to support the harbor grid, research only considers the battery use of PEVs [32]. Moreover most papers again only consider the benefits to the grid. As a result, an individual perspective is missing, which could be aimed at improving the financial benefits for the ship operator.

Furthermore, the reason why flexibility will become more important in a future grid is through the introduction of more RES. Whereas this topic is mentioned in some of the research, papers from [16] and [32] do not consider the influence of RES in their research.

Energy arbitrage could deliver significant cost reductions for an energy consumer. While this is a commonly discussed topic in the literature, this is only briefly discussed in [16] without any deeper analysis of the cost impact. The possibility to perform peak shaving is a more popular topic within the reviewed papers, but the aspect was considered mostly from a grid conducive perspective, as it would allow port authorities to delay the investments in electricity infrastructure.

Table 2.1: Comparing relevant studies with regards to Vessel-to-Grid participation

Vessel-to-Grid

Ref.	**On-board BESS**	**RES**	**Energy Arbitrage**	**Electricity cost reduction**	**Grid conducive**	**Peak shaving**
[16]	✗	✓	✗	✓	✓	✓
[30]	✗	✗	✓	✗	✓	✓
[32]	✓	✓	✗	✗	✓	✗
[31]	✗	✗	✗	✗	✓	✓
This study	✓	✓	✓	✓	✓	✓

Battery Energy Management Strategies

The opportunity for using onboard BESS as flexible loads would allow for significantly larger power and energy flexibility when compared to domestic flexibility. As the BESS of ships is orders of magnitude larger than their home counterparts. In the reviewed literature, however, most battery energy management strategies such as [33], [36], [37] a focus on home use. While [34] considering the use of a BESS for industrial use, it does not resemble the hotel load of a shore-power-connected ship.

Renewable energy sources such as solar PV and wind depend on weather effects for their energy production and as a result, are subject to uncertainty. It is therefore important to deal with the stochastic nature of renewable energy generation in the analysis of such systems. Whereas most studies recognize this importance, not all reviewed papers consider this in the results. When a deterministic analysis was made with perfect hindsight, this may lead to a positive bias resulting in a skewed view of the benefits of the system.

Multiple papers include an analysis of the effects of the battery parameters such as power and energy capacity in the optimization problem. Whereas some fail to include this. As a vessel operator will consider vessel-to-grid applications in the future, the battery size will be the most important aspect with respect to the investments needed. Since the battery size and power rating will subsequently influence the power electronics and other converters needed. Therefore it is important to make an analysis of some sort to determine the influence of battery parameters on the cost reduction of electricity for the vessel operator.

Table 2.2: Comparing relevant studies with regards to Battery energy management strategies

Battery Energy Management Strategy **Ref.**	**Industrial Scale**	**Wind Energy**	**Stochastic solution**	**Battery sizing**	**Day-Ahead scheduling**
[36]	✗	✓	✓	✗	✓
[37]	✗	✓	?	?	?
[33]	✗	✗	✗	✓	✗
[34]	✓	✗	✗	✓	✓
[35]	✗	✓	✓	✗	?
This study	✓	✓	✓	✓	✓

Contributions

This study will fill the gap in the literature by exploring the economic synergy of shore power and ship-to-grid integration. While this is done through a vessel operator-centered perspective, this research will also address other benefits to the electricity grid. The vessel will be operating with an onboard BESS of industrial scale. As the vessel will be operating in a HASG, the BESS will be controlled through an energy management system. The strategy of this EMS is based on day-ahead prices, as well as peak-power-related costs. Locally produced wind energy will partly provide the vessel with electricity. Since this is an uncertain process, the model will deal with the stochastic nature of wind energy. This will be done through a stochastic programming method in which an optimal schedule will be presented based on uncertainty in wind power generation and certain day-ahead prices, and load. The uncertainty in wind generation is presented through a set of representative scenarios with an associated probability of occurrence. The scenarios will be generated through three different variants of time series k-means clustering. Of these methods, the most suitable method will be applied to the problem. Subsequently, a stochastic approximation will be found. As the scope of this dissertation focuses on the problem as a whole it will aim to find approach the stochastic solution. The objective of this problem will be to minimize the costs of electricity for the vessel operator. This will be achieved by scheduling the BESS in the most cost-optimal way, through energy arbitrage on the day-ahead market.

Based on the state-of-the-art and the reviewed articles, this study will provide the following contributions to the scientific literature:

- A cost-reducing EMS from a vessel operator perspective will be developed for battery-equipped shore power-connected vessels, which is a novelty in the field of vessel-grid-integration.
- Developing an industrial scale day-ahead energy arbitrage scheduling model, considering grid limitations and capacity that deals with uncertainty in renewable energy generation.
- Sensitivity analyses for the vessel operator on the effects of various battery parameters such as C-rate and capacity on the cost reducing ability of BESS.
- Evaluation of the applicability of three wind scenario generation methods.
- Stochastic approximation to find the electricity-cost reductions.

3
Problem Definition and Formulation

This section will describe the complete energy system of the shore power connected vessel. All individual modules contributing to providing power to the vessel and constituting the final optimization problem will be discussed. The structure of each unit of the mentioned energy system will be discussed which includes extracting the relations between different units. That is, all the equations that describe the functions of each module as well as its interactions with other units will be specified. In this way, the problem formulation is extracted, which includes the objective function, technical and economic constraints of the units and other equations that must be considered in the effective and coordinated operation of the system.

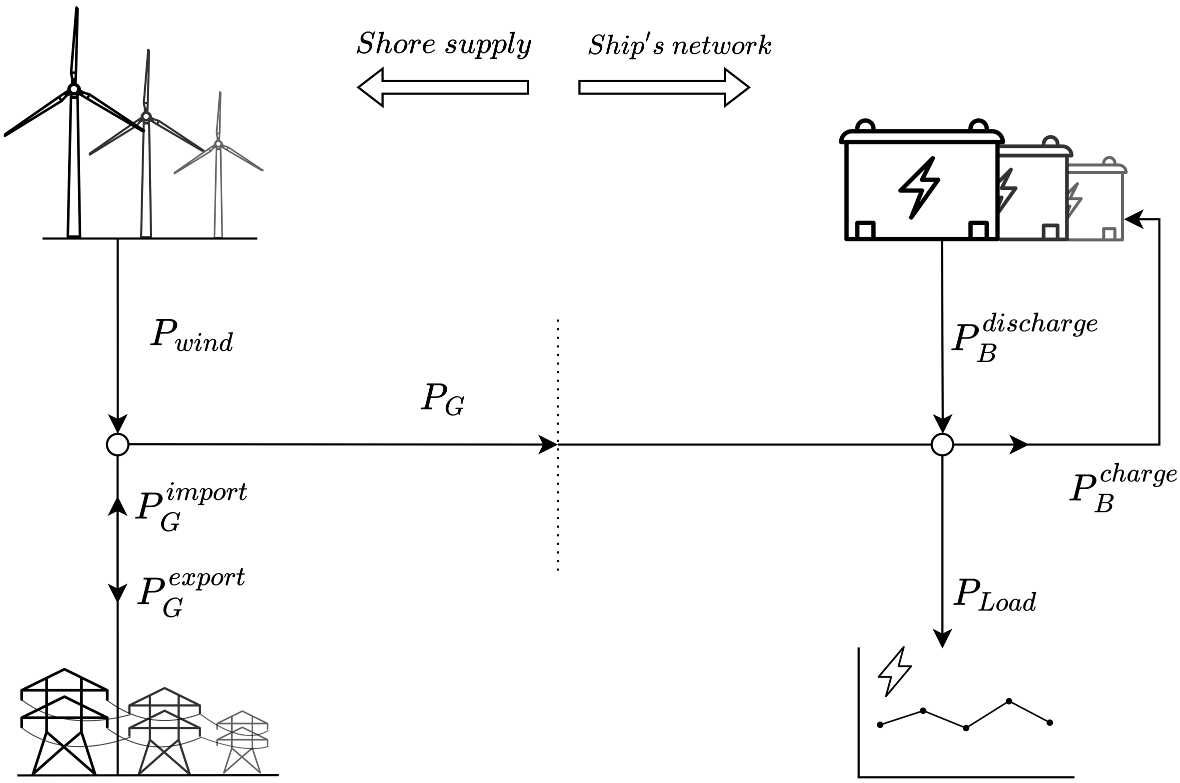

Figure 3.1: Energy flows through system

3.1. The wind power generation system

A local wind park is one of the two providers of electricity to the vessel. This wind park is connected to the vessel through the *e-house* which houses the power converters which adjust the voltage and frequency according to the requirements of the vessel. The *e-house* is indicated by the left node in Figure 3.1, which allows from P_{wind} and P_G^{import} to flow to the vessel. Moreover, the *e-house* is equipped with an energy meter so that the energy of the wind farm can be separated from that of the grid allowing for different tariffs.

3.1.1. The hourly energy production of the wind park

The amount of power produced by the wind farm is mainly determined by the actual wind speeds driving the turbine. Since data related to energy production is closely held by the wind park operator the power produced is deduced through the current wind speeds at the site.

The power produced by wind turbines is described by the power curve provided by the manufacturer. The power curve relates power to wind speed at the hub height. Since the available wind speed data is often measured at an arbitrary height, an empirical method for extrapolating the wind speed at the hub height from measured wind speeds.

As the surface roughness of the earth influences the airflow over it, this results in an ever-decreasing wind speeds as the wind speed is measured closer to the ground. This phenomenon is called wind shear and will be used for the extrapolation at the wind speed at hub height. As surfaces differ from place to place, the surface roughness of various landscapes differs as a result of this. By using the Hellman exponent one is able to approximate the surface roughness by surface type [48].

To conclude, the wind speeds at hub height is a function of surface roughness α, the wind speed at reference height v_0 and the ratio between reference height H_0 and hub height H as shown in equation 3.1 [49].

$$v_{hub} = v_0 \times \left(\frac{H}{H_0}\right)^{\alpha} \tag{3.1}$$

After this calculation, the wind power produced by the wind park is simply computed by multiplying the power curve value by the number of turbines. Finally resulting in wind park power production bound by a minimum and maximum production:

$$P^W = P^T \cdot n^T \tag{3.2}$$

$$0 \leq P^W \leq \overline{P^W} \tag{3.3}$$

3.2. Energy scheduling problem formulation

3.2.1. List of symbols

Symbol	**Definition**
Sets and Vectors	
T	Set of time periods (horizon length) $\{t \in \mathbb{N} \mid 1 \le t \le 96\}$
S	Set of reduced scenarios $\{s \in \mathbb{N} \mid 1 \le s \le 10\}$
Δ_t	Duration of time period (0.25h)
π_s	Vector with the scenario probabilities $\forall s \in S$
$P_{t,s}^{W}$	Wind scenario set $\forall t \in T, \forall s \in S$
Decision variables	
$P_{t,s}^{C}$	Charge power [MW] $\forall t \in T, \forall s \in S$
$P_{t,s}^{D}$	Discharge power [MW] $\forall t \in T, \forall s \in S$
$P_{t,s}^{G}$	Power flow through shore power [MW] $\forall t \in T, \forall s \in S$
State variables	
$E_{t,s}^{B}$	Energy stored in BESS at time t [MWh] $\forall t \in T, \forall s \in S$
$u_{t,s}$	Binary variable related to charging
$v_{t,s}$	Binary variable related to grid power exchange
Parameters costs	
λ_t^{DAM}	Day-ahead price data at time t [€/MWh]
λ^{NL}	GO tariff for local wind power [€/MWh]
λ^{BE}	GO tariff for grid power [€/MWh]
λ^{M}	Monthly power peak grid tariff [€/MW]
λ^{Y}	Yearly power peak grid tariff [€/MW]
c_t^{G}	Grid import costs at time t [€/MWh]
c_t^{W}	Wind import costs at time t [€/MWh]
c^{M}	Monthly grid costs [€/MW]
c^{Y}	Yearly grid costs [€/MW]
Parameters BESS	
$\overline{E_{t,s}^{B}}$	Maximum battery capacity [MWh] $\forall t \in T, \forall s \in S$
E_0	Energy in battery at time $t = 0$ [MWh] $\forall t \in T, \forall s \in S$
η_C	Charge efficiency [p.u.]
η_D	Discharge efficiency [p.u.]
η_{stb}	Standby efficiency [p.u.]
Power parameters	
$P_{t,s}^{W}$	Wind park power generation [MW] $\forall t \in T, \forall s \in S$
P_t^{L}	Power demand of vessel [MW] $\forall t \in T, \forall s \in S$
$P_{t,s}^{\iota}$	Power import from grid [MW] $\forall t \in T, \forall s \in S$
$\overline{P_{t,s}^{\iota}}$	Maximum power import from grid [MW] $\forall t \in T, \forall s \in S$
$P_{t,s}^{\epsilon}$	Power export to grid [MW] $\forall t \in T, \forall s \in S$
$\overline{P_{t,s}^{\epsilon}}$	Maximum power export to grid [MW] $\forall t \in T, \forall s \in S$
$\overline{P^{G}}$	Maximum power shore power cable [MW] $\forall t \in T, \forall s \in S$
$\overline{P_{t,s}^{C}}$	Maximum charge power [MW] $\forall t \in T, \forall s \in S$
$\overline{P_{t,s}^{D}}$	Maximum discharge power [MW] $\forall t \in T, \forall s \in S$

3.2.2. Objective function

The main objective of the EMS is to minimize costs for the operator of the vessel. This is done by dispatching the BESS in an optimal way to minimize transport costs and optimize for fluctuating spot prices on the DAM. The objective function is formulated to be adaptable to various scenarios represented by the variable 's' and their corresponding probabilities, as well as for a single scenario.

$$min \sum_{s \in S} \pi_s \sum_{t \in T} \Delta_t \cdot (c_t^G P_{t,s}^G + c_t^W P_{t,s}^W) \tag{3.4}$$

3.3. Constraints

The power balance constraint in equation 3.5 ensures that all power flows are in balance.

$$P_t^L + P_{t,s}^C = P_{t,s}^G + P_{t,s}^D \qquad \forall t \in T, \forall s \in S \tag{3.5}$$

The grid balance constraint 3.6 balances the power flows in the *e-house* on the left node.

$$P_{t,s}^G = P_{t,s}^W + P_{t,s}^{\iota} - P_{t,s}^{\epsilon} \qquad \forall t \in T, \forall s \in S \tag{3.6}$$

The grid import constraint 3.7 with binary variable v_t limits the amount of power that the wind park can export to the grid and prevents simultaneous importing and exporting to the grid. The mechanism works by setting $u_t = 1$ if $P_{t,s}^{\iota} > 0$, and $u_t = 0$ if $P_{t,s}^{\epsilon} > 0$. However, if $P_{t,s}^{\iota}$ or $P_{t,s}^{\epsilon}$ exceed certain limits or both have a value greater than 0, then u_t would be both 0 and 1, breaking the binary constraint, resulting in an infeasible solution.

$$P_{t,s}^{\epsilon} - v_{t,s} \cdot \overline{P^{\epsilon}} \leq 0 \qquad \forall t \in T, \forall s \in S \tag{3.7}$$

Similar to the previous constraint, equation 3.8 uses binary variable v_t to prevent simultaneous importing and exporting of electricity to the grid and limits the maximum import power.

$$P_{t,s}^{\iota} + v_{t,s} \cdot \overline{P^{\iota}} \leq \overline{P^{\iota}} \qquad \forall t \in T, \forall s \in S \tag{3.8}$$

3.3.1. The shore power service

Cold ironing is the method by which the vessel receives electricity. Both powers from the wind park and electricity imported from the grid are converted by power electronics in the *e-house*. This system is bound by power limitations as stated by Equation 3.9.

$$0 \leq P_{t,s}^G \leq \overline{P^G} \qquad \forall t \in T, \forall s \in S \tag{3.9}$$

The power flow of the cold ironing facility is unidirectional meaning that it can only provide electricity from the grid side to the vessel. Therefore P_G cannot be negative.

3.3.2. The battery energy storage system

In order to reduce the costs of electricity for the vessel operator, the operator should be able to control the power demand of the vessel through time. Since the load of the vessel is predetermined and can therefore not be controlled, the only decision variable is the charge- and discharge power of the onboard BESS.

The BESS state of charge is described by equation 3.10 which includes the charge and discharge efficiencies [50].

$$E_{t,s}^B = E_{s,t-1}^B \cdot \eta_{stb} + \eta_c \cdot \Delta_t E_{s,t-1}^C - \frac{\Delta_t E_{s,t-1}^D}{\eta_D} \qquad \forall t \in T, \forall s \in S \tag{3.10}$$

Equations 3.11 and 3.12 limit the maximum charge and discharge rates. Simultaneously, binary variable u_t prevents simultaneous charging and discharging. It work by the follow mechanism; if $P^D_{t,s} > 0$ then $u_t = 1$ and if $P^C_{t,s} > 0$ then $u_t = 0$. However in the situation at which $P^D_{t,s}$ or $P^C_{t,s}$ exceeds the limits or are both > 0, then u_t should be both 0 and 1 thus violating the binary constraint.

$$P^D_{t,s} - u_t \cdot \overline{P^C_{t,s}} \leq 0 \qquad \forall t \in T, \forall s \in S \tag{3.11}$$

$$P^C_{t,s} + u_t \cdot \overline{P^D_{t,s}} \leq \overline{P^D_{t,s}} \qquad \forall t \in T, \forall s \in S \tag{3.12}$$

The following equations ensure a battery operation remains within the physical capacity constraints 3.13 and does not allow discharging below 0% SOC 3.14.

$$\forall t, E^B_{t,s} \leq \overline{E^B} \qquad \forall t \in T, \forall s \in S \tag{3.13}$$
$$\forall t, E^B_{t,s} \geq 0 \qquad \forall t \in T, \forall s \in S \tag{3.14}$$

3.3.3. Transport costs of electricity

The transport fees for electricity are determined by the DSO. As these costs are calculated on a per-month basis, they are not included in the optimization problem. After optimization over t and s, the maximum grid-imported power demand $\overline{P^\iota_{t,s}}$ determines the maximum grid costs for the specific month. The transport costs as calculated are given in equation 3.15:

$$c^M = \lambda^M \cdot \overline{P^\iota_{t,s}} \qquad \forall t \in T, \forall s \in S \tag{3.15}$$

3.3.4. The total cost of electricity

The cost of electricity from the two different sources is determined by the sum of the price on the day-ahead market and to the source of electricity. When electricity is provided by the local wind park, guarantee of origin costs λ^{NL} are charged in addition to the day ahead prices as shown in Equation 3.16.

$$c^W_t = \lambda^{DAM}_t + \lambda^{NL} \qquad \forall t \in T \tag{3.16}$$

In the situation in which the vessel is partially or fully supplied by electricity from the grid, then guarantee of origin certificates are bought from a belgian renewable energy supplier as described by Equation 3.17.

$$c^G_t = \lambda^{DAM}_t + \lambda^{BE} \qquad \forall t \in T \tag{3.17}$$

4 Uncertainty modelling method

Energy optimization can be divided into two schools; deterministic and stochastic. The field of deterministic optimization works with certain parameters, as a result, there is only one optimal solution possible. Since renewable energy sources are subject to natural phenomena such as wind speeds, stochastic models are used to generate a more realistic representation. While wind speeds can be forecasted, a level of uncertainty surrounds this forecast. The ability to handle uncertainty will improve the quality of the simulation by representing the real-world situation in an improved way.

The aim of this chapter is to provide the necessary information for the energy scheduling programming problem described by the case study in Chapter 5. The chapter is divided into two main sections. The first Section 4.1 describes the uncertain parameters and the necessity for dealing with uncertainty. As general formulation for two stage stochastic programming is subsequently given as to provide context for applying approximation methods. Secondly, Section 4.2 elaborates on the k-means clustering method that is is used to reduce the number of historical scenarios. Three methods are tested with the provided wind data from section 5.2. From these tests a suitable method for scenario generations is found to generate scenarios for the stochastic programming problem in Chapter 5.

4.1. Approximating Uncertainty

4.1.1. Uncertain parameters

In Chapter 5 the importance of dealing with uncertainty in the dispatching problem was stressed. In the proposed energy scheduling problem three parameters; electricity prices, wind power production and the power of the load can be considered as the uncertain parameter. However, in order to simplify the optimization, only one parameter is considered to be uncertain. Firstly, uncertainty in the day-ahead electricity market only exist after the 24-hour time horizon. Since the energy scheduling problem will only concern a day ahead scheduling problem. This takes away the uncertainty since the scheduling problem will never exceed the previously mentioned 24-hour period in which the day-ahead prices are certain. Secondly, the energy demand of the vessel is relatively stable. Only with short duration spikes in power demand that do not have a big impact on the average energy consumption which makes dealing with that uncertainty not a priority. As a result, wind power production was chosen as the uncertainty variable in the stochastic programming problem.

In Chapter 2 various methods were reviewed for addressing wind uncertainty in an energy scheduling problem. This rest of this chapter will focus on the stochastic behavior of wind, provide the framework for the 2-stage stochastic programming problem including its requirements and will give an introduction to the various methods of generating wind speed scenarios that match the requirements of the chosen optimization method.

4.1.2. Stochastic process of wind

In dealing with the accurate modeling of wind power generation and the uncertainty that surrounds it, multiple methods have been described in the literature. Reference [51] describes three different approaches for dealing with uncertainty in wind generation in a imbalance minimization problem. The first method is accurate forecasting speeds which will naturally lead to a reduced level of uncertainty. The main disadvantage is the difficulty of accurately forecasting wind speeds due to the many environmental factors and technical challenges surrounding the forecast. The second method is coupling wind generation with predictable power generation such as gas turbines. Lastly, the third method is stochastic programming. In this method, multiple wind speed scenarios represent possible outcomes.

The optimal dispatch of the battery system is subsequently optimized over the different scenarios including their respective probability of occurrence [51].

Within uncertainty programming the decision maker can choose between multiple approaches to find the most optimal solution. The two most popular methods are; Robust Optimization (RO) and Stochastic Programming (SP) [52]. The main difference between the two approaches is the consideration of risk. As a result of the worst-case-scenario approach of RO, this often results in an over-conservative dispatch. The RO approach is very effective for systems that may never fail, such as the power supply to a hospital, but due to its conservativeness it almost never results in the most cost effective outcome. For the SP solution, a large number of scenarios is required to ensure a good solution quality, this increases the computational difficulty. Computational complexity and cost optimality form the main trade off between the two methods. In the case of this dissertation, the vessel will always be able to purchase power from the grid, the main risk in violating the expected wind power scenario is an increase in cost which does not affect the operation of the vessel. This dissertation will therefor focus on the latter approach due to its higher cost optimality and will reduce computational complexity by reducing the number of scenarios using the k-means clustering method described in section 4.2.1.

4.1.3. Stochastic programming

Stochastic programming describes the field optimization in which at least one of the input parameters is uncertain [53]. Many variant of stochastic programming exist. This research will describe the most common form, which is a two-stage stochastic programming problem. While this is ultimately a good method to find a cost effective solution under uncertain circumstances, this research will mainly focus on the bound surrounding this solution. Nevertheless, a general description of this type of optimization will be provided below, since the requirements for doing the approximation of the SP solution have many similarities.

As the name suggests, two-stage stochastic programming consists of two stages. In this scheduling problem, the first - certain - stage, constitutes the day-ahead prices including the corresponding certain constraints. The first-stage decisions are made prior to the realization of the uncertain parameters [54]. This here-and-know decision is therefore independent of the stochastic process.

The second-stage concerns the uncertain part, which is described by different scenarios and their corresponding probability. Logically, the second stage otherwise known as the wait-and-see decision is made after the results from the first stage are provided. Both stages can best be represented graphically in a scenario tree. Figure 4.1 shows a two-stage scenario tree. At the root of the decision tree, the first-stage decision is made. After this, all the random variables or vectors in the leaves of the second stage node are calculated. It should be noted that there are as many leaves as there are scenarios.

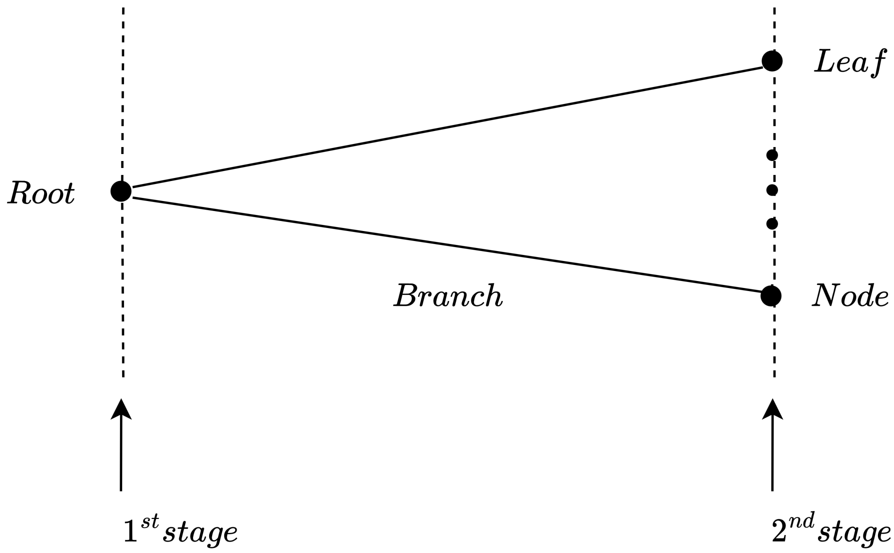

Figure 4.1: Scenario tree

The scenarios in the second stage can either be represented by a single value, when the problem consist of one-time step by value λ [54]. In the case of this problem, a time series consisting of multiple steps are considered and represented by a vector $\lambda(\omega)$ [54]. In the latter case, ω represents the scenario index and $N\Omega$ the total number of considered scenarios. The complete set of scenarios is represented by $\lambda\Omega$, i.e. $\lambda\Omega = \{(1), ..., \lambda(N\Omega)\}$. Finally, every single $\lambda(\omega)$ has a corresponding probability $\pi(\omega)$ the sum of which should be 1. This probability is described in equation G.15[54].

$$\pi(\omega = P(\omega|\boldsymbol{\lambda} = \boldsymbol{\lambda}(\omega)), \qquad where \sum_{\omega\in\Omega} \pi(\omega) = 1 \tag{4.1}$$

After identifying the scenarios and probabilities, the two-stage stochastic programming problems can be formulated as shown in equations (G.16, G.21)[54]. The identification of scenarios, will be done through a scenario generation algorithm described in Section 4.2.1. The method by which the corresponding scenario probabilities are calculated will also be presented in that section.

$$Minimize_{\mathbf{x}} z = \mathbf{c}^{\top}\mathbf{x} + \mathcal{E}\{Q(\omega)\} \tag{4.2}$$
$$\text{subject to } \mathbf{Ax} = \boldsymbol{b} \tag{4.3}$$
$$\boldsymbol{x} \in X \tag{4.4}$$
where

$$Q(\omega) = \Big\{\text{Minimize}_{\mathbf{y}(\omega)}\, \mathbf{q}(\omega)^{\top}\mathbf{y}(\omega) \quad \} \tag{4.5}$$
$$\text{subject to } \mathbf{T}(\omega)\mathbf{x} + \mathbf{W}(\omega)\mathbf{y}(\omega) = \mathbf{h}(\omega) \tag{4.6}$$
$$\mathbf{y}(\omega) \in Y\Big\},\ \forall\omega \in \Omega \tag{4.7}$$

The first- and second-stage variables are denoted by $\mathbf{x}$ and $\mathbf{y}(\omega)$ respectively. The variables $\mathbf{A}$, $\mathbf{b}$, $\mathbf{c}$, $\mathbf{h}(\omega)$, $\mathbf{q}(\omega)$, $\mathbf{T}(\omega)$, and $\mathbf{W}(\omega)$ are vectors and matrices with known values. It should be noted that the values in (G.16, G.21) can but do not have to be dependent on the stochastic scenario set $_{\Omega}$. The latter part of the problem (G.19, G.21), depicts the *recourse* problem.

Equations (G.16, G.21) can also be described in the deterministic form, which can subsequently be used by the solver. This results in equations (G.22, G.25)[54].

$$\text{Minimize}_{\mathbf{x}}, \mathbf{y}(\omega) \quad z = \mathbf{c}^{\top}\mathbf{x} + \sum_{\omega \in \Omega} \pi(\omega)\mathbf{q}(\omega)^{\top}\mathbf{y}(\omega) \tag{4.8}$$

$$\text{subject to} \quad \mathbf{A}\mathbf{x} = \mathbf{b} \tag{4.9}$$
$$\mathbf{T}(\omega)\mathbf{x} + \mathbf{W}(\omega)\mathbf{y}(\omega) \sim \mathbf{h}(\omega), \forall \omega \in \Omega \tag{4.10}$$
$$\mathbf{x} \in X, \mathbf{y}(\omega) \in Y, \forall \omega \in \Omega \tag{4.11}$$

The deterministic equivalent can either be described in a in a node-variable or scenario-variable way. In the node-variable formulation is decision point-based, while the latter is scenario-based. The two formulations differ from each other in terms of size and ease of computation. The node-variable formulation is relatively compact and more easily solved for a direct solution. While the scenario-based has neither of these properties, its structure is more suited for decomposition [54].

A node-variable formulation will be used in this dissertation as the focus is to approximate the SP solution, and decomposition methods such as Bender's are therefor not necessary. Moreover, the type of the approximation provided in Section 4.1.4 is a form of a direct solution further motivating the choice.

This section gave an overview of the requirements for handling uncertainty in linear programming problems. After considering the parameters in this optimization problem, wind was chosen to the only parameter to be considered uncertain in the final optimization problem. Considering the risk profile of the scheduling problem, SP was considered to yield the most realistic results from an economical perspective. However, due to the complex nature of SP, a alternative method for approximating this solution will be provided in Section 4.1.4.

4.1.4. Stochastic approximation

The use of a stochastic method leads to more insight into behavior under conditions of uncertainty. While this may lead to more realistic results it is considered 'good practice' to evaluate the use of the stochastic method [54]. In addition, the wait-and-see (WS) solution and expected outcome using the expected value (EEV) can provide the bounds of the SP solution without the added complexity of actually calculating the SP solution. The resulting lower complexity and resulting problem size of the deterministic approach of approximating the SP wile still providing sufficient insight motivates the choice for the approximation approach.

The relevance and accuracy of the stochastic method are assessed by two metrics. The Expected Value of Perfect Information (EVPI) is commonly used for two-stage stochastic programming problem evaluations. Besides this method, the Value of the Stochastic Solution (VSS) is used to evaluate the added benefit of the stochastic approach over the deterministic one.

Lastly, the *out-of-sample* assessment is used to judge the outcome quality of the model by inserting data for which the scenarios were not generated [54]. The mathematical formulation as well as the relevance of these methods will be provided in the following subsections.

Expected Value

Figure 4.2 shows the relation between the various approximations of the SP problem. Moving from left to right, the solution becomes increasingly less optimal. As a result of the relation, the WS and EEV solution respectively provide the upper and lower bound of the cost reduction. Prior to calculating the EVPI and VSS the EV, WS and EEV solutions have to be found. The following sections will describe how each is calculated.

The Expected Value (EV) provides the result that corresponds with the average deterministic scenario. In this solution, the mean value of the scenarios is calculated by multiplying the scenario values with the corresponding probability and subsequently adding all values. This mean scenario is used as an input for the deterministic problem which results in the EV solution [55]. The equation for the EV solution in provided in equation G.5.

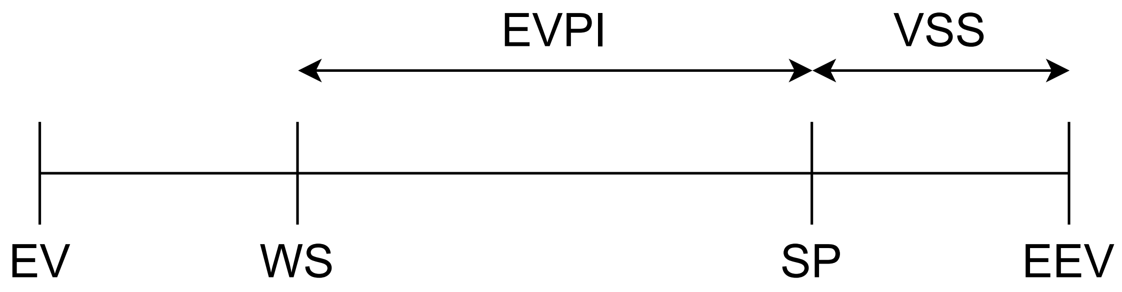

Figure 4.2: Relation between the various stochastic approach methods

The deterministic form of the expected value is described in equation [38]:

$$EV := \mathbb{E}_\omega \left[\min_{x \in X_0} g(E[\omega], x) \right] = \mathbb{E}_\omega [g(E[\omega], \bar{x})] \tag{4.12}$$

Wait-and-See solution

Equation 4.13 denotes the WS solution. It this solution is the optimal solution is made after observing the actual value of the various scenarios ω. As a result, for every value of scenario set ω there exists a different optimal solution. This set is defined denoted by $\hat{x}(\omega)$. The mean value of $\hat{x}(\omega)$ characterizes the WS solution [38].

$$WS := \mathbb{E}_\omega \left[\min_{x \in X_0} g(\omega, x) \right] = \mathbb{E}_\omega [g(\omega, \hat{x}(\omega))] \tag{4.13}$$

As it holds true that every optimal solution for the various scenarios is feasible but not necessarily optimal, it is given that[38]:

$$WS \leq SP \tag{4.14}$$

The difference between the WS solution and the SP problem is called the Expected Value of Perfect Information (EVPI). This value is described in Subsection 4.1.4

Expected result of the Expected Value solution

The EEV from equation 4.15 is calculated by fixing the first stage variables with the results of the EV solution [38]. The second stage is subsequently solved through stochastic programming for the chosen scenarios. The resulting value is less optimal than the SP solution, since the first stage is fixed at a sub-optimal value. The resulting outcome therefore reflects the true cost the deterministic solution [55].

$$EEV := \mathbb{E}_\omega [g(\omega, \bar{x})] \tag{4.15}$$

As the resulting value is less optimal than the SP approach, if follows that:

$$SP \leq EEV \tag{4.16}$$

It can be concluded that under weak conditions, the lower bound of the optimal value is given by the Wait-and-See solution, while the Expected result of the Expected Value provides the upper bound [38].

Expected Value of Perfect Information

The expected value of perfect information describes how much the decision maker is rationally willing to pay for a perfect forecast of the uncertain variable about the future [54].

The expected value of perfect information represents the quantity that a decision-maker is willing to pay for obtaining perfect information about the future. It constitutes a proxy for the value of accurate forecasts.

In the case study of this paper, wind speeds are assumed to be the uncertain parameter. The wind speeds of one year are summarized by 10 different scenarios ranging from low to high and from constant to fluctuating. Since these scenarios have a relatively high bandwidth, the ability of these scenarios to accurately forecast the future is relatively low. If this bandwidth can be reduced, or even represented by a line, then it means a better prediction resulting in better results in terms of money. The value of this line of *Perfect Information* with respect to the stochastic solution is described by the EVPI.

Assuming a minimization problem, the objective function for the two-stage stochastic programming problem is described by r^{S*} in which superscript S describes that it concerns the stochastic problem. On the other hand, the objective function for which there is no uncertainty is described by r^{P*}. In which the Perfect Information is denoted by superscript P. In the latter function, all decisions are made with perfect information about the future. A problem that is solved with perfect foresight is also known as the wait-and-see solution. For a minimization problem, the EVPI is calculated as:

$$EVPI_{min} = r^{S*} - r^{P*} = SP - WS \tag{4.17}$$

Value of the Stochastic Solution

The value of the stochastic solution describes the added value of the stochastic method over the deterministic approach.

In comparing the stochastic method with the deterministic approach, first, the deterministic method needs to be clarified. In this approach, the random variables from the stochastic one are replaced with the corresponding expected values. Solving this deterministic problem results in the optima for the first-stage variables, which will then be fixed to the original stochastic programming problem. The result is a problem that is solved scenario by scenario. The optimal value of this fixed first-stage problem is described by R^D where D describes the deterministic approach of this problem.

Calculating the value of the stochastic for a minimization problem is performed as

$$VSS_{min} = r^{D*} - r^{S*} = EEV - SP \tag{4.18}$$

Similar to equation 4.17 the stochastic solution is described by r^{S*}. In short, the VSS describes how the stochastic approach yields better results than the deterministic one and expresses it as a value. The relation between the quality metrics discussed is summarized in figure (4.2).

Out-of-Sample Assessment

The out-of-sample assessment describes the real-world value of the stochastic programming method by using data for which the model was not trained. Since all scenarios are a deduction of historical data, this is what the model has been 'trained' for. When using a new data set within the scenario framework, an assessment of the effectiveness of the stochastic method can be made.

Moreover, a comparison between different methods such as stochastic and deterministic can be made using out-of-sample simulations.

4.2. Scenario reduction

A historical data set will be used to solve the stochastic programming problem. This poses the problem of being computationally difficult to solve. In order to mitigate this, a representative set of scenarios needs to be chosen. The process of choosing a set that still contains most of the stochastic information of the original set is called scenario generation, which will be discussed in 4.2.1.

Popular methods for addressing scenario generation are fitting the data to a statistical model and subsequently generating a random sample from this set [56]. While this method will yield the desired properties for a reliable solution, it requires a large data set to achieve this. Generating a scenario set in which probability distance represents the true distribution requires smaller data sets to produce a reliable solution and yields a more stable solution with respect to the sampling approach[56].

In Chapter 2, the three most common methods within scenario generation were discussed and compared. In this comparison the **k-means clustering** proved to be a suitable method for this case. The first reason is its statistical certainty with regards to intertemporal relationship between between the wind speeds, since no synthetic data is being generated by this method. Building on this, the actual historical occurrence of the data results in a higher confidence level for the model user. The third argument, is that this form of clustering is highly versatile method which can also be applied on top of alternative scenario generation methods.

4.2.1. K-means clustering

The essence of k-means clustering is minimizing the Euclidean distance between k randomly chosen cluster centers and the data data that has to be clustered. The goal is to reduce the number of scenarios by identifying certain patterns collecting these in various clusters[57].

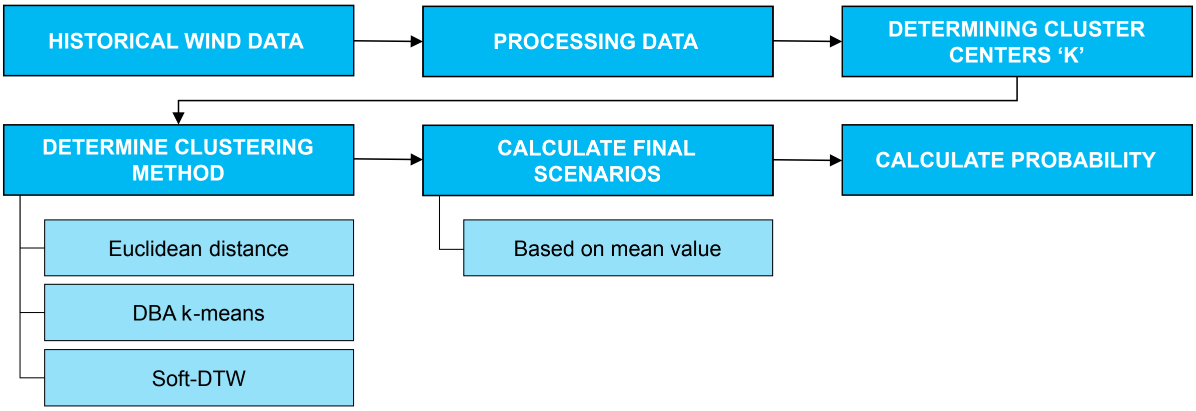

Figure 4.3: Clustering flowchart

Algorithm 1: General algorithm used for k-means clustering [58]

1 Randomly select k points as initial cluster centroids;
2 **repeat**
3   Assign every data-point to the closest cluster center thereby forming k clusters;
4   Determine the new centroid for each cluster;
5 **until** *the position of the centroid stays fixed*;
6 Observe *elbow* at which marginal benefit decreases;

Determining cluster centers

Determining the optimal number of clusters is an important park when applying the k-means clustering approach. The most common method for determining this is by using the elbow method. This method relies on measuring the inertia or variance of the data points and plots them against the number of clusters [58]. As the number of clusters is increased, their relevance will increase at first. At some point the marginal benefit of more cluster centers will decrease. At this point, the marginal gain thus drops which is indicated by the 'elbow' in the graph. The number of clusters indicated by the 'elbow criterion' provides information about the ideal k-value [58].

Algorithm 2: The Elbow method [58]

Initialize $k = 1$;
repeat
    Increase value $k + 1$;
    Measure the sum of Euclidean distance or Inertia;
until k *reaches stopping value* n;
Observe *elbow* at which marginal benefit decreases;

In Figure 4.4 the elbow criterion is applied to the set of historical wind data. Although this curve does not show a clear inflection point, a linear decrease in return can still be observed at 10 clusters. A k-value of 10 was therefor chosen.

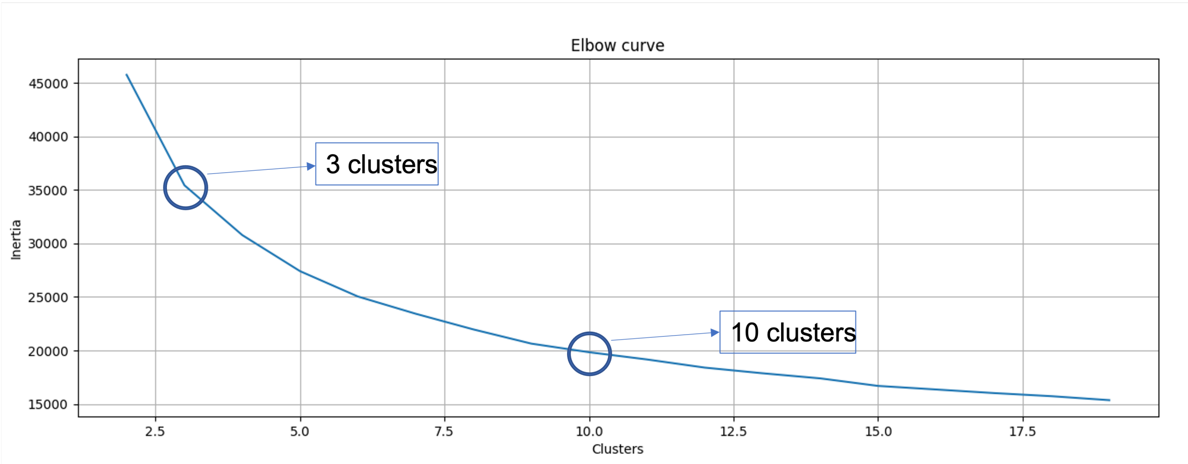

Figure 4.4: Elbow curve for historical 2022 wind data

Determining Clustering Method

Three clustering methods within the k-means type clustering will be tested. The most suitable method will be determined by the lowest inertial value given the same number of cluster centers. The three types that will be compared are *Euclidean k-means clustering*, *Dynamic Barycenter Averaging (DBA) k-means* and *Soft Dynamic Time Warping (Soft-DTW) k-means*.

Euclidean k-means clustering is the least complicated method. It works by applying the algorithm described in Algorithm 1. Patterns in time series can however show temporal displacements. When the Euclidean algorithm is applied on such data, it results in a flattening of the curve, causing it to lose data with regards to pattern. Euclidean k-means clustering is unable to properly capture the pattern.

The introduction of Dynamic Time Warping (DTW) deals with this problem by shifting or 'warping' the data in time in order to match other time series. Resulting in a cluster that more resembles the shape of the original data. By calculating the sum of the squared distances, DTW minimizes the distance between each element in X to the nearest point in Y [59]. Dynamic time warping forms the basis of the other two methods.

In DBA k-means clustering the barycenters are shifted with DTW. A barycenter, also described as cluster centroid, forms the average value of a group of time series in a cluster. In the DTW Barycenter Averaging (DBA) algorithm, the sum of squared DTW distance between the barycenter and the series in the cluster are minimized [59].

Lastly Soft-DTW k-means clustering is somewhat similar to the previous method, through its use of DTW. It differs however in one key aspect. In the soft-DTW algorithm the weighted sum of soft-

DTW distances are minimized between the barycenter and the series in the cluster. As a result, the centroids have an average shape that mimics the shape of the members of the cluster, regardless of where temporal shifts occur amongst the members [59].

Calculating final scenarios

As wind data shows little patterns, resulting scenarios after scenario reduction will therefore be less similar to the original data. Even with DTW the resulting scenario will be more resembling of the average wind speed of the selected clusters. As stated in the disadvantage section, with choosing a small number for k, even outliers will be added to one of the clusters. Since the average value of the cluster center is chosen, nor the extremes or the most volatile scenarios. The benefits of this method outweigh the disadvantages as if will be easier to compare the the cost reducing ability of the EMS for various average wind scenarios. The performance of the EMS during volatile winds scenarios should be tested by separately by applying simple heuristics to test the problem. Finally, the clustering method that will be applied to the stochastic approach will be chosen based on the smallest sum of distances to the cluster center, this is also named 'inertia'.

Calculate probability

Finally the probability of scenario per cluster is determined by the number of time series assigned to each cluster. The general equation is shown in Equation 5.1.

$$\frac{\text{number of scenarios per cluster}}{\text{total number of scenarios}} \times 100 \tag{4.19}$$

5
Case Study

The main objective of this chapter is to provide an overview of all the relevant information necessary for developing a cost-effective energy management system for this specific vessel in order to reduce the costs of electricity during cold-ironing. This case study will focus on the Semi-Submersible Crane Vessel Sleipnir which is operated by an offshore marine contractor. A picture of the vessel while it is at its berth place is shown in figure 5.1.

The introduction briefly touched upon these benefits of an onboard BESS during offshore operations as well as the challenging business case due to the vessel spending roughly 100 days per year in port. The aim for the EMS is to provide an additional cost benefit for the vessel operator and since Sleipnir spends approximately 100 days per year in port, making it a good candidate for this type of system. As a result, this could lower the barrier for vessel operators to invest in a BESS for both on- and offshore operations. As the Sleipnir is currently not equipped with an onboard BESS this chapter will provide a general description of the required equipment. Finally, the assumed battery specifications are described.

The outline of this chapter is as follows: The first section 5.1 provides an overview of the context of the vessel including power generations, grid connections, and the location in port. Subsequently, the necessary equipment and specifications are described. In the next section 5.2, the data collecting and processing is described which includes the power demand of the vessel, and wind power generation. In the last subsection 5.2.3, the tariffs and electricity price data is presented in order to determine the potential cost savings of using a BESS on the Sleipnir.

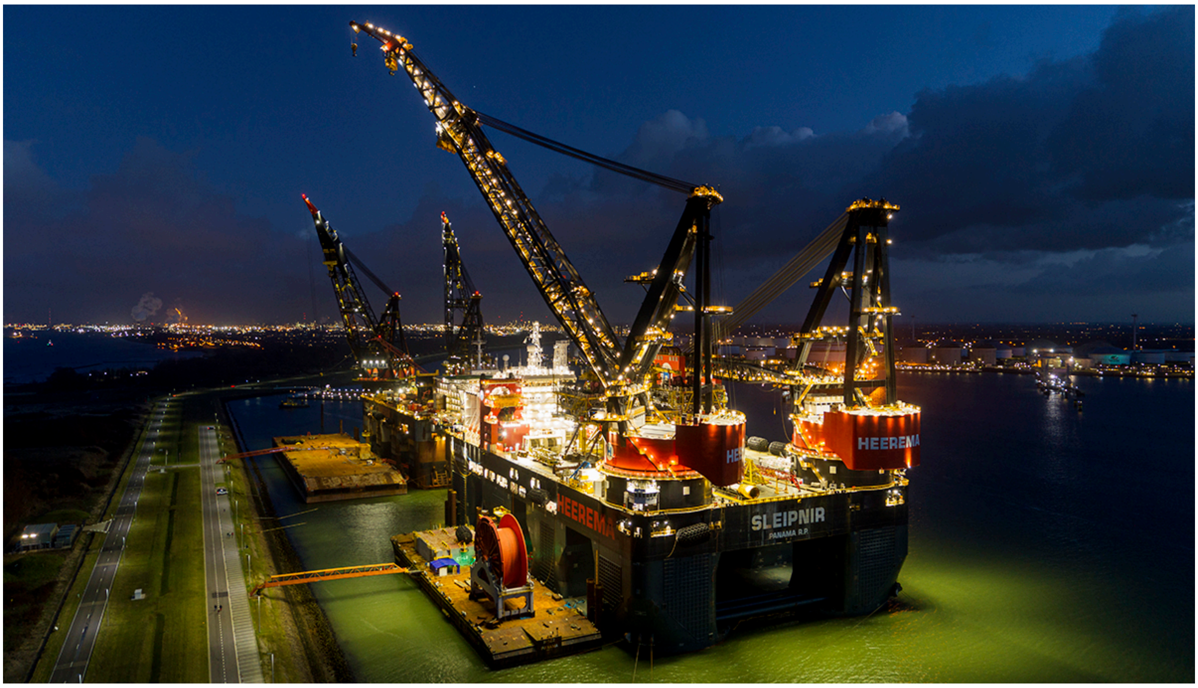

Figure 5.1: Overview of Sleipnir during first shore power tests in 2022

5.1. Overview and infrastructure

The satellite image in figure 5.2 provides a general impression of Sleipnir as it is connected to shore power in the Calland Channel. The vessel is connected to the Rozenburg wind park and the grid through the on-shore e-house as indicated by the colored lines.

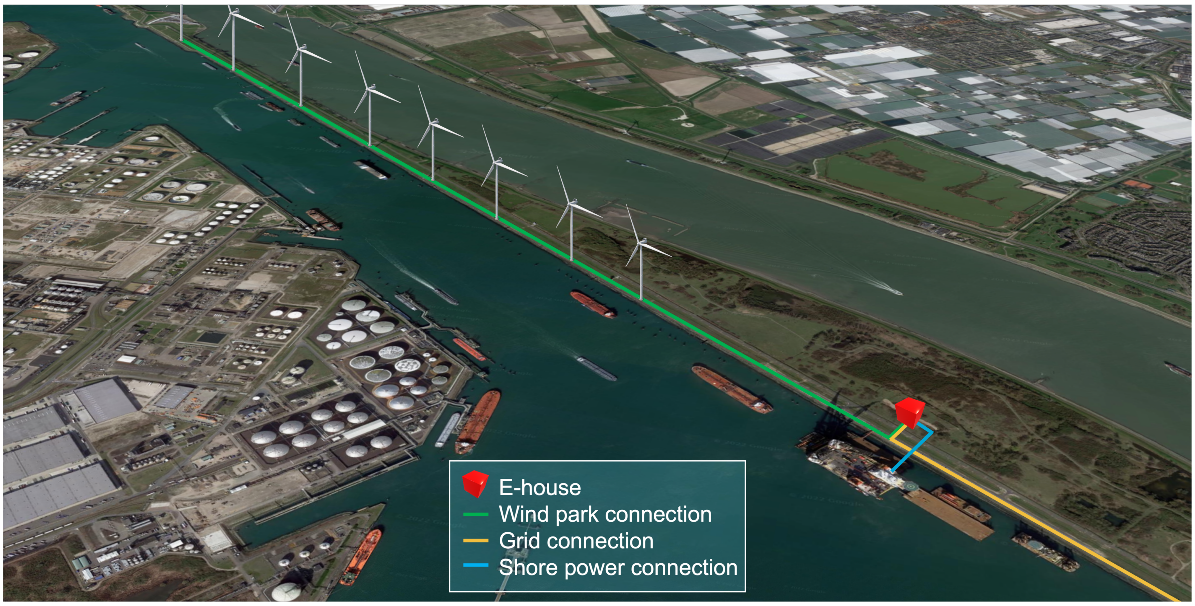

Figure 5.2: Overview of the vessel in Calland Channel

The shore power energy management system relies on three key infrastructural components for its function. The first component is power generation, including both renewable and from the grid. Secondly, transporting the power to the vessel through the *E-house* and shore power connection. Followed by the onboard BESS which will partially provide energy to supply the load of the vessel. These infrastructural components are all illustrated in figure 5.3 including the constraints and specifications. The specifications of the components will be described in more detail in the subsequent subsections.

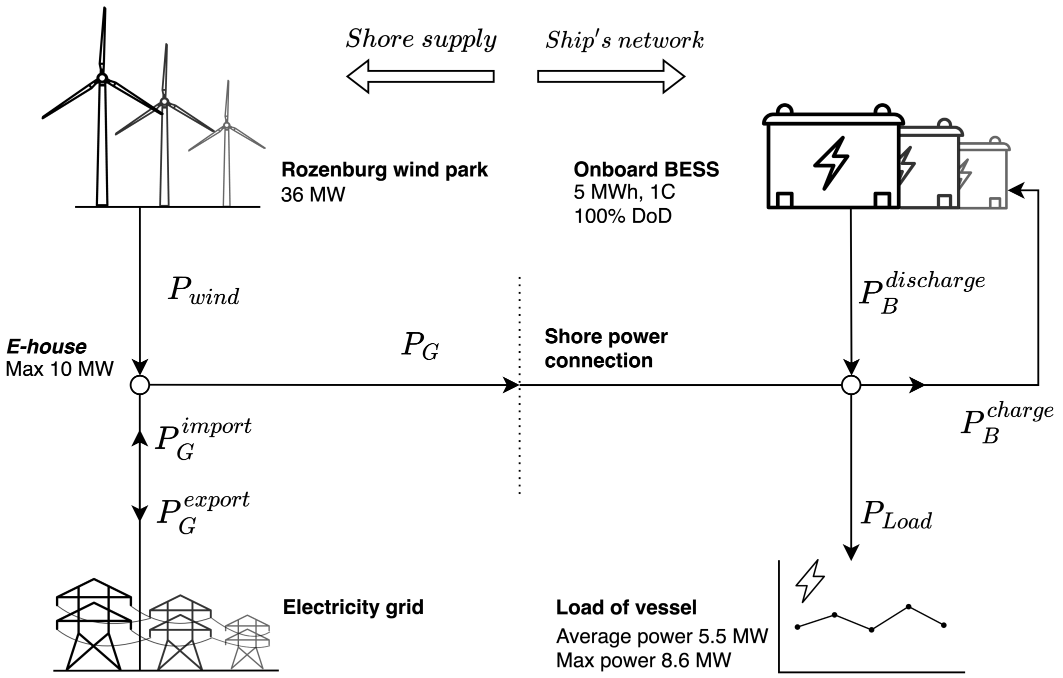

Figure 5.3: Overview of the vessel, and surrounding infrastructure

5.1.1. Power generation and transportation

Rozenburg wind park

A part of the electricity to the Sleipnir is provided by 'Windpark Landtong Rozenburg' which consists of 9 Vestas V126-3.45 wind turbines each of which is able to deliver a maximum of 3.45 MW [60] [61]. The total installed capacity is 34 MW, however, the actual power production is dependent on the wind speed at hub height [60]. The relation between wind speed and power production is visualized in the power curve shown in figure 5.4.

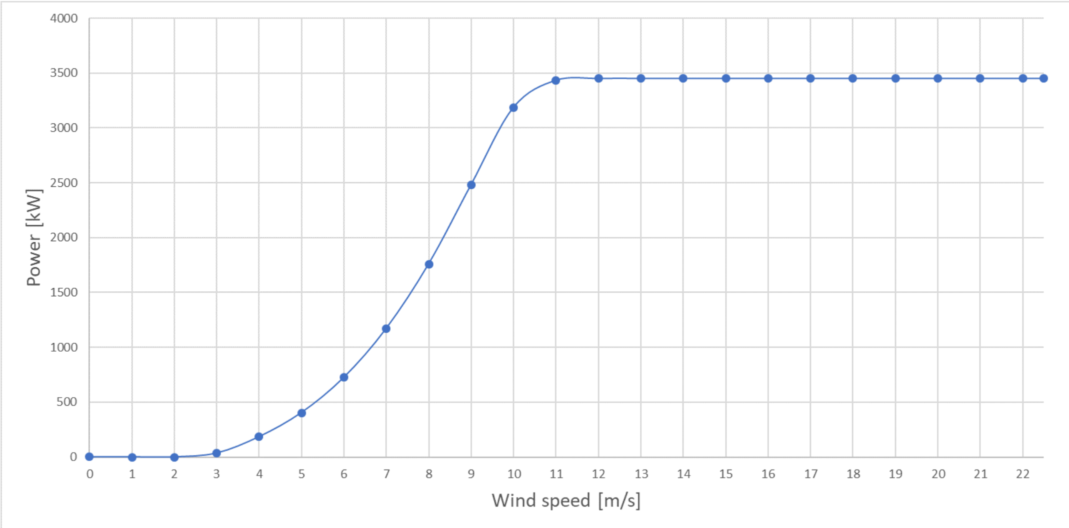

Figure 5.4: Vestas V126-3.45 MW Power Curve [62][63]

Table 5.1 describes in a discrete form, the curve which is shown in figure 5.4. These values are instrumental in accurately determining the power output of the Rozenburg wind park.

The cut-in wind speed of the turbine is set at 3 m/s after which the turbine will start producing electricity. As the wind speed increases the power output of the turbine also increases, reaching its maximum at a wind speed of 11 m/s. Beyond this point, the power output remains constant until the cut-out speed of 22.5 m/s is reached. At this point, the turbine enters the vane position and rotation is stopped.

Table 5.1: Power curve of Vestas V126-3.45 [62]

Wind speed [m/s]	Power [kW]
0	0
1	0
2	0
3	35
4	184
5	404
6	725
7	1172
8	1760
9	2482
10	3187
11	3433

Wind speed [m/s]	Power [kW]
12	3450
13	3450
14	3450
15	3450
16	3450
17	3450
18	3450
19	3450
20	3450
21	3450
22	3450
23	0

The second power source for the vessel is by importing electricity from the grid which is generally stable and reliable, as it is not subject to external factors that could disrupt the electricity supply. Therefore, no further information with regard to the power supply from the grid is necessary. The constraints imposed by the *E-house* do however need to be considered and will be discussed in the next section.

5.1.2. E-house and shore power connection to onboard grid

The necessary equipment to handle the power supplied by both the grid and wind park is located in the *E-house* on the shoreside near the vessel. The schematic presented in Figure 5.5 offers a comprehensive representation of the power electronic systems, both within the onshore *E-house* and aboard the vessel. The numbered components are described in Table 5.2. Within the *E-house*, the 25kV voltage is transformed to 11kV and the frequency is converted from 50Hz to 60Hz. The maximum operational power is limited to 10 MW by the electrical infrastructure of the shore power facility. This limit ensures a safe operation and avoids imbalance on the shore power grid. The power is subsequently transferred through the junction box and shore power cable to the vessel. At the vessel, the incoming voltage of 11 kV is first transformed to 4.16 kV. Subsequently, it is routed to the main switchboard which serves as the connection point to the battery energy storage system as well as the powergrid of the vessel.

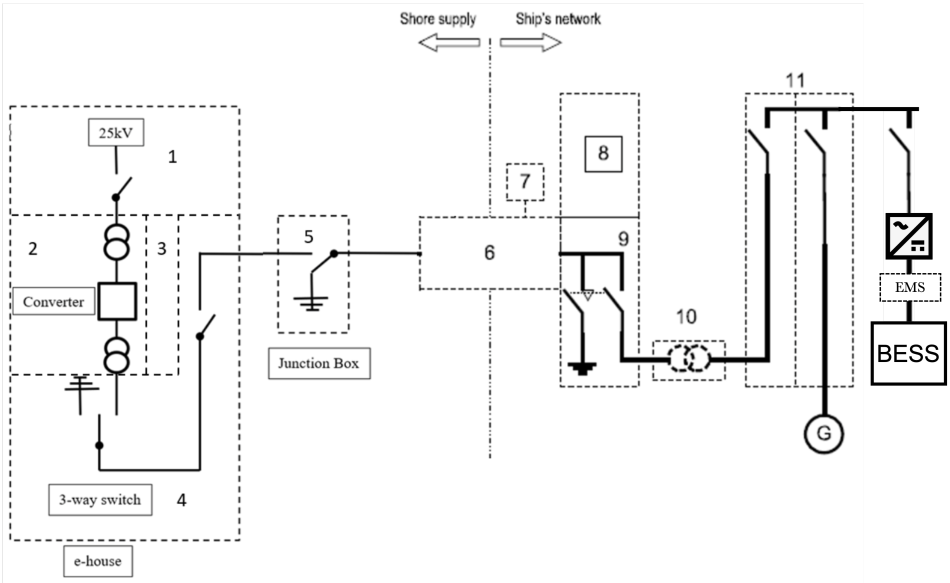

Figure 5.5: E-house to vessel diagram

Table 5.2: Key shore power components

Nr	IEC description	Location	Description
1	Shore supply system	E-house	Incoming current and breaker
2	Shore-side converter	E-house	25kV | 50Hz conversion to 11kV | 60 Hz
3	Shore-side protection relaying	E-house	Monitoring and protection device
4	Shore-side circuit-breaker and earth switch	E-house	Functionality covered by 3-way switch.
5	Control shore	E-house / onshore junction box	Connection e-house HV cable to 'offshore' HV cable with earthing switch.
6	Shore-to-ship connection and interface equipment	Power Pile / e-loop	Platform with 'offshore' junction box connection flexible HV cables
7	Control vessel	Vessel	Power Management System
8	On-board protection relaying	Vessel	Communication shore to ship through optic fiber connection.
9	On-board shore connection switchboard	Vessel	PS / SB connection rooms with the LCP
10	On-board transformer (where applicable)	Vessel	Thialf transformer 11:4.16 kV (N/A for Sleipnir & Aegir)
11	On-board receiving switchboard	Vessel	Sleipnir main switchboards: MS1, MS2

5.1.3. Battery specifications

In addition to the constraints imposed by the shore power infrastructure, it must also be acknowledged that the battery system possesses inherent limitations in terms of its power and energy capacity. An earlier internal study that was conducted on the use of onboard BESS forms the basis for the battery specifications in this case study. The previous study used used a BESS with a Lithium Ion NMC/Graphite cell type. Three configurations with regard to energy and power capacity and were considered. The power capacity was defined by C-rate, which is maximum allowable continuous charge and discharge power relative to energy capacity. I.e. a battery capacity of 5MWh with a C-rate of 0.5, has a maximum charge and discharge rate of 2.5 MW. The energy capacity ranged between 2.7 MWh to 5.5 MWh. All configurations had a maximum DoD of 50% and a C-rate of 3. A more detailed table of the battery specifications is provided in the Appendix in table E.1.

Three configurations with similar energy capacities are tested in this study. Table 5.3 presents the three configurations that were studied. It provides details on their respective energy capacities, maximum depth of discharge (DoD), and C-rate. The parameters in Table 5.3 all influence the functioning of a battery. These parameters will therefore be varied in order to analyze the effects on the performance of the EMS this will be performed in section 6.4. For the base case of this study a 5 MWh battery will be considered with an allowable DoD of 100% and a C-rate of 1.

Table 5.3: Battery specifications from Heerema hybridization study

	Low energy capacity	**Base case**	**High energy capacity**
Total System Energy [kWh]	2000	5000	8000
DoD max	100%	100%	100%
C-rate max	1C	1C	1C

It should be noted that the BESS from the prior study are high C-rate batteries, which are able to be fully discharged and charged in 20 minutes. This ability does not provide added befits for energy arbitrage, since prices are determined for every hour. However, its functionality is mostly advantageous during peak shaving, as peaks in power demand mostly occur during relatively short instances. The power profile will be discussed further in Section 5.2.1.

5.2. Data collecting and processing

5.2.1. Ship-side Power Demand

The cost of electricity is ultimately determined by the energy and power demand of the vessel. The EMS will utilize this information to optimally dispatch the BESS. This requires accurate data on the power demand of the vessel during its connection to the shore power system. The power demand of the vessel is registered within the company in the data aggregation program K-IMS on which power data is collected on a minute-by-minute basis. Since the energy scheduling is performed on a 15-minute-by-15-minute basis, the power has to be processed to match the time steps. The data processing will be discussed in this section.

As depicted in Figure 5.6, the bottom timeline illustrates the power demand of the vessel during an 11-day period. On this power demand timeline, three important sections have been highlighted. The significance of each section will be discussed below:

1. Section (1) represents the commissioning of the vessel. During this period power systems were tested at high peak loads for a longer duration. It shows a power demand of 8MW lasting roughly 4 hours. This long-lasting high power demand was synthetically produced by running two thrusters in opposite directions.
2. Section (2) represents a normal operational profile and will be used as a base case for power demand. The mean power demand during this period is 5.5MW with a short-lasting power peak of 8.6MW.
3. Section (3), similar to section (2), shows a normal power demand of the vessel. In this part the peak power demand is lower, however, it is occurring and lasts for a longer period. A part of this section will be used in the out-of-sample assessment.

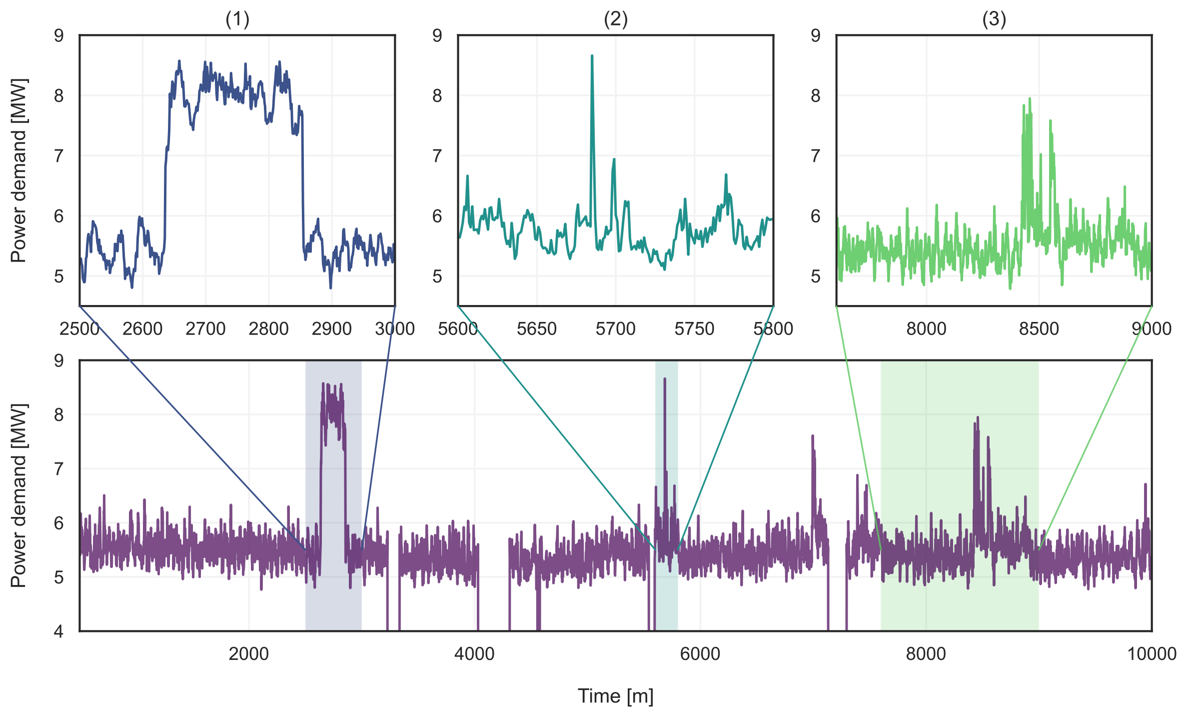

Figure 5.6: Sleipnir shore power demand over a 7-day period (27-02-2022 to 6-03-2022)

The energy capacity requirements of the onboard BESS were estimated by studying the histogram of the power demand shown in Figures 5.7 and 5.8. The distribution of the power demand of Sleipnir during the period from 27-02-2022 to 10-03-2022 is shown in figure 5.7. The mean value of the power demand is between 5MW and 6 MW. An enlarged version of the same histogram in figure 5.8 show a maximum peak at 8.6 MW lasting only for a short period. The maximum power demand and duration of power surges were estimated to remain below 20 minutes.

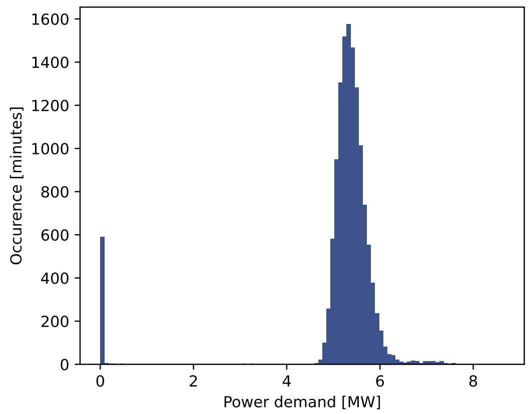

Figure 5.7: Histogram of power demand distribution of Sleipnir

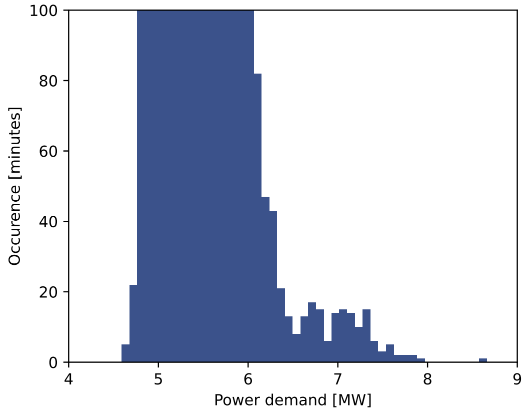

Figure 5.8: Enlarged histogram of power demand distribution of Sleipnir

The data from Figure 5.6 was processed so as to fit in a 15-minute-based model. This was achieved by down-sampling the minute-by-minute power demand to 15-minute periods. The down-sampling was performed on the representative power demand which included a power peak. This selection is shown in Figure 5.9. The lack of power demand data between hours 9-12 shown in Figure 5.9 was corrected by means of mean imputation during this period [64]. The corrected power demand shown in Figure 5.10 was used as the representative power demand in the day-ahead scheduling problem.

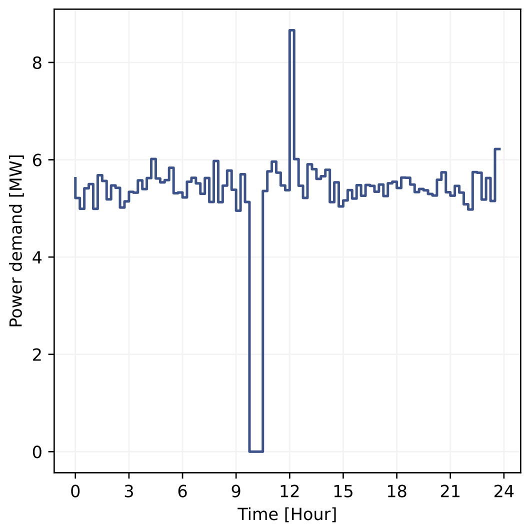

Figure 5.9: Power demand 15 minute intervals uncorrected

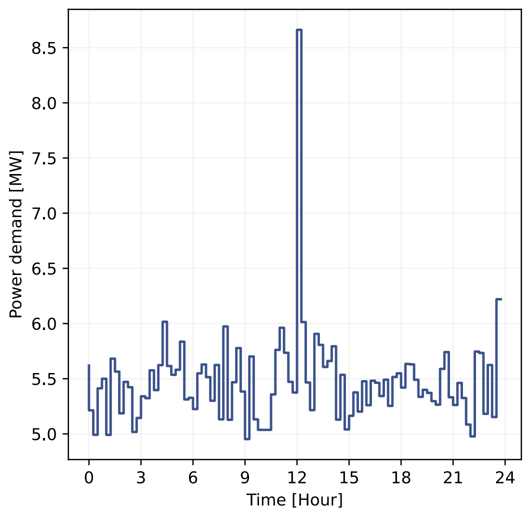

Figure 5.10: Power demand 15 minute intervals zero power replaced by mean value

5.2.2. Wind

Electricity is supplied to the vessel from both the grid and local Rozenburg wind park through the shore power system. While energy prices for both sources are determined on the DAM, the grid-related costs differ. For locally produced wind energy, the vessel operator is exempted from any transport costs. The equation for grid-related costs is presented in subsection 5.2.3. In order to determine the transport costs for the vessel operator, the energy produced by the wind park and supplied to the shore power facility has to be determined.

Energy generation

In order to ascertain the energy generated by the wind park on a 15-minute-by-15-minute basis, it is necessary to first determine the wind speeds at the site of the wind park. Similar to the data for the electricity spot prices, historical data provided the local wind speeds. The wind speed data was generated by the Hoek van Holland weather station (STN 330) which is operated by the KNMI. This weather station measures wind speeds at 13 meters above ground level [65]. A preview of the data released by the KNMI is shown in table 5.4. The station number is indicated by 'STN', the year and date by 'YYMMDD', hours are indicated by 'H' and lastly, the wind speed is indicated by 'FH' in 0.1 m/s.

Table 5.4: Hourly average wind speeds (FH) in 0.1 m/s at Hoek van Holland weather station. [65]

STN	YYYYMMDD	H	FH
330	20210101	1	20
330	20210101	2	30
330	20210101	3	30
⋮	⋮	⋮	⋮
330	20210101	22	50
330	20210101	23	60
330	20210101	24	40

During the year 2021, the wind speeds at the Hoek van Holland weather station were distributed in the Weibull distribution shown in figure 5.11. Since the peak shaving function of the BESS will only be relevant during periods at which the wind park cannot supply the peak power demand of the vessel. By utilizing this distribution in combination with the cut-in speed of the wind turbine, the probability of a peak in power demand coinciding with an insufficient supply of renewable energy can be determined.

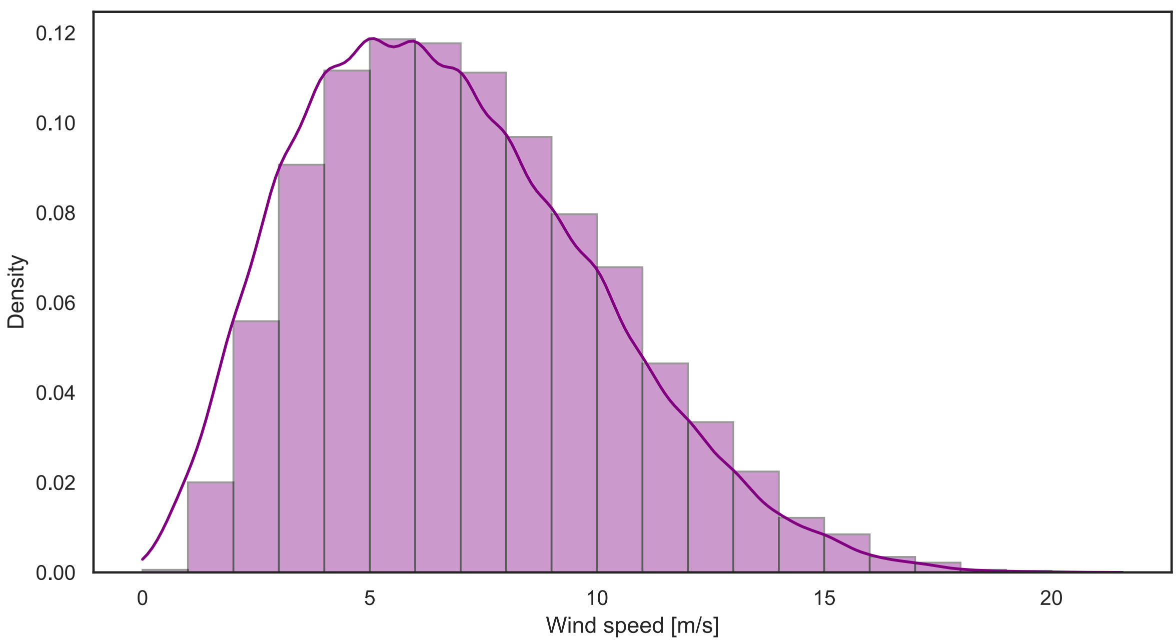

Figure 5.11: Wind speeds in 2021 histogram

Wind shear affects wind speed at different altitudes, the wind speed provided by KNMI is measured 13 meters above the ground level. However, the power output of wind turbines is based on the wind speed at the hub height of the turbine. Therefore, conversion of the measured data must be made to calculate the wind speed at hub height, to estimate the power output of the turbine[49].

The tip height of the turbine is 193 meters and the rotor diameter is 126 meters, this gives a hub height of 130 meters [60] [61]. The conversion based on known parameters is described by reference [49]. The conversion make use of reference height H_0 at which the wind speed is measured, the hub height H and the friction coefficient α or Hellman exponent described in Table 5.5. This yields the wind speed v_{hub} at hub height. Reference [48] uses a Hellman exponent of 0.143 to describe an open land surface which is the most common landscape in the Netherlands. In this report, a friction coefficient of 0.20 is used to describe the area of the Rozenburg wind park. Although there is a large open water surface surrounding the wind turbines, this coefficient was conservatively chosen considering the industrial land use at the site. As a result of the wind shear a 58% higher wind speed is observed at the hub height compared to the wind speeds measured by the Hoek van Holland weather station at 13 meters above ground level.

Table 5.5: Friction coefficient α for a variety of landscapes. [49]

Landscape type	**Friction coefficient α**
Lakes, ocean and smooth hard ground	0.10
Grasslands (ground level)	0.15
Tall crops, hedges and shrubs	0.20
Heavily forested land	0.25
Small town with some trees and shrubs	0.30
City areas with high-rise buildings	0.40

After deriving wind speed at hub height from the measured data, the generated power per turbine can be calculated by using the power curve. Finally the generated power has to be multiplied by the number of turbines to find the combined power output of the wind park.

Wind scenario time series k-means clustering

The wind speed data of 2022 at the berth location of the vessels will be reduced using the k-means clustering method. The three of clustering methods described in Chapter 4 were tested, which included Euclidean distance k-means, DBA k-means, Soft-DTW k-means clustering. The initial number of cluster centers was determined by means of an elbow plot 5.12. Since the elbow plot in Figure 5.12 does not show a clear inflection point, a value was found using heuristics. Figure 5.13 shows a the diminishing return of additional cluster centers more clearly at around 10 cluster centers.

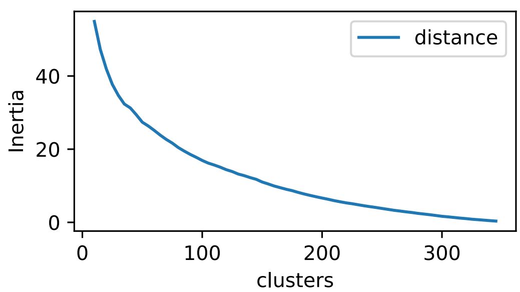

Figure 5.12: Elbow plot

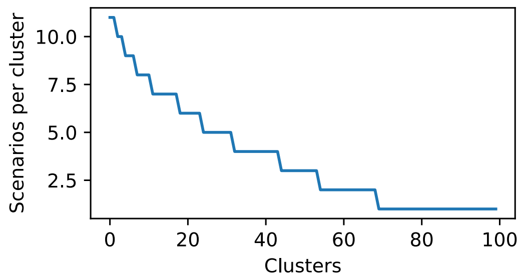

Figure 5.13: Number of scenarios per cluster

To invigorate the argument for choosing 10 clusters, a plot was made showing 100 Euclidean k-means cluster centers in Figure 5.14. This figure illustrates that most cluster centers contain only 1 to 4 clusters, while only a limited number contain 8 to 10 clusters. This shows that increasing the number of cluster centers does not lead to a significant improvement in the representativeness of the cluster center.

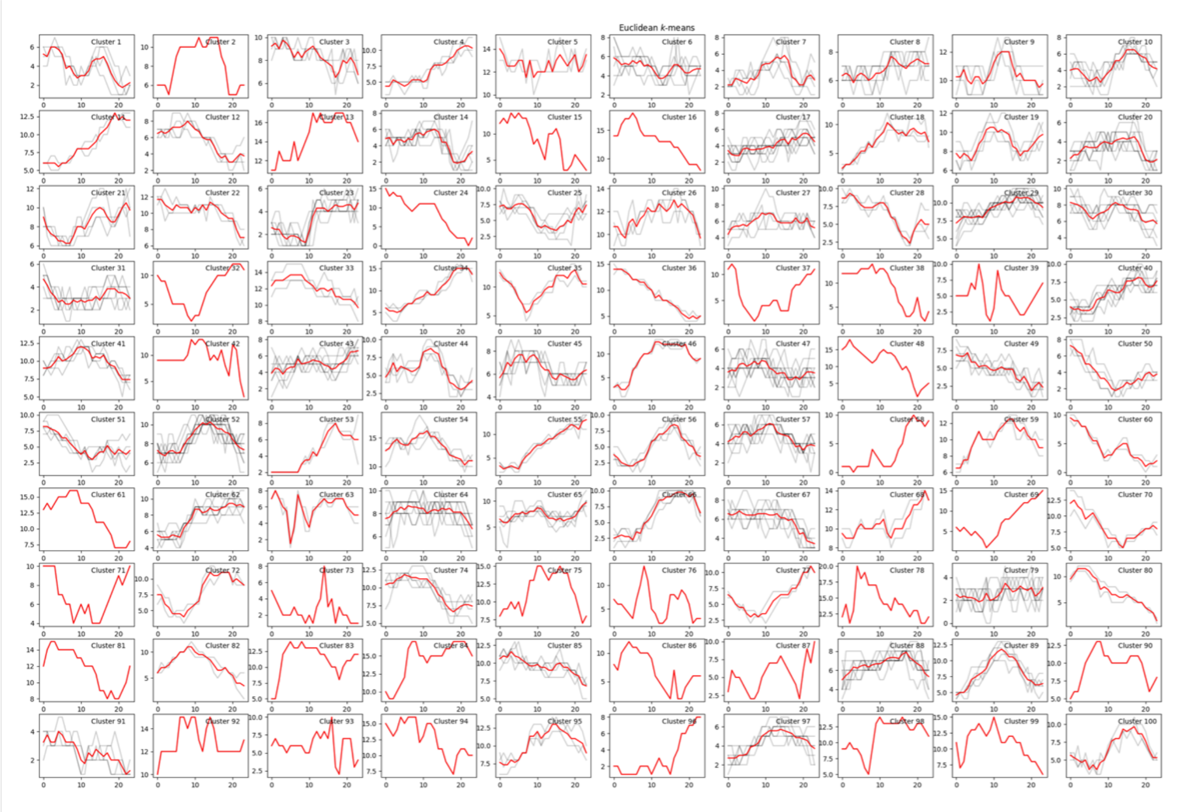

Figure 5.14: Daily wind speed scenarios of 2021 divided over 100 clusters

A lower inertia indicates that the sum of squared distances is closer to the cluster center. Table 5.6 shows the values of inertia for the three clustering methods. The DBA k-means clustering method was chosen as it presented the lowest inertia value.

Table 5.6: Inertia values for three k-means clustering methods

Cluster type	**Inertia value**
k-means	54.92
DBA k-means	21.33
Soft DTW k-means	690.46

When applying the DBA k-means clustering method, 365 wind speed scenarios are spread over 10 clusters. The resulting reduced cluster centers are shown in Figure 5.15. The black opaque lines represent the individual scenarios from historical data. The 10 red lines represent the cluster centers that form the reduced wind scenarios. The Euclidean k-means and soft DTW k-means scenarios can be found in Figures D.1 and D.3 in Appendix D. The probability of each scenario was determined by assessing the number of members per cluster center. The probability of with was calculated as shown in equation 5.1:

$$\frac{\text{number of scenarios per cluster}}{\text{total number of scenarios}} \times 100 \tag{5.1}$$

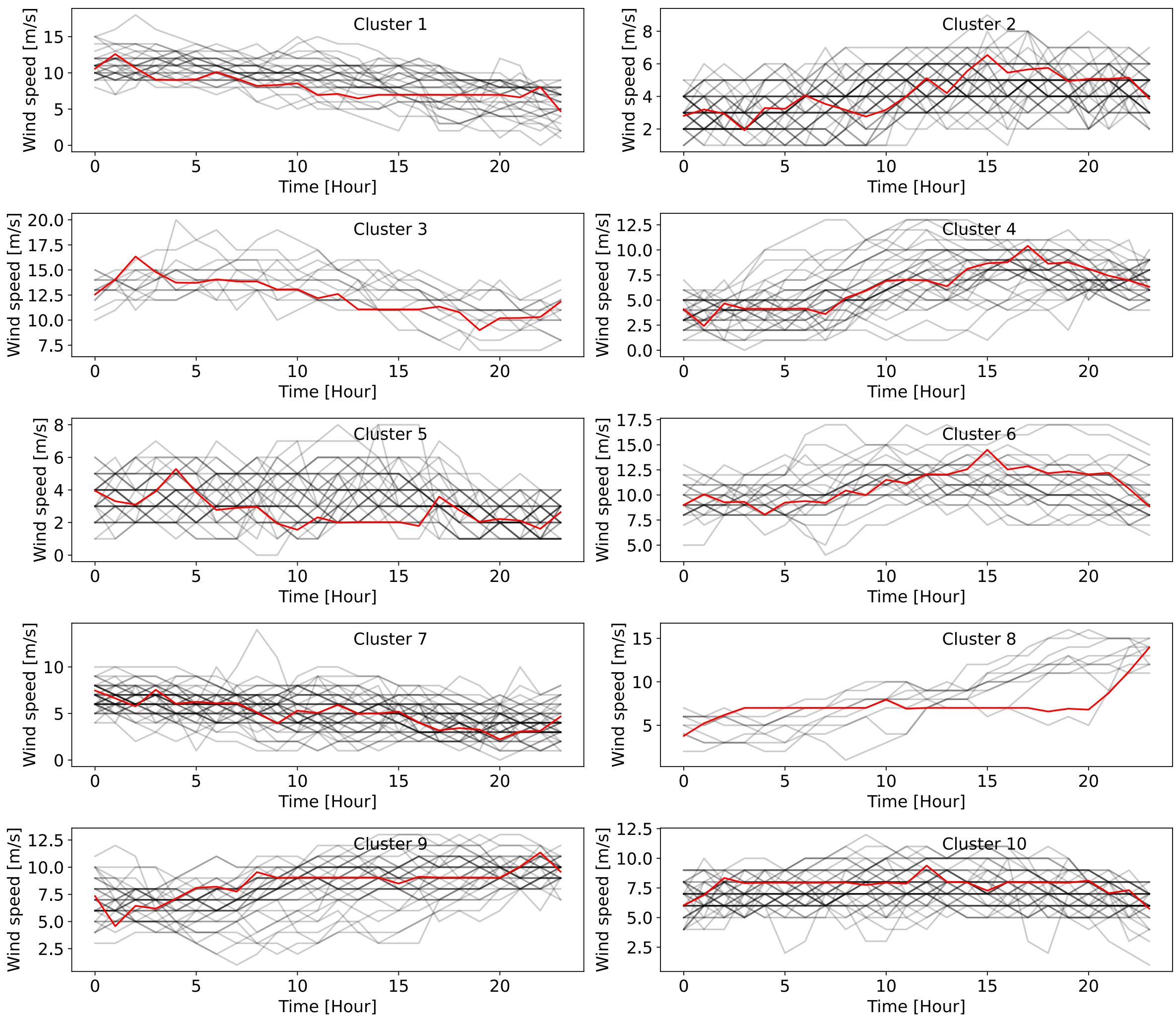

Figure 5.15: DBA k-means 10 clusters

Applying Equation 5.1 on the DBA k-means clustering methods gives the probability of each reduced scenario.

Table 5.7: Distribution of scenarios over cluster centers for DBA k-means method

DBA k-means Cluster	Count	Probability [p.u.]
1	32	0.11
2	52	0.077
3	14	0.115
4	39	0.03
5	41	0.096
6	23	0.145
7	56	0.055
8	10	0.175
9	41	0.142
10	51	0.055

The wind speed data is up-sampled and linearly interpolated to match the 15-minute time steps of the power demand. This is shown in the transformation from Figure 5.16 to 5.17.

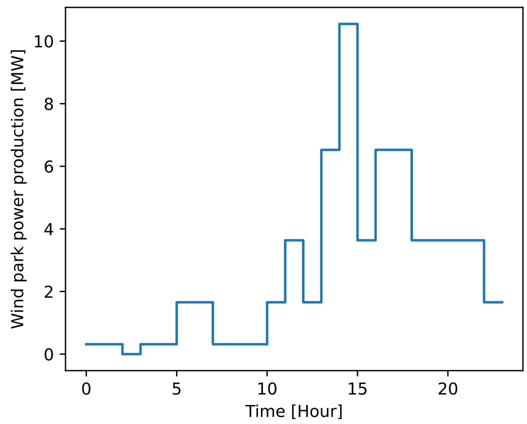

Figure 5.16: Power produced one hour intervals

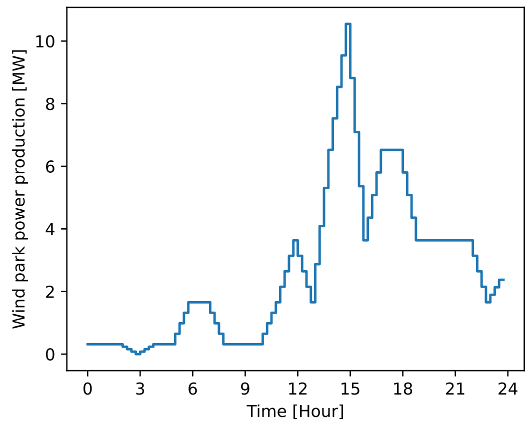

Figure 5.17: Power produced 15 minute intervals

As a final step, the 10 red cluster centers from 5.15 are represented in a single plot shown in Figure 5.18. The relative probability of each scenario is indicated by the color of each line. A lighter color indicates a lower relative probability.

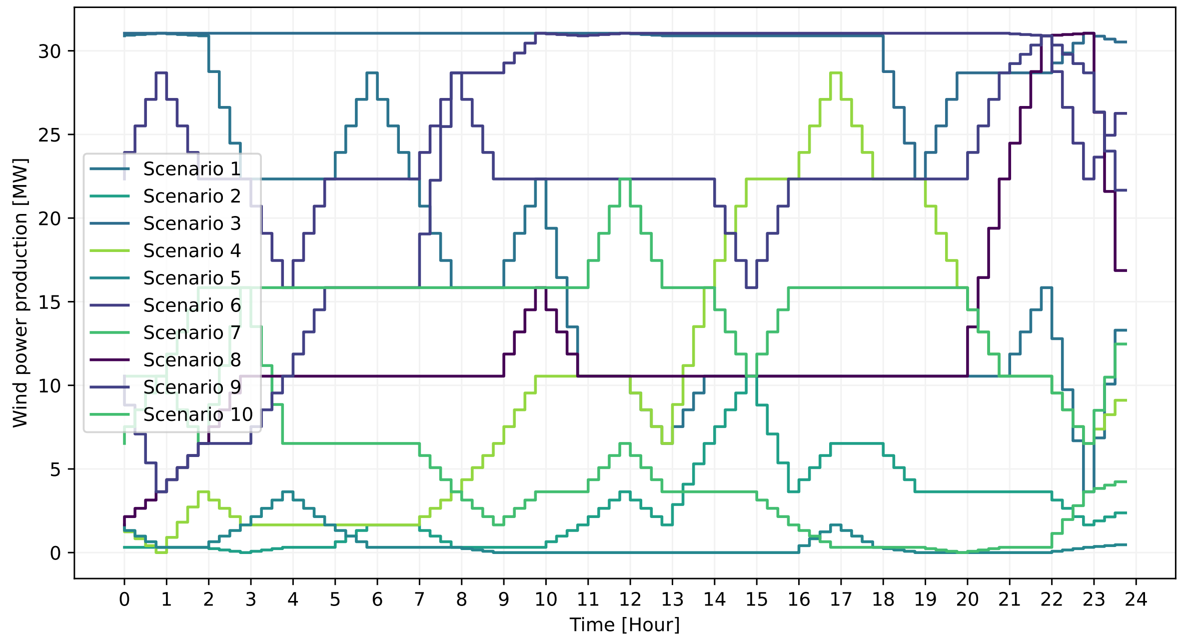

Figure 5.18: Wind power production 10 scenarios

5.2.3. Tariffs

The input for the market data is given in hour-by-hour steps as shown in table 5.8. This total electricity costs for the vessel operator are determined by multiplying the hourly day-ahead price λ_t by the total energy consumption during this hour. This yields the total costs of electricity bought on the day-ahead market during that hour C_t^{spot}.

Table 5.8: EPEX DAM Market prices data set 2021 [66]

Hour	Spot price [€/MWh]
1	48.19
2	44.68
3	42.92
⋮	⋮
22	44.88
23	45.00
24	47.20

The price developments throughout the year 2021 are shown in Figure 5.19. It should become clear from this figure, that both the volatility as well as the average prices for electricity increase towards the last months of the year. In order to make a representative analysis with regard to costs for the vessel operator, the prices of day 101 of 2021 provided a representative mean value and volatility were used in the base case scenario. Both the average cost and volatility will be varied in the analysis to observe the effects of the EMS during different price conditions.

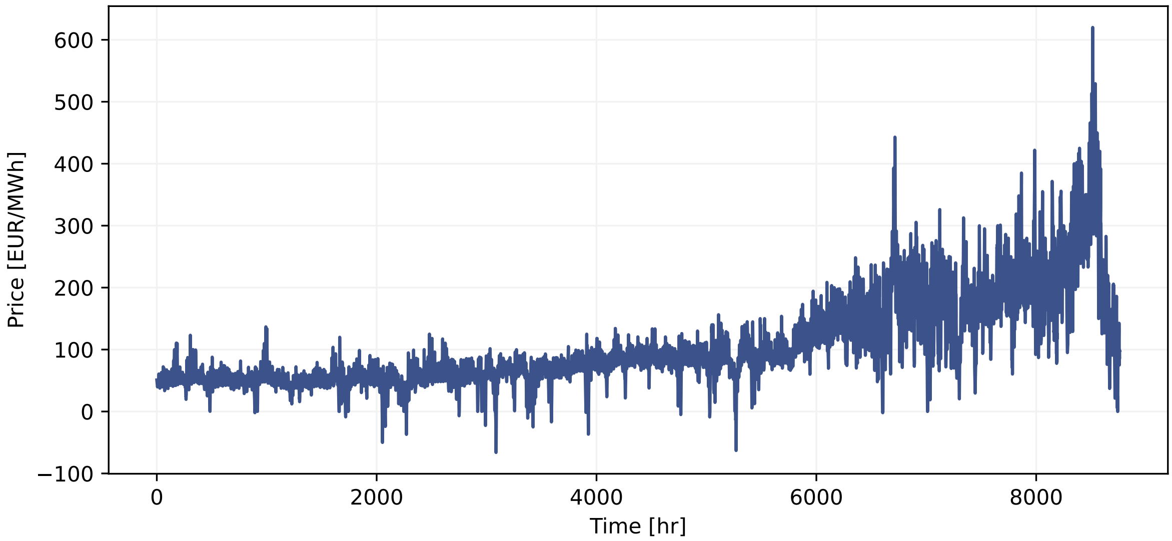

Figure 5.19: Day-Ahead prices 2021

As mentioned in subsection 5.2.2, other factors besides the DAM prices, influence the costs of electricity for the vessel operator. One of which is determined by the origin of electricity production which affects the transport costs of electricity as well as the Guarantee of Origin (GO) price for the vessel operator. The GO is a certificate that guarantees the renewable origin of electricity coming either from *HollandseWind* from the Rozenburg $\lambda^{GO,NL}$ wind park or from *Groene stroom Belgie* $\lambda^{GO,BE}$. In the model the fees are €5/MWh for $\lambda^{GO,NL}$ and €10/MWh for $\lambda^{GO,BE}$.

Transport costs of electricity

The transport fees for electricity are determined by the DSO. The electricity for shore power is delivered by DSO Stedin. The transport costs are calculated as: The highest load occurring in each consumption month separately, expressed in kilowatts, and determined as the average load of a 15-minute period unless agreed otherwise with Stedin. In 2023 this tariff is $\lambda_{2023}^{transport} = 2944$ €$/MW_{peak}/month$ maximum power demand per month as well as 4018 €$/MW_{peak}/month$ for the maximum yearly power demand. Both fees can be found in the Appendix H.

6
Results

In this chapter, the results of the cost-reducing energy management system are presented and discussed. This is done based on the two stochastic programming methods described in Chapter 4.1.4. Both the Expected value (EV) and Wait-and-See solution (WS) methods will be tested for four different energy management strategies. The results for the EV solution are presented in Section 6.2. The WS is subsequently presented in Section 6.3. A sensitivity analysis is finally performed in Section 6.4 which includes the sensitivity analysis for battery size, C-rate, day-ahead price volatility, variations in mean value of the day-ahead price, and the influence of grid tariffs on the cost-reducing performance of the EMS.

6.1. Overall performance

Four different strategies were considered to determine the most effective energy management strategy within the given conditions. The *(1) No BESS* strategy represents the baseline scenario, in which there is no BESS or EMS. The second strategy, *(2) Arbitrage*, involves dispatching the BESS to minimize electricity costs but does limit the import from the grid. The third strategy, *(3) Arbitrage + peak shaving*, incorporates both arbitrage and peak shaving, it limits the maximum power that can be imported from the grid. Finally, the *(4) Peak shaving* strategy only considers peak shaving.

The *'Base case'* scenario serves as the reference point for comparison with all other variations. The base case as described in Section 5.1.3 comprises a 5MWh, 1C, 100% DoD BESS. In addition, the day-ahead prices detailed in Section 5.2.3 and the power demand outlined in Section 5.2.1 were utilized. For the duration of the base case, a 100-day uninterrupted stay in port is assumed. The performance of the EV and WS methods for the base case scenarios are presented in Table 6.1 for the four strategies.

Table 6.1: Comparison of EV and WS solution

Scenario 100-days	***No BESS Total costs***	***Arbitrage Cost reduction***	***Arbitrage + Peak shaving Cost reduction***	**Peak shaving Cost reduction**
Expected value Solution	€828,800	€66,100 8.0%	€66,100 8.0%	€0 0.0%
Wait-and-See Solution	€1,180,147	€16,065 1.4%	€184,851 15.7%	€119,915 10.2%

Table 6.1 presents the results for the cost reductions achieved by four strategies within the expected value, and the wait-and-see solutions. The data shows that the arbitrage + peak shaving strategy results in the largest absolute and relative cost reductions. Additionally, the peak shaving strategy alone also exhibits a significant reduction in costs among the strategies analyzed within the wait-and-see approach. In Section 6.2, the results and performance of the EV solution will be discussed in greater detail, along with an examination of its limitations. Section 6.3 will subsequently present an analysis of the wait-and-see solution.

6.2. Expected value solution

The expected value solution presents a probable outcome for decision-makers to consider when making decisions. For the expected value solution, the expected wind speed was used, as this factor primarily determines the condition under which the EMS will provide value to the vessel operator. In order to calculate the expected value, the average wind scenario was used as an input. Based on 10 generated scenarios an average wind scenario was constructed, which subsequently determined the power produced by the wind park.

Figure 6.1 shows the load, expected wind power production, and power imported from the grid. The wind power production of 16 MW is sufficient to meet the power demand of the vessel for the complete duration of the simulation. As a result, EMS is unable to reduce costs by performing peak shaving, since grid tariffs are exclusively imposed on power imported from the grid. The absence of values for 'Grid import' confirms this observation. Despite this, energy arbitrage can still be utilized.

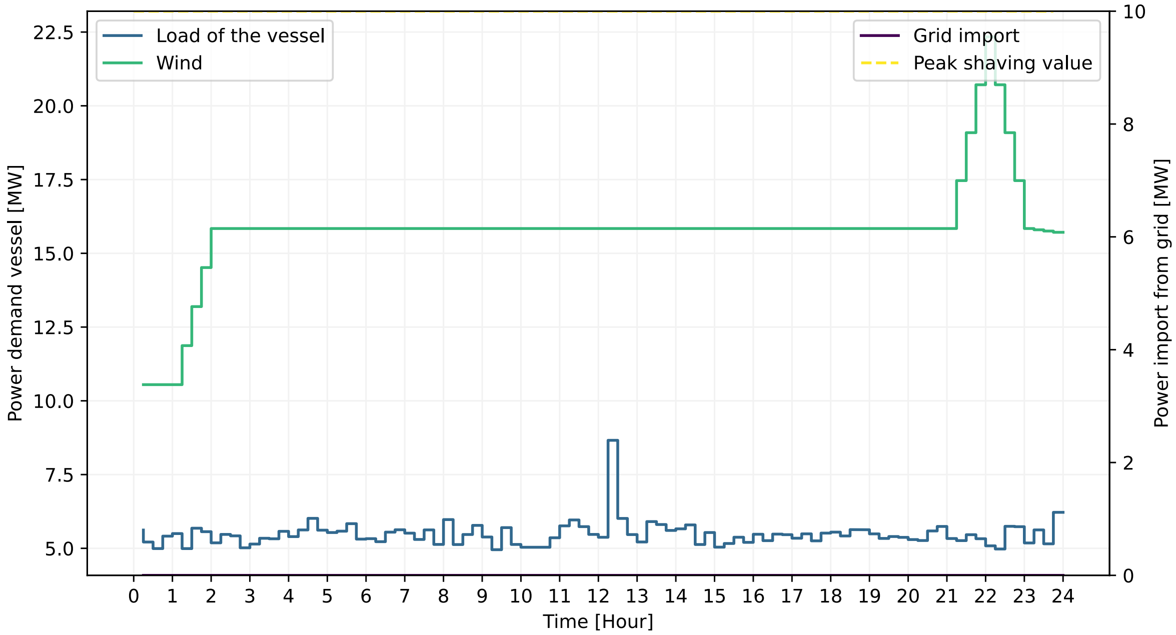

Figure 6.1: Grid import and wind power production
for the *arbitrage* & *arbitrage + peak shaving* strategies

Energy arbitrage is performed by the EMS as the vessel operates in a volatile electricity market. Figures 6.2 and 6.3, show the EMS optimally dispatching the battery in order to achieve the lowest electricity costs for the vessel operator. Consequently, the electricity costs are reduced by 8% while the grid tariffs remain zero as no power is imported from the grid.

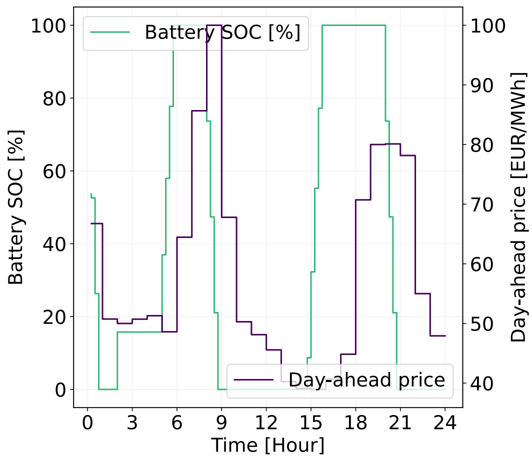

Figure 6.2: Battery SOC and day-ahead price for strategies (2 & 3)

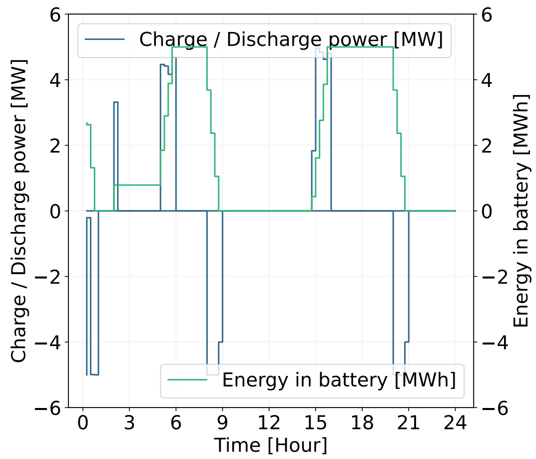

Figure 6.3: Charge, discharge power and energy stored in BESS for strategies (2 & 3)

Finally, the daily electricity costs for the four considered strategies are presented in Table 6.2. Based on these costs, strategy (2) and (3) are the most optimal in terms of reducing daily costs. However, these results do not consider the total costs for a longer port stay. An assessment of the cost reduction during a 100-day stay is given in the next section 6.2.1.

Table 6.2: Daily electricity costs for expected value solution under four EMS strategies

	No BESS	***Arbitrage***	***Arbitrage + Peak shaving***	**Peak shaving**
Energy costs [€/day]	€8288	€7627	€7627	€8288

6.2.1. Analysis of expected value solution

The primary objective of the EMS strategies is to reduce costs for the vessel operator. To evaluate the performance of these strategies, a scenario of 100 days in port is considered. The total costs for a 100-day stay in port is presented in Figure 6.4 for three strategies. The costs presented in this figure consist only of energy-related costs since the expected value assumes there is no import of electricity from the grid. As a result, Figure 6.4 demonstrates that the peak shaving strategy in this case has no effect on cost reduction for the vessel operator, as wind power covers the complete power demand of the vessel. From this point forward, for the purpose of conciseness, the term *peak shaving* will be represented by the abbreviation PS in the figures.

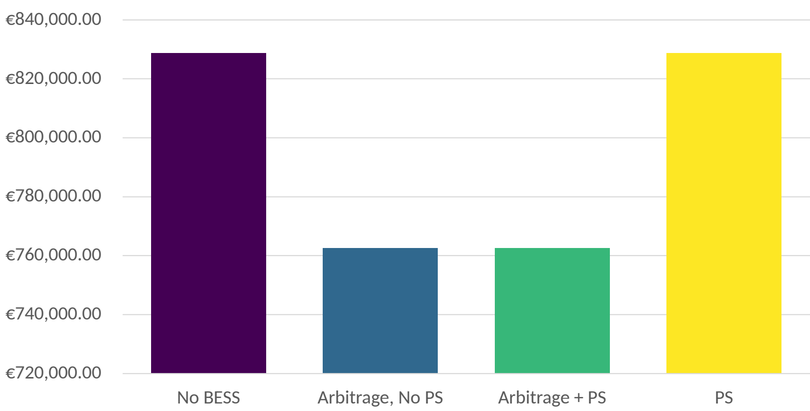

Figure 6.4: Expected 100-day costs

Figure 6.4 demonstrates that the cost reduction for both the *arbitrage* without peak-shaving and the *arbitrage + peak shaving* case is significant as the algorithm is able to capitalize on price volatility while keeping grid import tariffs low. The final strategy, which only uses peak shaving, results in no overall cost reduction. As previously mentioned, Figure 6.1 illustrates no net import of electricity from the grid. Resulting in both monthly, and yearly grid costs of €0.00, as the peak load can be covered entirely by generated wind energy, eliminating the need for grid imports. By presenting such an unlikely scenario, the EV solution highlights its limitations.

The use of the expected value solution for wind power profiles has the potential to be effective, but an important factor must be considered in order to accurately assess its effectiveness. This factor is the inherent variability of wind speeds, which can vary throughout the day and from day to day. This variability has a significant impact on the results of using this solution, as periods of low wind production increase the demand for the vessel operator to import electricity from the grid. In the event of a scenario in which a high peak power demand coincides with a period of low wind, the capacity of the BESS may be inadequate to meet the power requirements, thereby necessitating the importation of electricity from the grid. This subsequently leads to an increase in the associated grid-related costs for the vessel operator. Overall, the use of the expected value solution for wind power profiles must take into account the variability of wind speeds in order to accurately predict its effectiveness.

The results of using the expected value solution for wind power production, in this case, show that it is generally able to fully provide the vessel with the necessary energy. However, this result is likely to be overly optimistic, particularly in regard to grid costs. This is due to the inherent variability of wind speeds, which can impact the ability of the solution to accurately predict the amount of energy that will be available from wind power production. As a result, the estimated grid costs may not be accurate and could be significantly higher in reality. It is important to consider the potential impact of wind speed variability in order to accurately assess the effectiveness of this solution.

The wait-and-see solution, which takes into account various wind generation scenarios, will be used in the next section of this study. This approach provides a more realistic representation of the potential impact of wind on grid costs, as it accounts for the inherent variability of wind speeds. By considering a range of wind scenarios, this solution is able to provide a more accurate prediction of the potential impact on grid costs. This is important in order to accurately assess the effectiveness of using wind power production in this specific context.

6.3. Wait-and-see solution

The wait-and-see solution provides a solution under uncertainty by optimizing various scenarios. Each scenario has a corresponding probability of occurrence. The sum of all scenarios are multiplied by its probability results in the WS solution. In this way, a decision maker is able to see the behavior of the energy management system in varying weather conditions, which will influence the realized cost reduction as well as the optimal parameters of the BESS.

The scenarios and probabilities are the result of the DTW k-means clustering method described in section 4. The probability of the ten wind speed scenarios are given in table 6.3 and will be used for determining the costs for the vessel operator. The weighted combinations of the scenario outcomes form the final wait-and-see solution. Table 6.3 shows the wait-and-see solutions for the four different strategies applied to the base case described earlier in Section 6.1.

Table 6.3: Wait-and-See solutions, four strategies (costs of energy in €/day)

Scenario	***Probability [p.u.]***	***No BESS***	***Arbitrage***	***Arbitrage + Peak shaving***	**Peak shaving**
Scenario 1	0.11	€8290	€7629	€7628	€8290
Scenario 2	0.077	€8661	€7963	€7999	€8661
Scenario 3	0.115	€8288	€7626	€7626	€8288
Scenario 4	0.03	€8438	€7779	€7784	€8438
Scenario 5	0.096	€8885	€8210	€8378	€8885
Scenario 6	0.145	€8288	€7627	€7626	€8288
Scenario 7	0.055	€8545	€7879	€7879	€8545
Scenario 8	0.175	€8306	€7631	€7630	€8306
Scenario 9	0.142	€8292	€7631	€7631	€8292
Scenario 10	0.055	€8288	€7627	€7627	€8288
Wait-and-see solution		€8397	€7729	€7747	€8397

As every WS solution involves multiple scenarios, plotting all scenarios may be confusing. Three EMS Strategies; *No BESS*, *Arbitrage*, and *Arbitrage + PS* are respectively shown in Figures 6.5, 6.6 and 6.9 to demonstrate the effects of different dispatch strategies for grid import power demand.

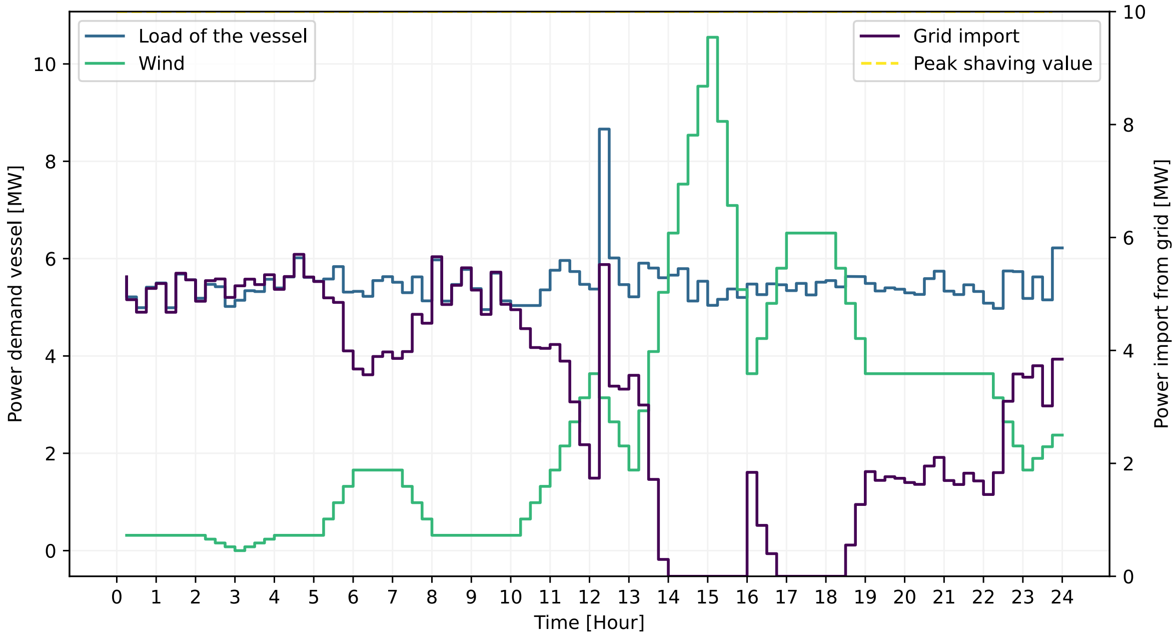

Figure 6.5: Strategy (1), No Arbitrage, No Peak Shaving
Illustrative example, wind scenario (2/10)

In the *No BESS* base case shown in Figure 6.5, the grid import power follows the power demand of the vessel during periods with no wind power generation. During periods of wind power generation, the power generated by the wind park is subtracted from the power imported from the grid. During the peak power demand at t=12 h, the wind park is able to partially supply this demand thus limiting the effect on grid imports. While this is beneficial for this specific scenario, other scenarios with low wind power generation show a peak grid import power similar to the peak in power demand of 8.6 MW which will increase grid-related costs.

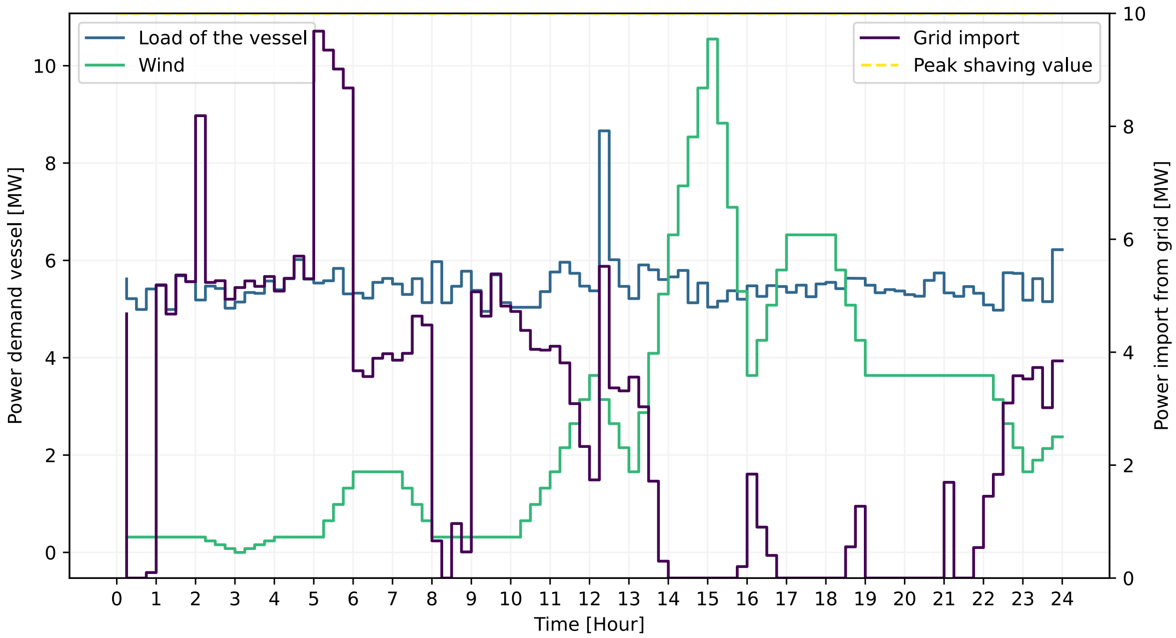

Figure 6.6: Strategy (2), Arbitrage
Illustrative example, wind scenario (2/10)

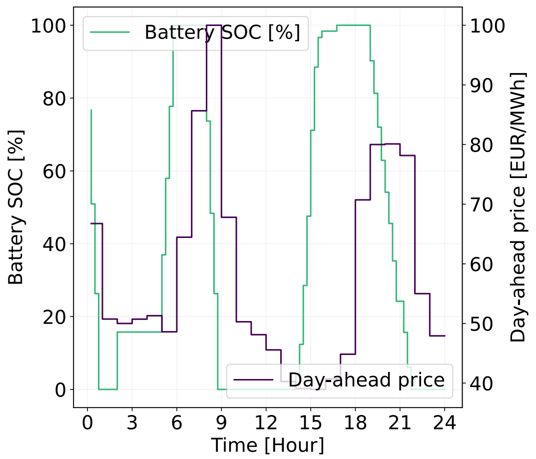

Figure 6.7: Charge and discharge rates strategy (2)

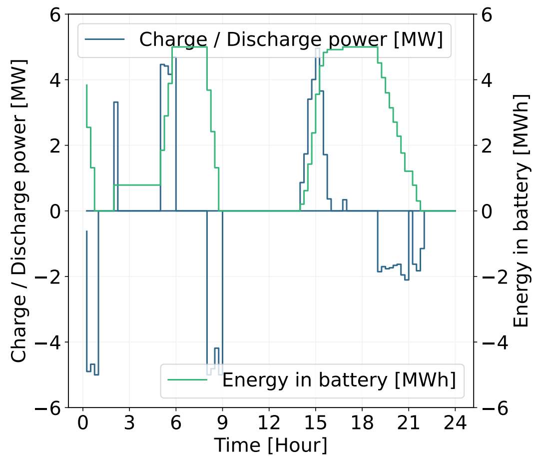

Figure 6.8: Day-ahead price and battery scheduling strategy (2)

The unrestricted *arbitrage* dispatch strategy in Figure 6.6 shows a completely different grid import pattern compared to the *No BESS* strategy in Figure 6.5 or the *arbitrage + peak shaving* and *peak shaving* strategies that are shown later. This divergent pattern explains the disappointing results with regard to the cost-reducing ability of the strategy of only 1.4%. To facilitate energy arbitrage, grid imports approach 10MW during hours 5 to 6. This is a result of the arbitrage strategy as a large amount of energy is purchased for a low price on the day-ahead market as depicted by figure 6.7. As grid costs are determined on a monthly basis, they are not included in the optimization.

As a result, the optimization prioritizes arbitrage without considering the effects of grid import power on grid costs. During most periods, the wind park is able to supply sufficient power to meet the full, or partial power demand of the vessel, resulting in no additional grid import costs. However, when a peak power demand coincides with a period with limited or no wind power production such as in Figure 6.8, the EMS will import power from the grid. As the purchase of large quantities of energy during a limited time period yields the best results for the *arbitrage strategy*, peaks in power demand will occur more often resulting in increased grid costs when compared to the *No BESS* or business as usual case.

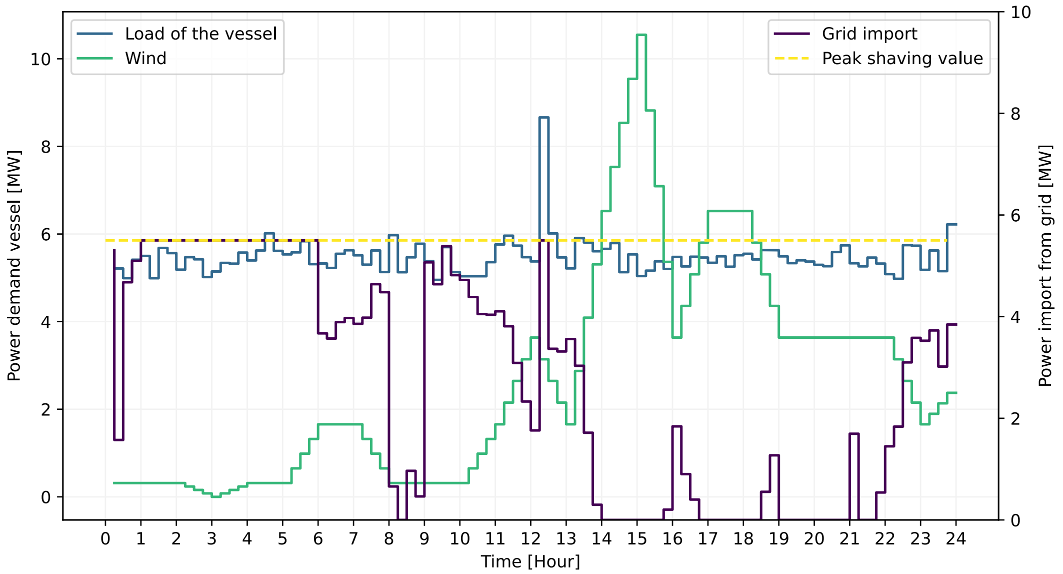

Figure 6.9: Strategy (3), Arbitrage + Peak Shaving
Illustrative example, wind scenario (2/10)

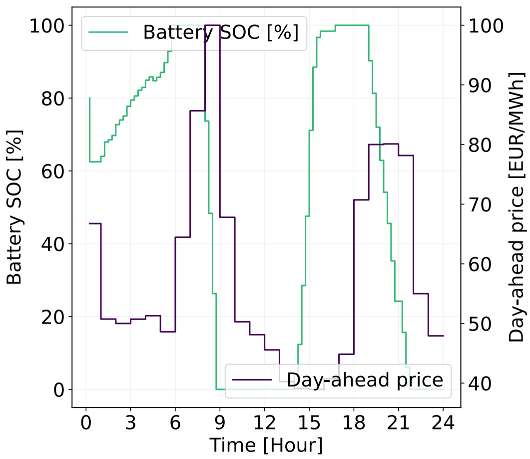

Figure 6.10: Charge and discharge rates strategy (3)

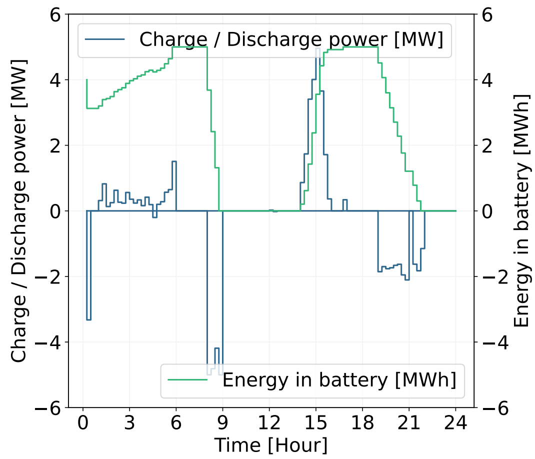

Figure 6.11: Day-ahead price and battery scheduling strategy (3)

The combination of peak shaving and arbitrage is shown in Figure 6.9 in which the grid import is limited to 5.5MW. It should be noted that limited grid import power does not limit importing power from the wind park as wind power can be used at no extra grid costs. In addition to limiting grid import costs, the *arbitrage + peak shaving* strategy restricts the ability of the EMS to fully exploit the effects of the arbitrage strategy. This is demonstrated by the battery SOC in Figures 6.10 and 6.11 which shows are slower and less optimal increase with respect to the day-ahead prices when compared to the SOC in Figures 6.7 and 6.8. In summary, the *arbitrage + peak shaving* strategy limits the induced peak in power demand by the *arbitrage* strategy as well as peaks in power demand from the vessel as shown in Figure 6.8. As a result, this strategy has the highest cost-reducing performance of the tested strategies.

6.3.1. Analysis of Wait-and-see solution

Similar to the expected value solution, the EMS is evaluated for various strategies. This time the strategies can be tested under a range of wind scenarios which provides more insight into the conditions that drive certain decisions and costs. Moreover, it will result in a more robust and realistic solution as the most negative scenario i.e. the scenario with the highest grid import determines the grid costs. A situation as in section 6.3 in which grid costs are absent is prevented.

The number of wind scenarios in the WS solution results in the same number of solutions with regard to daily expected electricity costs. The values that were previously described in Table 6.3 are now visualized in Figure 6.12. Overall, a similar distribution in daily electricity costs is observed. The *arbitrage* and *arbitrage + peak shaving* strategies both result in the lowest daily expected costs of electricity. The data presented in Figure 6.12 appears to indicate that strategies (2) and (3) yield the most favorable outcomes in terms of cost reduction. However, it is crucial to also take into account the grid-related costs associated with these strategies, as these costs can significantly impact overall cost efficiency.

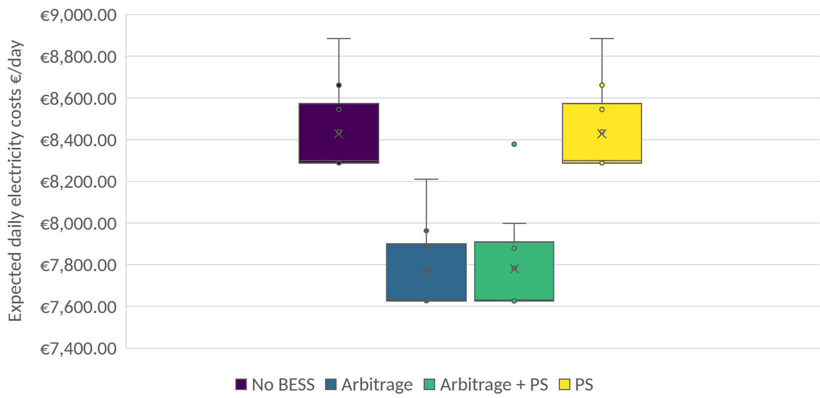

Figure 6.12: Outcomes of the wait-and-see solution

During a 100-day stay in port, the vessel operator is subject to costs of electricity as well as yearly- and monthly grid-related costs. Figure 6.13 presents the absolute cost distribution during this period while Figure 6.14 presents the relative distribution of costs. Contrary to what was presented in Figure 6.12, Figure 6.13 reveals that the arbitrage strategy is less effective over a 100-day period. Furthermore, it is apparent that although the total costs may have decreased, the yearly peak grid-related cost exhibits a marked increase when the arbitrage strategy is implemented, as demonstrated in Figure 6.13. The increased grid costs is a direct outcome of the utilization of an unrestricted arbitrage strategy. As this approach seeks to optimize cost reduction through arbitrage, it subsequently elicits a substantial demand for grid importation, thus leading to an increase in grid costs.

An effective method to mitigate the negative impacts of high arbitrage power demand is through the implementation of grid import constraints. This can be achieved by limiting the maximum power that the vessel can import from the grid. The arbitrage + peak shaving strategy clearly demonstrates this effect as the yearly grid-related costs are reduced by approximately 50% in comparison to the arbitrage strategy.

In the context of arbitrage operations, the EMS repeatedly charges and discharges the BESS at a high frequency, with approximately two complete cycles per day. This frequent usage can result in significant stress on the BESS, potentially impacting its overall performance and longevity in the long term.

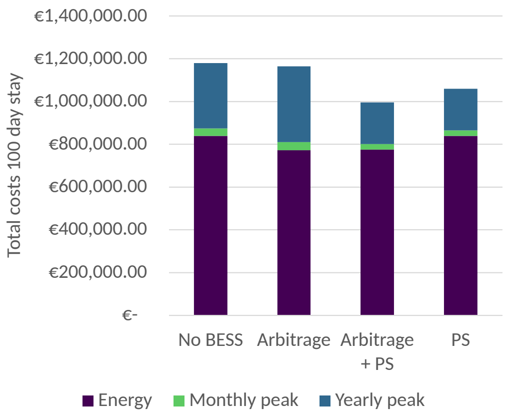

Figure 6.13: Cost distribution for a 100 day stay in €

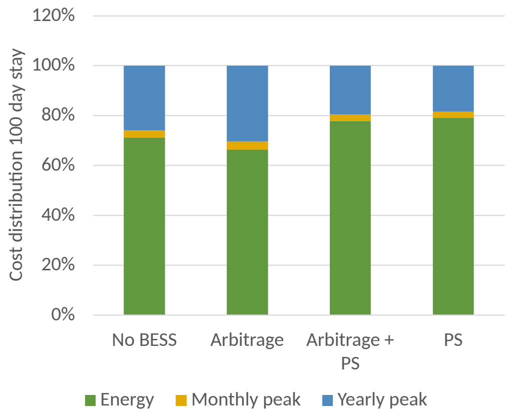

Figure 6.14: Cost distribution for a 100 day stay in %

A peak shaving-only strategy was implemented as a final approach, in which the potential cost reductions of peak shaving were considered separately from the negative impacts of charge- and discharge cycles in arbitrage operations. The results of this strategy, as shown in Figure 6.15, indicate a cost reduction of 11%. While the cost reduction is lower than that achieved through the combination of arbitrage and peak shaving, this strategy has the added benefit of limiting the stress on the BESS. It is worth noting that a lifetime assessment of the BESS to further investigate the effects of arbitrage on it, could be an interesting next research step. However, it falls outside the scope of this current study. In addition, decision-makers should be aware of the risk related to limiting the grid import constraints. As an increased power demand during a longer duration with no wind power production may result in a blackout. In light of the given circumstances, utilizing soft constraints may offer a more optimal solution.

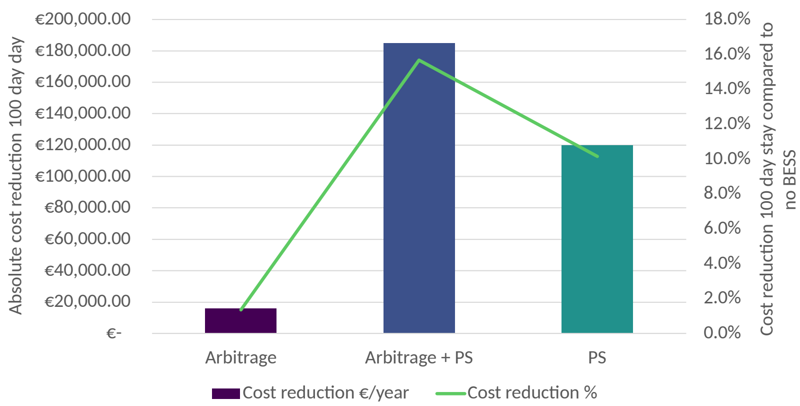

Figure 6.15: Cost reductions four strategies for base case scenario

As illustrated in Figure 6.15, the combination of *arbitrage + PS* strategies has been found to provide the greatest cost reduction for vessel operators, yielding a 16% reduction in costs. However, this strategy also leads to increased stress on the BESS due to the frequent discharge and charge cycles. In contrast, the *arbitrage* strategy, while also causing stress on the BESS, also results in larger grid-related costs, resulting in a limited cost reduction of 2%. The peak shaving strategy, while not achieving the highest cost reduction, is a viable alternative as it reduces costs by 11%, or €120,000 per year, without inducing additional stress on the BESS.

In addition to the cost reductions already achieved in the base case scenarios, in order to fully assess the cost-reduction capabilities of the EMS, it is necessary to conduct sensitivity analyses under a variety of conditions. These analyses will be performed in Section 6.4 and will serve to evaluate the performance of the EMS under varying specifications.

6.4. Sensitivity analysis

The EMS will operate in a wide range of price conditions which makes it difficult to accurately determine its performance as it is dependent on those conditions. In addition, the system's performance is subject to its architecture and specifications. As a combination of all factors will finally determine the performance a sensitivity analysis is made. By consistently altering only one variable, the decision-maker is able to gain insights on how each variable influences the performance of the complete system.

6.4.1. Grid Tariffs

One of the two cost-reducing methods of the EMS is limiting electricity import from the grid by peak shaving. This section shows how varying grid tariffs affect the performance of the EMS. Throughout the recent three years, grid tariffs have increased by 50% as presented in Appendix H. The sensitivity analysis in Figures 6.18 and 6.19 shows the performance of the EMS under varying grid tariffs.

Grid tariffs make up 20-33% of costs as is shown in Figures 6.16 and 6.17. As a result, increased grid tariffs will negatively impact grid costs. While the overall costs for a 100-day stay rose from €1,059,986 to €1,180,147 from 2021 to 2023, Figure 6.18 shows an increased absolute cost for the vessel operator as grid tariffs increased by 50% from 2022 to 2023. Moreover, the relative cost reduction increased with increased grid tariffs as displayed in Figure 6.19. Thus by adopting either the *arbitrage + ps* or *peak shaving* strategy, vessel operators are able to hedge against an increase in grid tariffs.

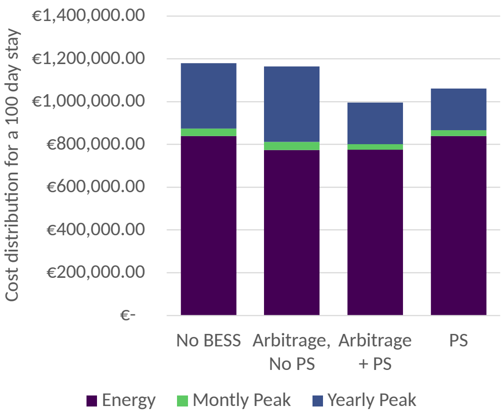

Figure 6.16: Cost distribution for a 100 day stay in €

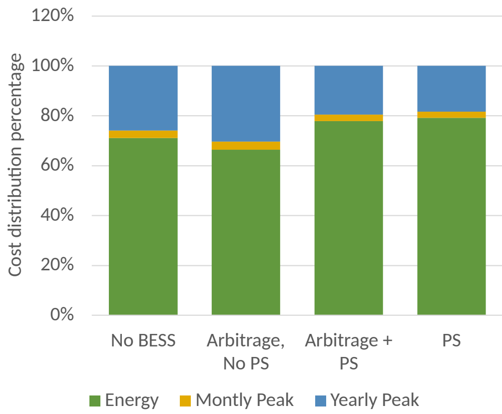

Figure 6.17: Cost distribution for a 100 day stay in %

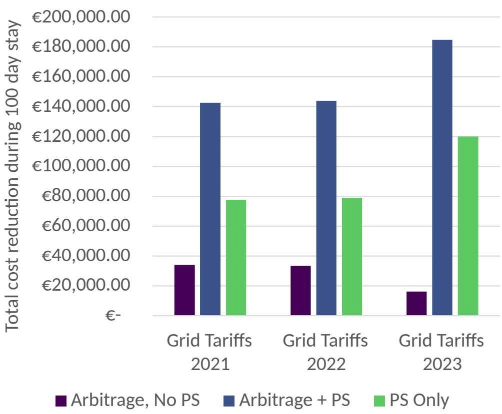

Figure 6.18: Grid tariff sensitivity on cost reduction

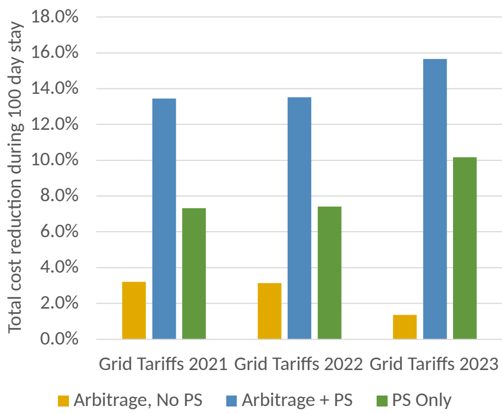

Figure 6.19: Grid tariff sensitivity on cost reduction percentage

6.4.2. Price volatility

Energy costs account for approximately 75% of the total shore power costs for a vessel operator. Electricity prices are reduced by energy arbitrage, which relies on volatile prices. This section assesses the influence of volatility on the performance of the EMS under higher and lower volatility rates with respect to the base case.

Figure 6.20 presents the three price scenarios. In the more volatile scenario, the prices are processed to deviate 20% more from the mean while the opposite is applied to the 20% less volatile scenario.

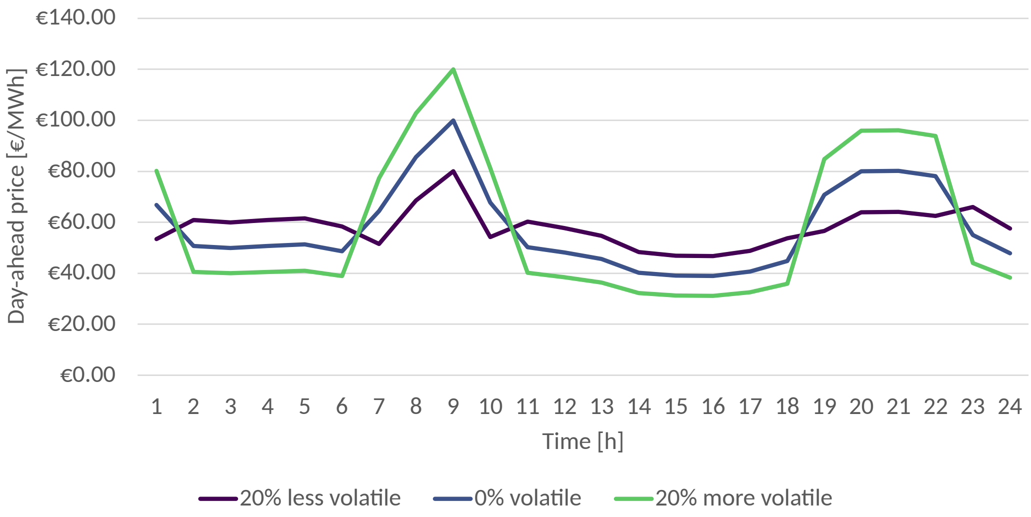

Figure 6.20: Volatility of day-ahead prices

The results of the three price scenarios are presented in Figures 6.21 and 6.22. As the volatility of the day-ahead prices changes, the grid-related costs remain at the same value as these values are not influenced by the day-ahead price. For the arbitrage-based EMS strategies, an increase in effectiveness is observed as volatility increases. Increased volatility from -20% to +20% caused the cost-reducing for the *arbitrage* and *arbitrage + peak shaving* strategies to increase by 4.8% and 4.7% respectively. Whereas this results in a hedging strategy for the vessel operator, it poses a risk, especially for the *arbitrage* strategy since a volatility decrease of 20% resulted in a net cost increase.

As volatility is decreased, the cost reduction for the *arbitrage* strategy resulted in a cost increase of 0.8% as costs reduced by arbitrage were no longer sufficient to balance costs as a result of induced grid import. The *arbitrage + peak shaving* strategy, resulted in a 13.5% cost reduction despite the reduction in volatility. A cost reduction which, despite the sensitivity to reductions in volatility, still shows the best performance. Exceeding the *peak shaving* strategy that achieved a 10.2% cost reduction despite being unaffected by varying volatility. Adapting the *arbitrage + peak shaving* strategy will result in an increased cost reduction performance in an environment with increased day-ahead price volatility. Despite a decreased performance in less volatile electricity markets, this strategy still performs best.

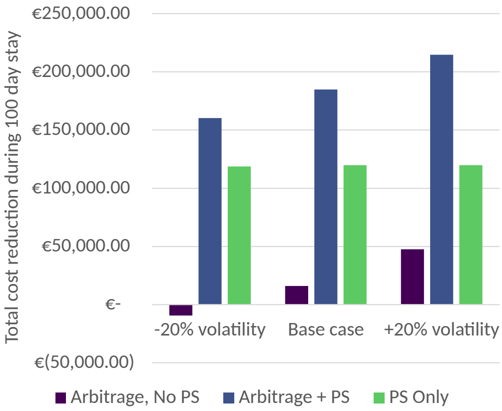

Figure 6.21: Volatility sensitivity

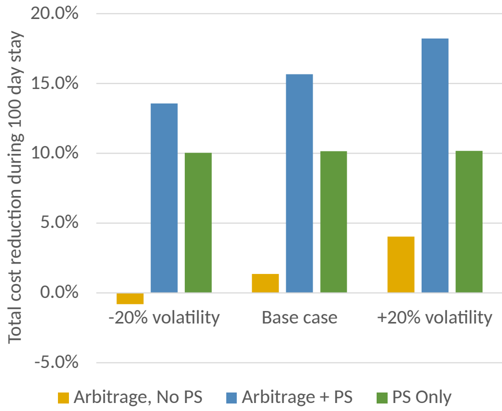

Figure 6.22: Volatility sensitivity percentage

6.4.3. Day-ahead prices

The analysis in this section covers the EMS performance under increased day-ahead prices without changes to volatility. The three price scenarios are generated by increasing and reducing the base case prices by 20%. The three scenarios are shown in Figure 6.23.

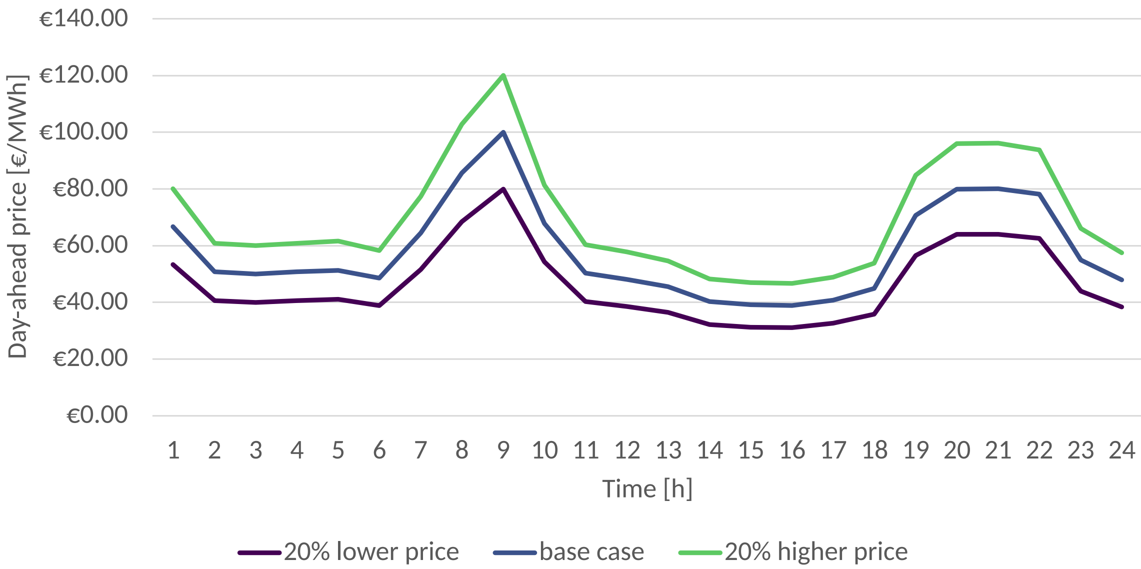

Figure 6.23: Variable mean in day-ahead prices

As the price conditions are varied, grid-related costs remain the same as can be deduced by the constant cost reduction for the peak shaving strategy in Figure 6.24. An increase in day-ahead prices results in a larger absolute cost reduction achieved through the *arbitrage* and *arbitrage + peak shaving* strategy by the EMS. However, since energy costs form a relatively larger part of the total costs, the percentual cost reduction decreases as the mean value of day-ahead prices decreases as shown in figure 6.25. As the day-ahead prices are lowered and increased by 20% with respect to the base case, the *arbitrage + peak shaving* cost reduction decreases from 16.8% to 14.8% and the *peak shaving* reduces from 11.7% to 9.0%. The decrease in performance, albeit small, is not insignificant. An increase in day-ahead prices under similar volatility conditions will result in a relative decrease in the performance of the EMS. Nonetheless, the *arbitrage + peak shaving* strategy performs the best in all conditions, compared to the other strategies.

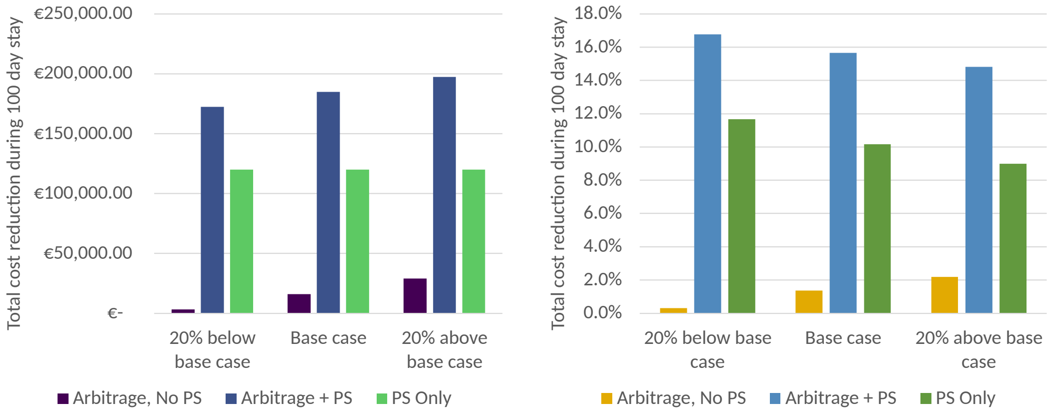

Figure 6.24: Sensitivity day-ahead prices

Figure 6.25: Sensitivity day-ahead prices

6.4.4. BESS energy capacity

The energy capacity of the BESS is a significant factor in the costs of the EMS, determining the influence of energy capacity on the performance should therefore be evident. Different battery sizes affect the cost reduction for the vessel operator in different ways. Figures 6.26 and 6.27 show the achieved cost reduction by three battery capacities.

A clear decrease in the costs of electricity can be observed for the *arbitrage + peak shaving* and *peak shaving* as the energy capacity of the system increases. Although a diminishing return can be observed as the BESS capacity increases, 4.5% from 2 to 5 MWh versus 7.3% from 5 to 8 MWh, the cost reduction for the *arbitrage + peak shaving* and *peak shaving* strategy reach the maximum cost reductions of 20.2% and 12.1% respectively. While the previous strategies show a linear increase in cost reductions, the *arbitrage* scenario shows a decreased reduction of 0.9% from 2 to 5MWh followed by an increase from 1.4% to 4.4% as the energy capacity is increased to 8MWh. Again, this is the result of an induced grid import power at the 5 and 8 MWh capacities. While the 8MWh BESS could make up for this increased grid cost by utilizing the increased capacity energy arbitrage, the 5MWh capacity did not allow for this. Contrary to this, the 2MWh battery was limited by the smaller power capacity, as the C-rate of 1 resulted in a maximum power capacity of 2MW. This limited the ability of the 2MWh BESS to induce large grid import power, which prevented additional grid costs.

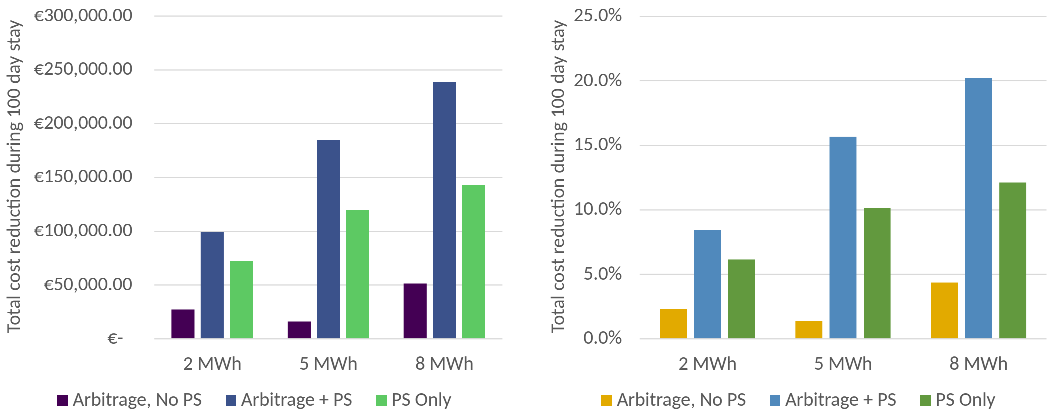

Figure 6.26: BESS energy capacity sensitivity

Figure 6.27: BESS energy capacity sensitivity percentage

6.4.5. C-rate

The rate at which the BESS can charge and discharge is the second most important battery parameter. A sensitivity analysis was made, in order to determine the influence of the C-rate on the ability of the battery to achieve a cost reduction for the vessel operator.

The effects of the cost-reducing performance of the EMS at various C-rates are shown in Figure 6.28. In general, an increase in the total cost reduction can be observed as the C-rate increases. This increased benefit persists for the *arbitrage + PS* and *PS only* strategies, as C-rate is increased from 0.2 to 1, the cost reductions increase from 7.1% and 3.1% to 15.7% and 10.2% respectively. Contrary to this, after an initial increase a decrease in cost reduction is observed for the arbitrage strategy. The reason why this is only prevalent in the arbitrage is due to the same balance between induced grid imports and arbitrage benefits described in the previous subsection. As a result of increased C-rates, first the added benefit of arbitrage outweights the increased costs due to increased grid import. After the peak cost reductions of 5.2% at a C value of 0.4, the increase in induced grid imports starts to outweight the added arbitrage benefits, leading to an overall relative decrease in cost reductions achieved by the *arbitrage* strategy.

As the C-rate approaches 1, a stabilization of the expected cost is observed for the *arbitrage + PS* and *PS only* strategies. This effect is a result of the pricing method for the vessel operator. Because tariffs are determined on an hourly basis, the battery can achieve its maximum cost-reducing effect by completely discharging when the day-ahead price is at its highest point. As the battery is discharging its energy to the vessel, it eliminated the need to purchase power at this high price point. To reach the maximum effect, the battery must partially supply the vessel with energy during this complete hour since any excess power will otherwise be purchased from the grid. As a result, no additional cost reductions can be achieved with arbitrage by increasing the C-rate.

An increase in C value above 1 can have beneficial effects during peak shaving. As peaks in power demand often occur during periods lasting for short periods of minutes. In this case, a high C-rate BESS can provide peak power without being oversized in terms of energy capacity. Since the conducted tests included energy arbitrage which requires a significant energy capacity, lower energy capacity batteries with high C-rates were not considered in this research.

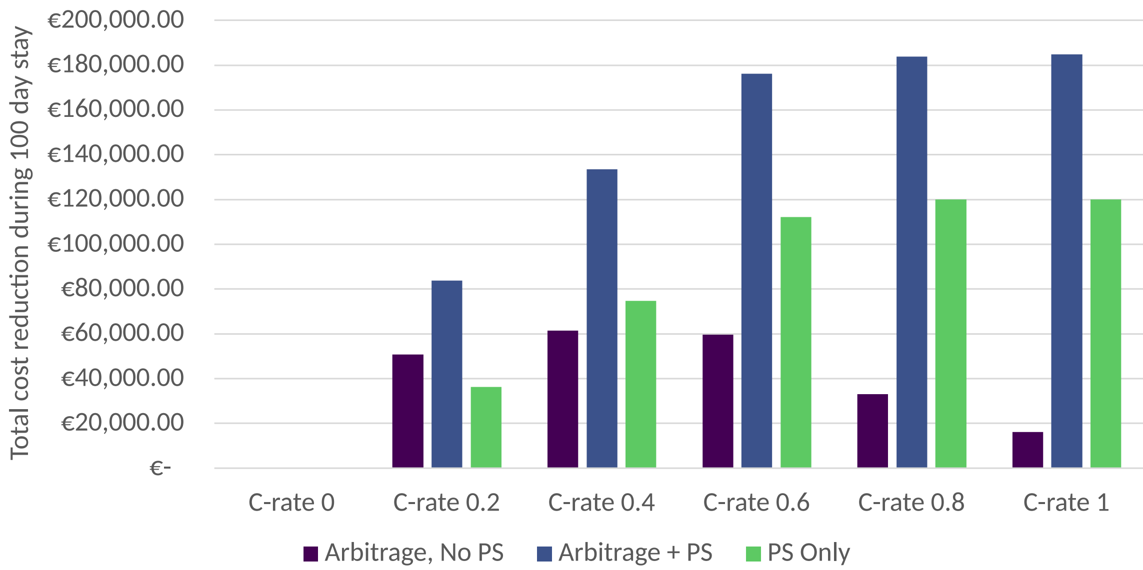

Figure 6.28: Sensitivity C-rate BESS

6.5. Results summary

To conclude this chapter, a summary of the relative cost reduction is provided in Table 6.4. In a comparison of two stochastic optimization approaches, the wait-and-see solution was found to produce the most realistic outcomes. The better performance of the WS solution can be attributed to its consideration of multiple wind scenarios. As the cost-reducing ability of the system is heavily dependent on extreme scenarios, the incorporation of multiple scenarios in the WS approach exposed the EMS to these scenarios, which resulted in a more accurate solution. As the WS approach provided the most accurate results, the cost-reducing performance of three strategies within the WS was tested and analyzed through a sensitivity analysis. The outcome of these tests gave varying results. Considering all factors, the *peak shaving* strategy is the overall best-performing strategy.

Table 6.4: Summary of results

	No BESS 100-days	***Arbitrage Cost reduction***	***Arbitrage + Peak shaving Cost reduction***	***Peak shaving Cost reduction***
Expected value Solution	€828,800	€66,100 8.0%	€66,100 8.0%	€0 0.0%
Wait-and-See Solution	€1,180,147	€16,065 1.4%	€184,851 15.7%	€119,915 10.2%
2021 grid costs		3.2%	13.5%	7.3%
2022 grid costs		3.1%	13.5%	7.4%
2023 grid costs		1.4%	15.7%	10.2%
-20% volatile		-0.8%	13.5%	10.0%
+20% volatile		4.0%	18.2%	10.2%
+20% day-ahead		2.2%	14.8%	9.0%
-20% day-ahead		0.3%	16.8%	11.7%
2 MWh BESS		2.3%	8.4%	6.1%
5 MWh BESS		1.4%	15.7%	10.2%
8 MWh BESS		4.4%	20.2%	12.1%
C = 0.2		4.3%	7.1%	3.1%
C = 0.4		5.2%	11.3%	6.3%
C = 0.6		5.0%	14.9%	9.5%
C = 0.8		2.8%	15.6%	10.2%
C = 1.0		1.4%	15.7%	10.2%

The *arbitrage* strategy performed the worst of the three strategies, as it induced additional grid imports through performing arbitrage. This resulted in increased grid costs, which in most cases reversed the cost reduction brought about by performing energy arbitrage. For the base case scenario the arbitrage strategy was able to decrease the costs by 1.4% or €16,065 during a 100-day stay. The most promising results from *Arbitrage* strategy are found in the increased day-ahead price scenario, as it is the only strategy that shows an improvement cost reduction under this condition. Nevertheless, this cost reduction is with 2.2% still smaller than the other two strategies.

The *arbitrage + peak shaving* strategy performed the best in both absolute and relative cost reduction. While the ability to perform arbitrage was slightly reduced by constraining the import power, it prevented the unwanted increase in grid costs thus it profited from both reducing energy and grid import costs. For the base case, the *arbitrage + peak shaving* strategy reduced costs by 15.7% or €184,851. Moreover, through sensitivity analyses the *arbitrage* and *arbitrage + peak shaving* strategy performed 4.5% better under conditions with a 20% increase in day-ahead price volatility, while the *peak shaving* strategy showed no improvement. As price volatility was decreased by 20%, the *arbitrage* strategy showed an increase in costs, resulting in a negative benefit to the vessel operator. By performing arbitrage the BESS underwent 2 charge-, and discharge cycles per day, which has a large impact on the lifetime of the BESS. A real life implementation of such a system is therefore doubtful.

To achieve a cost reduction without the negative consequence of frequent charge cycles the *peak shaving* strategy stands out. The *peak shaving* strategy had the second best cost reducing performance during all tests. In the base case this strategy reduced the overall costs by 10.2% or €119,915 during a 100-day stay. The *Peak shaving* strategy is the least effected by BESS energy capacity while still providing a significant cost reduction. It showed an increase of 1.9% and a decrease of 4.1% as the energy capacity was respectively increased and decreased by 3 MWh. As the sensitivity to battery capacity is low for this strategy, and energy capacity is the main driver of costs for a BESS, shows this to be a promising strategy. Considering the negative effects on the lifetime of the battery in the *arbitrage* strategy, the *peak shaving* strategy is the overall best-performing strategy.

7
Conclusion & Recommendations

This chapter will provide the answers to the research questions in section 7.1. The subsequent sections **??** will give a reflection on the research and the limitations of the research are also addressed. Finally, suggestions for future research are given in section 7.3.

7.1. Answers to the research questions

This section starts with the sub-questions followed by the main question, as the sub-questions have been constructed in order to answer the main question.

7.1.1. Sub-questions

1. What **energy management strategies can be performed considering infrastructural constraints** of the shore power connection, the grid, and the BESS?

   The shore power connection of the case study uses unidirectional frequency converters, which limits the ability of a vessel-to-grid application. However, as the BESS and load are both located behind the meter, there is an opportunity for behind-the-meter application leading to cost reduction for the vessel operator. The cost reductions that can be achieved by this application are mainly peak-shaving and energy arbitrage. In a day-ahead scheduling approach with ***energy arbitrage***, a cost reduction is achieved by shifting the load and charging the BESS at the lowest day-ahead price point. During periods of high electricity prices, the vessel is able to reduce the imported electricity consumption by relying on the BESS, thereby reducing the overall costs of electricity.

   In addition, the vessel operator is exempted from grid costs when the vessel is supplied by local wind power. The EMS should therefore base the dispatch of the battery on the expected wind power production. The stochastic nature of wind speeds and the subsequent wind power production does not guarantee a perfect forecast, using ***uncertainty modeling methods*** for approaching the optimal scheduling under uncertainty is therefore important.

   Lastly, the vessel operator has to pay a monthly, and yearly fee for the highest power demand during that month or year for the grid connection. As this fee can be a significant portion of the total shore power costs of the vessel operator, the energy management strategy should include the ability for ***peak shaving***.

2. **Which type of support services and participation** in the short-term electricity market **can generate economic benefit to the ship operator** during cold ironing using an onboard BESS?

   It can be concluded that vessel operators can utilize the onboard BESS to generate economic benefits by performing two strategies. The first strategy is peak shaving. The occasional peak in the power demand of the vessel puts added stress on the electricity infrastructure within the port. The DSO charges peak power costs for both the maximum power demand during a month as well as max power demand for the year. The combination of these costs makes up roughly 30% of the total operational costs related to shore power for the vessel operator during the season. By employing peak shaving, the vessel operator supplies peaks in power with the onboard BESS, thereby reducing the strain on the grid and moreover lowering the power-related costs from the DSO. In addition to the economic benefit for the vessel operator, peak shaving alleviates power demand on the local grid which may delay or prevent additional investments in grid reinforcements.

The second form of participation is energy arbitrage. This strategy reduces costs for the vessel operator by purchasing electricity at lower day-ahead price points, which is provided to the load of the vessel during a period during which energy prices peak. As a result, the vessel operator reduces the total costs by 1.4%. However, energy arbitrage not in combination with peak shaving leads to an increase in power demand. This reverses the supporting benefit to the grid and vessel operator. The combined strategy of arbitrage and peak shaving prevents this, and in addition results in the largest cost reduction for the vessel operator of 15.7% without inducing additional power demand on the grid.

3. What factors influence the **optimal energy and power specifications for an onboard BESS for Vessel-to-Grid participation**?

   There are two specifications, C-rate and Energy capacity that determine the specifications of the BESS. The optimal choice of specifications depends on the conditions under which the EMS is operating which ultimately determines the choice of EMS strategy that the vessel operator will employ.

   Energy capacity is the first and most crucial factor to be discussed since it is the primary driver of costs for a BESS. The performed sensitivity analysis on energy capacity showed improved performance as the energy capacity was increased. A maximum cost reduction of 20.2% was achieved by the *arbitrage + peak shaving* strategy a 4.5% increase from the 5MWh BESS. For the *peak shaving* strategy, a maximum cost reduction 12.1% was observed for the 8 MWh BESS which was only a marginal improvement of 1.9% compared to the 5MWh BESS. As energy capacity is the main factor in determining arbitrage performance, ***increased volatility conditions*** will favor large energy capacities. The other factor determining energy capacity is the ***power demand of the vessel*** during its connection to shore power. As peaks in power demand last for longer periods or occur more often, a larger energy capacity is required. The added benefit is that the power capacity or C-rate increases linearly with BESS energy capacity.

   The main factors influencing the C-rate of the BESS are the grid tariffs. ***An increase in grid tariffs*** results in a higher potential benefit for peak shaving. From the sensitivity analysis on C-rate, it can be concluded that the *arbitrage + peak shaving* and the *peak shaving* strategies show improved performance as C-rate is increased. While a higher C-rate results in the largest cost reduction, the increase from a C-rate of 0.4 to 0.6 results in the highest relative increase as cost reduction for the *peak shaving* strategy increase from 6.3% to 9.5%. As the C-rate approaches 1, the cost reduction ability levels off at 15.7% for the *arbitrage + peak shaving* strategy and 10.2% for the *peak shaving* strategy. At C-rates higher than 1 no additional benefit can be observed due to the fact that day-ahead prices are determined on an hourly basis. Therefore discharging the battery at a faster than one hour rate does not result in an increased cost reduction.

4. What is a suitable scenario generation method **for generating wind data scenarios from historical data?**

   Of a wide variety of options, DTW k-means clustering was considered to be a suitable scenario generation method. Firstly, k-means clustering is generally easily implemented and guarantees convergence. Additionally, the clustering method scales to large data sets, and finally, the intertemporal relationship between data points is preserved. Of the three tested methods, ***the DTW k-means expressed the highest resemblance*** to the original data set.

7.1.2. Main Question

This study concludes by emphasizing the impact of adopting a cost-effective energy management strategy for operators of BESS-equipped vessels. The potential for cost reduction, as an increased number of hybrid vessels will enter the fleet, is significant. A conservative estimate suggests a reduction of up to 10% in operational costs with minimal additional expenditures for necessary equipment. In addition to the vessel operator, the EMS benefits the DSO as it mitigates power demand on the grid. Consequently, this can be answered in response to the main research question:

How to develop a cost-effective energy management strategy for a semi-submersible crane vessel (SSCV) to increase the economic benefits for the ship operator which uses cold-ironing service via an on-board BESS?

It can be concluded that the *peak shaving + arbitrage* strategy resulted in the best cost reduction results considering all factors. The *peak shaving* strategy reduced shore power costs for the vessel operator by 15.7% or €184,851 over a 100-day period. This energy management strategy was derived from the wait-and-see solution which was demonstrated to be superior to the expected value solution as it derived the solution from a range of wind power production scenarios, it resulted in a more realistic representation of the grid-related costs. The wind power production scenarios were reduced and generated from historical wind data through a DBA k-means clustering method. The data was reduced from 365 to 10 scenarios with a respective probability of occurrence.

While the *Arbitrage + Peak shaving* strategy demonstrated better a cost-reducing performance across all tested scenarios and exhibited improved performance under more volatile day ahead market conditions, the implementation of arbitrage resulted in significant stress on the BESS as it underwent two daily charge- and discharge cycles. As a consequence, this may lead to a rapid reduction in the lifetime of the system. The *peak shaving* strategy, which reduced costs by 10.2% or €119,915 during the 100-day stay, shows limited cycling and should be considered when a reduced number of charge and discharge cycles is preferred.

7.2. Reflection

The results of this study can be interpreted from multiple perspectives. First and foremost, this work has presented a novel method for utilizing onboard BESS for operators of hybrid vessels during the connection to shore power. By employing one of the presented methods, hybrid vessel operators are able to significantly reduce the costs of electricity and grid-related costs by up to 15.7% on a yearly basis.

The strategies presented here can be used by ship owners to identify additional business cases for the onboard BESS. Moreover, this work provides an assessment of various scenarios and sensitivities providing tools for determining the BESS specifications under various conditions. Additionally, this research can function as a road map for vessel operators that are currently unable to finance onboard BESS due to an insufficient return on investment. As result, the additional cost reductions presented here may increase the efficiency of a part of the vessel fleet by lowering the threshold for investments in onboard BESS.

Furthermore, the use of grid-integrated vessels through shore power can help port authorities with a solution for grid-related problems. Grid congestion and long lead times can hinder the deployment of renewable infrastructure. Added demand for shore power-connected vessels aggravates these problems if not handled in the correct way. The peak-shaving solution presented in this work can function as a proof of concept for a new concept of alleviating these problems.

Based on this study, the Port of Rotterdam and research institute TNO have shown interest in this topic and are currently exploring possibilities to use a containerized battery on board a crane vessel for peak shaving and energy arbitrage. After the completion of this thesis, research will be conducted with various suppliers as well as the technical crew of the vessel to study the economic viability as well as the necessary requirements and challenges regarding the implementation of the EMS presented in this work.

7.3. Recommendations for future research

First, improvements with regard to the optimization could be made by increasing the time horizon. The current day-ahead scheduling approach that was conducted, although it was exposed to multiple wind power production scenarios, did not provide any information on the workings of the system for multiple consecutive days. As longer run can provide more accurate information on the behavior of the system.

Further improvements in the optimization could be made by changing the modeling method to recourse modeling. The problem with the optimization right now is that there is no risk of recourse related to the peak shaving mode. In other words, the constraint put on the maximum import tariff cannot be violated. The introduction of risk management such as chance constraints or a form of recourse actions could contribute to a better modeling method. Moreover, recourse modeling would allow for simulating a monthly dispatching problem in which recourse costs could be appointed for crossing certain thresholds in the peak power demand. Doing this would weigh the benefits of utilizing the full power potential of the grid with its additional costs. In the current modeling method, this number can only be roughly approached.

Improvements in handling risk could be made with the introduction of chance constraints. Building on the previous statement, chance constraints would allow for violating certain important parameters such as the grid import power limits. When change constraints would be instated and we work with an uncertain load, other researchers can play with the allowable risk in working with unknown power demand.

The most optimal solution presented in this work employed the arbitrage strategy. While the cost-reducing effects of this EMS strategy were outstanding, it did stress the BESS with two daily charge and discharge cycles. Based on the information from studies conducted on onboard BESS, frequent cycling was not recommended. In order to study the effects of arbitrage on battery degradation would improve the results. After a degradation analysis, a substantiated consideration could be made with regard to the use of the arbitrage strategy.

As the EMS will ultimately be used in an uncertain environment, interesting future research could consider a model in which all conditions are uncertain and explore the behavior of the model in a two-stage stochastic programming model which makes use of weather forecasts.

Lastly, while the effects of a single grid-connected vessel on congestion are limited, research on the aggregated benefits of multiple BESS-equipped vessels in a Harbor-Area Smart Grid could be conducted to show the benefits of combining the flexibility of multiple vessels.

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A
Appendix

Windpark name	**Capacity [MW]**
Windpark Slufterdam	50.4
Windpark Zuidwal	24
Windpark Maasvlakte 2	116.7
Windpark Dintelhaven	15
Windpark Suurhoffbrug	12
Windpark Landtong Rozenburg	36
Windpark Nieuwe Waterweg	18
Windpark Hartel II	24
Windpark Hartelbrug II	40
Total capacity [MW]	336.1

Table A.1: Total wind generation capacity in the Port of Rotterdam. [67]

B Appendix

B.1. Electricity Markets

As stated earlier the level of success will be quantified in terms of money. In this case study, this can either be through earnings from trading or cost reductions through active participation in electricity markets. This literature study will focus on the Dutch electricity market since the shore power case study is located in the port of Rotterdam. Electricity markets are continuously adapting to new producers, users, and use cases. In order to have a known base to work with, an overview of relevant electricity markets for revenue generation is given in this paragraph. The scope of this study will be limited to the current electricity market in terms of regulations, structure, and pricing.

The Dutch electricity market is divided into the wholesale market and the balancing market which can be seen in figure B.1. The main difference between these markets is the time frame in which they operate. For the wholesale market, all transactions take place prior to the final 'delivery' of electricity. The balancing market on the other hand, takes place in real-time. In the paper of [68] an oversight of the Dutch electricity market is given from 2015. Figure B.1 gives a visual representation of the wholesale market which is divided into three main sections based on the length of time until the delivery.

Futures market

Within the wholesale market, the *European Energy Derivatives Exchange (ENDEX)* futures market serves the market furthest away from the point of consumption. In this market contracts for energy delivery to the Dutch high voltage grid are traded for different durations. This can be weeks, months, or years in advance. Within these time frames, there are nine different contract types [68]. One of these is the "Dutch Power Base Load" future (DPBL) [68]. This contract ensures the delivery of 1 MWh for each hour throughout the contract delivery period which extends from midnight on the first day of the period to midnight of the last day of the contract period [69]. There are also more specific contracts i.e. the "Dutch Power Peak Load" (8–20) (DPPL8–20) which only applies to weekdays from 08:00 to 20:00.

The aforementioned contracts all expire 48 hours before the physical delivery. At the time of expiration, the contract is converted to a day-ahead contract and the supplier is now required to deliver. This process is done through market-clearing which is performed by EPEX [68]. Adjusting this position is however still possible through trading in the EPEX spot market [68].

Spot market

The spot market is divided into two markets, the day-ahead market (DAM) and the intraday market (IDM). On the DAM the electricity prices for the next day are determined on a per hour basis. The DAM opens at 00:00 CET from this point buyers and sellers can anonymously place orders for different volumes and prices. At 11:00 CET the TSO publishes the Available Transfer Capacity (ATC) [68]. The ATC is defined as "the transfer capacity remaining available between two interconnected areas for further commercial activity over and above already committed utilization of the transmission networks [70]." Then at 12:00, the market closes, and with the help of an algorithm called COSMOS which processes all bids taking into account all physical constraints. [68] The hourly prices are determined by maximizing social welfare after this, the results of the auction are published at 12:55 CET [68]. The prices of the DAM are limited by the EPEX to 3000 (Euro/MWh) and -500 (Euro/MWh). The monthly volume traded on the Dutch spot market equated to 2760 GWh in October 2021 [71].

Intraday market

Once the hourly electricity prices are determined and the day-ahead market closes, the intraday power market opens for market participants for further adjustments to their positions [68]. The IDM is always open and positions can be adjusted up to 5 minutes before final delivery once the prices from the DAM are determined [68]. The prices on the IDM are considerably higher compared to the DAM and are capped between -99,999.90 (Euro/MWh) and +99,999.90 (Euro/MWh) [68]. The volume traded on the IDM is generally much smaller than on the DAM with around 515 GWh compared to 2760 GWh on the DAM [71]. Although a future scenario in which battery-equipped vessels are participating in the intraday market is conceivable. This is not yet of interest to the current situation in the case study for Heerema. Besides this, it will probably also require the intervention of an aggregator to achieve the required volumes needed to participate in this market.

Balancing market

It is vital for electricity grids to always be balanced so that supply and demand are continuously in harmony. Since no model or market can precisely predict the actual demand and production a system should be in place in order to resolve imbalances in the grid [68]. This is performed in real-time in the balancing market. The balancing market is regulated by the Dutch TSO (TenneT) which requires all producers above 60 MW to make bids on spare capacity which it is willing to provide [68]. The balancing market is also where most ancillary services are being provided. These include frequency containment reserves (FCR) and frequency restoration reserves (FRR). The balancing market will not be of interest for this case study, since the balancing ancillary services are aimed at the high voltage transmission system instead of the distribution grid. An aggregator could however make this a possible future scenario.

Congestion management GOPACS

Congestion is a problem that can occur on the distribution grid when the capacity of the transformers and cables reaches its limit and become unable to handle the power. Congestion is likely to occur during peak loads or generation. The mitigation of peaks can therefore contribute to the reduction of congestion. The flexibility of batteries can be used to flatten such power peaks on the distribution grids. GOPACS is a market platform introduced with the aim of reducing congestion by allowing parties within the distribution grid to monetize their flexibility [72]. In this market, parties are able to utilize their flexibility to generate revenue while simultaneously reducing congestion problems. The flexibility of battery-equipped vessels connected to shore power are hypothetically able to provide this service in the whole port area. A white paper of [73] states that for BESS operators the GOPACS market forms an important source of additional revenue.

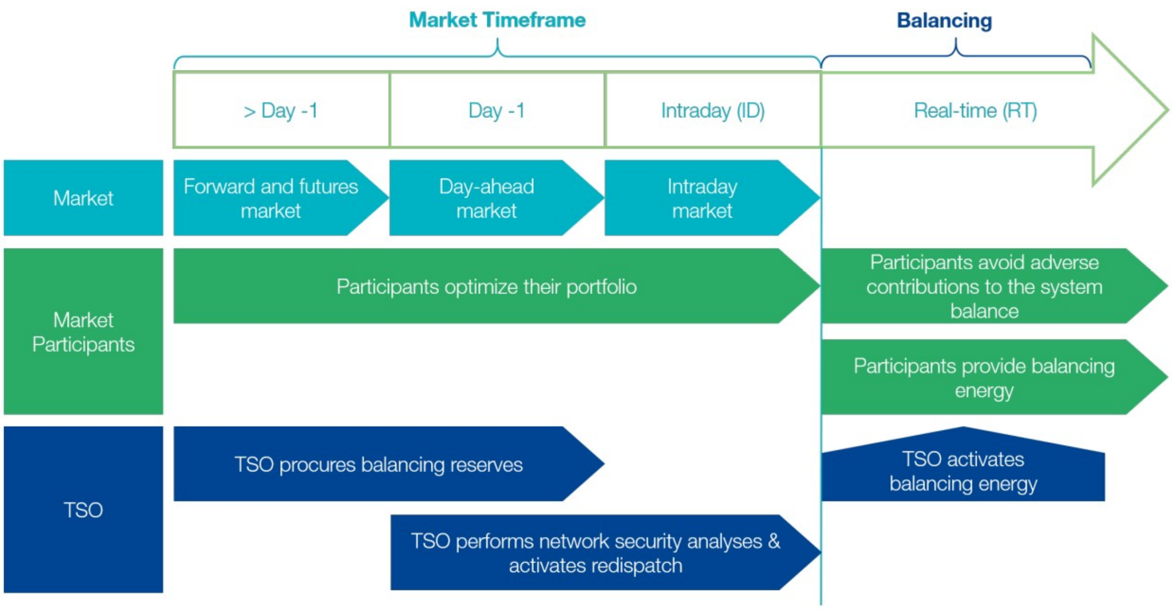

Figure B.1: Tennet market overview [19]

C
Appendix

C.1. Energy management systems

A prerequisite for a viable business case for BESS utilization during shore power connection at berth is the ability to reduce the costs of electricity or in the best case generate revenue. As mentioned in Chapter 1 many studies have been performed on energy management systems to reduce electricity costs. Building on the previous section, this chapter will elaborate on these studies, explain their differences, and explore which approach is most relevant for the case study described in chapter 5.

C.1.1. BTM - Behind-the-meter

The field of revenue-generating-, or cost-reducing energy management strategies (EMS) can be divided into two main categories. Behind-the-meter (BTM) and In-front-of-the-meter (FTM) systems. The main reason for differentiating between the two is for regulatory use [74]. A practical distinction between BTM and FTM is that the first can be considered a being beneficial for the owner while the latter is more advantageous for the grid [74]. BTM systems are used in systems such as solar PV-powered households to increase self-consumption of solar energy or to reduce the costs of the grid connection thus providing an economic benefit to the stakeholder [74]. Industrial use cases can also be found at solar and wind parks where BTW storage applications can prevent curtailment. Since this will mainly focus on consumer benefit, BTM will be regarded as the main category of interest. However, since BTM and FTM are mostly different on a regulatory basis, some generally non-consumer beneficial aspects of FTM will also be regarded such as maximal utilization of RES. Table **??** provides different technically feasible strategies for BTM battery utilization. Some of these different strategies will be explored further in this section. Other strategies such as power outages and ramp control are outside the scope.

Table C.1: "Technically feasible applications of large-scale Li-ion BESS connected to any level of the electric network or to isolated microgrids" As part of a complete table from: [75]

BTM	Commercial & Industrial	Increase PV Self-Consumption Tariff Optimization Backup Power UPS	Time Arbitrage Ramp Control Peak Power Reduction Power Outages Power Quality
	Aggregation	Virtual Power Plant	Grid Services Wholesale Markets Demand Response

- **Commercial Industrial**
- Time arbitrage/ Time of use (TOU)
- Peak Power Reduction
- Power quality

- **Aggregation**
- Grid services
- Wholesale markets (DAM & IDM)
- Demand response

Time arbitrage / Time of use / Renewables

Arbitrage is defined as buying an asset or product for a certain price on a market and subsequently selling it in another market for a higher price [76]. This can be done on either a stock exchange, currency exchange, or the electricity market. An important boundary condition is the price differential. Any form of arbitrage in the electricity market needs a time lag between buying and selling. Nevertheless, we make a distinction between time arbitrage and price arbitrage. Within time arbitrage the time of storage is most important, think of the storage of renewable energy to prevent curtailment. One can also think of preventing grid congestion, but this will be discussed in more detail later. Although this form of arbitrage is promising, the implementation of a stand-alone BESS is not yet proven to be economically feasible [75]. However, this does not mean that these types of systems are not being built. Economic benefit can be achieved if, for example, grid reinforcement can be avoided by investing in a BESS.

Price arbitrage

Within price arbitrage, the price of electricity is leading in making a buying or selling decision. The goal here is to derive economic benefit from the price difference between the purchase and sale price [77]. Selling back the electricity to the grid is however not a necessary precondition for EA. Another way in which this can result in economic benefit is when the electricity is utilized by the energy demand behind the meter of the application to which it is attached hence the name behind-the-meter. A necessary prerequisite for doing energy arbitrage is the presence of variable electricity prices. Since Heerema is a large industrial customer for electricity it pays the variable day-ahead prices for electricity. One advantage of price arbitrage on board vessels equipped with BESS is that the investment in storage has already been made. The on-board battery will be used primarily for other purposes such as peak-shaving and spinning reserve during offshore operations. As a result, it is not economically necessary to recover the battery costs through EA. The cost reduction in this case provides a faster return on investment and not the full return on investment.

Peak power reduction

Peak power reductions are another form of reducing energy costs. Industrial electricity consumers pay the usual energy costs as well as grid connection costs [74]. These are called transmission costs. Transmission costs are determined by the maximum power the customer uses from the grid. Heerema's shore power connection is operated by DSO Stedin. The transport costs are determined by Stedin by averaging the peak power over fifteen minutes [78]. For the highest peak power in the year, Heerema pays the transport costs. However, because the Sleipnir and Thialf are connected to shore power only 100 days a year, it is important to keep the transport costs as low as possible. In addition, Heerema also makes use of local wind generation. No transport costs are charged for this. During optimization, this must also be taken into account so that optimal use can be made of it.

Also within peak power reductions, there is a distinction between BTM and FTM. As for EA, BTM peak power reductions are aimed at reducing costs for the customer [74]. FTM peak reduction works to the benefit of the energy provider [74].

For the case study, an elaborate deconstruction of the electricity bill will be included in the optimization program since significant savings can be realized when peak demand will remain relatively low.

Power Quality

Reactive power compensation (QC) [74] In a perfect alternating current grid, the current and voltage are in phase. Inductive- or capacitive loads can respectively draw a lagging or leading current with respect to the voltage. This will result in a current that is out of phase with the voltage. As a result, this may cause inefficient transmission and wastes capacity [79]. In some liberalized energy markets tariffs are imposed on industrial consumers that consume electricity at a power factor below 0.95 in order to incentivize for solutions and mitigate losses [79]. The agreement with the Port of Rotterdam states that VAr rates will be charged according to the rates of the grid operator. The rates that Stedin charges for VAr are a fraction of the total price and will therefore not be regarded [78].

Aggregation / Virtual power plant

Under aggregation three technically feasible strategies can be defined which are; grid services, participation in wholesale markets, and demand response. The reason why they are attributed under aggregation is that these use-cases require scale [75]. As discussed in subsection B.1 BESS can reduce congestion problems by shifting peak demand or supply. When the capabilities of a single battery are multiplied and controlled by a single aggregator other use-cases are unlocked. In the section 1.1.3 a brief description is given of the flexibility potential of a completely vessel-to-grid connected port. Unlocking the full potential of such a system will have to be performed by an aggregator. Since in this thesis the perspective of the ship operator is taken, the perspective of the aggregator will not be regarded.

Stacking, dynamic stacking

In the previous subsections, many methods for generating revenue or cost reduction are given. Yet the versatility and contractility of power in a battery allows for the combination of multiple revenue-generating strategies. Combining multiple strategies is called stacking and is what enables BESS to move from cost reduction to revenue-generating. This process is described by [75] and can the principle is shown in figure**??**. In this thesis revenue stacking will be regarded in order to maximize the potential of the BESS.

C.1.2. FTM - In-front-of-the-meter

System-conducive or FTM applications are applications that primarily serve the grid. Whereas BTM applications serve a commercial goal, FTM does not have this as a primary purpose. This lack of economical incentive will ensure that commercial parties have no interest in them, for this reason, they are often made mandatory by the DSO or TSO [74] [74]. As stated before, FTM differs from BTM mostly on paper. As is stated in C.1.1, a collection of BESS is able to provide grid services trade in wholesale markets and have demand control. Considering this, models that are applied for FTM purposes can also be applied to BTM purposes. Since the scope is on the economic benefits of cold-ironing, FTM applications will not be considered further.

D
Appendix

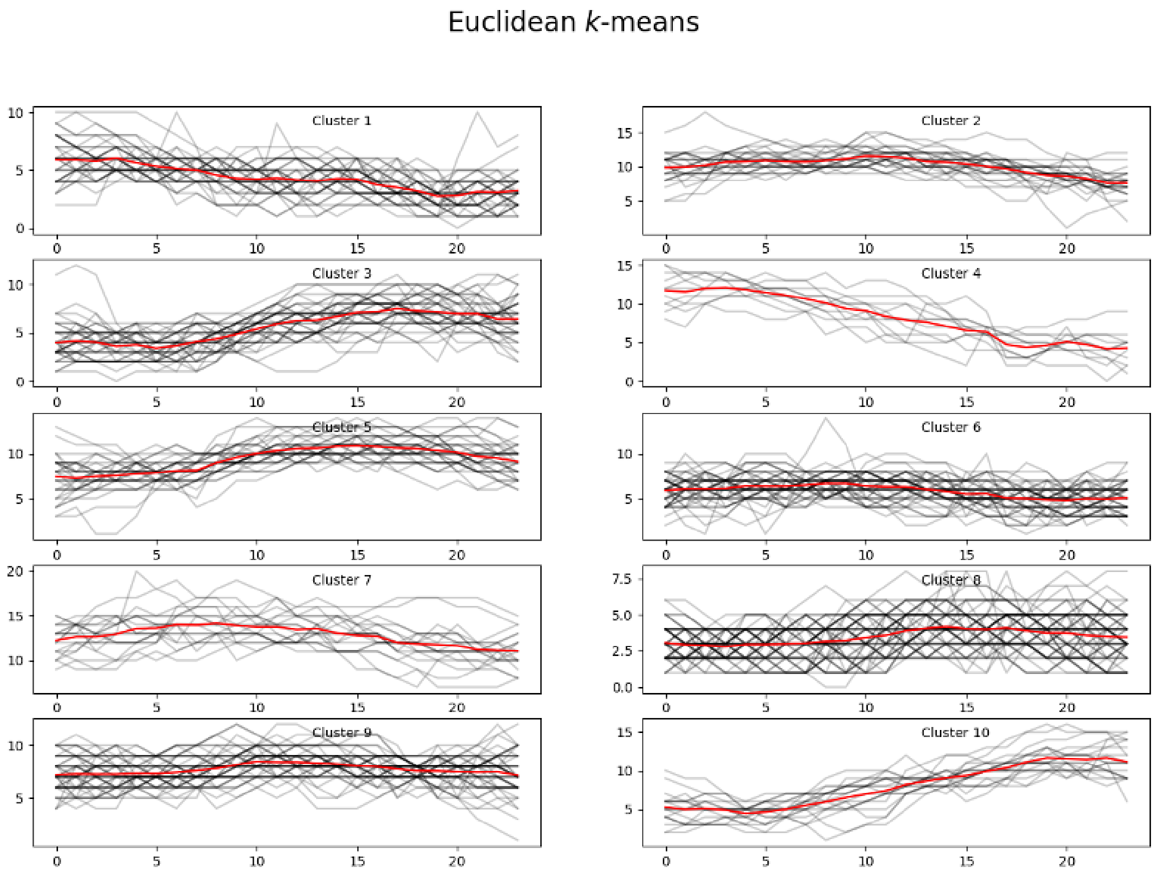

Figure D.1: Euclidean k-means

Table D.1: Distribution of scenarios over cluster centers for Euclidean k-means method

Euclidean k-means		
Cluster	**Count**	**Probability [%]**
7	64	17.5
5	53	14.5
8	52	14.2
2	42	11.5
0	40	11
4	35	9.6
1	28	7.7
6	20	5.5
9	20	5.5
3	11	3

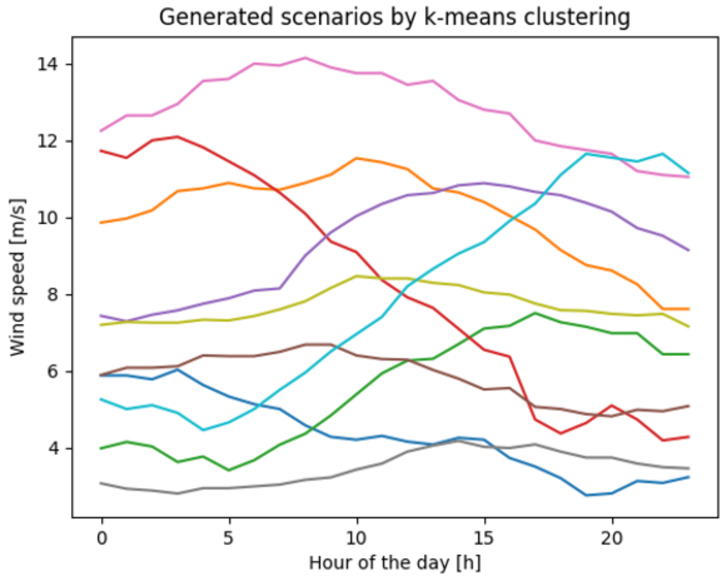

Figure D.2: Eulidean k-means 10 scenarios

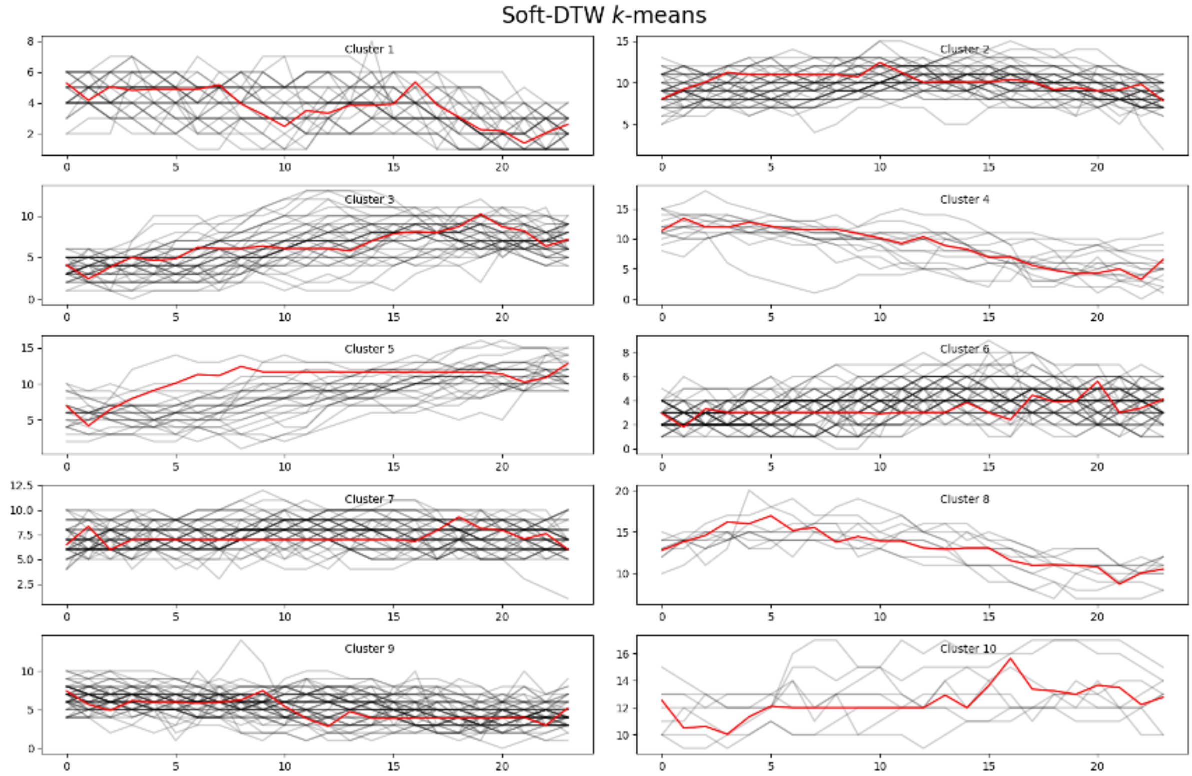

Figure D.3: Soft DTW k-means

Table D.2: Distribution of scenarios over cluster centers for Soft DTW k-means method

Soft DTW $-means

Cluster	Count	Probability [%]
6	56	15.3
1	52	14.2
9	51	14
4	41	11.2
8	41	11.2
3	39	10.7
0	32	8.8
5	29	7.9
2	14	3.8
7	10	2.7

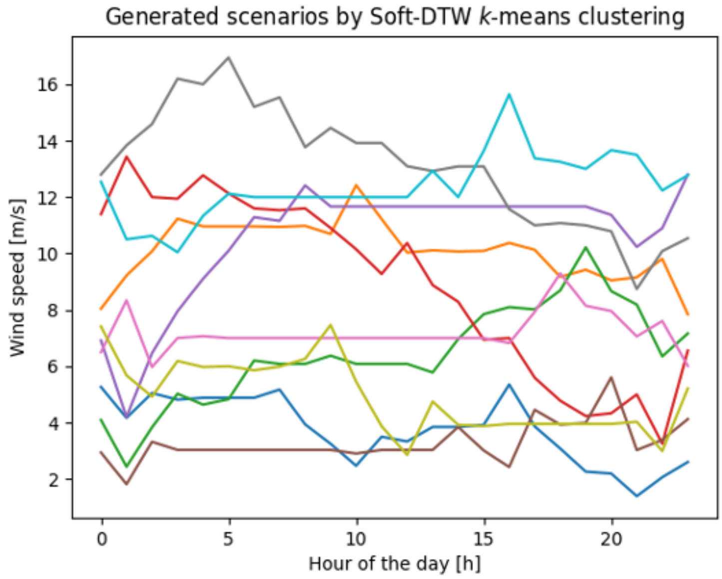

Figure D.4: Soft DTW k-means 10 scenarios

E
Appendix

Battery spec sheet

Figure E.1: Corvus battery specifications

Battery Pack Datasheet

Corvus Energy	**Customer:** Heerema Marine Contractors
	Project Name: TBD
	Location: TBD
	Corvus Technical Spec: CE-11757-24-FEB-2021

1	**Battery Pack**	
1,1	**Description**	Orca Energy
1,2	**Model**	E2250V1-AR-MB-VAC-ST-X
1,3	**Cell details**	Manufacturer: LG Chem Type: Lithium Ion NMC/Graphite
1,4	**Cell configuration**	2p264s
1,5	**Pack manufacturer**	Corvus Energy Inc
1,6	**Class compliance**	DNV-GL Type Approval Certificate: TAE000026N
1,7	**Flag state compliance**	TBD
2	**Electrical**	
2,1	**Voltage**	1100 VDC max 800 VDC min
2,2	**Energy**	124,3 kWh
2,3	**Capacity**	128 Ah
2,4	**Maximum current**	750 A
2,5	**Short Circuit**	Max (BoL): current: 14,9 kA L/R: 0,16 ms
		Min (EoL): current: 6,4 kA L/R: 0,10 ms
2,6	**C-Rate – Peak**	Discharge: 6C Peak – maximum rating for 10 seconds
		Charge: 3C
2,7	**C-Rate – Continuous**	Discharge: 3C Continuous – complete charge or discharge
		Charge: 3C
2,8	**C-Rate – RMS**	1.85C RMS – indefinite alternating charge and discharge
2,9	**BMS Power required**	voltage: 120-240VAC freq: 50/60Hz Typical: 135VA
		power: 170VA nominal, with surges between 170-340VA for <200ms at start-up
2.10	**Fan Power required**	voltage: 200-240VAC freq: 50/60Hz Max: 600VA Typical: 300VA
2,11	**BMS Communication protocol**	Modbus TCP
2,12	**EMC**	IEC 61000-4, CISPR16-1, 2, IEC60945-9
3	**Mechanical**	
3,1	**Size**	865 mm Wide 738 mm Deep 2241 mm Height
3,2	**Weight**	1628 kg
3,3	**Cooling**	Air Temperature range 15 - 20 °C
3,4	**Cooling heat load**	See Technical Specification
3,5	**Air flow through the rack**	Maximum: 1800 m^3/h Typical: 600 m^3/h
3,6	**Ingress Protection**	System IP44
3,7	**Vibration & Shock**	UNT 38.3, DNVGL-CG-0339 Class A, IEC 60068-2-6
3,8	**Installation location**	Other machinery space
4	**Safety**	
4,1	**Voltage Isolation**	5 kV (IEC 60947-2)
4,2	**Disconnect circuit**	Hardware-based fail-safe for over-temperature, over-voltage, under-voltage
4,3	**Disconnect contactor rating**	Full load
4,4	**Emergency stop circuit**	Hard-wired
4,5	**Short circuit protection**	Fuses included
4,6	**Battery side ground fault detection**	Integrated
4,7	**Maximum current parameter**	Updated 2x per second
4,8	**Faults communicated**	Over-voltage, under-voltage, over-temperature; hardware failure; over-charge; over-discharge
4,9	**Thermal runaway anti-propagation**	Passive; Cell-level; DNV-GL Pt.6 Ch.2, NMA 2016 circular
4.10	**Thermal runaway gas exhaust ducting**	Integrated

5	**Configuration Options**	**Selected**	**Notes**
5,1	**DC bus pre-charge circuit**	No	
5,2	**Black start (E1050 - E2450 only)**	No	
5,3	**UPS capability**	No	
5,4	**Custom color**	No	

F
Appendix

G
Stochastic Optimization

G.1. Stochastic programming

Time dependency

In order for the model to handle with uncertainty, a multiple time step two-stage stochastic programming has to be adopted. In order for this to be solved, a set of different wind scenarios needs to be provided. Since we are looking at short term battery dispatching, irregularities should be accounted for, and no average wind speeds can be used. This must therefor be represented in multiple time series representing possible realizations of wind speeds along the period of a day[80]. Many approaches in the literature use marginal distributions to generate scenarios for every time step in the scenario [80]. While this might be an appropriate approach for values independent from each other, this does not apply for wind speeds. The reason is because there exists an inter temporal relation between wind speeds prior to the next data point as one might intuitively know. While it is possible that wind speeds makes large steps in speed, it is highly unlikely. The resultant scenario would be highly variable, and not representative for actual wind scenarios. A method representing this time-dependency should therefor be used. This method is described in subsection **??**[80].

The exploration of two-stage stochastic programming has given an insight in the requirements for coming to a solution. The stochastic programming method requires scenarios for which it should optimize in the form of time series. As the computing time grows exponentially with the number of scenarios a method for generating a limited number of scenarios has to be found.

G.2. Two-Stage Stochastic Programming Formulation

Now that the relevant scenarios have been generated and reduced to a set of 10 the final two-stage stochastic programming problem can now be formulated. In the first part of this chapter in subsection G.1 a general description of stochastic programming was provided for the specific problem. This section will elaborate on the two methods for formulating a two-stage stochastic programming problem by means of chance constraint or recourse modelling. Secondly a motivation for the chosen method is given. Lastly, the two-stage problem will be formulated.

G.2.1. General 2 stage formulation

G.2.2. Handling constraints

Chance constraints

Depending on the problem one can either choose for a two-stage problem with recourse modelling or chance constraints [38].

"chance constraints arise as tools for modeling risk and risk aversion in random linear programs, interpreted as here-and-now decision problems [38]."

Recourse modelling

"It is fair to say that recourse models are the most important class of models in stochastic programming, both in theory and in applications. Recourse models are reformulations of decision problems that model stochastic infeasibilities by means of corrections afterwards [38]."

G.2.3. 2-stage formulation with recourse

We start of with a random parameter in the constraints. **Do we have random parameters in the constraints of my problem?**

$$(\mathrm{LP}_0(\omega)) \quad \min_{x\in\mathbb{R}^n} \left\{ cx : \begin{array}{c} Ax = b \\ T(\omega)x \sim h(\omega) \\ x \in X \end{array} \right\} \tag{G.1}$$

The lower and upper bounds are described by set X.

$$X = \left\{x \in \mathbb{R}^n : x^l \leq x \leq x^u\right\} \tag{G.2}$$

Lower and upper bounds, are most commonly described as $x^l = 0$ and $x^u = \inf$. Furthermore $Ax = b$ describes the deterministic equality constraint m_1. The m random (in)equality constraints are described by $T(\omega)x \sim h(\omega)$. In which $T(\omega)$ is an $m \times n$ matrix and $h(\omega)$ a $m \times 1$ vector that both depend om random variable ω [38].

Since the decision problem has to decide on x before knowing the value of ω the random constraints of the linear problem $LP(\omega)$ needs to be transformed to random constraints. As this problem deals with a recourse problem, these constraints are modelled as soft constraint [38]. Soft constraints can be violated, this violation will however come at a cost, thereby explaining the name *recourse* model. The cost of this violation does have an influence on the optimal choice of x. The second stage variables $y \in \mathbb{R}^p$ describe how violations are dealt with [38].

Recourse structure

The formal structure for a recourse model is described by (Y, q, W) in which:

$Y = \left\{y \in \mathbb{R}^p : y^l \leq y \leq y^u\right\}$, usually $Y = \{y \in \mathbb{R}^p : y \geq 0\}$, the recourse actions that are feasible are described by set y

q is a $1 \times p$ vector of *unit recourse costs*

W is an $m \times p$ matrix, the *recourse matrix*

This leads to the following $LP(\omega)$ problem with recourse:

$$\text{(SLPwR)} \quad \min_{x\in X} \left\{ cx + \mathbb{E}_\omega[\underbrace{\min_{y\in Y}\{qy : Wy \sim h(\omega) - T(\omega)x\}}_{\text{second-stage LP}}] : Ax = b \right\} \tag{G.3}$$

Note that in the second-stage part of G.3 the relation $Wy \sim h(\omega)$ is the same as in the random constraints in equation G.1 [38].

Recourse model in a compact form

Introducing additional functions gives rise to a clearer picture of the recourse action and its cost. In this compact form, the recourse part is split up in a *second-stage value function*G.4 and a *expected value function*G.5.

$$v(z) := \min_{y\in Y}\{qy : Wy \sim z\}, \quad z \in \mathbb{R}^m \tag{G.4}$$

$$Q(x) := \mathbb{E}_\omega[v(h(\omega) - T(\omega)x)], \quad x \in \mathbb{R}^n \tag{G.5}$$

Equation G.4 describes the cost of recourse when the random constraint $T(\omega)x \sim h(\omega)$ is violated. Similarly, equation G.5 describes the expected value of the recourse cost. Both equations leads to a minimization problem similar to G.3 presented in G.6.

$$\min_{x\in X}\{cx + Q(x) : Ax = b\} \tag{G.6}$$

Modelling Deterministic equivalent Recourse Formulation

Implementing optimization with recourse in a model, requires a deterministic equivalent formulation of the SLPwR problem given below.

$$(LP_1(\omega)) \quad \min_{x,y(\omega)} cx + \mathbb{E}_\omega[qy(\omega)] \tag{G.7}$$

$$\begin{aligned}
\text{s.t.}\quad & Ax = b && \text{first-stage constraint} && \text{(G.8)}\\
& T(\omega)x + Wy(\omega) \sim h(\omega) \forall\omega \in \Omega && \text{second-stage constraint} && \text{(G.9)}\\
& \underset{\substack{\uparrow\\ \text{first-stage}\\ \text{decisions}}}{x \in X} \quad \underset{\substack{\uparrow\\ \text{second-stage}\\ \text{decisions}}}{y(\omega) \in Y} && && \text{(G.10)}
\end{aligned}$$

For large scale problems the following equation describes the large scale deterministic formulation.

$$\begin{array}{lcccccccccl}
\min_{x\in\mathbb{R}^n y^S\in\mathbb{R}^p s=1,\dots,S} cx & + & p_1 \cdot qy^1 & + & p_2qy^2 & + & \cdots & + & p_Sqy^S & & \text{(G.11)}\\
Ax & & & & & & & & & = b & \text{(G.12)}\\
T^1x & + & Wy^1 & & & & & & & \sim h^1 & \text{(G.13)}\\
T^2x & & & + & Wy^2 & & & & & \sim h^2 & \\
\vdots & & & & & & \ddots & & & & \\
T^Sx & & & & & & & + & Wy^S & \sim h^S & \\
x \in X & & y^1 \in Y & & y^2 \in Y & & & & y^S \in Y & & \text{(G.14)}
\end{array}$$

In equations (G.11, G.14) the recourse action is modelled by $y^s = Y(\omega^s)$ when ω^s of ω occurs. Being a linear program it is easily solved by a solver. Yet it comes with a main disadvantage being the exponential growth once more and more variables and constraints are added. As an example, even a reasonable amount of 20 variables and 10 constraint can lead to an enormous matrix. As the size of the matrix is $n + pS$ variables and $m_1 + mS$ constraints, this leads to a value of $S = 10^{20}$. It is therefor of the utmost importance to limit the distribution of ω to a small discrete set for the equation to remain tractable [38].

General formulation

This is a repetition of the beginning of this chapter, but this description is (temporarily)included here to improve readability.

$$\pi(\omega = P(\omega|\boldsymbol{\lambda} = \boldsymbol{\lambda}(\omega)), \qquad where \sum_{\omega \in \Omega} \pi(\omega) = 1 \tag{G.15}$$

After identifying the scenarios and probabilities two-stage stochastic programming problem can be formulated as follows in equations (G.16, G.21)[54].

$$Minimize_{\mathbf{x}} z = \mathbf{c}^{\top}\mathbf{x} + \mathcal{E}\{Q(\omega)\} \tag{G.16}$$

$$\text{subject to } \mathbf{Ax} = \boldsymbol{b} \tag{G.17}$$

$$\boldsymbol{x} \in X \tag{G.18}$$

where

$$Q(\omega) = \Big\{ \text{Minimize}_{\mathbf{y}(\omega)}\, \mathbf{q}(\omega)^{\top}\mathbf{y}(\omega) \quad \} \tag{G.19}$$

$$\text{subject to } \mathbf{T}(\omega)\mathbf{x} + \mathbf{W}(\omega)\mathbf{y}(\omega) = \mathbf{h}(\omega) \tag{G.20}$$

$$\mathbf{y}(\omega) \in Y \Big\}, \ \forall \omega \in \Omega \tag{G.21}$$

The first- and second-stage variables are denoted by $\mathbf{x}$ and $\mathbf{y}(\omega)$ respectively. The variables $\mathbf{A}$, $\mathbf{b}$, $\mathbf{c}$, $\mathbf{h}(\omega)$, $\mathbf{q}(\omega)$, $\mathbf{T}(\omega)$, and $\mathbf{W}(\omega)$ are vectors and matrices with known values. It should be noted that the values in (G.16, G.21) can but do not have to be dependent on on the stochastic scenario set $_{\Omega}$. The latter part of the problem (G.19, G.21), depicts the *recourse* problem.

$$\text{Minimize}_{\mathbf{x}}, \mathbf{y}(\omega) \quad z = \mathbf{c}^{\top}\mathbf{x} + \sum_{\omega \in \Omega} \pi(\omega)\mathbf{q}(\omega)^{\top}\mathbf{y}(\omega) \tag{G.22}$$

$$\text{subject to} \quad \mathbf{Ax} = \mathbf{b} \tag{G.23}$$

$$\mathbf{T}(\omega)\mathbf{x} + \mathbf{W}(\omega)\mathbf{y}(\omega) \sim \mathbf{h}(\omega), \forall \omega \in \Omega \tag{G.24}$$

$$\mathbf{x} \in X, \mathbf{y}(\omega) \in Y, \forall \omega \in \Omega \tag{G.25}$$

H
Appendix

ELEKTRICITEIT TARIEVEN 2021

Aansluiting en transport voor grootverbruikers

STEDIN.NET | VOOR DE NIEUWE ENERGIE GENERATIE

ELEKTRICITEIT
TARIEVEN 2021

Sinds de invoering van de Elektriciteitswet (1998) en de Gaswet bestaat er een onderscheid tussen de energieleverancier, de netbeheerder en het meetbedrijf. Stedin draagt als netbeheerder zorg voor het beheer en onderhoud van het elektriciteitsnet in uw regio.

In dit tariefblad vindt u een overzicht van de aansluit- en transportvergoedingen voor elektriciteit. Deze tarieven gelden voor grootverbruikers (> 3 x 80A) met een aansluiting op het elektriciteitsnet van Stedin.

DISCLAIMER

Dit tariefblad is met de grootst mogelijke zorg samengesteld. Desondanks kunnen aan de gegevens geen rechten worden ontleend. Maandtarieven kunnen als gevolg van afronding afwijken van de gereguleerde ACM-tarieven.

WAT BETAALT U?

Aan Stedin betaalt u vergoedingen voor het transport van elektriciteit en de aansluiting op het elektriciteitsnet. Deze vergoedingen dekken onder andere de kosten voor de aanleg en onderhoud van het regionale elektriciteitsnet en de aansluiting.

Naast deze kosten die u aan Stedin betaalt, betaalt u ook voor de levering van elektriciteit (inclusief energiebelasting), de elektriciteitsmeter en de periodieke meteruitlezing. Deze kosten worden echter niet door Stedin in rekening gebracht, maar door uw energieleverancier en meetbedrijf.

EENMALIGE AANSLUITVERGOEDING

Voor het maken van een nieuwe aansluiting op het elektriciteitsnet betaalt u een eenmalige aansluitvergoeding (tabel 1). Als de aansluitkabel langer is dan 25 meter, betaalt u een bedrag per meter meerlengte (tarief meerlengte).

Tabel 1 - Eenmalige aansluitvergoeding

Aansluitcapaciteit	Aansluitvergoeding in € excl. BTW per aansluiting[1]	Tarief meerlengte in € excl. BTW per meter[2]
> 3 x 80A t/m 3 x 125A	4.530,00	51,00
> 3 x 125A t/m 175 kVA	5.750,00	54,00
> 175 kVA t/m 630 kVA	39.800,00	90,00
> 630 kVA t/m 1.000 kVA	41.000,00	100,00
> 1.000 kVA t/m 1.750 kVA	50.000,00	269,00
> 1.750 kVA t/m 3.000 kVA	213.000,00	340,00
> 3.000 kVA t/m 10.000 kVA	290.000,00	382,00

[1] Exclusief de kosten voor een vereiste meetinrichting

[2] Als er een verbinding tussen knip en beveiliging van meer dan 25 meter nodig is

PERIODIEKE AANSLUITVERGOEDING

Jaarlijks betaalt u een vast bedrag om de aansluiting in stand te houden (periodieke aansluitvergoeding).

Tabel 2 - Periodieke aansluitvergoeding

Aansluitcapaciteit	Aansluitcategorie[3]	In € excl. BTW per jaar	In € excl. BTW per maand
	LS[5]	35,0000	2,9167
> 80A t/m 175 kVA	Trafo MS/LS	83,0000	6,9167
> 175 kVA t/m 1.750 kVA	MS-distributie	765,0000	63,7500
> 1.750 kVA t/m 3.000 kVA	Trafo HS+TS/MS	1.680,6137	140,0511
> 3.000 kVA t/m 10.000 kVA	Trafo HS+TS/MS	8.360,0000	696,6667[4]
> 10.000 kVA	TS	Maatwerk	Maatwerk

[3] Geldt voor aansluitingen aangelegd na 1 januari 2007. Aansluitingen die daarvoor zijn angelegd, zijn ingedeeld op basis van aangesloten netvlak. De aansluitcategorieën zijn weergegeven in volgorde van oplopend netvlak

[4] Voor aansluitingen > 3.000 kVA en ≤ 10.000 kVA. Daarnaast geldt een periodieke aansluitvergoeding voor meerlengte > 3MVA van € 6,3500 per meter per jaar

[5] Geldt alleen voor aansluitingen aangelegd vóór 1 januari 2007: grootverbruik aansluitingen die op LS-net zijn aangesloten

TRANSPORTVERGOEDING

De transportvergoeding bestaat voor grootverbruikers uit een vast- en een variabel deel (tabel 3). Het vaste deel is het transportonafhankelijk tarief (vastrecht). Het variabele deel bestaat uit het transportafhankelijk tarief – afhankelijk van het gecontracteerde transportvermogen en het feitelijk afgenomen maximale vermogen – en een deel dat afhankelijk is van het verbruik. Het gecontracteerde transportvermogen is het maximaal benodigde vermogen dat u verwacht op enig moment in het jaar nodig te hebben.
Ook betaalt u voor eventueel extra blindverbruik.

Tabel 3 - Transportvergoeding (alle bedragen zijn excl. BTW)

Transportcategorie	Grens gecontracteerd transport-vermogen[6]	Transportdiensten					
		Vastrecht	Variabele tarieven[11]				
		Transport in € per maand	kW contract in € per maand per kW	kW max in € per maand per kW[7]	Dubbel tarief normaal in € per kWh[9]	Dubbel tarief laag in € per kWh[10]	Blind verbruik in € per kVARh
LS	t/m 50 kW	1,50	0,7292	-	0,0357	0,0220	0,0082
Trafo MS/LS	51 t/m 150 kW	36,75	1,9167	1,5665	0,0094	0,0094	0,0082
MS	151 t/m 1.500 kW	36,75	1,0296	1,5665	0,0094	0,0094	0,0082
Trafo HS+TS/MS reserve	> 1.500 kW	230,00	0,9583	0,8515[8]	-	-	0,0082
Trafo HS+TS/MS	> 1.500 kW	230,00	1,9167	2,4600	-	-	0,0082
TS reserve	> 1.500 kW	230,00	0,9083	0,8792[8]	-	-	0,0082
TS	> 1.500 kW	230,00	1,8167	2,5400	-	-	0,0082

[6] Geldt voor aansluitingen aangelegd na 1 januari 2007. Daarnaast geldt dat de transportcategorie (netvlakniveau) niet hoger kan zijn dan de aansluitcategorie (zie tabel 2)

[7] De hoogste, in elke verbruiksmaand afzonderlijk opgetreden, belasting uitgedrukt in kilowatt (kW), en bepaald als gemiddelde belasting van een periode van 15 minuten tenzij anders met Stedin is overeengekomen

[8] Wordt per week berekend

[9] Geldt van maandag t/m vrijdag van 7.00 uur tot 23.00 uur

[10] Geldt voor alle overige uren en op feestdagen, te weten: Nieuwjaarsdag, 2e Paasdag, Koningsdag, Hemelvaartsdag, 2e Pinksterdag, 1e en 2e Kerstdag.

[11] Als waarden niet zijn ingevuld, betekent dit dat de tariefdrager niet van toepassing is voor deze specifieke categorie

TRANSPORTKOSTEN BLINDVERBRUIK

Dit tarief wordt in rekening gebracht als de arbeidsfactor buiten de grenzen valt, zoals vastgelegd in de artikelen 2.1.5.6 en 2.1.5.6.a van de Netcode Elektriciteit.

BEHEERGEBIED ELEKTRICITEIT

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MEER INFORMATIE

De tarieven in deze brochure maken onderdeel uit van de Tarieven- en vergoedingsregeling als bedoeld in artikel 15 van de Algemene Voorwaarden Aansluiting en Transport Stedin Elektriciteit 2008 voor afnemers > 3 x 80A (niet zijnde producenten) en de Algemene Voorwaarden Aansluiting en Transport Stedin Elektriciteit 2008 voor producenten of zoals deze gewijzigd zullen worden. De Tarieven- en vergoedingsregeling en Algemene Voorwaarden kunt u inzien op **www.stedin.net** of opvragen bij onze Klantenservice.

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