Sarah Blanc

Multi-objective optimization for the design of electrified IWT network

Master Thesis

Delft University of Technology

Supervision

First Supervisor
Prof. Dr. Bilge Atasoy
Second Supervisor
Dr. Alex Kirichek
Third Supervisor
PhD. Jayvee Ramos

8.8.2024

Preface

The topic of this thesis, the optimization of maritime battery swapping systems for inland waterway transportation, addresses a critical aspect of sustainable maritime transport. As the world focuses more and more on reducing carbon footprints and enhancing energy efficiency, the maritime industry must also evolve. This research explores innovative solutions to one of the industry's pressing challenges-efficient energy management through battery swapping technology. Throughout this research, I have delved into the complexities of multi-objective optimization, balancing investment costs with operational efficiencies. The journey has been intellectually stimulating and personally rewarding, providing me with crucial insights and a deeper understanding of the complexities involved in maritime transport.

This master thesis marks the end of my academic journey towards earning a MSc degree at TU Delft. The work presented herein represents the intersection of academic study, research, and practical application. I am deeply grateful to my supervisors, whose expertise and guidance have been helpful in shaping this thesis. Their feedback and support have been crucial in refining my ideas and enhancing the quality of my research. I would also like to extend my gratitude to my colleagues and friends for their constructive discussions and moral support.

A special thank you goes to my parents and brother, who have supported me throughout this journey abroad. Their support, encouragement, and sacrifices have been the foundation upon which I have built this achievement. Without their belief in me and their constant support, this endeavor would not have been feasible.

As I present this thesis, I am aware that it is not just an academic requirement but a stepping stone towards my future career. I hope that the findings and insights presented here will contribute to the ongoing efforts to make maritime transport more sustainable and efficient.

Sarah Blanc
Delft, August 2024

Contents

List of Figures

List of Tables

Abstract

The ongoing global push towards energy transformation and decarbonization underscores the urgent need for reducing greenhouse gas emissions, particularly in the maritime sector, which accounts for a significant portion of global trade and emissions. This study focuses on inland waterway transportation (IWT) as a key area for implementing zero-emission solutions, especially through the use of battery swapping technology. Given the average age and expected lifespan of vessels in the IWT sector, the transition to renewable energy-powered, zero-carbon ships is imperative for achieving climate neutrality by 2050. The need for immediate action is critical, as maritime transport, which facilitates 80-90% of global trade, contributes approximately 3% of yearly greenhouse gas emissions. This research delves into the complexities of multi-objective optimization, balancing investment costs with operational efficiencies. It provides an in-depth sensitivity analysis of the impact of battery capacity, battery costs, the availability of docking station spots, loading of vessels on the overall system configuration. The results show that higher battery capacities lead to fewer required batteries and docking stations, enhancing network efficiency and reducing investment costs. The current battery costs, whether slightly increased or decreased, do not significantly alter the network design. The primary impact is on the total costs, which are influenced by changes in battery costs rather than adjustments in the network design. The study also reveals that the availability of spots at docking stations presents mixed outcomes, where additional spots can either increase or decrease total costs. Therefore, this variable warrants further study. Investigating the optimal number of spots at central DS could lead to a more efficient network configuration, reducing overall costs and improving operational efficiency. Finally, the loading situation of the vessels have a big impact on the network design, where unloaded vessels lead to less batteries and DS used.

The study further explores the effects of varying the weights assigned to three different cost objectives: investment, batteries times at terminal, and space loss. The first hypothesis suggests that less weight given to the loss space objective results in a smaller number of DS and batteries, as well as less sharing of batteries. This is because the model aims to minimize battery occupancy on vessels to avoid associated costs, leading to more frequent swaps and the need for more DS. The second hypothesis posits that prioritizing the "at terminal" times objective reduces total costs, as "at terminal" costs are generally lower than investment and loss space costs. The findings confirm these hypotheses, showing significant impacts on network design and total costs based on the weight distribution. Key results indicate that no single scenario studied in this thesis dominates across all cost factors. However, two runs achieve superior outcomes in three out of the four cost categories. These runs show similar values for the number of batteries at terminals and on vessels, suggesting that "at terminal" cost and investment cost objectives are not conflicting, unlike the loss space objective which appears to be independent. In conclusion, the study emphasizes the importance of carefully attributing and balancing weights to each cost objective to optimize network design and total costs. Moreover, the findings support the continued development of higher battery capacities and strategic resource allocation to enhance the efficiency and sustainability of IWT. The significance of this research lies in its potential to inform the deployment of renewable energy-powered, zero-carbon ships, contributing to global efforts to mitigate climate change and promote sustainable development in the maritime sector.

Nomenclature

Acronyms and Abbreviations

AES	All-electric ships
BSS	Battery swapping station
C	Celsius
DS	Docking station
EE	Energy efficiency
ESS	Energy storage system
EV	Electric vehicle
FC	Fuel cell
GHG	Greenhouse gas
HFO	Heavy fuel oil
ICE	Internal combustion engine
IMO	International maritime organization
IWT	Inland waterway transport
LNG	Liquefied natural gas
MDO	Marine diesel oil
MOO	Multi-objective optimization
NG	Natural gas
OR	Operations research
vLHV	Volumetric lower heating value
ZE	Zero-emission

Chapter 1

Introduction

Nowadays, energy transformation and decarbonisation of the economy are critical global priorities. These efforts focus on transitioning from fossil fuel-based energy sources to renewable and low-carbon alternatives. The aim is to significantly reduce greenhouse gas emissions, mitigate climate change, and promote sustainable development. Immediate action is specifically imperative in the maritime sector, which plays a crucial role in global trade and is a significant contributor to greenhouse gas emissions. Indeed, about 80 to 90% of the global trade is facilitated by maritime transport, which also accounts for about 3% of yearly greenhouse gas (GHG) emissions measured in carbon dioxide (CO_2) equivalent. This represents about 9% of the emissions linked to the transportation industry. Comparable to Germany's emission levels [7], the worldwide shipping sector would be the sixth or seventh highest emitter of CO_2 if it was a country. Currently, around 99% of the energy needed in the maritime industry is met by fossil fuels, with diesel and marine fuel oil making up as much as 95% of the total demand [8]. The International Maritime Organization (IMO) issues a warning, stating that GHG emissions from the maritime sector might rise by 50% to 250% by 2050 compared to 2008 levels if corrective action is not taken. This considerable variation in anticipated GHG emissions highlights the unpredictability of the sector's development over the next 30 years. The main reason for this expected GHG increase is the growth that the maritime sector has enjoyed in recent decades. Indeed, according to statistics on maritime commerce from 1990 to 2020, the volume of commodities loaded at ports worldwide has nearly tripled compared to 1990 [9]. And, as per the IMO, there might be another 40% to 115% increase in marine traffic by 2050 when compared to 2020 levels. However, even if it makes a large contribution to global greenhouse gas emissions, international shipping is still a reasonably effective and environmentally friendly means of transportation, especially when compared to air and land transportation [10].

Despite the global picture, there are opportunities for regional progress. Inland waterway transportation (IWT) presents a unique scenario within the maritime sector. Here, factors like shorter routes, specific vessel types, and established infrastructure create favorable conditions for alternative solutions to significantly reduce greenhouse gas emissions. Given the average age of the current fleet of vessels within the IWT sector and the expected technical lifespan of vessels of around 25-30 years, the development of new ship and engine designs should take place between 2025 and 2035. It is imperative to acknowledge that the ships scheduled for deployment in the next five to ten years will have a substantial impact on energy consumption and carbon emissions from the present until 2050. This emphasises how critical it is to establish favourable conditions for the deployment of renewable energy-powered, zero-carbon ships.

1.1 Problem description

This section provides an in-depth exploration of the key issues and context surrounding this research on maritime battery swapping technology. The sub-sections detail the current state of the inland shipping sector, the role of the Netherlands within the IWT sector, and the electrification of IWT.

Lastly, it introduces the concept of containerized battery swapping, highlighting its potential.

1.1.1 Inland shipping sector & its decarbonisation

IWT plays an important role for the transport of goods in Europe, with an approximate 6.3% share of the total freight volumes. More than 41,000 kilometres of waterways connect hundreds of cities and industrial regions, with 13 European member states having an interconnected waterway network [11]. IWT is distinguished from other modes of transportation by its enormous growth potential, while other modes suffer from capacity constraints and traffic jams. IWT is therefore a competitive substitute for rail and road freight. Specifically, it provides an eco-friendly substitute for energy usage and noise discharge. IWT ensures an elevated degree of security, particularly when transporting hazardous materials. It also helps to relieve traffic on severely used road networks in places with high population densities. Thus, IWT has prompted the European Commission to prioritize its expansion as part of the Sustainable and Smart Mobility Strategy, with ambitious goals to increase these modes of transport by 25% by 2030 and 50% by 2050.

Through the 2030 Climate Plan and the European Green Deal, the European Union has taken a bold stance on sustainable development in keeping with the worldwide commitment to lessen the effects of climate change [12]. With the ultimate goal of reaching climate neutrality by 2050, these strategic initiatives lay out a bold program to significantly reduce GHG emissions, with a target of at least 55% by 2030 compared to 1990 levels. It is anticipated that every economic sector, including shipping, will help to accomplish this challenging environmental objective [13]. PATH2ZERO [14] is one of the multiple measures that have been developed to help to achieve the goal of decarbonising the maritime sector. PATH2ZERO stands for PAving THe way towards Zero-Emission and RObust inland shipping. The path to zero-emission shipping remains uncertain due to many unknowns surrounding the technology, infrastructure, and logistics required for a complete transition, and thus needs further studies. The goal of this huge project is to present a thorough study of the potential and difficulties involved in moving IWT to a zero emission (ZE) paradigm. In order to evaluate the effectiveness of recently developed methods (such as electricity, E-fuels, and bio-fuels [15]) for lowering GHG emissions from inland shipping, the PATH2ZERO effort aims to create a digital twin model of the canal network. This model will consider individual vessels, logistics, and infrastructure. It will analyze new technologies, but also policy changes and future scenarios to identify the best path to zero-emission shipping.

To support and direct the maritime industry's decarbonisation goals, the International Renewable Energy Agency (IRENA) has compiled a list of initiatives. The four categories into which these initiatives are separated are shown in Figure 1.1. IRENA emphasizes the importance of multi-stakeholder collaboration and information sharing across diverse sectors for achieving impactful decarbonisation. In Section 2.1.1, stakeholders are identified through a broad lens that includes all entities that may have an impact on or influence this project, with the end goal being a more significant contribution to the decarbonisation vision. In addition, IRENA is in favour of using multiple strategies to achieve sustainable shipping. It focuses on lowering emissions at ports, boosting renewable fuel blends with certifications, increasing consumer knowledge through labelling, and levelling the playing field for renewable fuels through carbon price and energy efficiency regulations. It also emphasises how crucial it is to conduct in-depth research and development projects aimed at comprehending the potential and environmental effects of renewable fuels for transportation. IRENA also stresses the need for strategic planning and collaboration to secure sufficient renewable energy resources and develop advanced engine technology to enable the transition to greener fuels, as developed in Section 2.2. Lastly, they emphasise the necessity of financial tools and rewards to promote the use of carbon-neutral shipping systems. It also highlights how crucial it is to do research, work together, and make calculated investments in the creation of infrastructure and renewable fuels in order to facilitate the shift to a sustainable maritime sector.

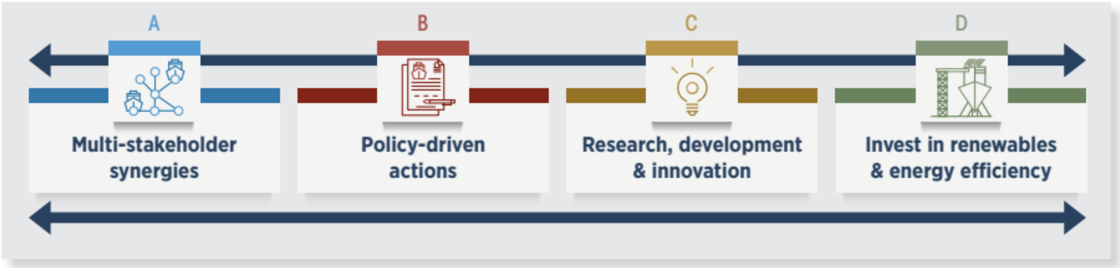

Figure 1.1: Actions to achieve decarbonisation ambitions [1]

1.1.2 The Netherlands: a European leader in IWT

With a long history in IWT, the Netherlands has not only shaped its own economic landscape, but has also become a key player in the global European IWT industry. With the densest network in Europe (over 6,700 km), its waterways efficiently connect major industrial centers, ports and agricultural regions (see Figure 1.2). This, combined with its strategic position as a gateway between Europe and the world, facilitates seamless multi-modal transport and makes a significant contribution to global trade flows.

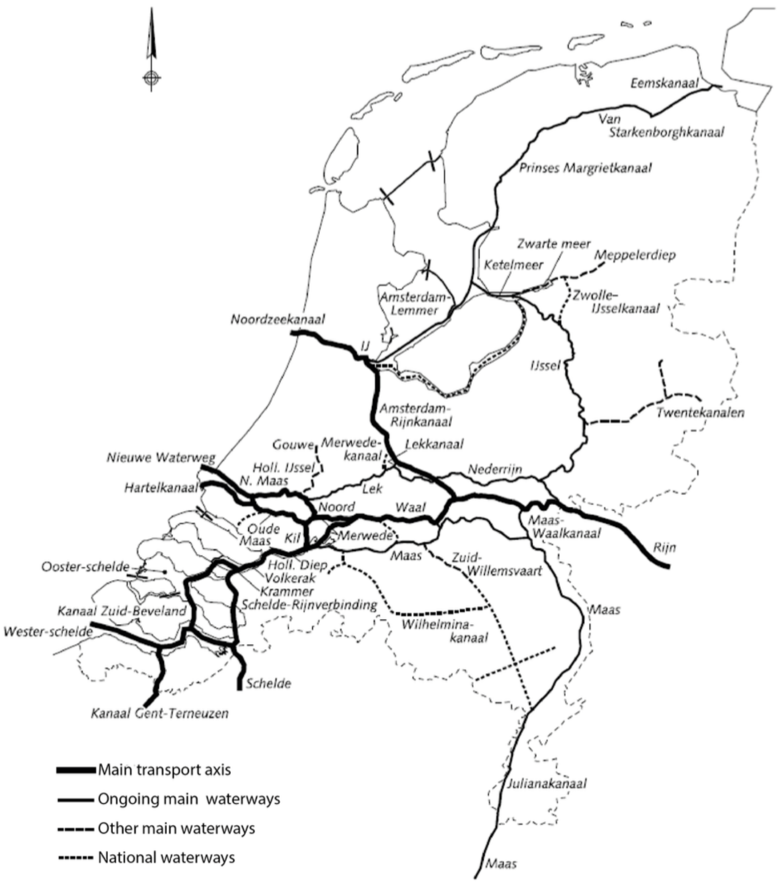

Figure 1.2: The Dutch inland waterway network [2]

In 2020, the Netherlands recorded the highest volume of freight transported per inhabitant with 20 tonnes and 49% of the registered freight transport vessels on EU inland waterways [16]. Recognising the need for sustainability, the Dutch government has set ambitious targets to achieve a carbon-neutral IWT sector by 2050. This ambition is fuelling constant innovation, as evidenced by projects such as PATH2ZERO [15]. In addition, the Netherlands actively collaborates with other countries and plays a leading role in organisations such as the European Barge Union and the Central Commission for the Navigation of the Rhine, sharing best practice and developing sustainable solutions for IWT.

1.1.3 Electrification of IWT

The electrification of IWT presents an opportunity to enhance its efficiency and environmental sustainability [17]. It uses a dual strategy for supplying power to ships that are docked. First of all, it permits "cold ironing" which spares ships from using their auxiliary engines while berthed by connecting them to the onshore grid for power [18]. Secondly, electrification makes it possible to recharge the batteries of hybrid or fully electric boats. However, changes to the energy refuelling of all-electric ships (AESs) provide significant difficulties for a number of stakeholders, including ships, ports, and grids. Energy Storage Systems (ESSs) onboard ships, especially fully battery-powered and plug-in hybrid electric ships, have limited capacity and require significant power during navigation. As a result, ESSs frequently need to perform energy refuelling operations at intermediate ports in order to support further navigation [19][20]. A solution to this issue is to make sure there is a sufficient supply of energy storage devices all along the sailing routes, and (renewable) electricity available at the shore to enable charging during peak-load times.

Currently, the three primary methods that AESs can refuel are through cable charging, wireless charging, and battery swapping. Some ports have established the required infrastructure to provide these services, especially for the cable charging process [21]. But because of the increasing cable sizes brought about by advances in charging technology, manual connection by crew members may become unfeasible in the future when vessel charging power levels approach tens of megawatts. The delay in connecting the heavy cables may result in a reduction in the charging energy given to the vessel. To answer this issue, techniques for inductive power transfer have been proposed for wireless charging at ports. However, tracking receiver coils in the dynamic tide and wave cycles, and placing transmitter coils optimally at the shore to maximise power transfer efficiency present obstacles. An alternative involves employing autonomous robots to handle the connection of heavy cables for traditional wired charging and cold ironing [22]. However, one point that needs to be taken into account is that, for battery-powered vessels and ferries adhering to predetermined schedules, the charging procedure is confined to a critical time-frame. Thus, inconvenience and lost revenue may result from disturbances and problems in an unstable power grid that hinder or slow down the charging process [23]. Moreover, since the size of the batteries needed is significantly higher than for electric vehicles (EVs), the charging procedure takes a lot longer. This results in even more time and financial losses. Thus, the idea of battery container swapping has been put out as a solution to this problem [22]. This aspect is the main focus of this thesis, and is further developed and discussed in section 1.1.4. Nevertheless, regardless of the type of alternative (wired, wireless, or swapping), a major obstacle to the broad deployment of AESs and a major cause of "range anxiety" among vessels is the lack of infrastructure. Consequently, to encourage the switch to electric fleets, a critical step is to establish a dense and efficient network of charging/swapping stations along shipping routes.

1.1.4 Containerized battery swapping: a game changer for IWT

As previously indicated, battery swapping stations, or battery storage systems (BSSs), are showing promise as a solution to boost the switch to zero-emission IWT. BSSs function by swapping out empty batteries on board ships for fully charged ones at designated port facilities [24]. Standardised battery packaging enable this creative solution, which has several advantages over conventional wired and wireless charging techniques [25]. One of the key benefits of BSSs is rapid energy replenishment, which enables far faster refuelling times than conventional charging methods [26].

The first Dutch ship ("Alphenaar") to use this technology is said to finish the swapping procedure in just 15 minutes, increasing port utilisation and vessel operational efficiency. BSSs reduce the possibility of income losses for ship owners by separating battery charging from the vessel's operating hours. Adoption is also encouraged by the lower initial ship owners' costs associated with building or renovating vessels because big, costly batteries are no longer necessary. Indeed, in an ideal scenario, a third-party entity manages the battery life cycle, encompassing health monitoring, decommissioning, and repurposing, while ship owners subscribe to a battery leasing service, minimizing investment and operational costs [27]. However, implementing BSSs requires significant upfront capital expenditures by ports or battery swapping stations operators (such as the company ZES) for battery stock and the mechanical infrastructure for swapping operations [21].

Another advantage is that BSSs offer centralized and controlled battery charging compared to the often decentralized nature of battery charging stations (BCSs) [28]. Thus, the local power grid is less negatively impacted by demand changes thanks to this accumulation of charging loads. Also, by optimising the charge of spare batteries and supplying extra services to the grid, BSSs can provide new revenue streams [29]. However, BSSs are mostly appropriate for inland vessels and short-distance ferries because of the intrinsic capacity constraints of battery packs [19]. Another drawback is to find a way to accommodate the diverse demands of various vessel sizes and energy requirements. Indeed, it necessitates complex planning and operational adjustments. The lack of international standards for both swapping stations and battery packs currently prevents seamless use across different networks, restricting vessels with varying battery types and brands. Last but not least, ship owners understandably express concerns about the transparency and accuracy of information regarding the health and capacity of swapped batteries. Research on BSS operation and management strategies is lacking, despite the encouraging outcomes of practical BSS implementations [30]. To fully use this technology for a sustainable IWT future, further research needs to delve into the effective deployment of BSS and the associated batteries, battery leasing models, and grid integration strategies. This thesis will prioritize the critical challenge of effectively deploying BSS, laying the groundwork for a sustainable future in IWT. Section 2.3 explores the battery swapping process in detail, discussing its primary components.

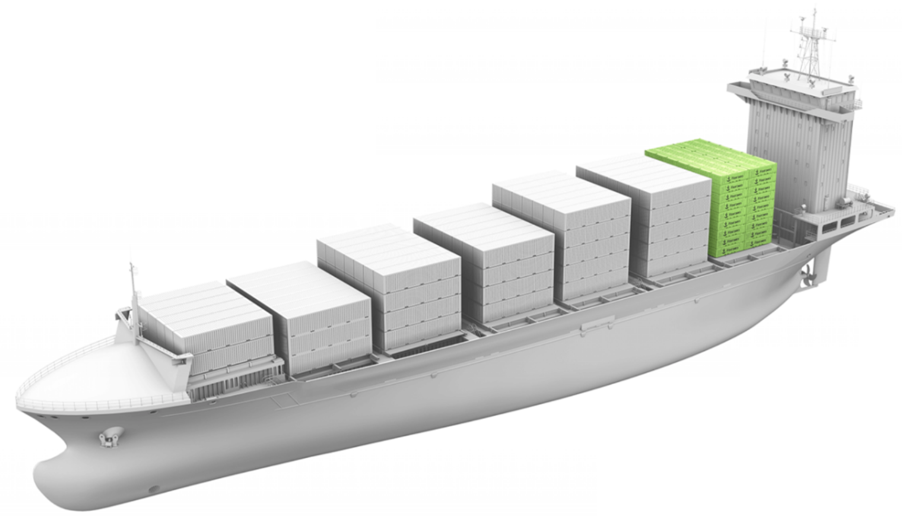

Figure 1.3: Vessel loaded with the containerized batteries (swapping technology) [3]

1.2 Research objectives and questions

This thesis aims to develop a comprehensive understanding of the integration and mapping of a viable ZE logistics and energy system, the battery swapping system. This research aims to identify the most effective logistics design for the distribution of batteries and the placement of docking stations. The design will encompass the following elements: determining the number of required batteries, identifying the number and locations of docking stations, and developing a battery distribution plan. This plan will outline where and when batteries should be charged to ensure they are available with the necessary charge level at the appropriate time and place. The design will consider potential vessel demand, including the number of ships, their routes, loading, and power requirements, along with a set of pre-identified possible docking station locations. The logistics plan will be subject to constraints such as the reduced autonomy of vessels compared to those using diesel fuel, the lost space due to the batteries containers and the availability of docking and stocking spaces at docking stations and on vessels. Furthermore, the optimization process incorporates multiple objective functions to accurately model real-world scenarios and complex decision-making processes.

The following main research question is established:

How can a multi-objective logistics design be developed for battery distribution and docking station location within a designated IWT dutch network section?

The main research question is answered together with the following sub-questions:

1. What are the characteristics of the Dutch inland shipping sector, and its sustainable alternatives to fuel?
2. Considering factors like route lengths, power requirements, and desired autonomy levels, what are the optimal number and locations of batteries and docking stations within the network section, while also considering the trade-offs between different objectives in the logistics design process?
3. How do vessel capacity reduction due the battery containers impact the design and results, and how can these constraints be integrated into the optimization model?
4. How do the varying times of battery containers at terminals impact the design and results, and how can these constraints be integrated into the optimization model?

To answer these questions, a methodology will be developed to model a maritime ZE transport network and understand the performance of the system under various characteristics and limitations. The methodology must be flexible enough to evaluate design changes as well as the sensitivity of parameters. Table 1.1 provides an overview of the subquestions and their related applied methods.

1.3 Research perspective, scope, and limitations

This research focuses on a designated section of the Dutch IWT network. The specific section is chosen based on data availability and representativeness of the overall network. More details about the network can be found in Section 4.1. Moreover, it will focus on the four vessel types that are most frequently utilised in the selected network segment (see Section 4.3). This emphasis preserves practical relevance while enabling a thorough study. The thesis will present a section detailing the various stakeholders involved in the electrification of IWT in the Netherlands to highlight the complexity of this process (see Section 2.1.1). However, the optimisation process is taken from a swapping station and batteries operator point of view (for example ZES).

The limitations of this study can be listed as the following:

Table 1.1: Method used for each sub-question

How can a multi-objective logistics design be developed for battery distribution and docking station location within a designated IWT dutch network section?

Subquestion	**Method**
1. What are the characteristics of the Dutch inland shipping sector, and its sustainable alternatives to fuel?	Literature review Expert/Industry interviews
2. Considering factors like route lengths, power requirements, and desired autonomy levels, what are the optimal number and locations of batteries and docking stations within the network section, while also considering the trade-offs between different objectives in the logistics design process?	Optimization model Case study Numerical experiments Sensitivity analysis
3. How do vessel capacity reduction due the batteries containers impact the design and results, and how can these constraints be integrated into the optimization model?	Numerical experiments Sensitivity analysis
4. How do the varying times of battery containers at terminals impact the design and results, and how can these constraints be integrated into the optimization model?	Numerical experiments Sensitivity analysis

- Base case scenario analysis: It will utilize a base case scenario to establish a reference point for comparison. This may limit the "generalisability" of the findings to real-world scenarios with varying factors.
- Focus on electricity: The study will primarily examine the transition to electricity as an energy carrier, while other potential alternatives or combinations of energy sources may not be explored.
- Technological assumptions: It may make assumptions about technological advancements or their specific implementation, which could impact the validity of the analysis.
- External factors: It may not fully account for external factors such as regulatory changes, economic conditions, or consumer behavior, which could influence the adoption and impact of electricity-powered logistics.

1.4 Research contribution

Here are the key contributions of this thesis:

- It develops a new framework for designing IWT battery logistics that considers multiple, and conflicting objectives. It goes beyond traditional single-objective approaches, providing a more comprehensive picture of trade-offs involved.
- Secondly, this research analyzes real-world data from the twelve most used routes and four most common vessel types within a designated dutch IWT network section. This leads to a practical and data-driven design solution tailored to the specific characteristics of the chosen network section.
- Thirdly, it considers the space lost and weight occupied by the battery containers and analyzes their impact on the network design.
- Finally, it also considers the varying times of the battery containers at terminals and the costs associated, and analyzes the impact on the network design.

1.5 Outline

The remainder of this report is organized as follows. Chapter 2 answers the first sub-research question, and is divided into two parts. Firstly, information about the background of the Dutch inland shipping sector is provided. Then, a literature review is provided by discussing sustainable alternatives, as well as the battery swapping process, its main components and the existing models for battery swapping technologies. The thesis methodology is discussed in Chapter 3, encompassing short introductions to Operation & Research, and the model with its requirements, assumptions and simplifications. The conducted case study and its numerical experiments are presented in Chapter 4, and respond the third and fourth sub-research questions. Together with Chapter 3, Chapter 4 also aims to provide answers to the second sub-research question. Finally, concluding remarks and recommendations are provided in Chapter 5.

Chapter 2

Background and Related Literature

2.1 Dutch inland shipping sector

The Dutch IWT sector plays a crucial role in the Netherlands' economic landscape. It provides a reliable and efficient mode of transportation for goods, contributing significantly to supply chains and international trade. Nonetheless, in its quest for sustainability and ongoing expansion, the Dutch IWT sector faces a unique set of difficulties, just like any other dynamic industry. This section delves into the key stakeholders involved in the sector and the specific challenges that need to be addressed to guarantee a thriving and long-lasting Dutch IWT network.

2.1.1 Stakeholders

In this project, three different groups of stakeholders can be observed: the primary stakeholders (in blue), the secondary stakeholders (in green) and the influential stakeholders (in orange) (see Figure 2.1). Primary stakeholders are directly involved in the implementation and utilization of electric technologies. They include shipowners and operators, shipbuilders and shipyards, port authorities and terminal operators. These stakeholders will have a direct impact on the success or failure of electric adoption in the maritime industry. Secondary stakeholders are indirectly involved in the adoption of these technologies. They include engine manufacturers, battery manufacturers, technology providers, environmental organizations, and regulatory bodies. These stakeholders can influence the adoption of electric propulsion through their products, services, or regulatory framework. And finally, the influential stakeholders are not directly involved in the adoption of this new technology, but they can exert influence on the decision-making of primary and secondary stakeholders. They include consumers, labor unions, local communities, and media coverage. Their mapping can be seen in Figure 2.1.

Within the primary stakeholder group, shipowners and operators (such as those represented by the World Shipping Council (WSC) [31] and the European Community Shipowners' Associations (ECSA) [32]) own or operate vessels and bear the responsibility for the deployment and upkeep of these electric fleets. Their concerns centre on the dependability, performance, and affordability of electric technology. Furthermore, the responsibility for designing, constructing, and maintaining electric ships lies with the shipbuilders and shipyards, who are represented by organisations like the Society of Naval Architects and Marine Engineers (SNAME)[33] and the International Shipbuilders' Association (ISA)[31]. They must acquire new skills and competencies with this new technology in order to satisfy the expectations of this developing market. Lastly, the ports and terminals where ships are loaded and unloaded are managed by port authorities and terminal companies. The European Sea Ports Organisation (ESPO)[34] and the International Association of Ports and Harbours (IAPH)[35] are two examples of associations/organizations that represent them. To support electric vessels, they must make investments in services and infrastructure, such as exchanging facilities.

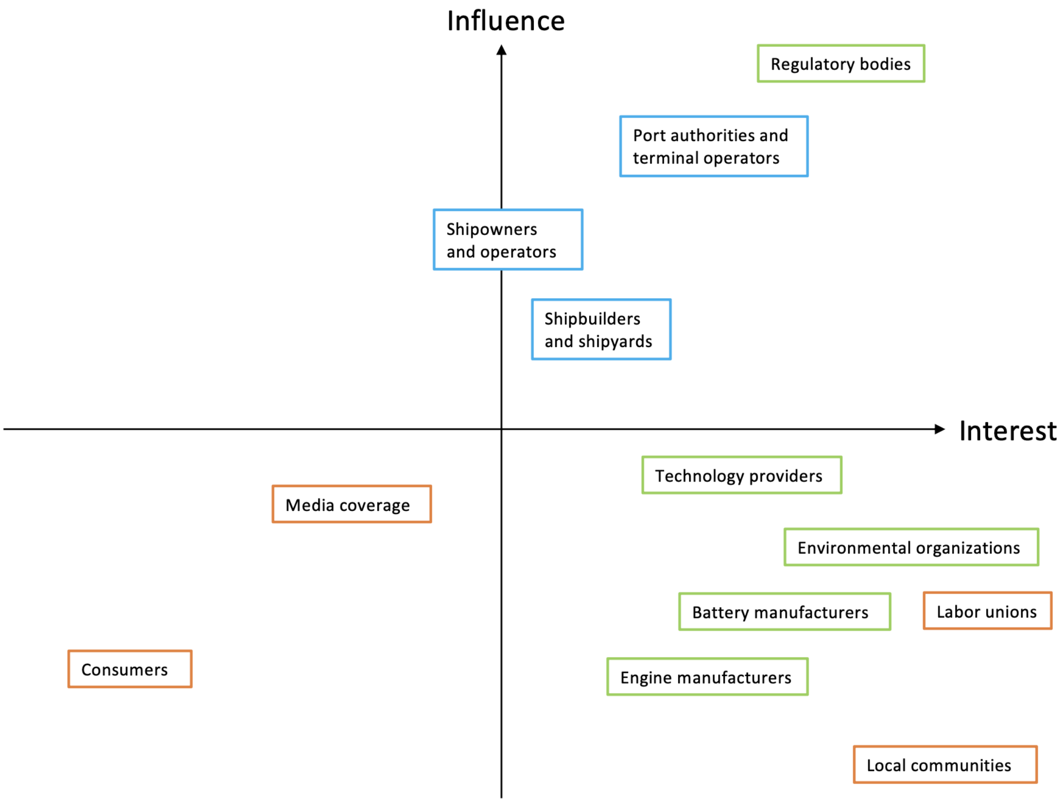

Figure 2.1: Stakeholders mapping

The engine manufacturers are some of the secondary stakeholders; they design and produce engines for use in ships. To keep ahead of the competition and satisfy the changing demands of the emerging electric maritime industry, they must make research and development investments. Wärtsilä [36] and MAN Energy Solutions [37] are two examples of stakeholders in this group. The battery manufacturers, such as CATL [38] and SK innovation [39], produce batteries for electric transportation modes, potentially including those used in ships. To keep up with the rising demand, they must boost production capacity and enhance battery performance. In contrast, technology companies create hardware and software for the maritime sector, such as data analytics tools, communication systems, and navigation systems. They will have to modify their products to accommodate electric boats. In addition, environmental groups like the Ocean Conservancy [40] and the Environmental Defence Fund (EDF) [41] seek to implement sustainable practices in the maritime sector, such cutting emissions and increasing energy efficiency. They should support the adoption of electric vessels as a way to achieve these goals. Last but not least, the regulatory agencies establish guidelines and standards, such as safety and emissions criteria, for the maritime sector. The regulations will have to be updated to allow for the use of electric vessels.

Finally, in the group of the influential stakeholders, the consumers of goods transported by sea may be willing to pay higher priced products shipped on electric vessels, if this aligns with their environmental values. Moreover, a positive media coverage of electric inland shipping could raise awareness of the technology's benefits and encourage its adoption. The labor unions are interested in the potential impact of the transition to electric fleet on employment in the logistics industry. And finally, the local communities are affected by the installation of electric charging stations and other infrastructure. On the other hand, they can also be positively affected by the reduction in noise pollution and improvement in air quality.

2.1.2 Challenges

Several shipping firms operating multiple ships and a large number of independent contractors, each owning a single ship, define the Dutch IWT network. As such, it is unlikely that individual shipowners will spend a lot of money on stations and costly battery swapping systems. This poses a serious dilemma, sometimes known as a "chicken and egg" scenario: shipowners are reluctant to switch to a battery-electric system in the absence of conveniently accessible swapping stations. However, businesses are hesitant to make investments in the absence of a sizable fleet of fully functional battery-electric ships. A Dutch national growth fund recently set aside 50 million euros to build 14 docking stations, electrify 45 ships, and deploy 75 battery containers in order to address this problem. Ultimately, the objective is to achieve 150 battery-electric ships by 2030 and 400 by 2050 [42].

To further complicate matters, this industry often has a deeply rooted familial aspect. Many ships are handed down through the generations, fostering strong emotional bonds among families who see their ships as treasured legacy as much as equipment. The nostalgic tie that certain generations have to diesel-powered vessels may make the switch to electric systems more difficult. Even while shipowners are aware of the environmental advantages of electrification, breaking away from the engine's familiar noise and the routines they have developed around conventional fuel sources can be a big obstacle. Encouraging a seamless transition in the business and attaining widespread adoption of electric ships need addressing this sentimental factor in addition to the infrastructure and economic issues.

2.2 Sustainable alternatives for marine energy carrier

Several studies, such as [43], have shown that while numerous measures can be implemented and combined to reduce CO2 emissions in transportation, achieving complete decarbonisation in the long term necessitates a systematic shift from fossil fuels to alternative energy sources. This transition cannot be achieved through a single, isolated measure; it requires a comprehensive approach. This section explores these potential solutions, focusing on alternative energy sources that can be combined with electricity in the future to ultimately decarbonise the inland waterway transport (IWT) sector. This chapter provides a high-level overview of the various possibilities. They will be introduced to the reader, but further exploration of each option is beyond the scope of this thesis.

Despite growing concerns about climate change, the vast majority of the global shipping fleet continues to rely on fossil fuels. Remarkably, 98.8% of ships continue to run on fossil fuels, with heavy fuel oil (HFO) making up the majority of this use (about 72%). Liquefied natural gas (LNG) comprises a comparatively small percentage (2%) of the fuel mix, with marine diesel oil (MDO) accounting for approximately 26% of the total [44]. Positively, cleaner options are being incorporated into the design of 21% of newly ordered ships. A ship's cargo capacity and environmental impact are both influenced by the fuel it uses. This is due to the fact that a fuel's volumetric lower heating value (vLHV) establishes how much energy can be held in a specific volume. In simpler terms, fuels with higher vLHVs pack more energy into less space, allowing ships to carry more cargo without sacrificing fuel range. Currently, most ships use MDO and LNG, which have vLHVs of 35.9 GJ/m3 and 20.2 GJ/m3, respectively [45]. Table 2.1 shows the volumetric energy density and the temperature storage of alternative energy carriers, compared to the MDO and LNG.

The challenge to find attractive storage solutions for marine purposes is specially true for energy carriers stored under high pressure or very low temperature due to complexity and space occupation of the storage systems, expressed via the lower volumetric energy density. Figure 2.2 depicts a forecast of the fuel/alternative distribution across various vessel types. The visualization suggests three dominant contenders emerging: battery, hydrogen, and methanol. Considering this, and in addition to batteries being the main subject of this thesis, the following section briefly explores the two other alternatives, aiming to provide the lecturer with a broader context for understanding

Fuel type	Volumetric energy density GJ/m^3	Storage temperature (°C)
Marine diesel oil (MDO)	35.9	20
Liquid natural gas (LNG)	20.2	-162
Compressed hydrogen	7.5	20
Liquid hydrogen	8.5	-234
Ammonia	11.3	-33
Liquefied bio methane (LBM)	21.0	-162
Methanol	15.8	20

Table 2.1: Volumetric energy density & storage temperature of energy carriers

the issue and its potential solutions.

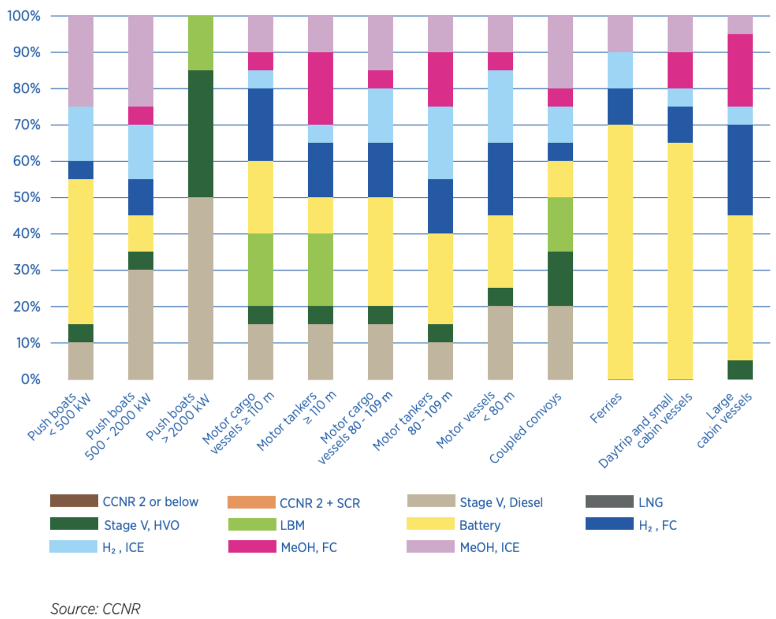

Figure 2.2: Innovative transition pathway: technology share for each fleet family in 2050

2.2.1 Hydrogen

As the shipping sector searches for alternative fuels that meet the IMO's emission reduction standards, hydrogen emerges as a viable long-term solution. Due to its adaptability, it can be used in internal combustion engines that have substantially lower emissions than those that use standard fuels, or it can be used in fuel cells (FCs) for the production of clean power [46]. Grey hydrogen generation [47] is the major method of producing hydrogen gas and CO_2 from natural gas. However, significant emissions result if the CO_2 created during this process is not caught. The conversion of natural gas via CO_2 capture and storage, on the other hand, is seen as more environmentally friendly and is known as "blue hydrogen". Electrolysis is a significant method of producing hydrogen by splitting water molecules into hydrogen and oxygen gas with the use of electricity. If this electricity comes from a renewable source, this generated hydrogen is called green hydrogen. Thus, green hydrogen is therefore one of the cleanest alternative fuels available [47][48].

Transportation is already noticing the impact of hydrogen fuel cells, especially in public transportation. Using hydrogen power, several of London's famous double-decker buses are already operational [49]. China began investigating this clean fuel in 2009, and in 2016 Foshan City was the first to widely implement hydrogen-powered public transportation [50]. But for vessels, things work differently. Although they are still in the early stages of research, hydrogen fuel cells and engines have enormous potential. Successful marine trials in 2016 provided a glimpse of this future [51]. Ongoing projects like Nemo H_2, Zero-V, and ZEMSHIP ([52], [53]) demonstrate advancements in hydrogen-fueled FCs on ships. Although scaling up for large ships is difficult, there are important lessons and impetus to be gained from other industries' successes. Although it may take some time to transition from London buses to freight driven by hydrogen, the marine sector may see a clean revolution of its own far sooner than anticipated.

However, despite the potential of hydrogen, challenges persist in its production and utilization. The primary concern is the exorbitant expenses of engine retrofits, ship storage, and H_2 bunkering in comparison to MDO [46]. In terms of energy efficiency, electrolytic hydrogen, for example, loses a lot of energy. Indeed, it contains between 30 and 45 percent less energy than the power used for the electrolysis process. Subsequently, the energy losses incurred in converting hydrogen back into electricity in a fuel cell (FC) render the process less energy-efficient than directly utilising electricity [54]. An additional disadvantage of employing H_2 as a fuel is that it would necessitate a total overhaul of the ship's engine and fuel systems, making it incompatible with a "drop-in" strategy [46]. In addition, hydrogen gas is extremely combustible, which increases the possibility of explosions in the case of a leak. A hydrogen filling station in Sandvika saw an incident that serves as an example [55]. Finally, because hydrogen has a poor energy density, ships need big tanks to store it. In fact, compared to traditional fuel oil, it takes up to seven times as much space, which reduces cargo capacity. Hydrogen is frequently compressed or kept in liquid form to reduce storage difficulties; this requires high-pressure tanks or cooling to minus 253 degrees Celsius. But a different approach for long-distance transportation entails binding hydrogen within ammonia (NH_3).

2.2.2 Liquefied Bio Methane (LBM)

Liquefied Bio Methane (LBM), also known as bio-LNG, is a renewable fuel, that aims to revolutionize the IWT sector [56]. Unlike traditional diesel fuel, LBM is produced by capturing and purifying biogas derived from organic waste sources like sewage treatment plants, landfills, and even agricultural residues. This biogas is then cooled to a frigid -162°C, transforming it into a liquefied state â LBM. This procedure removes undesirable elements like carbon dioxide and water vapour in addition to concentrating the methane content and making it extremely energy-dense for effective transportation.

The application of LBM in IWT offers a compelling solution to the industry's environmental woes. Compared to fossil fuels, LBM boasts significantly lower greenhouse gas emissions, particularly nitrogen oxides and particulate matter [56]. This results in cleaner water and air near inland waterways, which frequently cross over densely inhabited towns and environmentally delicate areas. There are several difficulties involved in incorporating LBM into IWT, though. One major obstacle is the development of infrastructure. Along inland waterways, bunkering stations (facilities built expressly to refill vessels with LBM) are hard to come by. It also costs a lot of money up front to build new IWT vessels with engines that work with LBM or to retrofit existing ones. The cost of LBM itself can also be higher than traditional fuels, due to the relatively nascent production capacity [57].

2.2.3 Methanol

Like many alternative fuels, methanol has two options: powering ICEs directly or acting as a hydrogen carrier for FCs. Methanol benefits from existing infrastructure for transport and storage, simplifying transition [58]. While it offers a 25% CO_2 reduction compared to HFO when made from natural gas (NG), a full life-cycle analysis paints a different picture. Studies suggest methanol from NG might even have 10% higher GHG emissions than HFO [7]. The solution to this is the green methanol. Produced through renewable energy (e-methanol) or biomass (bio-methanol), this variations offer truly sustainable choices. Bio-methanol uses biomass, while the latter comes from renewable electricity. It stands out as a sustainable option because of its renewable origin and low carbon impact compared to its fossil fuel counterparts. However, large-scale supply of biomass remains a challenge, with efficient conversion methods still under development. As a result, e-methanol is emerging as the most sustainable choice, benefiting from a virtually zero carbon footprint thanks to its renewable electricity source. This approach exploits established and mature processes, powered by abundant renewable sources such as solar and wind energy.

Methanol has been powering specialised maritime applications such cruise ships, ferries, and smaller vessels for a number of years. Shipping firms seeking to decarbonise find it to be an appealing alternative due to its readily available nature, variety of manufacturing sources, and simplicity of storage and transportation. Since 2020, there has been a sharp increase in orders for methanol-powered chemical tankers and container ships. Industry giants such as Maersk and Klaveness Combination Carriers are betting on this fuel, with Klaveness launching the world's first methanol-powered container ships in 2023. A key advantage of methanol is its compatibility with existing engines. Unlike other alternatives such as hydrogen, it requires minimal modifications, making it a practical solution for immediate decarbonisation efforts in the shipping industry.

2.2.4 Ammonia

Ammonia, which becomes liquid at a relatively mild temperature of minus 33°C, offers a higher energy density than pure hydrogen, making it more manageable for storage and transportation [59]. However, there are drawbacks to using ammonia as an energy transporter, most notably its expense and energy loss. Ammonia use raises further safety concerns [60]. Because of its limited flammability range, it is safe to store on board. It does, however, carry some toxicity hazards; exposure to excessive doses may result in lung damage, blindness, or even death [61]. As such, stringent safety protocols are essential.

While both ammonia FC and internal combustion engine (ICE) applications are still in their early stages, with limited real-world use in shipping [62], they hold significant potential. The process of producing ammonia (Haber-Bosch) is well-established and may be modified to use renewable energy using electrolyzers, in contrast to the technology needed to produce hydrogen [48]. Prominent companies testing ammonia-powered internal combustion engines (ICEs) include Japan Engine Corporation, Wartsila, and MAN Energy Solutions. The results of these tests are encouraging [63]). Gas turbines provide an alternative, although they are less desirable than internal combustion engines (ICEs) due to their reduced efficiency [63]. However, regardless of the technology selected, major modifications to the engine and fuel system are required ([48], [63]). With South Korea and Japan making significant investments in RD, East Asia is leading the world in ammonia development. This dedication is demonstrated by the National Maritime Research Institute's collaboration with J-ENG and the RD efforts of Daewoo Shipbuilding and Hyundai Mipo Dockyard ([64]; [65]). Looking ahead, future ammonia engines are expected to take the form of dual-fuel and ignition-based technologies, paving the way for wider deployment and a cleaner shipping industry. While challenges remain, the early steps taken by these major players suggest that ammonia could be a key player in the fight against maritime emissions.

2.2.5 Summary

Compared to traditional marine diesel fuel, the potential alternatives suffer from significantly lower energy density, and necpessitating complex storage solutions. Additionally, as illustrated in Figure 2.2, their production often relies on electricity. In facts, these alternative fuels require 2 to 3 times the renewable electricity reference (direct use). Thus, as long as the power demand induced by electric vessels isn't too high, electricity is the best option. However, while directly utilizing renewable electricity seems attractive, a large-scale shift to electric vessels could strain the power grid. Thus, a combination of electricity, hydrogen and methanol appears to be the best solution in the long term.

Alternative fuel	**Volumetric energy density MWh**
Lqiuid hydrogen	2.1
Green methanol	3.3
Green ammonia	3.1

Table 2.2: Alternative fuel requirements compared to 1 [MWh] of renewable energy (direct use)

A recent MariGreen project feasibility study highlights the potential of hydrogen as an energy carrier for IWT, particularly in inland navigation [66]. The Rhine Hydrogen Integration Network of Excellence (RH2INE) further exemplifies this by aiming for ten hydrogen-powered vessels operating between Rotterdam and Duisburg by 2024 [67]. Methanol presents another good option due to its energy density, which is closer to that of marine diesel fuel, and its relatively similar storage requirements. However, considering the current limitations of alternative fuels, electricity emerges as the most viable near-term solution for IWT. Battery swapping technology, as explored in this thesis, offers a promising approach to optimize electric IWT operations. In the long term, a combination of electric, hydrogen, and methanol propulsion systems might offer a more comprehensive solution, but further research and infrastructure development are necessary.

2.3 Battery swapping

The following sections explore the battery swapping process in detail, discussing its primary components, providing a literature review of previous models used for battery swapping, and the relevant methodologies.

2.3.1 Description of the battery swapping process

Two methods are used to replenish exhausted batteries in a battery swapping and charging system: central charging at battery charging stations (BCSs) [68] and local charging at BSSs ([69], [70]). While BSSs offer the advantage of quick service for users, concerns arise regarding service quality and cost-efficiency [69], [70]. Additionally, managing complex BSS infrastructure and ensuring spatial and safety considerations can be challenging [71]. On the other hand, central charging at BCSs eliminates these concerns and empowers grid operators with enhanced flexibility. This approach facilitates optimal load balancing [72] and seamless integration of renewable energy sources [73]. But because BCSs and BSSs are spread out geographically, a reliable logistics infrastructure is essential to moving batteries between them so that their operations can be coordinated. This process creates a closed-loop battery logistics system by transporting charged batteries from BCSs to BSSs and gathering exhausted ones for return. In contrast to a centralised model, the BCSs will be located on-site at battery swapping locations.

This thesis restricts its scope to local charging at BSSs. The decision stems from the logistical challenges and significant battery volume required to manage the transport of hundreds of containers for battery swapping across a wider area. Building on successful small-scale trials, the next step is to implement this strategy by developing and producing, on a larger scale, swappable battery containers. Additionally, infrastructure to facilitate battery changing needs to be planned and built on a larger scale. Docking or swapping stations will be crucial to ensure vessels have continued access to batteries. For large-scale adoption, a flexible and readily scalable technology is crucial, achieved by open access and standardization. Open access allows any vessel equipped with an exchangeable battery to swap it at any docking station. This minimizes downtime and eliminates dependence on individual battery charging speeds. Standardization of batteries and interfaces (connections between batteries, docking stations, and vessels) facilitates easy system expansion.

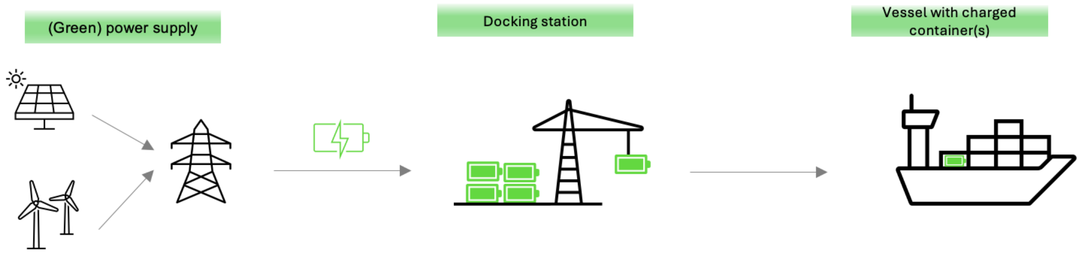

Figure 2.3: BSS system description

The three main parts of the exchangeable battery system are: batteries, docking stations, and vessels, as shown in Figure 2.3. Together, these elements function in a cycle. Docking stations charge the batteries, with a power sale price levied for the electricity. Once charged, the batteries are swapped and used to power the vessels. Docking stations function as battery swap points for electric ships. With the rapid and effective battery changes offered by these stations, vessels can continue their travels with the least amount of downtime. To ensure this system operates effectively, a network of easily accessible charging stations or docking points is crucial. Beyond providing power for charging, docking stations can leverage idle batteries for grid stabilization and participation in energy market applications like Frequency Containment Reserve (FCR). In essence, this means using charged batteries waiting at docking stations to help regulate the electricity grid's balance. However, at this stage of development, not enough vessels would be using this technology to significantly impact the energy grid. Therefore, it had been decided not to account for this benefit in the main body of this thesis. But since it could become a relevant topic in the future, a section has been developed about this in Appendix A.4.

2.3.2 Main components of the battery swapping technology

As mentioned in the previous section, the integration of the battery swapping technology involves a comprehensive examination of three main components: batteries, docking stations, and vessels.

Batteries, proposed by ZES, are modular lithium-ion units housed within 20-foot containers [4]. These batteries provide a number of benefits, such as a high energy density and adaptability to new and retrofitted vessels. However, challenges arise regarding capacity limitations influenced by factors such as temperature and charging regimes. Additionally, power losses and ageing represent significant concerns, potentially diminishing battery efficiency and lifespan over time. Notwithstanding these challenges, it is projected that continuous improvements in battery technology and the achievement of economies of scale will progressively lower costs, improving the system's overall viability and sustainability.

Docking stations serve as critical infrastructure elements in ensuring the seamless availability of charged batteries for vessels. The ZES-designed docking stations are modular and adhere to open standards, allowing for easy replication and scalability across different locations, an example of such stations can be seen in Figure 2.4. The numbers in the figure correspond to the following information:

1. Grid connection station;
2. Power distribution container;

3. Power interface container;

4. Docking platform for placement of ZES-packs;

5. Connector (energy and data communication between ZES-packs and docking station);

6. Charging column for E-vehicles (E-buses, E-trucks, etc.) with standard combined charging system connection (this sixth element is optional).

However, there are still difficulties in choosing the best locations for docking stations when taking into account things like grid connectivity and distance to container terminals. Moreover, there is a close relationship between the design of docking stations and the expenses associated with investment and operation, including the quantity of charging spots and their power capacities. To balance cost-effectiveness and operational efficiency, this calls for an iterative optimisation process.

Figure 2.4: Example of a ZES docking station [4]

Finally, the retrofitting of **vessels** is an essential aspect of integrating exchangeable batteries into existing fleets. Barge operators must pay for this process in a number of ways, including as crew training, possible income loss during retrofitting periods, and the cost of buying and installing connectors. Furthermore, carrying batteries onboard results in a real loss of revenue due to the restricted cargo capacity. The amount of power needed by a vessel varies greatly depending on a number of parameters, including cargo, hull form, speed, and weather. This makes it more difficult to measure power usage precisely and choose the best operating tactics. Operating difficulties are further exacerbated by the requirement for greater time at terminals and maybe additional stops for battery changes or speed modifications.

In conclusion, the successful implementation entails addressing technical challenges associated with battery performance and infrastructure design, optimizing logistical considerations, managing retrofit costs, and ensuring operational efficiency. A sum up can be found in Figure 2.5.

Furthermore, it calls for a cautious balancing act between the goals of environmental sustainability and economic viability. The battery swapping system has the ability to completely transform IWT by combining cutting-edge technology with operational know-how and strategic planning. It does this by providing a more effective and environmentally friendly fuel substitute for conventional fuel-based propulsion systems.

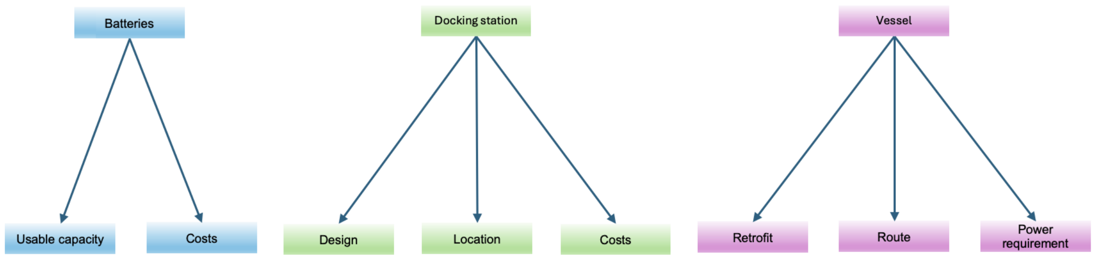

Figure 2.5: Three main components and their challenges

Considering the eight factors illustrated in Figure 2.5, the model has the following implications:

1. Usable capacity: Each battery's maximum usable capacity is included as a fixed parameter in the model. While external factors like temperature aren't considered, the impact of aging on capacity reduction can be analyzed by individually adjusting the maximum usable capacity for each battery.

2. Batteries costs: The cost of acquiring (capital expenditure) for each battery is modeled as an independent variable. This allows to account for differences in battery types and ages. However, the cost of operating the batteries (operational expenditure) is not included in this model.

3. Design: Each DS has parameters that define its number of charging stations, storage spaces, and charging capacity. The number of charging stations and storage units are determined by the size of the terminal.

4. Location: Terminals included in the route, where vessels stop, are identified as potential DS locations. Land availability and grid connection are assumed for each of these locations.

5. DS costs: The Capex are modelled as a parameter for each DS separately. The Opex costs are not considered.

6. Retrofit: The model does not account for the retrofitting costs. However, the revenue loss due to space occupied by battery containers is incorporated into the objective function as a financial penalty.

7. Route: No intermediate stop are allowed in the model.

8. Power requirement: The input of the model defines power requirements for each vessel type at each time step. Changes in speed, wind, or waves are reflected by adjustments to the power requirement at each step. However, speed and external conditions themselves are not directly included as model variables.

2.3.3 Literature review on models of maritime battery swapping

The beginning of this section explores various models proposed in recent studies to optimize the design and operation of BSS in the maritime sector. Interestingly, all four models identified originated from master thesis research (2021-2022), highlighting the nascent stage of this field. Although there isn't much research specifically on battery swapping optimisation for IWT and maritime transportation, this section also dives into models from other modes of transportation to gain insights into their relevance. The choice of buses and trucks is based on the material that is currently accessible and their operational resemblance to IWT vessels (big vehicles, established routes/schedules). While not the main focus, electric cars provide useful goals, limitations, and variables that can be adjusted to IWT with the right adjustments. This combined approach seeks to create the foundation for maritime models by drawing on a variety of transport modes.

IWT

Models based on static optimization: the first three studies present static optimization models, analyzing factors like infrastructure placement and operational costs without explicitly considering time-based dynamics.

- Energy replenishment location model (Haahjem, 2022 [74]): This model builds upon existing location and network optimization frameworks. It considers factors like energy storage capacity, facility location, and network optimization for scenarios with multiple vessels, energy hubs, and charging stations. The objective function minimizes total costs, encompassing voyage expenses, lost opportunity cost due to onboard battery storage space, and service costs associated with replenishing energy. Haahjem further adapts this model for hydrogen fuel, incorporating insulation factors and hydrogen replenishment costs.

- Flow-refueling location with path-based optimization (Driessen, 2022 [2]): This model combines flow-refueling location and path-based static optimization approaches to determine optimal placement of charging stations. Its objective function maximizes the total energy utilized by battery-electric ships within a defined network.

- Battery swapping as a minimum cost flow problem (Odegaard, 2022 [75]): This work proposes a model that views battery swapping as a variant of the minimum cost flow problem. It aims to identify the most cost-effective route through a network by pinpointing ports suitable for battery swapping technology and determining the number of battery modules required for each leg between established stations. The objective function minimizes the combined cost of establishing battery swapping stations and supplying batteries to vessels throughout their journeys.

Model with discrete time integration: the final study incorporates a time dimension into the analysis.

- Mixed-integer linear programming (MILP) model with discrete time (Pina, 2021 [4]): This model utilizes a MILP framework with discrete time steps. Its objective is to determine the optimal number and locations of docking stations, alongside the required number of batteries. The model minimizes the total investment cost associated with batteries and docking stations.

While the aforementioned models provide valuable insights, further research is necessary to develop comprehensive BSS optimization frameworks. Future models could integrate factors like:

- Multi-objectives optimization: current models often focus on minimizing costs or maximizing energy utilization. However, real-world scenarios involve competing objectives.

- Integration with renewable energy sources: exploring the potential of powering BSS with renewable energy sources like solar and wind.

- Grid integration: exploring the potential for BSS to act as a distributed energy storage system. During off-peak hours, batteries can be charged using renewable energy sources. During peak demand periods, excess energy stored in charged batteries can be fed back to the grid, improving grid stability and potentially generating additional revenue for BSS operators.

Other transportation modes

As Zhan et al. (2022) [76] highlight, battery swapping has emerged as a popular solution for efficient refueling of EVs, addressing the time limitations inherent in traditional charging methods. Significant research has explored diverse facets of EV battery swapping, encompassing the establishment of battery-swapping stations, inventory management, optimal charging schedules, assignment problems, and comprehensive analyses involving cost-benefit and pricing considerations ([77], [76]). Determining the ideal location and size for battery-swapping stations has garnered significant research attention. Numerous studies ([78]; [79]; [80]; [81]) have tackled this challenge by leveraging a powerful tool: optimization models. These models, often employing a location-routing problem framework, help in achieving several goals:

- Stations locations: The formulation of electric vehicle (EV) location models draws significant inspiration from early challenges encountered in locating gas stations. These models, grounded in the assumption of refueling demand, can be categorized into node-based, arc-based, and flow-based models [82]. In contrast to the node-based model, the flow-based model posits that refueling demand manifests as traffic flow passing through refueling facilities, aligning more closely with real-world scenarios [83]. Originating from the concept of maximum coverage, the objective of this model is to optimize the location of facilities to maximize the capture of traffic flow.

- Efficient sizing: In the initial phase, determining the number of batteries and chargers becomes practically significant in the context of random vehicles arrivals, variable battery statuses, and unpredictable charging durations ([84], [85]). An optimal approach involves promptly replacing depleted batteries upon arrival at the battery swapping station and simultaneously initiating the charging process. However, the costs associated with chargers and batteries constitute crucial factors influencing battery inventory [86]. To address this, a mathematical model is established, targeting the annual average cost of facilities, while considering the power station's scale and daily battery exchange demand as constraints. The model is solved using the differential evolution method [87]. By optimizing the battery charging mode, a BSS optimization model with the maximum battery inventory is constructed. Subsequently, various charging schemes are devised to minimize battery costs. The specified scale and capacity serve as rigid constraints, while customer waiting time is considered a soft constraint influencing electrical charging station capacity.

Previous research show significant operations advantages from battery swapping for electric buses [88]: swifter refueling minimizes schedule disruption, reduced wait times and lower stress on batteries compared to fast charging potentially extend lifespan, bidirectional power flow in swapping stations enables grid integration by charging during off-peak hours and injecting power during peak demand, optimized schedules and minimized emissions result from buses staying on track, and cost-effectiveness benefits both bus operators and station owners thanks to economies of scale in battery management and potentially lower electricity costs. Regarding the optimization models used in previous studies with electric buses, Kun et al. (2020) [89] use an Integer Linear Program (ILP) and a two-stage Stochastic Program (SP) to optimize the design and operation of a BSS considering battery swapping robots, local charging, and demand uncertainties. Ayad et al. (2021) [90] propose a multi-objective mixed-integer nonlinear programming (MINLP) model for designing fully electrified public bus transit systems using battery swapping. The model optimizes battery capacities, charger capacities, number of chargers and batteries at the BSS, while considering costs, traffic conditions, and energy consumption. Regarding operation and grid integration, El-Taweel et al. (2023) [91] formulate an optimization model for scheduling BSS operations while minimizing costs through exploiting low electricity prices and providing grid ancillary services. The model integrates bus fleet requirements, power distribution network constraints, and battery degradation impact. An investigation of the economic viability of BSSs is made by Kocer et al. (2023) [92], by optimizing their location and size within a microgrid system. The model maximizes revenue by considering swap station services and potential grid regulation services. Finally, Wu et al. (2018) [24] propose a model to minimize BSS costs by optimizing the charging schedule for swapped batteries. The model considers battery usage, charging damage, and electricity cost variations, utilizing a hybrid optimization algorithm.

Recognizing the impact of battery degradation, Deng et al. (2023) [93] develop a mathematical model to minimize the total system cost, including upfront investment and long-term battery wear for electric trucks. The model, formulated as a nonlinear optimization problem, is solved efficiently through a proposed solution procedure. Additionally, a battery charging management strategy is presented to further reduce degradation costs. The study emphasizes the model's ability to capture the trade-off between initial battery purchase cost and long-term degradation, highlighting the value of optimized charging strategies for cost-efficient BSS operation. Furthermore, a study by Liu et al. (2023) [94] investigates the integration of ETs with charging/swapping capabilities and BSSs into an integrated energy system. Focusing on optimizing system operation and minimizing investment costs, it establishes operational models for ETs and BSSs considering flexible charging/discharging options. Further, it proposes an optimized scheduling model utilizing stepped carbon trading. The optimization aims to minimize carbon emissions, improve economic performance, and enhance the system's ability to utilize renewable energy, while meeting the charging and swapping needs of ETs and coordinating various energy demands (electrical, thermal, cooling). This highlights the potential of BSSs to contribute to broader energy system optimization and sustainability goals.

Summary

In the context of IWT in the Netherlands, several key modeling approaches stand out as particularly relevant for optimizing BSS:

1. Mixed-Integer Linear Programming (MILP) models are ideally suited to handle the intricacy of BSS optimisation. Their flexibility in handling various constraints and decision variables makes them effective for this application. Specifically, MILP can optimize both the location of battery swapping stations and the allocation of batteries, ensuring minimal total costs while meeting operational requirements.

2. The operation of battery swapping systems can be simulated over time by incorporating a dynamic approach. This is essential for monitoring battery levels during the course of the system's operation, giving a more thorough insight of its behaviour. Dynamic models can help anticipate challenges and optimize the charging and swapping schedules, which is particularly beneficial in the early stages of developing this technology.

3. While existing studies on IWT have focused on relatively small networks, expanding the model to cover a more extensive and realistic network is necessary. The outputs of the model will be more reliable and applicable to actual marine operations due to this wider scope, which will better reflect real-world conditions.

4. Current models in IWT have not yet incorporated multi-objective optimization, despite its proven effectiveness in other modes of transport, such as electric vehicles. Adopting a multi-objective mixed-integer linear programming (MILP) approach with the following objectives can enhance the model's relevance and utility:

   - Upfront investment: minimize the initial costs associated with establishing battery swapping stations and procuring batteries.
   - Operational costs: optimize operational costs over the long term, ensuring the cost-effectiveness of battery swapping for the BSS operators' (ZES) clients.
   - "At terminal" times: minimize the times, where batteries are at terminal, ensuring that the battery utilization is as high as possible.

To sum up, given the nascent stage of research in battery swapping for maritime transportation, mixed-integer linear programming, coupled with a dynamic simulation of battery levels and a multi-objective framework, provides a robust foundation for optimizing BSS in IWT. Expanding the model to a larger, more realistic network will ensure its applicability to real-world scenarios, ultimately supporting the transition to more sustainable maritime transport in the Netherlands.

2.3.4 Relevant methodologies

Multi-objective optimisation (MOO) is the process of simultaneously optimising several goals, many of which are competing or in conflict. Instead of searching for a single ideal solution, this method seeks to identify a set of options that reflect trade-offs between several objectives [95]. As one of the main advantage, finding a range of acceptable solutions gives the decision-makers a choice of options to pick from [95]. This optimisation technique helps balance many aims and restrictions, making it especially helpful in real-world problems involving several criteria or objectives [96]. Indeed, instead of looking for one "best" answer, it looks for a set of Pareto-optimal, or non-dominated, options, in which no solution outperforms another in terms of all criteria. As a result, the trade-offs involved in decision-making can be better understood [97]. In other words, it enables a more thorough study of the solution space. Multi-objective optimisation does, however, have some disadvantages. The optimisation issue can get more complex when managing a large number of objectives, particularly when restrictions are present [98].Furthermore, determining the relative relevance of each target and outlining the trade-offs between them can also be difficult [97]. Thus, making decisions can occasionally be challenging when dealing with competing goals and striking a balance between them [99].

To address these challenges, various methods and approaches have been proposed. For instance, the weighted sum method in multi-objective optimization allows for the adjustment of weights to reflect the relative inter-relationships of different objectives, providing flexibility to meet the preferences of decision-makers [97]. Progressive multi-objective optimisation is another strategy. This technique enhances the relevance of the solutions obtained by including the preferences of decision makers into the optimisation process [99] . Additionally, through efficient exploration of the solution space, evolutionary algorithms like genetic algorithms and particle swarm optimisation have shown successful in tackling multi-objective optimisation problems ([100]; [101]). Lastly, large-scale problems can effectively use approximation methods to estimate the Pareto front. In fact, a visual representation of the Pareto front (the set of non-dominated solutions in multi-objective optimization) can aid in decision-makers' comprehension of the trade-offs between goals. The multi-objective procedures used in this thesis can be seen in Section 4.5.8.

Chapter 3

Methodology

This section delves into the methodological framework employed in this research. An operations research-based multi-objective optimization model is developed and described in detail. This model strikes a balance between various objectives while considering relevant factors impacting the system.

3.1 Operations research and optimisation

The field of operations research (OR) uses a variety of quantitative and qualitative models to help with decision-making in situations involving complicated problem-solving [102]. It includes structuring, analysing, and resolving issues pertaining to the creation and functioning of intricate human systems through the application of modelling methodologies [103]. Providing a quantitative foundation for executive decision-making, it is also regarded as the scientific method of resolving decision problems [104]. The origins of OR can be found in World War II, when a group of British scientists started making decisions about how best to use war material using science [105]. Moreover, OR is seen as a range of tasks that includes analysing current data, assessing operational procedures, and putting new tactics and technology into practice. Particularly in the context of public health programs, policy, planning, and implementation, OR has grown to be an essential component of practice [106].

OR offers a robust framework for tackling complex decision-making problems. This structured approach, followed in this thesis and outlined by Hillier and Lieberman (2013) [107], comprises six key steps, that can be seen in Figure 3.1:

1. Definition of the problem and gathering of relevant data (see Chapters 1 and 2): Clearly recognising the problem at hand is the first step. This stage establishes the framework for the entire analysis. It requires a thorough comprehension of the goals, limitations, and extent of the issue. It is necessary to collect pertinent data related to the issue from a variety of sources. The information in this data is what powers the next actions.

2. Representation of the problem through a mathematical model (see Chapter 3): The next stage is to create a mathematical model after the problem is well defined and data has been gathered. This model converts intricate interactions into equations and variables in order to provide a simplified picture of the real-world issue. The particulars of the situation must be taken into consideration when selecting the modelling technique. Queuing theory, network optimisation, and linear programming are popular methods.

3. Development of a computer-based procedure for deriving solutions (see Chapter 3): Once the mathematical model has been constructed, the emphasis switches to identifying the best solutions. In this step, the model is analysed and workable solutions are derived by applying computational approaches (see Appendix C). In this procedure, specialised software programs

like solvers and optimisation algorithms are essential. These tools effectively go through the model's intricacies, locating solutions that meet the predetermined goals and limitations.

4. Test and refinement of the model (see Chapters 3 and 4): The resulting solutions are carefully evaluated in this step using data and observations from the real environment. Any differences between the actual behaviour of the system and the predictions made by the model can be found with the use of this critical examination. The model may be improved on the basis of these results by adding more variables, changing some of the parameters, or even using a different modelling strategy. Testing and improving the model iteratively guarantees that it accurately captures the issue and generates dependable solutions.

5. Preparation for the ongoing application of the model (see Chapters 4 and 5): The model must be carefully prepared before being released into the actual world. Making sure the model is easily available and intelligible to stakeholders, especially management, is the task at hand. For those in charge of putting the model's recommendations into practice, this can entail developing user-friendly interfaces, thorough documentation, and training programs. In order to prevent irrational expectations, it is also necessary to properly convey the model's potential drawbacks and limits.

6. Implementation (not done in this thesis): Finally, the moment arrives to put the model into action. This step involves integrating the chosen solution into the real-world operations. This may involve adjusting existing processes, allocating resources, or making strategic decisions based on the model's insights. Close monitoring and ongoing evaluation are crucial during this phase to ensure the solution delivers the desired outcomes and identify any further refinements needed.

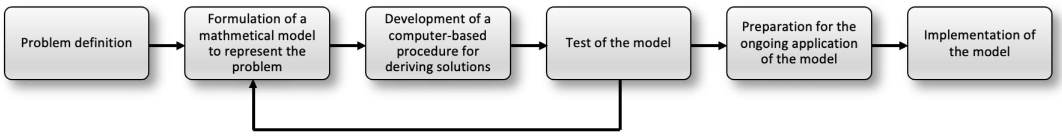

Figure 3.1: Six key steps of OR

3.2 Optimisation of BSS

Depending on the nature of the issue, various tools can be used to optimise BSS activities [108]. Classical combinatorial optimisation algorithms such as integer linear programming offer answers for discrete choice problems with restrictions. Sequential decision-making frameworks are chosen when the best option is dependent on changing factors because they enable judgements to be made at each time step based on available information and potential future developments. Ultimately, multi-objective optimisation algorithms search for solutions that successfully strike a balance between several competing goals (see Section 3.3 for more details).

In this thesis, the primary focus is on the placement of docking stations, determining the number of batteries, and their strategic allocation. However, the complexity of the entire BSS system remains of great interest. Numerous aspects must be carefully studied and aligned to develop an efficient and optimized battery swapping network. Thus, a summary of BSSs' fundamental technological features may be seen in Figure 3.2. These stand for the crucial areas of attention that engineers must optimise and modify while putting a BSS system into place. When several BSSs are spread around a service zone in real-world situations, determining where to put them optimally

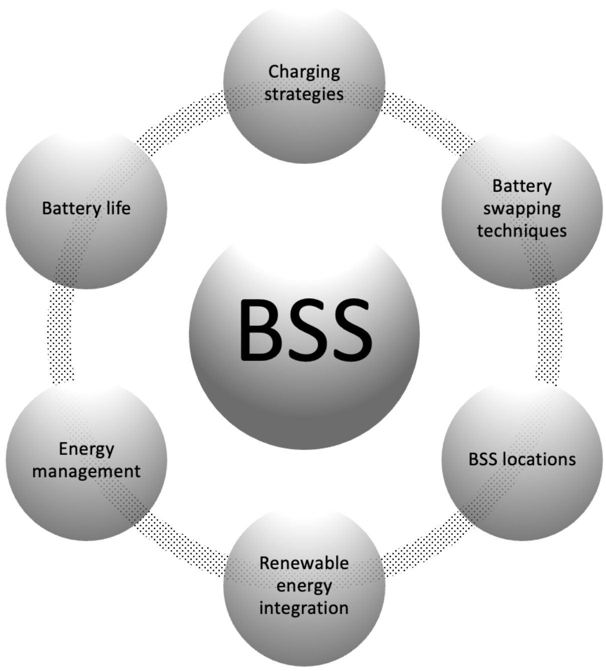

Figure 3.2: Different technical aspects of battery swapping technology

becomes a crucial optimisation issue that needs careful thought. Four major areas offer chances for optimisation from the standpoint of the BSS operator: the use of the electrical grid, charging process management, initial construction planning, and swapping service response. It is important to note that while almost all studies focus on electric vehicles (EVs), many elements can be applied to maritime transport with few or even no modifications. Firstly, according to study by Wang et al. (2020) [109], the location choice should take into account variables including marine traffic, swapping demand, and power grid capacity. Choosing the starting battery count for a new BSS is another crucial component of construction planning, considering the high cost of battery packs [24]. Secondly, models for charging process management that are optimised should be studied. Wu et al. (2017) [110] investigated how these models could dynamically modify the charging power to balance the need for refilled batteries against possible damage from rapid charging. Thirdly, Zhang et al. (2020) [111] argue that some operators could benefit from using optimal service response systems to manage swapping demands due to restricted battery availability and lengthier charging periods compared to conventional techniques. Waiting times might be reduced and swaps could be prioritised with this strategy. With respect to the electrical grid, every BSS must obtain a significant quantity of energy from the power grid [26]. For BSSs, the grid can set up special rules like cumulative electricity amounts [112], immediate power constraints [113], and diverse or time-of-use electricity pricing [24]. Thus, in order to finalize the BSS model, it is imperative to investigate optimisation models for the electrical grid.

3.3 Battery swapping model

The goal of this study is to create an optimisation model that will allow the fleet of interchangeable batteries and the IWT network's docking station locations to be managed together. In order to effectively match batteries with the pre-planned sailing paths of the vessels, the model takes a battery-centric approach, tracking battery location and charge level. The model is formulated as a deterministic optimisation problem, given the well-defined nature of vessel demand, including sailing routes, power requirements, and port sites. Additionally, because modelling vessel locations, power requirements, battery locations, and charge levels is appropriate, a discrete time representation with bi-hourly time steps is employed. To ensure flexibility and scalability as per the requirements, the network representation is simplified. Numbers are used to identify terminals, and at each time step, vessel sailing profiles are modified to reflect the position of the vessel (sailing or at terminals). Because of this, a particular node-arc network topology is no longer necessary, making it easier to modify and expand the model to accommodate various network topologies. For the purpose of determining the ideal number of batteries, docking station locations, and battery capacity to successfully supply the vessels' electrical power consumption, this thesis presents a mixed-integer linear programming (MILP) model with discrete time steps. Formulating the problem using MILP offers the advantage of guaranteeing (sub-)optimal solutions since all objective functions and constraints can be expressed as linear equations. The commercial solver Gurobi is employed to solve the developed MILP model.

In Figure 3.3, a general overview of the model with the inputs and outputs is shown.

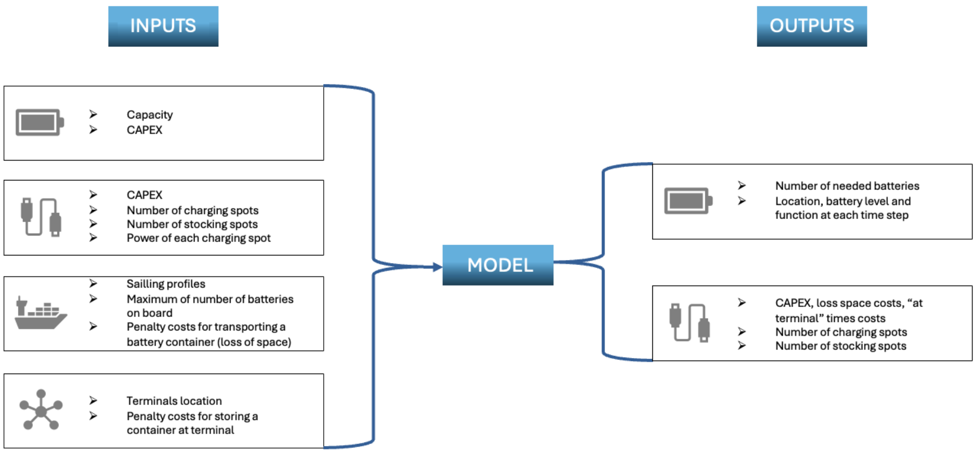

Figure 3.3: Model overview

3.3.1 Model requirements

The key model requirements for this research are:

- *Multi-objective optimization*: The model should be equipped to handle multiple objectives simultaneously.
- *Scalability*: The model should be designed to scale efficiently. This guarantees its application in the future to a larger network segment that includes more vessels, terminals, and maybe smaller time increments for finer-grained analysis.
- *Time scale*: All of the selected vessels' operational routes within the network segment should be represented by the model.
- *Fleet and route flexibility*: The model needs to be adaptable to analyze different fleet compositions. This includes allowing for variations in vessels types, routes, and power consumption.
- *Scenario analysis*: In order to evaluate the effects of numerous aspects on the best logistics design, the model should enable the exploration of multiple scenarios. This can involve things like fluctuations in battery capacity, the ability of docking stations to charge and stock batteries, or the availability of docking on vessels.

3.3.2 Model assumptions

The following assumptions are made to simplify the model and achieve the highest computational efficiency possible:

Battery characteristics

- *Lithium-ion technology*: The model assumes a homogeneous fleet of lithium-ion batteries. This excludes complexities of managing different battery technologies like hydrogen fuel cells.
- *Simplified battery aging*: Battery ageing is not explicitly considered because of its complexity and the short timescale represented (48 hours). Different maximum usable battery capacities for various battery types can, nevertheless, be used to indirectly capture power losses and fluctuation caused by use, temperature, and ageing.
- *Average usable capacity*: An average usable capacity value is used in the model to represent battery capacity variability caused by variables such as temperature and charging schedules. To take different ageing and charging conditions into consideration, different battery capacities can be modelled.
- *Charge before deployment*: Batteries are assumed to be fully charged (i.e. battery level of 100%) before being placed on a vessel.
- *Minimum battery level*: A minimum battery level of 5% at any time is set to avoid full discharge and maintain a safety margin for unforeseen power demands.

Docking Stations

- *Limited locations*: Docking station locations are restricted to terminals where vessels stop during their routes. Pre-identified terminals with guaranteed space and grid connection are assumed.

Vessels

- *Real-world sailing profiles*: The model uses real world sailing profiles (routes and power consumption) provided by EuRIS and Rijkswaterstaat.
- *Indirect speed and distance*: Vessel speeds and distances are not explicitly modeled. Energy consumption per time step in the sailing profiles can be adjusted to indirectly account for these factors.
- *Quick battery swapping*: The time a vessel stops at a terminal is assumed sufficient for battery loading or unloading. No additional time is factored in for swapping batteries.

Other considerations

- *Limited cost scope*: Only capital expenditures for batteries and docking stations are considered. Some operational costs are included via the space lost and at terminal times. However, in a more realistic scenario, additional costs should be taken into account, such as electricity costs for charging the batteries or labor costs for operating and maintaining the batteries and docking stations.
- Simplified vessel retrofit: Costs for vessel retrofit are not included.
- *Revenue losses*: The revenue losses due to reduced cargo capacity to accommodate batteries are included in the model (see Section 4.5.5 for detailed calculations), and based on the transportation costs of 1 battery container from terminal A to terminal B.

- *100% service level*: A 100% service level is assumed, meaning all vessel power demands must be met.
- *Loaded vs unloaded*: The weight, thus speed, of the vessels are different when loaded or unloaded. This is taken into account in section 4.5.4.

3.3.3 Model simplifications

The key model simplifications are listed below. It is important to mention that these simplifications are necessary to achieve a balance between model complexity and computational feasibility. The selected simplifications enable for effective analysis in a reasonable amount of time while concentrating on capturing the essential elements of the issue. The observed results can still offer insightful design information for the battery logistics system, and the model can be further improved in the future to take into account more intricate details.

- Time scale and complexity: Due to running time limitations, the model focuses on the four most common vessel types identified in the study and 14 sailing vessels in total. This reduces the complexity of simulating a larger fleet. Furthermore, the sailing profiles will be represented using a maximum of 24 time steps (of 2 hours each). This captures the essential aspects of routes and power consumption without excessive detail.
- Battery management: For simplicity, batteries are assumed to charge and discharge linearly over time. Moreover, if a vessel has multiple batteries, only one is used to power the vessel in each time step.
- Battery representation: Variations in battery age, size, energy losses, and degradation are indirectly captured by using different maximum capacities for different battery types.
- Fixed sailing conditions: The model assumes that external factors like sailing speed, and weather do not influence the vessels' sailing profiles (sailing times and power consumption).

3.3.4 Mathematical formulation

The notation used for this mathematical formulation is provided in Table 3.1.

Table 3.1: Mathematical model

Sets and indices		
V	Set of vessels	$v \in V$
B	Set of batteries	$b \in B$
T	Set of battery swapping terminals	$t \in T$
P	Set of time periods p	$p \in P$
Parameters		
Batteries		
cb_b	Capex of battery b	[€]
cap_b	Maximum capacity of battery b	[kWh]
mlv	Minimum battery level charge required to be used in vessel	[%]
mlb	Safe operating range for the battery to prevent full discharge	[%]
Terminals		
cds_t	Capex of one charging station at terminal t	[€]
cht_t	Number of charging points of a DS installed at terminal t	[unit]
$maxDS_t$	Number of spots of a DS installed at terminal t	[unit]
pw_t	Power of each charging spot t	[kW]
Vessels		
chv_v	Number of batteries that can be fitted in vessel v	[unit]
$sp_{v,t,p}$	Sailing route $\begin{cases} 1 & \text{if vessel } v \text{ is at terminal } t \text{ at time } p \\ 0 & \text{otherwise} \end{cases}$	
$pen_{v,p}$	Costs for transporting a battery container on vessel v at time period p	[€]
$penbis_p$	Costs for storing a container at a terminal at time period p	[€]
$scaler_1$	Converter of operational costs into long-term costs, for the loss of space	
$scaler_2$	Converter of operational costs into long-term costs, for the time at terminal	
Others		
M_1	A large number	[-]
M_2	A small number	[-]
Initial values		
$Lb_{b,0}$	Battery level of battery b at start of the horizon ($p = 0$)	
$Ut_{b,t,0}$	$\begin{cases} 1 & \text{if battery } b \text{ is at terminal } t \text{ at time } p = 0 \\ 0 & \text{otherwise} \end{cases}$	
$Uv_{b,v,0}$	$\begin{cases} 1 & \text{if battery } b \text{ is on vessel } v \text{ at } p = 0 \\ 0 & \text{otherwise} \end{cases}$	
$k0_{b,t,0}$	$\begin{cases} 1 & \text{if battery } b \text{ is at terminal } t \text{ and is being charged at } p = 0 \\ 0 & \text{otherwise} \end{cases}$	
$m0_{b,v,0}$	$\begin{cases} 1 & \text{if battery } b \text{ is on vessel } v \text{ and the battery is being used at } p = 0 \\ 0 & \text{otherwise} \end{cases}$	

Variables	
n_b	$\begin{cases} 1 & \text{if battery } b \text{ is being used} \\ 0 & \text{otherwise} \end{cases}$
u_t	$\begin{cases} 1 & \text{if terminal } t \text{ is being used as DS} \\ 0 & \text{otherwise} \end{cases}$
$x_{b,t,p}$	$\begin{cases} 1 & \text{if battery } b \text{ is at terminal } t \text{ at time period } p \\ 0 & \text{otherwise} \end{cases}$
$y_{b,v,p}$	$\begin{cases} 1 & \text{if battery } b \text{ is on vessel } v \text{ at time period } p \\ 0 & \text{otherwise} \end{cases}$
$k_{b,t,p}$	$\begin{cases} 1 & \text{if battery } b \text{ is being charged at terminal } t \text{ at time period } p \\ 0 & \text{otherwise} \end{cases}$
$m_{b,v,p}$	$\begin{cases} 1 & \text{if battery } b \text{ is providing energy to vessel } v \text{ at time period } p \\ 0 & \text{otherwise} \end{cases}$
$l_{b,p}$	Level of battery b at time period p

A visual representation of the variables can be seen in Figure 3.4.

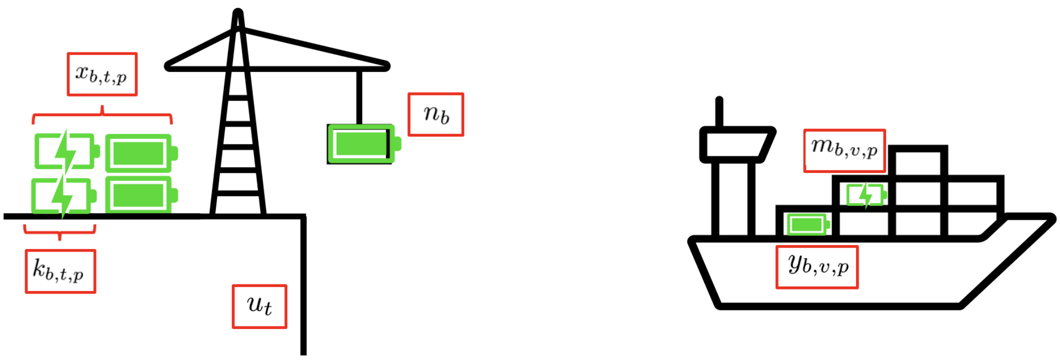

Figure 3.4: Variables and their meaning

The mathematical formulation then follows as:

$$\min \quad \sum_{b \in B} n_b \cdot cb_b + \sum_{t \in T} u_t \cdot cds_t \tag{3.1}$$

$$\min \quad \sum_{b \in B} \sum_{v \in V} \sum_{p \in P^*} y_{b,v,p} \cdot pen_{v,p} \cdot scaler_1 \tag{3.2}$$

$$\min \quad \sum_{b \in B} \sum_{t \in T} \sum_{p \in P^*} x_{b,t,p} \cdot penbis_t \cdot scaler_2 \tag{3.3}$$

Subject to:

$$n_b \cdot M_1 \geq \sum_{v \in V} \sum_{p \in P^*} m_{b,v,p} \qquad \forall b \in B \tag{3.4}$$

$$u_t \cdot M_1 \geq \sum_{b \in B} \sum_{p \in P^*} x_{b,t,p} \qquad \forall t \in T \tag{3.5}$$

$$1 \geq \sum_{b \in B} m_{b,v,p} \geq pc_{v,p} \cdot M_2 \qquad \forall v \in V, \forall p \in P^* \tag{3.6}$$

$$cht_t \geq \sum_{b \in B} k_{b,t,p} \geq 0 \qquad \forall t \in T, \forall p \in P^* \tag{3.7}$$

$$l_{b,p} \leq l_{b,p-1} + \sum_{t \in T} (pw_t \cdot k_{b,t,p}) - \sum_{v \in V} (pc_{v,p} \cdot m_{b,v,p}) \qquad \forall b \in B, \forall p \in P^* \tag{3.8}$$

$$cap_b \geq l_{b,p} \geq cap_b \cdot mlb \qquad \forall b \in B, \forall p \in P^* \tag{3.9}$$

$$(y_{b,v,p} - y_{b,v,p-1}) \cdot mlv \cdot cap_b \leq l_{b,p} \qquad \forall b \in B, \forall v \in V, \forall p \in P^* \tag{3.10}$$

$$\sum_{t \in T} x_{b,t,p} + \sum_{v \in V} y_{b,v,p} = n_b \qquad \forall b \in B, \forall p \in P^* \tag{3.11}$$

$$x_{b,t,p} \leq x_{b,t,p-1} + \sum_{v \in V} (y_{b,v,p-1} \cdot sp_{v,t,p}) \qquad \forall b \in B, \forall t \in T, \forall p \in P^* \tag{3.12}$$

$$y_{b,v,p} \leq y_{b,v,p-1} + \sum_{t \in T} (x_{b,t,p-1} \cdot sp_{v,t,p-1}) \qquad \forall b \in B, \forall v \in V, \forall p \in P^* \tag{3.13}$$

$$\sum_{b \in B} x_{b,t,p} \leq maxDS_t \qquad \forall t \in T, \forall p \in P^* \tag{3.14}$$

$$\sum_{b \in B} y_{b,v,p} \leq chv_v \qquad \forall v \in V, \forall p \in P^* \tag{3.15}$$

$$k_{b,t,p} \leq x_{b,t,p} \qquad \forall b \in B, \forall t \in T, \forall p \in P \tag{3.16}$$

$$m_{b,v,p} \leq y_{b,v,p} \qquad \forall b \in B, \forall v \in V, \forall p \in P \tag{3.17}$$

$$n_b \in \{0,1\} \qquad \forall b \in B \tag{3.18}$$

$$u_t \in \{0,1\} \qquad \forall t \in T, \forall v \in V \tag{3.19}$$

$$x_{b,t,p}, k_{b,t,p} \in \{0,1\} \qquad \forall b \in B, \forall t \in T, \forall p \in P \tag{3.20}$$

$$y_{b,v,p}, m_{b,v,p} \in \{0,1\} \qquad \forall b \in B, \forall v \in V, \forall p \in P \tag{3.21}$$

$$l_{b,p} \in \mathbb{R}_+ \qquad \forall b \in B, \forall p \in p \tag{3.22}$$

With the following initial values:

$$x_{b,t,0} = Ub_{b,t,0} * n_b \qquad \forall b \in B, \forall t \in T \qquad (3.23)$$

$$y_{b,v,0} = Uv_{b,v,0} * n_b \qquad \forall b \in B, \forall v \in V \qquad (3.24)$$

$$k_{b,t,0} = k0_{b,t,0} * n_b \qquad \forall b \in B, \forall t \in T \qquad (3.25)$$

$$m_{b,v,0} = m0_{b,v,0} * n_b \qquad \forall b \in B, \forall v \in V \qquad (3.26)$$

$$l_{b,0} = L_{b,0} * n_b \qquad \forall b \in B \qquad (3.27)$$

As a reminder, the objective functions are developed from the perspective of a battery and swapping station operators (such as ZES), see Figure 3.5. The model considers three objective functions:

1. Minimizing costs (3.1): This involves reducing the initial investment (capital expenditure) required for batteries and DS at each terminal.
2. Minimizing the space lost (thus profit loss) of the barge operators (3.2): This objective function is designed for ZES to minimize their impact on their clients, the barge operators, to prevent losing them as customers. A scalar is applied to the operational costs to reflect a long-term vision, ensuring that this objective function accounts for long-term expenditure, such as the costs in the first objective function.
3. Minimizing time at terminal ("at terminal")(3.3): This objective aims to minimize the total time batteries spend at terminals, encompassing both charging and storage periods. By reducing terminal dwell time, this objective contributes to optimizing battery usage and overall system efficiency.

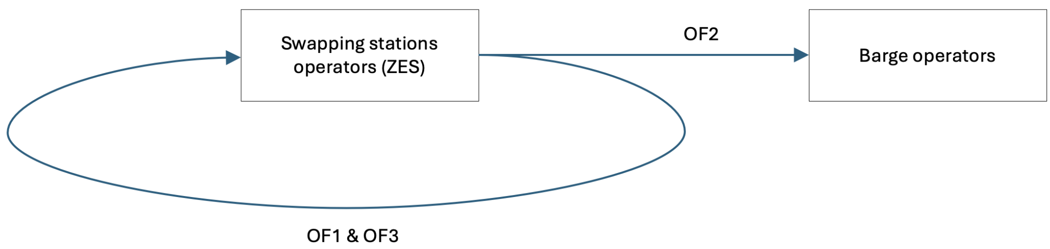

Figure 3.5: Graphical representation of the objective functions

The distinctions of the proposed model with respect to the literature [4] are highlighted in orange. The batteries and terminals' utilisations are determined by constraints 3.4 and 3.5. Constraint 3.6 prohibits a vessel from using more than one battery at the same time by requiring that a single battery power the vessel throughout each time step. Constraint 3.7 guarantees that the number of charging containers does not surpass the available charging points at each terminal for each time step. The battery charge level is controlled at each time step by constraint 3.8. This limitation guarantees that the power needs of the vessel are fulfilled continuously during the operation. Constraint 3.9 requires that the battery level stay between a predetermined minimum level that acts as a safety margin and the battery's full capacity in order to guarantee safe operation and prevent total discharge. Additionally, this requirement ensures that battery stays non-negative. Batteries must satisfy a minimal charge level in order to be put aboard boats, according to constraint 3.10.

The location of the batteries is limited to the vessel or specific terminals by constraint 3.11. The paths of the vessels to the batteries are matched by constraints 3.12 and 3.13, preventing a battery that is not aboard a vessel from moving within the network. Constraint 3.14 ensures that the number of containers at each DS does not exceed the number of spots that are offered by the DS. Similarly, constraint 3.15 ensures that the number of batteries containers on each vessel does not exceed the maximum allowed number. Constraint 3.16 and constraint 3.17 force the battery to be at a docking station to be charged and to be on a vessel to provide it with energy. Constraints 3.18, 3.19, 3.20, and 3.21 define the binary variables. Finally, constraint 3.22 defines the positive real variable. Constraints 3.23, 3.24, 3.25, 3.26, and 3.27 represent the initial values at the first time step (p =0).

3.4 Model verification

To ensure the model's functionality, a series of scenario analyses were conducted. This entailed methodically changing some parameters after beginning with a baseline model configuration. The logical consistency of the generated solutions was then evaluated. Firstly, the most straightforward verification is to check whether this model produces the same results under identical conditions with the existing literature [4]. This verification has been done and confirmed. Then, for further verifications, smaller-scale scenarios were created for verification due to computational time constraints. It contains 3 docking stations, as well as 3 vessels. A visual representation of the network structure used for the verification is provided in Figure 3.6.

Figure 3.6: Network for verification

The routes and frequencies used for the verification can be seen in Figure 3.7.

	City 1	City 2	Time	Distance	Ship type*	Daily trips	Rounded	Trips for 43 days**
1	Antwerp	Rotterdam	11h33	127km	C3b	4.74	5	204
3	Moerdijk	Rotterdam	3h15	35km	C3b	1.93	2	83

Figure 3.7: Routes and frequencies for verification

The results of the 5 other verification tests can be see in Table 3.2.

Test	Variable	Value	#DS	# batteries	batteries/V	DS/V	Capex/V [€]	T1	T2	T3
1	Sailing profiles	no movement	0	0	0	0	0			
2	maxDS	1 ($<$ initial values)	unfeasible	unfeasible	unfeasible	unfeasible	unfeasible	-	-	-
3	cap	100000	0	3	1	0	955.555			
4	cht	0 for all	unfeasible	unfeasible	unfeasible	unfeasible	unfeasible	-	-	-
5	DS costs	11350000								
	cap	5000	0	6	2	0	1910000			

Table 3.2: Model verifications

1. The first test case involves modifying the sailing route so that the vessels remain stationary at all times. Since the vessels aren't moving, it would be logically expected that the model finds a solution that requires no battery or DS, resulting in zero cost. And indeed, the model delivers exactly that outcome.

2. The second test involved initializing each docking station with two batteries at time zero (p $=0$) while limiting the maximum number of available spots to just one per station. This scenario inherently leads to an unfeasible model, as evidenced by the model's output.

3. The third test focuses on significantly increasing battery capacity. This allows each vessel to operate throughout all time steps using a single battery, eliminating the need for battery swaps or charging stations. Consequently, the total number of batteries required is equal to the number of vessels (three in this case). This approach also eliminates the need for docking stations, as reflected in the model's results.

4. The fourth test removes charging spots from all three docking stations. Consequently, the model should identify this scenario as infeasible because vessels must swap batteries within 24 hours. This expectation aligns with the observed outcome.

5. The last verification scenario combines high capacity requirements with high docking station installation costs. In this case, a single battery cannot provide enough power for the entire trip, necessitating the use of two batteries. However, under this scenario, DS stations are not utilized.

Thus, the model has been successfully verified: the model's internal consistency and adherence to the intended design was verified. The next chapter delves into the model's implementation for the chosen case study and numerical experiments. This implementation will showcase the model's practical application and its ability to generate valuable insights within the specific context.

Chapter 4

Case study and numerical experiments

There are numerous software choices available for creating and using MILP models. Python was the programming language used in this study, and Visual Studio Code served as the integrated development environment for running the code. Gurobi was also chosen as the optimisation problem's commercial solver. The model's binary variable count significantly impacts computational time during optimization. Despite Gurobi's pre-solver capabilities that reduce problem size, solving instances with more than four vessels and 24 time steps proved computationally expensive. To address part of this limitation, access to more powerful computing resources from TU Delft was necessary. Examples of the input file can be found in Appendix B. This section dives into the chosen case study, presenting the results obtained through the conducted numerical experiments.

4.1 Network

This research focuses on a specific section of the Dutch IWT network. The data used to define this network section is derived from Rijkswaterstaat, the executive agency of the dutch ministry of infrastructure and water management. The end network contains 13 ports, that can potentially be DS.

Time Period: The analysis period covers a timeframe from March 1st to April 12th, 2024.

Network Scope:

- *Routes*: The network focuses on the twelve most frequently used direct routes (both directions) within the designated section. These routes represent A-to-B journeys without intermediate stops.
- *Ports*: The network encompasses thirteen ports, eleven located within the Netherlands, one in Germany, and one in Belgium. This inclusion ensures the network reflects cargo flow entering and exiting the Netherlands through its bordering countries.

A visual representation of the final network structure is provided in Figure 4.1. As evident from the visualization, the network captures a significant portion of the Dutch IWT network, highlighting the most heavily utilized waterways.

4.2 Sailing profiles

The route data for this network section is derived from Rijkswaterstaat, covering the same period from March 1st to April 12th, 2024. This data includes the daily number of trips for each route,

Rotterdam	T1
Antwerp	T2
Moerdijk	T3
Amsterdam	T4
Alphen	T5
Wanssum	T6
Nijmegen	T7
Bergen	T8
Alblasserdam	T9
Duisburg	T10
Oosterhout	T11
Tilburg	T12
Veghel	T13

Figure 4.1: Graphical representation of the selected network

considering both directions (as visualized in Figure 4.2). To obtain realistic sailing times and distances for each route, data was sourced from Eurisportal, a platform that provides live sailing information on chosen routes. The vessel type assigned to each route reflects the most commonly used vessel type on that specific route within the analyzed timeframe (March 1st to April 12th, 2024). This approach ensures the model accounts for the typical vessel types operating on different routes within the network.

	City 1	City 2	Time	Distance	Ship type*	Daily trips	Rounded	Trips for 43 days**
1	Antwerp	Rotterdam	11h33	127km	C3b	4.74	5	204
2	Amsterdam	Rotterdam	9h00	113km	M8	3.21	3	138
3	Alphen	Rotterdam	5h10	35km	M8	2.72	3	117
4	Nijmegen	Wanssum	3h43	43km	M8	2.19	2	94
5	Moerdijk	Rotterdam	3h15	35km	C3b	1.93	2	83
6	Duisburg	Rotterdam	17h03	222km	M11	2.91	3	125
7	Oosterhout	Tilburg	2-3h	22km	M8	2.81	3	121
8	Rotterdam	Veghel	10h28	105km	M6	2.72	3	117
9	Moerdijk	Oosterhout	1h49	24km	M8	2.05	2	88
10	Bergen	Rotterdam	6h52	83km	M8	1.98	2	85
11	Alblasserdam	Nijmegen	7h26	97km	M8	1.86	2	80
12	Alblasserdam	Rotterdam	1h29	15km	M8	1.37	1	59

* Most used vessel types for this route
** Data from March 1st to April 12th

Figure 4.2: Routes and frequencies for the selected network

To represent vessel activity within the network, sailing profiles were constructed for each route. These profiles encompass a two-day timeframe, effectively doubling the frequency of the actual routes identified in the data. Due to limitations in computational resources, vessel selection during route construction aimed to minimize the total number of vessels required to service all routes. The optimization process identified a fleet of fourteen vessels to efficiently cover the designated network section. This fleet composition is further described in the next subsection.

4.3 Vessels

As mentioned earlier, this research focuses on four distinct vessel types within the IWT network, with a total of 14 vessels. These types are differentiated by their time-dependent power requirements while sailing. To estimate the power consumption for each vessel type, an interpolation method was employed, based on the literature [4]. This interpolation leverages the maximum load capacity of each vessel type to determine its power requirements at each time step during its journey. The power consumption is per time step (i.e. two hours of sailing).

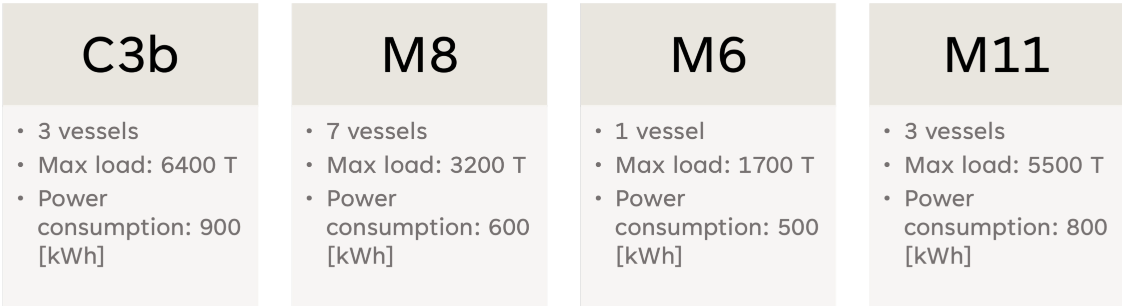

Figure 4.3: Vessels types with their characteristics

4.4 Base case

The base case scenario has the following parameters and initial characteristics:

- One objective function: the installation costs of the DS and batteries.
- Capex of battery: 955.500€.
- Maximum capacity of battery: 2900 kWh.
- Minimum battery level charge required to be used in vessel: 100%.
- Safe operating range for the battery to prevent full discharge: 10%.
- Capex of one charging station at terminal t: 1.350.000€.
- Number of charging points of a DS installed at terminal: between 4 and 2, depending on the size and importance of each terminal.
- Number of spots of a DS installed at terminal: between 8 and 4, depending on the size and importance of each terminal.
- Power of each charging spot: 1000 kW.
- Battery levels at start of period: 100%.
- Number of batteries at each terminal at start of period: 3 batteries.
- Number of batteries charging at each terminal at start of period: 0.

- Number of batteries on each vessel at start of period: 3.
- Number of batteries providing energy on each vessel at start of period: 1.
- All vessels are fully loaded at every time steps.

4.5 Results

This section presents the findings of the computational model. First, the results for the base case scenario are presented. Subsequently, a sensitivity analysis is conducted, in order to assess the influence of three key input parameters: battery capacity, battery costs, and the number of battery storage spots available at terminals. Thereafter, the impact of loaded or unloaded vessels on the model's outputs is studied. Following this, the space inefficiency caused by transporting batteries on board vessels is taken into account and studied. Finally, the results section is concluded with an analysis considering the multi-objective perspective of the study. The results are accompanied by a consistent set of operational metrics. The names and purposes of these metrics are detailed in Table 4.1. This model prioritizes batteries, so specific origin-destination (OD) pairs won't be directly analyzed. The design centers on the batteries themselves, leading to a global system perspective. Due to the model's structure, examining OD pairs becomes complex. Indeed, vessels can travel across various OD pairs within the two-day timeframe. Since the results are battery-oriented, the ability to control or precisely visualize specific OD pairs is limited.

Metric/output	Description
Number of vessels	The total count of vessels involved in the scenario. Impacts the scale of operations and resource needs.
Objective function	The objective function(s) being optimized.
Number of batteries	Total number of batteries used. Critical for understanding energy storage capacity and costs associated.
Number of docking stations	Total count of docking stations (DS) required. Important for infrastructure planning and cost estimation.
Locations of the DS	Specific locations of docking stations. Important for geographical distribution and logistics.
Total capex [€]	Total investment required for economic assessment. It depends on which objective functions are taken into account.
Number of batteries per vessel	Average number of batteries per vessel. It indicates the distribution of resources and operational strategy.
Number of DS per vessel	Average number of docking stations per vessel. It evaluates accessibility and recharging convenience.
Shared batteries	Number of batteries shared among vessels. Important for resource utilization and efficiency.
Costs per vessel [€/vessel]	Average cost per vessel. It includes operational and investment costs for economic assessment.
Optimality gap [%]	Difference between the current solution and the best theoretical bound. As a measure of optimization efficiency.

Table 4.1: Dictionary of operational metrics (output): definitions and significance of each output metric used in the analysis.

To ensure consistency in the analysis, a ***hypothesis*** is formulated for each experiment. This hypothesis is then tested against the results and thoroughly analyzed. Finally, an ***Managerial***

insights: (recommendation) is provided, summarizing the key takeaways of each experiment. This recommendation is written to be comprehensible and practical for a DS and battery operator, such as ZES.

4.5.1 Base case scenario

The base scenario has the input given in Section 4.4, and its only objective function is the total Capex (see equation 3.1 in the model). The key results can be seen in Table 4.2.

	Scenario
Number of vessels	14
Objective function	Investment costs
Number of batteries	49
Number of DS (DS)	6
Locations of the DS	T1, T2, T3, T4, T9, T10
Total capex [€]	54,919,500
Number of batteries per vessel	3.5
Number of DS per vessel	0.428
Shared batteries	15 batteries shared by 2 vessels
Costs per vessel [€/vessel]	3,922,281
Optimality gap [%]	42.7

Table 4.2: Detailed breakdown of the base case scenario results

The base scenario considers a fleet of 14 vessels with a single objective function. This simplicity in objective function allows for a focused optimization, prioritizing investment cost minimization. As can be seen in Table 4.2, a total of 49 batteries are required to support the fleet, which results in an average of 3.5 batteries per vessel. Six DS are established at specific locations (T1, T2, T3, T4, T9, and T10). The total capital expenditure is 54,919,500€. This includes the costs associated with procuring the batteries, and setting up the DS. Thus, the average cost per vessel, calculated as 3,922,281€reflects the significant upfront investment required to transition to a battery-swapping system. While the average cost per vessel is high, it is important to consider the long-term operational savings and environmental benefits of transitioning to a battery swapping system. The reduction in fuel costs and emissions over time could offset the initial investment. With 0.428 DS per vessel, it is evident that the DS are shared resources, strategically placed to serve multiple vessels. This efficient allocation reduces the need for one-to-one docking station-to-vessel correspondence. Shared batteries are also part of the strategy, with 15 batteries being shared by two vessels. This sharing mechanism optimizes battery usage and reduces the total number of batteries needed, thereby lowering costs. The optimality gap of 42.7% would indicate a potential difference between the current solution and the best theoretical bound. In other words, it is not possible to guarantee that the solution is optimal yet in practice it might be already very close to the optimal solution. It is important to note that the complexity and large size of the model, due to the numerous variables, high number of vessels, and extensive network, limits the precision that can be achieved. The number of computational cores available for solving the model is insufficient, causing the optimization process to stall around this optimality gap. Despite this, the optimal function value has stabilized, implying that the solution may be close to the actual optimum, but the model struggles to prove its optimality definitively. These remarks hold for the whole results section.

Figure 4.4: Locations of the docking stations in the base case scenario (in red)

A visual representation of the docking stations can be seen in Figure 4.4. The DS for the base case are located in Rotterdam (T1), Antwerp (T2), Moerdijk (T3), Amsterdam (T4), Alblasserdam (T9), and Duisburg (T10). Rotterdam, Moerdijk, and Alblasserdam are key locations where many vessels routes cross and vessels stop, making it logical to have DS there. These DS can also be seen in a network representation made by ZES (see Figure 4.5), where these three terminals are key nodes. Antwerp and Duisburg also warrant DS due to the long trips to these destinations within the network and the high frequency of trips to and from these locations. Despite the potential benefits of expanding the network to connect more cities to these two terminals, it remains logical to establish DS at there, given their significant roles within the European inland waterway network. While Amsterdam may not be a central hub in the network, it remains a significant draw for vessels due to its own unique attractions. This ongoing vessel traffic justifies the presence of a DS in Amsterdam. With these remarks, the model has been successfully validated. Indeed, the model's accuracy in representing the real-world system for the purposes of this study is confirmed.

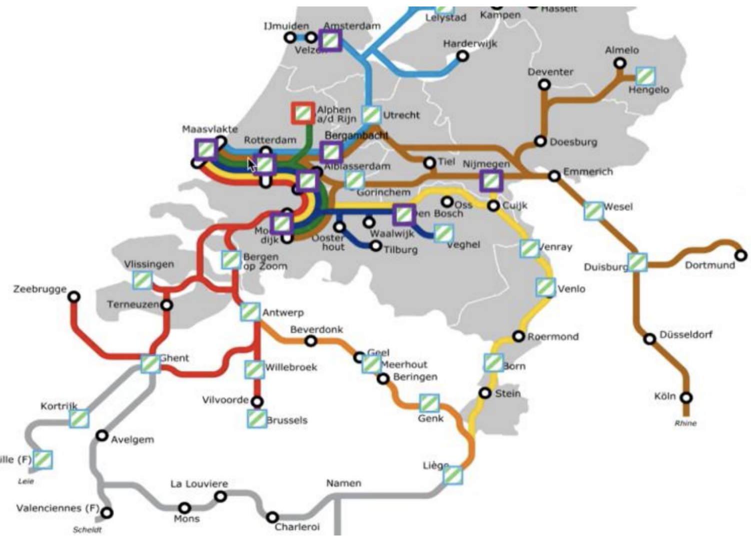

Figure 4.5: Network representation by ZES

4.5.2 Influence of battery capacities, costs and available spots at DS

This section aims to provide a sensitivity analysis on the impact of battery capacity, battery costs, and the available number of storage spots at the docking station. These three aspects are studied separately to understand their individual effects on the overall system configuration.

Battery capacities

The hypothesis on the impact of battery capacities is the following:

"Higher battery capacity leads to a reduction in the number of batteries and DS used."

The rationale behind this hypothesis is that higher capacity batteries can store more energy, allowing vessels to travel longer distances without needing frequent recharges. Consequently, fewer batteries are required to meet the energy demands of the fleet. Additionally, with longer travel capabilities, vessels can rely on fewer, strategically located DS. These docking stations are typically situated at key terminals within the network, which act as hubs. By centralizing recharging points at these critical locations, the system can operate efficiently with a reduced number of DS, optimizing both the infrastructure and operational costs.

The results presented in Table 4.3 investigates the influence of battery capacity on the metrics presented in Table 4.1. The table explores five different scenarios with battery capacities ranging from 2,700 to 10,000 kWh (the base case scenario is indicated by a salmon color in the "Battery capacity" row). The results highlight how changes in battery capacity affect the overall system configuration and costs. Consistently, across all scenarios, the number of vessels and the number of objective functions remain the same at 14 and 1 (investment costs), respectively. This stability ensures that the comparison focuses solely on the impact of varying battery capacities.

	Scenarios				
Battery capacity [kWh]	2,700	2,900	3,200	4,000	10,000
Number of vessels	14	14	14	14	14
Objective function	Invest.	Invest.	Invest.	Invest.	Invest.
Number of batteries	49	49	47	37	22
Number of DS	7	6	6	3	1
Locations of the DS	T1, T2, T3, T4, T9, T10, T13	T1, T2, T3, T4, T9, T10	T1, T2, T3, T4, T10, T12	T1 T2 T10	T1
Total capex [€]	56,269,500	54,919,500	53,008,500	39,403,500	23,371,000
Batteries per vessel	3.5	3.5	3.357	2.643	1.571
DS per vessel	0.5	0.428	0.428	0.214	0.071
Shared batteries	13 by 2 V	15 by 2 V	17 by 2 V	11 by 2 V	6 by 2 V
Costs per vessel [€]	4,019,250	3,922,281	3,786,321	2,814,536	1,597,929
Optimality gap [%]	44.6	42.7	45.5	37.4	21.3

Table 4.3: Detailed breakdown of the influence of different battery capacities on various operational metrics

As anticipated by the hypothesis, as battery capacity increases, the number of batteries required decreases significantly. For instance, with a capacity of 2,700 kWh, 49 batteries are needed, whereas only 22 batteries are required for a capacity of 10,000 kWh. Because each higher-capacity battery can store more energy, fewer batteries are needed to meet the same total energy demand. Thus, vessels equipped with higher capacity batteries can operate for longer periods before needing to swap or recharge their batteries. This reduces the frequency with which they need to visit DS. As a result, the number of batteries per vessel decreases with increasing capacity, highlighting improved efficiency. At 2,700 kWh, there are 3.5 batteries per vessel, similar to the base case. At 10,000 kWh, only 1.571 batteries per vessel are needed. Similarly, the number of DS decreases with increasing battery capacity, confirming again the hypothesis. The base case of 2,900 kWh requires 6 DS, while the highest capacity of 10,000 kWh requires only 1 DS. Because vessels need to swap batteries less frequently, the total number of DS required to support the fleet decreases. With fewer batteries and less frequent swaps, the docking station infrastructure can be consolidated into fewer, more strategically located stations. One can observe that a critical shift occurs between batteries with capacities of 3200 kWh and 4000 kWh. Within this range, the number of required DS decreases significantly. The DS that remain in use are the ones that are key nodes or far away (such as Antwerp and Duisburg) in the network. Ultimately, with even higher battery capacities, only a single docking station in Rotterdam is sufficient. This aligns with Rotterdam's central role in the network, as it's a major port with a high volume of vessel traffic. This reduces the overall infrastructure cost and simplifies the logistics. Indeed, the total capital expenditure decreases with increasing battery capacity, from 56,269,500€for a capacity of 2,700 kWh to 23,371,000€for a capacity of 10,000 kWh. The sharing of batteries among vessels remains a consistent strategy across scenarios. The analysis of the number of shared batteries in relation to battery capacity reveals an interesting trend. Initially, as battery capacity increases, the number of shared batteries also goes up, peaking at a capacity of 3,200 kWh where there are 17 shared batteries by 2 vessels. This increase can be attributed to the higher energy demands being met more efficiently through shared use. However, beyond this peak, the number of shared batteries starts to decline. For example, with a battery capacity of 4,000 kWh, the shared batteries drop to 11 by 2 vessels, and further decrease to 6 by 2 vessels at 10,000 kWh. This decline is due to the fact that higher capacity batteries enable vessels to travel longer distances without needing frequent swaps. Consequently, these batteries stay longer on the vessels, reducing the opportunity for sharing within the 48-hour time period. Thus, while larger battery capacities initially encourage more shared usage, surpassing a certain threshold results in diminished sharing due to extended operational times. To sum up, the main key insight is the economy of scale: higher battery capacities lead to significant reductions in the number of required batteries and DS, translating into lower total investment costs.

Managerial insights: *Although a capacity of 10,000 kWh may not be feasible in the near term, even intermediate capacities such as 3,200 or 4,000 kWh demonstrate substantial changes in network design. These capacities lead to lower investment costs, highlighting the importance of pursuing higher battery capacities. Therefore, it is advisable to continue efforts in developing and improving battery technologies to achieve these benefits.*

Battery costs

The hypothesis on the impact of battery costs is the following:

"Lower battery costs would lead to a higher number of used batteries and fewer DS."

This hypothesis can be explained by the fact that once battery costs are sufficiently low, it becomes more cost-effective to transport a larger number of batteries and minimize the use of DS. By carrying more batteries, vessels can reduce the need for frequent recharges and thereby decrease the necessity for extensive DS infrastructure. This shift allows for lower investment in DS, as the network relies more on the availability of low-cost batteries to maintain operations efficiently.

Table 4.4 investigates the influence of varying battery costs on the same key metrics from Table 4.1. It explores four different scenarios with battery costs ranging from 650,000€to 1,250,000€(the base case being the one colored in salmon). As for the previous table, the number of vessels and the number of objective functions remain the same at 14 and 1 (investment costs), respectively. This stability ensures that the comparison focuses solely on the impact of varying battery costs.

	Scenarios			
Battery costs [€]	650'000	800,000	955,500	1'250'000
Number of vessels	14	14	14	14
Objective function	Invest.	Invest.	Invest.	Invest.
Number of batteries	51	50	49	49
Number of DS	5	5	6	6
Locations of the DS	T1, T2, T3, T9, T10	T1, T2, T3, T9, T10	T1, T2, T3, T4, T9, T10	T1, T2, T3, T4, T10, T12
Total capex [€]	39,900,000	46,750,000	54,919,500	69,350,000
Number of batteries per vessel	3.643	3.571	3.5	3.5
Number of DS per vessel	0.357	0.357	0.428	0.428
Shared batteries	13 by 2 V	15 by 2 V	15 by 2 V	13 by 2 V
Costs per vessel [€/vessel]	2,850,000	3,339,286	3,922,281	4,953,571
Optimality gap [%]	41.6	42.4	42.7	43.0

Table 4.4: Detailed breakdown of the influence of different battery costs on various operational metrics

As can be seen in Table 4.4, the number of batteries required slightly decreases as battery costs increase, from 51 batteries at 650,000€to 49 batteries at 955,500€and 1,250,000€. This suggests a marginal reduction in battery requirements as batteries costs rise. It makes sense that the more expensive the batteries are, the fewer will be used to minimize costs. Thus, the number of batteries per vessel shows a slight decrease with increasing costs, from 3.643 batteries per vessel at 650,000€to 3.5 batteries per vessel in the base case and higher cost scenarios. Inversely, the number of DS varies slightly across scenarios, with 5 DS needed at lower battery costs (650,000€and 800,000€), increasing to 6 DS in the base case (955,500€) and higher cost scenarios (1,250,000€). This indicates that with fewer batteries, more DS are required to support the fleet efficiently. Regarding the locations of the DS, they only change across scenarios with slight variations. For instance, at lower battery costs, DS are located at T1, T2, T3, T9, and T10. As costs increase, an additional station is added at T4 or T12. Despite the differences between the scenarios (as shown in Figure 4.6), all four cases share four common terminals that are always used. These terminals, previously discussed in the results, can be considered key points within the network. The total investment costs increases significantly with rising battery costs, from 39,900,000€at 650,000€to 69,350,000€at 1,250,000€. The primary and main reason for this significant increase in Capex is the direct correlation between the cost per battery and the total number of batteries needed. Higher battery costs directly inflate the total investment required. Furthermore, the number of needed batteries doesn't fluctuate significantly. Indeed, having one or two batteries less doesn't have a huge impact on the total costs. Similarly, costs per vessel increase with higher battery costs. For a battery cost of 650,000€, the cost per vessel is 2,850,000€, while for the highest cost of 1,250,000€, it rises to 4,953,571€. Regarding the sharing of batteries among vessels, it remains a consistent strategy across scenarios. The number of shared batteries is highest in the base case and intermediate cost scenarios, with 15 batteries shared by 2 vessels. This trend diminishes slightly at the lowest and highest cost scenarios. The cause of this behavior remains unclear.

Figure 4.6: Locations of the common docking stations of all cases in red, the other used locations are in blue

To sum up, the key results of this experiment are:

- Battery costs have an important impact on total Capex and per vessel costs. Higher battery costs lead to increased total expenditures, reflecting the critical role of battery pricing in the economic viability of the system.
- Slight variations in the number of batteries and DS required suggest that while battery costs affect total costs, they do not drastically alter the infrastructure needs. However, with fewer batteries, more DS are needed to answer the demand.
- Despite the differences between the scenarios, all four cases consistently utilize four common terminals. These terminals serve as key points within the network. Their consistent use across various scenarios highlights their strategic importance and reliability as central hubs in the distribution system. This suggests that these terminals are crucial for maintaining the network's efficiency and effectiveness, regardless of changes in battery costs. Their strategic location and capacity likely make them indispensable for optimizing the overall logistics and transportation flow within the network.

Managerial insights: *To achieve a significant shift as mentioned in the hypothesis, battery costs would need to decrease more substantially than the range used in this experiment. Given the current technological landscape, such a significant reduction in battery costs does not seem feasible or realistic. Therefore, the current battery costs, whether slightly increased or decreased, do not significantly alter the network design. The primary impact is on the total costs, which are influenced by changes in battery costs rather than adjustments in the network design. As a result, it is crucial to focus on other factors that can optimize the network, as substantial changes in battery costs alone are unlikely to provide significant improvements.*

Number of spots available at DS

The hypothesis on the impact of the number of spots available at DS is the following:

"More spots available at DS would decrease the number of used DS and increase the sharing of batteries."

This hypothesis is based on the idea that central terminals, where many vessels pass through, can function as "swapping" hubs. These hubs would be capable of storing and handling a large number of batteries, allowing most battery swaps to occur there. As a result, fewer DS would be needed elsewhere in the network. By concentrating the battery swapping activities at central hubs, the overall network can operate more efficiently with a reduced number of DS while maximizing the sharing of batteries.

Table 4.5 investigates the influence of varying number of spots available at DS on the same key metrics (presented in Table 4.1). It explores four different scenarios with varying additional spots available at DS: the base case (no additional spots), +2 spots, +4 spots, and +8 spots. In this context, "spots available at DS" refers to the number of charging spots and the maximum number of available spots at each terminal, where batteries can be stored even if they are not being charged. Once again, the number of vessels and the number of objective functions remain the same at 14 and 1 (still investment costs), respectively. This stability ensures that the comparison focuses solely on the impact of varying spots available at DS.

	Scenarios			
Spots available at DS	base case	+2	+4	+8
Number of vessels	14	14	14	14
Objective function	Invest.	Invest.	Invest.	Invest.
Number of batteries	49	52	48	50
Number of DS	6	4	6	5
Locations of the DS	T1, T2, T3, T4, T9, T10	T1, T2, T10, T12	T1, T2, T3, T4, T9, T10	T1, T2, T3, T10, T12
Total capex [€]	54,919,500	55,086,000	53,964,000	54,525,000
Number of batteries per vessel	3.5	3.714	3.428	3.571
Number of DS per vessel	0.428	0.286	0.428	0.357
Shared batteries	15 by 2 V	12 by 2 V	12 by 2 V	16 by 2 V
Costs per vessel [€/vessel]	3,922,281	3,854,571	3,894,643	3,894,643
Optimality gap [%]	42.7	44.8	43.7	45.5

Table 4.5: Detailed breakdown of the influence of different numbers of battery spots available at the DS on various operational metrics

As can be seen in Table 4.5, the total capex unexpectedly increases in the +2 spots scenario (55,086,000€) compared to the base case (54,919,500€). This might be due to increased complexity and suboptimal solutions caused by the higher computational demand caused by additional potential solutions to cover. Scenarios with +4 (53,964,000€) and +8 (54,525,000€) spots show a decrease in capex compared to the base case scenario, indicating a potential improvement in investment efficiency when more spots are available. Indeed, interestingly, the +4 scenario has less batteries but the same amount of DS, and inversely for the +8 scenario (same amount of batteries but less DS). In facts, the base case requires 49 batteries, which increases to 52 with +2 spots, drops to 48 with +4 spots, and slightly rises to 50 with +8 spots. The base case and +4 spots scenarios both use 6 docking stations, while +2 spots reduce this to 4, and +8 spots use 5 docking stations. However, the base case, +4 and +8 spots scenarios share some similar DS locations (T1, T2, T3, T10), suggesting a stabilized configuration that might be near-optimal for those settings. As previously discussed, these locations are the key node locations within the network. Overall, the results of this experiment show instability and a lack of coherence, likely due to dependencies on the initial conditions and inputs provided to the model. Specifically, the initial location of batteries at time p=0 plays a crucial role. If the hypothesis holds, the batteries need to be transported to the hubs initially, which can take more than the 48-hour simulation period used in this study. Additionally, the process of moving batteries to hubs necessitates the use of multiple DS, increasing the overall number of DS needed. Despite these inconsistencies, observable trends still emerge from the results. Notably, as the number of DS decreases, the number of batteries increases. This trend suggests a shift towards fewer DS with more centralized battery handling, ultimately leading to a decrease in total costs per vessel.

Managerial insights: *Given the trends observed, the availability of more spots at DS could significantly impact network design. Therefore, this variable warrants further study. Investigating the optimal number of spots at central DS could lead to a more efficient network configuration, reducing overall costs and improving operational efficiency.*

4.5.3 Summary of results with one objective

As shown in Figure 4.7, despite some variations, the number of DS and batteries per vessel remains relatively stable across the different experiments. Notably, the base case is centered, indicating a relatively balanced number of DS and batteries compared to other experiments. The cost of batteries primarily influences the number of batteries per vessel, while both battery capacity and the availability of spots at terminals impact the number of DS and batteries used. Unfortunately, it is challenging to draw the Pareto front because the total costs depend on the battery costs, which vary in some cases.

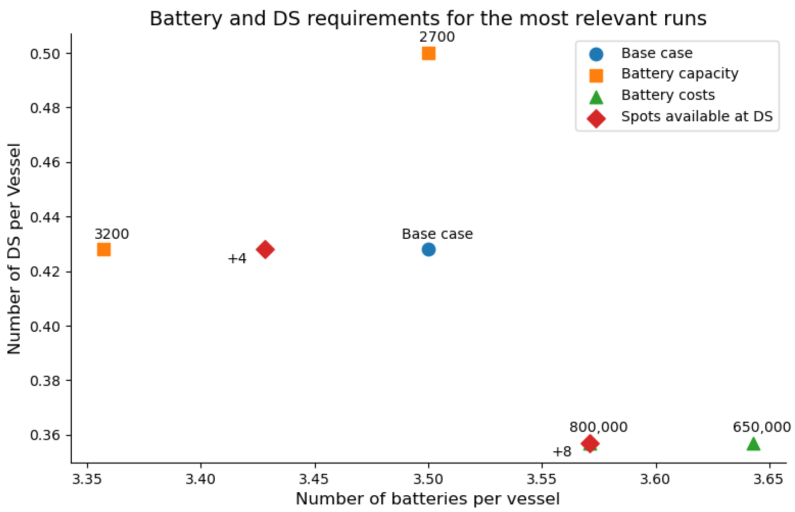

Figure 4.7: Battery and DS requirements for the most relevant runs

4.5.4 Loaded vs unloaded

This section examines the implications of considering that vessels are not always fully loaded. It delves into the relevant data, analyzes how this factor influences the inputs, and explores its effects on the results.

Data

Data from Rijkswaterstaat has enabled a data analysis revealing a difference in the average speed of each vessel type when loaded versus unloaded. As illustrated in Table 4.6, it is evident that vessels travel faster when unloaded, with C3b category vessels exhibiting speeds nearly twice as fast as when they are loaded.

Vessel type	**Loaded speed km/h**	**Unloaded speed kn/h**
M6	14.1	18.7
M8	13.6	19.2
M11	14.5	19.0
C3b	8.4	15.4

Table 4.6: Vessels speed when loaded and unloaded

Changes in input

This change in speed affects the sailing profiles. When vessels move faster, they reach their next destination earlier. Consequently, the sailing profiles have been adjusted to reflect this. Four scenarios have been developed:

1. All vessels are loaded at all time steps.
2. All vessels are unloaded at all time steps.
3. All vessels are loaded at p=0, unload their goods at the next port, then travel unloaded to the following port, and repeat this cycle.
4. The same as scenario 3, but with 50% of the vessels loaded at p=0.

The new sailing profiles induce new fleet composition, that can been see in Figures 4.8 and 4.9. Furthermore, although the speed changes, the instant power consumption remains the same. This is because, while the vessels are lighter, they achieve higher speeds by using the same amount of power.

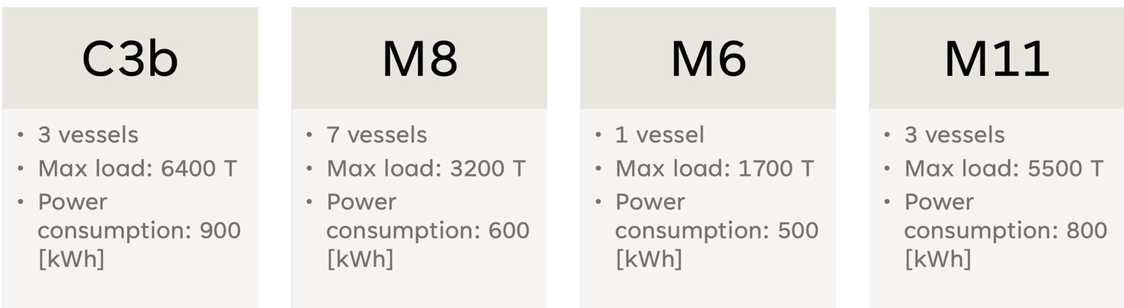

Figure 4.8: Fleet composition for scenarios 1, 3 and 4

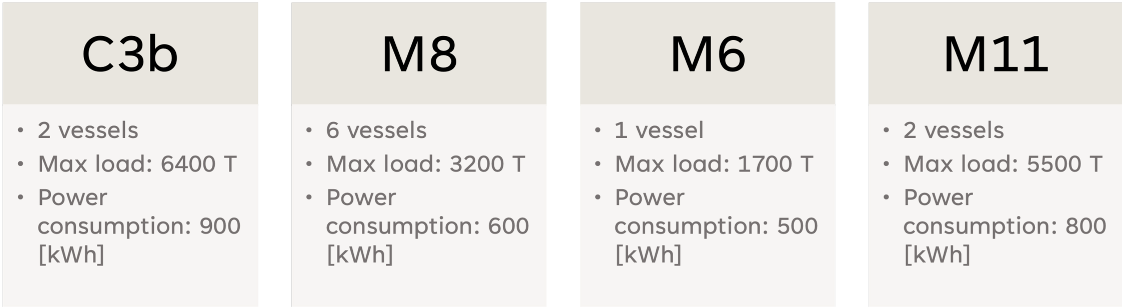

Figure 4.9: Fleet composition for scenario 2

Analysis of the results

The hypothesis on the impact of vessels loading is the following:

"The less loaded the vessels are, the fewer batteries and DS are used."

This hypothesis assumes that, for the same period of time and the same number of trips, less loaded vessels will operate more efficiently. When vessels are less loaded, they can travel at higher speeds. This increased speed results in shorter travel times and reduced overall energy consumption for the same number of trips. Consequently, vessels require fewer batteries and, therefore, fewer battery swaps. As a result, the overall need for DS is reduced, optimizing the network by minimizing the infrastructure required to support the operations.

The analysis presented in Table 4.7 investigates the influence of different loading conditions on the same key metrics (in Table 4.1). It explores the four different scenarios described above. As previously mentioned, the number of vessels varies slightly across scenarios, with 14 vessels in the 100% loaded, 50%-50% fully loaded at t=0, and 50%-50% half loaded at t=0 scenarios, and 11 vessels in the 100% unloaded scenario. Each scenario maintains a single objective function (investments costs).

As can be seen in Table 4.7, the number of batteries required decreases significantly in the 100% unloaded scenario (32 batteries) compared to the 100% loaded scenario (49 batteries). As already mentioned, this reduction is due to fewer vessels, but also to the faster travel speeds of unloaded vessels, which together reduces the overall energy demand. Thus, the number of docking stations also decreases in the 100% unloaded scenario (4 DS) compared to the 100% loaded scenario (6 DS). In the mixed loading scenarios, the number of batteries required falls between the two extremes, with 40 batteries in the 50%-50% fully loaded at p=0 scenario and 42 batteries in the 50%-50% half loaded at p=0 scenario. This reduction is due to the faster travel speeds of the vessels when they are unloaded. Thus, it also reduces the overall energy demand. The locations of the DS vary slightly across scenarios, reflecting the adjusted sailing profiles and optimized routes based on loading conditions. For example, the 100% unloaded scenario includes DS at T1, T2, T10, and T12, while the 100% loaded scenario includes DS at T1, T2, T3, T4, T9, and T10. Notably, the terminals T1, T2, and T10 are constant across all scenarios. T1 remains the central hub of the network. Terminals in Belgium (T2) and Germany (T10) are farther away, resulting in longer travel times for vessels regardless of their loading state (loaded or unloaded). Regarding the investment costs, it decreases significantly in the 100% unloaded scenario (35,976,000€) compared to the 100% loaded scenario (54,919,500€). This is due to the reduced number of batteries and DS required for unloaded vessels. Thus, costs per vessel decrease significantly in the unloaded scenario (3,270,545 €) compared to the loaded scenario (3,922,281€). The mixed loading scenarios have intermediate investment costs values. This reflects the balance between loaded and unloaded travel phases. The sharing of batteries varies across scenarios, with 15 batteries shared by 2 vessels in the

	Scenarios			
Loaded (L) vs Unloaded (U)	100% L	100% U	50%-50% fully L at t=0	50%-50% half L at t=0
Number of vessels	14	11	14	14
Objective function	Invest.	Invest.	Invest.	Invest.
Number of batteries	49	32	40	42
Number of DS	6	4	5	5
Locations of the DS	T1, T2, T3, T4, T9, T10	T1, T2, T10, T12	T1, T2, T3, T10, T12	T1, T2, T3, T9, T10
Total capex [€]	54,919,500	35,976,000	44,970,000	46,881,000
Number of batteries per vessel	3.5	2.909	2.857	3.0
Number of DS per vessel	0.428	0.363	0.357	0.357
Shared batteries	15 by 2 V	9 by 2 V 4 by 3 V	17 by 2 V 2 by 3 V	16 by 2 V 1 by 3 V
Costs per vessel [€/vessel]	3,922,281	3,270,545	3,212,143	3,348,643
Optimality gap [%]	42.7	43.5	29.0	47.1

Table 4.7: Detailed breakdown of the influence of different loading scenarios on various operational metrics

100% loaded scenario, reducing to 9 shared by 2 vessels in the 100% unloaded scenario but with 4 batteries shared by 3 vessels. This variation can be attributed to the different energy demands and operational requirements in each scenario: the less used are the batteries, the more they can be shared. Thus, the possibility for sharing increases. Interestingly, there are cases where a battery is shared between 3 vessels over the running time of 2 days. This occurs because of the efficiency and scheduling optimization within the network, where batteries are strategically rotated among vessels to maximize their utilization and ensure continuous operations. To sum up, the loading conditions significantly influence the operational and financial aspects of the system. Fully unloaded vessels require fewer resources and lower costs, while fully loaded vessels necessitate more batteries and docking stations. The mixed loading scenarios have intermediate resources needs and investment costs values. Based on this analysis of different loading conditions, the scenario where vessels are 50% loaded and 50% unloaded with fully loaded at p=0 is selected for further analysis from section 4.5.8 on. This scenario offers a balanced approach, optimizing battery and docking station usage while maintaining operational efficiency. Most importantly, the scenario is among the closest to the reality of IWT, where vessels are both, loaded and unloaded within a time frame of two days.

Managerial insights: *This experiment highlights the critical importance of realistic modeling in capturing the true impacts of vessel loading conditions on network design and costs. The significant differences observed in total investment costs, sometimes exceeding 20%, emphasize the need for accurate and detailed simulation of real-world conditions. Therefore, it is crucial to incorporate realistic loading scenarios in future studies to ensure the network design is realistic, efficient and cost-effective.*

4.5.5 Lost space

To optimize the use of space on vessels, it is essential to consider the trade-offs between carrying battery containers versus goods containers. This section delves into the influence of this factor on the overall network design and the resulting outcomes.

Data

According to Wärtsilä, the battery containers are 20 ft containers, weighting approximately 27 tons each. In general, filled with goods, a Twenty-foot Equivalent Unit (TEU), which corresponds to a 20 ft container, typically weighs around 2.5 tons. Using these data points, it is possible to infer that to maintain the same weight on the vessel, one battery container (27 tons) is equivalent to approximately ten goods containers (10 x 2.5 tons = 25 tons). However, a sensitivity analysis will be conducted using equivalences of 5, 8 and 10 good containers to explore different scenarios and their impacts on the system. Cost data from the website Searates indicates that the cost for transporting one 20 ft container varies depending on the route. For example, shipping from Rotterdam to Antwerp costs about 2,400€, and from Rotterdam to Duisburg around 2,700€. The travelling times for these two trips are respectively 11 hours 30 minutes and 17 hours. Consequently, via the linear regression that can be seen in Figure 4.10, the costs in function of the travelling time are determined. For clarity, the legend accompanying the Figure defines the units and meaning of each axis. Linear regression was chosen as the most simplified but suitable method to calculate this function. This is because a logical assumption can be made that there is a fixed cost associated with each trip, regardless of the distance traveled. On top of this fixed cost, an additional cost is incurred for each kilometer (or minute) spent traveling. This makes sense since, even for a short trip lasting 30 minutes, the total cost won't be close to zero.

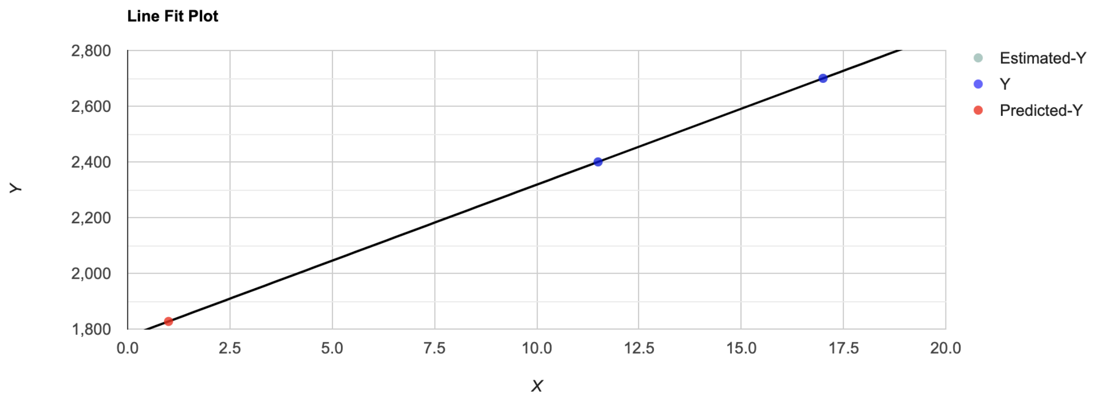

Figure 4.10: Linear regression to get the transportation costs function (X is the time in hours, Y is the costs in €)

Changes in the model

This significant weight difference implies a revenue loss for the barge operators when opting to carry battery containers. Since the BSS operators should aim to keep its clients, they have to minimize their impacts on them. In this scenario, they should aim to minimize the revenue loss of the barge operators. Thus, the penalty for lost cargo space needs to be factored into the overall cost-benefit analysis of implementing battery swapping systems. In the optimization model, this penalty costs can be included as an additional objective to ensure a comprehensive evaluation (see equation 3.2). However, a scaling factor should be applied to this new objective function to align it with the long-term costs, ensuring consistency with the investment costs. In the context of financial decision-making, it is crucial to accurately compare different types of costs associated with business operations and investments. The methodology of converting operational costs into long-term costs using the concept of present value is described below. By doing so, it enables a meaningful comparison between operational (loss costs in this case) and investment costs. To convert the annual operational costs into a present value, one uses the formula for the present value of an annuity. This formula allows to determine the equivalent value today of a series of future cash flows, considering the time value of money. The formula for the present value of an annuity is:

$$PV = C \cdot \left(\frac{1-(1+r)^{-n}}{r}\right)$$

Where:

- PV = Present value
- C = Annual operational cost
- r = Discount rate
- n = Number of years

A time horizon (n) should be chosen to accurately reflect the expected useful life of the investment. For this analysis, a period between 5 years and 20 years is selected. This range is chosen to capture the full lifecycle of the investment, taking into account both the initial implementation phase and the subsequent operational period during which the investment generates returns. A shorter horizon might not fully encompass the benefits and potential cost savings realized over time, while a longer horizon ensures that the long-term impacts and value of the investment are thoroughly evaluated. Moreover, selecting an appropriate discount rate is critical in this process, as it accounts for the time value of money, reflecting the opportunity cost, inflation, and risk associated with the cash flows. In general, a discount rate between 5% and 10% is used, justified by the following considerations:

- Cost of capital: The average cost of borrowing and the return required by equity investors is typically around 5% for a stable company in a low-risk industry.
- Inflation: A moderate inflation rate of 2-3% is expected in the Eurozone, necessitating a higher discount rate to ensure real returns.
- Risk premium: An additional premium is included to account for the uncertainties and risks associated with the future operational costs and the business environment.

In this project, the operational costs (losses) are what aims to be minimized for every two days of operation. Given this frequency, it is essential to annualize these costs to understand their long-term impact. There are approximately 365 days in a year, translating to about 182.5 operational cycles (2 days per cycle) per year. Thus, the annual operational cost is calculated as follows:

$$\text{Annual operational cost} = \text{Loss cost for 2 operational days} \cdot 182.5$$

Thus, the scaler to be put in the objective equation 3.2 is the following:

$$182.5 \cdot \left(\frac{1-(1+r)^{-n}}{r}\right)$$

Having determined the equation for the present value, it is essential to understand the influence of time periods and discount rates on the present value. Therefore, three experiments are designed to represent the total loss costs for the scenario where all vessels sailing during the two days modeled in this thesis are transporting a single battery container (see Tables 4.8, 4.9, and 4.10). Each experiment expresses a different equivalence between one battery containers and the good containers (5, 8, and 10). As can be seen in the Figures, the higher is the equivalence (5, 8,10), the higher is the present value. In a similar way, the higher is the time horizon, the higher is the present value.

5 years	8 years	10 years	20 years	Discount rate
103,506,963	154,519,259	184,607,377	297,940,293	5%
90,628,234	127,544,748	146,901,238	203,538,024	10%

Table 4.8: Present value of the ordinary annuity for 1 battery container being 10 good containers [€], taken into account that all vessels transport 1 battery container during the 2 days modeled

5 years	8 years	10 years	20 years	Discount rate
82,963,596	123,851,314	147,967,745	238,807,105	5%
72,640,951	102,230,493	117,745,267	163,141,164	10%

Table 4.9: Present value of the ordinary annuity for 1 battery container being 8 good containers [€], taken into account that all vessels transport 1 battery container during the 2 days modeled

5 years	8 years	10 years	20 years	Discount rate
51,785,086	77,306,810	92,360,057	149,061,121	5%
45,341,790	63,811,319	73,495,474	101,831,161	10%

Table 4.10: Present value of the ordinary annuity for 1 battery container being 5 good containers [€], taken into account that all vessels transport 1 battery container during the 2 days modeled

Finally, the lower is the discount rate, the higher is the present value.

Analysis of the results

In the analysis of the loss cost associated with transporting batteries, it is impractical to examine every possible scenario. Therefore, a representative subset of cases is selected to provide meaningful insights while maintaining manageability. The selection is based on choosing the highest, lowest, and an intermediate case from the present value calculations (Tables 4.8, 4.9, and 4.10). This approach ensures that the analysis captures a wide range of potential outcomes. The three selected cases are:

1. Case 1: lowest present value of loss costs
   - Scenario: This value corresponds to the present value of the ordinary annuity for one battery container being 5 good containers, over a period of 5 years with a 10% discount rate.
   - Scaler: $182.5 \cdot \left(\frac{1-(1+r)^{-n}}{r}\right) = 691.8$.
2. Case 2: highest present value of loss costs
   - Scenario: This value corresponds to the present value of the ordinary annuity for one battery container being 10 good containers, over a period of 20 years with a 5% discount rate.
   - Scaler: $182.5 \cdot \left(\frac{1-(1+r)^{-n}}{r}\right) = 2274.4$.
3. Case 3: intermediate present value of loss costs
   - Scenario: This value corresponds to the present value of the ordinary annuity for one battery container being 8 good containers, over a period of 10 years with a 10% discount rate.

- Scaler: $182.5 \cdot \left(\frac{1-(1+r)^{-n}}{r}\right) = 1121.4$.

After running the model for Case 1, with a weight of 75% arbitrarly assigned to the investment cost objective function, it is found that the loss costs were excessively high compared to the investment costs. Consequently, all docking stations were utilized, and a significant number of batteries were required. To address this, it was decided to halve the loss costs. The initial hourly loss costs were based on a linear regression derived from shipping costs from Rotterdam to Antwerp (approximately 2,400€) and from Rotterdam to Duisburg (around 2,700€). However, these numbers represent the price to transport a container, not the actual profit for the barge owner. The effective profit, and thus the losses, are lower than these amounts. Two types of trials were conducted: one assuming the profit was half of the transportation costs and another assuming it was a fourth of the transportation costs. Also, it can be argued that more weight should be given to investment costs from a DS operator's perspective. Indeed, their first priority status to maximize their profit or minimize their costs. As a result, a total of five cases were initially tested on the most favourable scaler, which is in Case 1. The hypothesis on the impact of the revenue loss and the weight attributed to the investment objective is the following:

"The smaller the percentage of transportation costs attributed to revenue loss and the more importance given to the investment objective, the closer the shifting point will be."

This hypothesis is based on the premise that high loss costs can significantly skew the results. By reducing the percentage of transportation costs attributed to revenue loss and simultaneously giving more weight to the investment objective, the influence of loss costs is minimized. This adjustment prevents loss costs from excessively impacting the outcomes, leading to a more balanced solution. The shifting point, where the balance between cost objectives is optimized, becomes closer and more distinct, allowing for clearer insights into the trade-offs involved.

	Scenarios				
	Case 1.1	Case 1.2	Case 1.3	Case 1.4	Case 1.5
Specificities	Full 75%	1/2 75%	1/2 90%	1/4 75%	1/4 90%
Number of vessels	14	14	14	14	14
Objective functions	Invest. Lost space	Invest. Lost space	Invest. Lost space	Invest. Lost space	Invest. Lost space
Number of batteries	48	40	39	39	40
Number of DS	12	12	10	11	9
Locations of the DS	T1, T2, T3, T4, T5, T6, T8, T9, T10, T11, T12, T13	T1, T2, T3, T4, T5, T7, T8, T9, T10, T11, T12, T13	T1, T2, T3, T4, T6, T8, T9, T10, T11, T13	T1, T2, T3, T4, T5, T6, T8, T9, T10, T11, T13	T1, T2, T3, T4, T6, T9, T10, T11, T13
Total costs [€]	294,445,866	124,994,085	80,431,970	85,146,781	63,376,872
Optimality gap [%]	37.7	38.0	40.4	36.6	44.9

Table 4.11: Detailed breakdown of the trials conducted to determine the scenarios of space lost

The scenarios vary by the fraction of transport costs (full, 1/2, 1/4) attributed to the revenue loss for the barge operator, and the weight assigned to the investment objective function (75%, 90%). All scenarios consider both investment costs and lost space as objective functions, reflecting a multi-objective optimization approach. Moreover, the number of vessels remains constant at 14 across all scenarios, ensuring comparability of results. First of all, one can observe that the smaller the fraction of transport costs (full, 1/2, 1/4) attributed to the revenue loss for the barge operator, the more balanced the results. By balanced results, it is meant that the lost costs are not so high and significant that the investment costs do not matter anymore. This is shown by all or almost all DS being utilized, resulting in total costs that are very high. However, even more significant is the weight attributed to the objective function of investments. Indeed, scenarios with higher weights on the investment objective (e.g., 90% in Cases 1.3 and 1.5) tend to reduce the number of DS, leading to lower Capex. Conversely, scenarios with lower weights on the investment objective (e.g., 75% in Cases 1.1, 1.2, and 1.4) tend to utilize more resources, including more DS, leading to higher Capex. This can be explained by the fact that, in absolute terms, the objective function for lost space is significantly larger. Therefore, assigning more weight to the investment function allows for a more balanced solution, enabling trade-offs between the two objective functions. It is important to note that from the perspective of ZES, in the first stage of the design, it makes sense to prioritize their initial investment over any other factor.

Managerial insights: *Based on these findings, it is advisable to continue with Case 1.5 for further analysis and decision-making. This case presents the most balanced output, minimizing the excessive influence of loss costs and offering a clear view of the trade-offs between different objectives. By focusing on Case 1.5, one can derive the most meaningful insights and optimize the network design effectively.*

Based on the previous managerial insights, Case 1.5 is further tested with the initial three different cases (see Table 4.12). Once again, the number of vessels and the number of objective functions remain the same at 14 and 2 (lost space and investment costs), respectively. As expected, Case 2 and Case 3 provide results that imply the need for more batteries and more docking stations. The loss costs projected in the long term are significantly higher, which consequently reduces the relative importance of the investment cost objective function. Thus, in order to get realistic results, it is chosen to continue the thesis with Case 1 (one battery container being 5 good containers, over a period of 5 years with a 10% discount rate). Indeed, Case 1 offers a more balanced approach, considering both the investment and operational costs without overwhelming the model with excessive loss costs.

In table 4.11, one can see Cases 1.4 and 1.5. These cases are identical except for the weight assigned to the investment cost objective in the function. One can observe a significant change in the model's behavior and output as the weight increases from 75% to 90%. To further refine this shift and identify the exact tipping point, a sensitivity analysis is conducted. The results are presented in Table 4.13. The hypothesis on the impact of the weights attributed to each of the two objectives is the following:

"The more importance given to the investment objective, the fewer DS are used. Additionally, due to fewer DS and less emphasis on loss costs, the total costs also decrease."

This hypothesis is grounded in the understanding that prioritizing the investment objective leads to a reduction in the number of DS required. By focusing more on investment costs, the network design aims to minimize initial expenditures, which in turn reduces the infrastructure needed, such as DS. Additionally, with less weight given to loss costs, the total costs are further lowered, as these costs have less influence on the overall optimization. This results in a more cost-effective network configuration, balancing investment efficiency with operational needs.

As can be seen in Table 4.13, the scenarios vary by the weight assigned to the investment cost objective, ranging from 80% to 97.5%, with a corresponding reduction in the weight of the lost space objective. Once again, the number of vessels remains constant at 14 across all scenarios,

	Scenarios		
Lost space	Case 1	Case 2	Case 3
Number of vessels	14	14	14
Objective function	Invest. Lost space	Invest. Lost space	Invest. Lost space
Number of batteries	40	40	40
Number of DS	9	12	11
Locations of the DS	T1, T2, T3, T4, T6, T9, T10, T11, T13	T1, T2, T3, T4, T5, T7, T8, T9, T10, T11, T12, T13	T1, T2, T3, T4, T5, T6, T8, T9, T10, T11, T13
Total costs [€]	63,376,872	158,285,657	92,237,724
Number of batteries per vessel	2.857	2.857	2.857
Number of DS per vessel	0.643	0.857	0.786
Shared batteries	12 by 2 V 2 by 3 V	14 by 2 V 3 by 3 V	16 by 2 V 3 by 3 V
Costs per vessel [€/vessel]	4,526,919	11,306,118	6,588,408
Optimality gap [%]	44.9	37.9	41.0

Table 4.12: Detailed breakdown of the influence of the different space loss scenarios, based on the scenario of Case 1.5, on various operational metrics

ensuring comparability of results. The number of batteries remains relatively stable across the scenarios, ranging from 39 to 41. This consistency suggests that the battery requirements are not highly sensitive to the variations in the weight given to the investment objective function. However, the number of DS decreases as the weight given to the investment objective function increases. This makes sense because prioritizing investment costs leads to a reduction in the number of DS to lower overall expenditures. Contrarily, when less weight is attributed to the investment objective function, there are more DS because the model prioritizes operational efficiency and convenience. More DS mean that vessels can access battery swapping services more frequently and conveniently, reducing downtime and improving overall efficiency. However, this comes at the cost of higher investments in infrastructure. There is no single shifting point in this trend. Instead, the number of DS decreases gradually as more weight is given to the investment objective function. This indicates a steady reallocation of resources to minimize investment costs progressively.

Managerial insights: *The weights assigned to each objective can significantly affect the design of the network and the total costs incurred. It is crucial to prioritize the objectives appropriately and assign well-reflected weights to achieve a balanced and efficient network configuration. Therefore, careful consideration should be given to the weighting process to optimize both investment and operational outcomes effectively.*

4.5.6 New base case scenario

To ensure a more realistic foundation for the next part of the thesis, a new base case scenario is constructed that incorporates the results obtained so far. This new base case scenario has the following parameters and initial characteristics (the changes compared to the previous base case scenario are highlighted in orange):

	Scenarios				
	Case 1.5	Case 1.5.1	Case 1.5.2	Case 1.5.3	Case 1.5.4
Specificities	1/4 90%	1/4 80%	1/4 85%	1/4 95%	1/4 97.5%
Number of vessels	14	14	14	14	14
Objective functions	Invest. Lost space	Invest. Lost space	Invest. Lost space	Invest. Lost space	Invest. Lost space
Number of batteries	40	39	39	39	41
Number of DS	9	11	10	8	7
Locations of the DS	T1, T2, T3, T4, T6, T9 T10, T11, T13	T1, T2, T3, T4, T5, T6 T8, T9 T10, T11, T13	T1, T2, T3, T4, T6, T8 T9, T10 T11, T13	T1, T2, T3, T4, T7, T9 T10, T13	T1, T2, T4, T6, T9, T10 T11
Total costs [€]	63,376,872	75,970,287	69,502,215	55,205,520	52,505,401
Number of batteries per v.	2.857	2.857	2.786	2.786	2.928
Number of DS per v.	0.643	0.786	0.714	0.571	0.5
Shared batteries	12 by 2 V 2 by 3 V	13 by 2 V 1 by 3 V	15 by 2 V 3 by 3 V	16 by 2 V 2 by 3 V	14 by 2 V 2 by 3 V
Costs per vessel [€/vessel]	4,526,919	5,426,449	3,626,035	3,433,178	3'750'385
Optimality gap [%]	44.9	41.2	42.2	47.0	47.0

Table 4.13: Comparison of the different space loss scenarios, where one battery container is equivalent to five good containers, varying the weight attributed to each objective.

- Two objective functions: the installation costs of the DS and batteries, and the costs associated with space lost. The weights attributed to each function are respectively 90% and 10%.
- The second OF is based on effective profits that are 25% of the transport costs, and the present value of the ordinary annuity for one battery container being 5 good containers, over a period of 5 years with a 10% discount rate.
- Capex of battery: 955.500€.
- Maximum capacity of battery: 2900 kWh.
- Minimum battery level charge required to be used in vessel: 100%.
- Safe operating range for the battery to prevent full discharge: 10%.
- Capex of one charging station at terminal t: 1.350.000€.
- Number of charging points of a DS installed at terminal: between 4 and 2, depending on the size and importance of each terminal.
- Number of spots of a DS installed at terminal: between 8 and 4, depending on the the size and importance of each terminal.
- Power of each charging spot: 1000 kW.
- Battery levels at start of period: 100%.

- Number of batteries at each terminal at start of period: 3.
- Number of batteries charging at each terminal at start of period: 0.
- Number of batteries on each vessel at start of period: 3.
- Number of batteries providing energy on each vessel at start of period: 1.
- Vessels are 50% of the time loaded and 50% unloaded with all being fully loaded at p=0.

The DS locations of this new base case scenario can be seen in Figure 4.11.

Figure 4.11: DS locations for the new base case scenario (in red)

4.5.7 Third objective function: "at terminal" times

This section introduces a new objective function (see 3.3) that considers the difference between the number of designated charging spaces for battery containers at the terminal and the available storage space. In other words, once fully charged, batteries can be stored at the terminal. However, storing containers at the terminal incurs costs per square meter. Therefore, this third objective function aims to minimize the time batteries spend at the terminal ("at terminal" times), effectively maximizing their utilization. To ensure consistent comparison with the other two objective functions, these "at terminal" times need to be converted into monetary costs. This scaler expresses the transition to the total monetary cost associated with the "at terminal" times of these containers (in [€/2h/container]), but also the conversion of the costs into long-term costs. As for the costs associated to the loss of space, the concept of present value is used. In order to be consistent, the scaler of 691.8 is used.

When dealing with containers at terminals, several unavoidable charges and fees are associated with the handling and storage of these containers. Understanding these fees is crucial for effective cost management. The key charges include Terminal Handling Charges (THC), gate storage fees, and demurrage fees. The THC is a fee collected by terminal operators for services such as loading, unloading, storing, moving, and maintaining containers at a terminal. These charges cover the operational costs incurred by the terminal for managing the containers. Gate storage fees are incurred for the space occupied by containers in the terminal yard, warehouse, or container depot. The storage period begins when containers enter the storage facility and ends when they leave. Ports generally offer a few free days (typically 3-7 days) to load or unload containers. If containers are removed from the terminal within these free days, gate storage fees are not applicable. However, if containers are delayed due to port congestion or other external factors, gate storage fees must be paid. These fees are charged for the extended use of the terminal space beyond the allotted free days. Demurrage fees are charged by carriers for the delayed use of containers within the terminal. Similar to gate storage fees, demurrage fees apply when containers are not removed from the terminal within the free days assigned by the shipping company. The main difference is that demurrage fees are paid directly to the carriers, while gate storage fees are collected by the terminal through the carriers. In some ports, these fees may overlap, and both may be applicable simultaneously.

Country	**THCs in USD (Origin)**	**THCs in USD (Destination)**
Germany	270	270
Singapore	178	178
India	130	124
UK	225	225
Japan	242	242

Table 4.14: THCs for 20ft dry containers in different countries in 2022 [6].

In the context of this thesis, the terminal would constantly house some battery containers. This ongoing presence of battery containers implies that the free storage period typically offered by the port would not apply. Instead, the storage and handling of battery containers would be more akin to a "rental" agreement for a portion of the terminal's space. This arrangement would include a fixed cost for the designated area within the terminal, similar to leasing a portion of the terminal's storage capacity. From the website Container-xChange [6], we get a breakdown of THC fees for 20ft dry containers in different countries in 2022 (see Table 4.14). In Germany, the costs are 250€per container, which includes loading, unloading, and other handling costs. By analyzing these costs and supported by data from another source, fbazoom [114], which mentions that storage costs can go up to 90€per container per day, it can be deduced that it is reasonable to attribute approximately 90€par day and per container of this THC costs to storage. Thus, the fee per container, per 2 hours, is about 7.5. Thus, the scaler pen_t is equal to 7.5 [€/2h/container].

4.5.8 Multi-objective analysis

This section focuses on exploring the impact of varying the weights attributed to each of the three objective functions on the optimal solutions. Multi-objective optimization is a critical aspect of decision-making in complex systems, where different criteria must be balanced to achieve the best overall outcome. By adjusting the weights assigned to each objective, one can observe how the optimal solutions shift in response to these changes. This approach allows to understand the trade-offs between different objectives and how they affect the overall system performance, and identify the most balanced and effective solutions that achieve a desirable compromise between investment costs, space lost, and "at terminal" times. As a reminder, the three objective functions used in this thesis are:

1. Investment costs: focus on minimizing the initial capital expenditure required for setting up the infrastructure, including docking stations and battery containers. These costs are

a crucial consideration for stakeholders looking to optimize their return on investment and ensure the financial viability of the project.

2. Space lost: aim of minimizing the loss of revenue for barge owners due to the space occupied by battery containers that could otherwise be used for transporting goods containers.

3. "At terminal" times: aim of minimizing the time that battery containers spend at the terminal. These times represent an opportunity cost, as resources that are not being utilized efficiently contribute to higher operational expenses and reduced system effectiveness.

Weighting sum method

This method involves combining multiple objective functions into a single composite objective function. Each objective function is assigned a weight that reflects its relative importance. The solver then optimizes this single weighted objective function. It is useful in scenarios where there is a clear understanding of the relative importance of each objective. The equation of the objective function is:

$$F = \sum_{i=1}^{3} w_i f_i(x) \quad = w_1 \cdot f_1 + w_2 \cdot f_2 + w_3 \cdot f_3$$

where w_1, w_2, w_3 are the weights for the objective functions f_1, f_2, f_3 respectively. f_1 is the investment costs objective, f_2 the loss space and f_3 the "at terminal" times.

To understand the impacts of different priorities in multi-objective optimization, three base scenarios are analyzed where each objective function is given the full weight individually (see Table 4.15). The two hypotheses for these cases are the following:

"When all weight is given to the investment objective, this results in fewer batteries and DS used."

"When all weight is given to minimizing "at terminal" times, more batteries are used, but there is less sharing of them."

These hypotheses are grounded in the fact that prioritizing the investment objective means minimizing the costs associated with batteries and DS. This leads to the smallest possible use of these resources, as the model aims to reduce capital expenditures to the minimum. For the second hypothesis, when minimizing "at terminal" times is prioritized, vessels are configured to transport as many batteries as possible. This approach reduces the number of batteries left at terminals, increasing the usage of batteries but reducing their sharing. The focus here is on maximizing the operational efficiency and minimizing downtime, leading to a higher number of batteries in transit.

In table 4.15, the three basic scenarios are presented, each focusing solely on one objective function to facilitate comparison: investment costs, loss space costs, and "at terminal" times. Each scenario has 14 vessels, with variations in the number of batteries, docking stations (DS), total costs, and optimality gaps. In Base 1, where the focus is entirely on minimizing investment costs, one sees the use of 42 batteries and 5 DS. This results in the lowest total cost of 46,881,000€. Shared batteries are distributed with 16 shared by 2 vessels and 1 shared by 3 vessels, resulting in a cost per vessel of 3,348,642€. In Base 2, the objective is to minimize loss space costs. This scenario utilizes 44 batteries and 13 DS, leading to the highest total cost among the scenarios at 164,510,040€. The cost per vessel is significantly higher at 11,750,717€with the same shared battery distribution as Base 1. The substantial increase in the number of DS reflects the need for more frequent battery swaps, which drives up costs. Base 3 focuses on minimizing "at terminal" times, resulting in the highest number of batteries at 56 and 13 DS. The total cost is 129,712€and the cost per vessel drops to 9,265€the lowest among the three scenarios. The shared batteries reduce to 6 shared by 2 vessels, emphasizing a strategy to have more batteries on vessels to reduce "at terminal" times. The high number of batteries indicates an aggressive approach to reducing "at terminal" times, which, while effective in this respect, complicates the optimization process.

	Scenarios		
	Base 1	Base 2	Base 3
w_{invest}[%]	100	0	0
w_{space}[%]	0	100	0
$w_{atTerminal}$[%]	0	0	100
Number of vessels	14	14	14
Objective functions	Invest.	Lost space	At terminal times
Number of batteries	42	44	56
Number of DS	5	13	13
Locations of the DS	T1, T2, T3, T9, T10	T1, T2, T3, T4, T5, T6, T7, T8, T9, T10, T11, T12 T13	T1, T2, T3, T4, T5, T6, T7, T8, T9, T10, T11, T12 T13
Total costs [€]	46,881,000	164,510,040	129,712
Number of batteries per vessel	3.0	3.143	4.0
Number of DS per vessel	0.357	0.929	0.929
Shared batteries	16 by 2 V 1 by 3 V	16 by 2 V 1 by 3 V	6 by 2 V
Costs per vessel [€/vessel]	3,348,642	11,750,717	9,265
Optimality gap [%]	46.8	35.8	56.0

Table 4.15: Detailed breakdown of the basic scenarios with only one objective each, in order to be able to compare the results

Managerial insights: *Both hypotheses have been verified through the analysis. The results show that the design of the network varies significantly depending on the objective that is prioritized. This underscores the importance of carefully considering the weights and priorities assigned to each objective. If the primary goal is to focus on the physical design of the network, the investment costs objective is more relevant, as it directly influences the infrastructure and resource allocation.*

The rest of the experiments have been divided into four blocks, each containing three experiments. In the first three blocks (runs 1 to 9), each block maintains a constant weight for the investment objective (0.8, 0.9, 0.95). The fourth block (runs 10 to 12) assigns a consistent weight to the space loss objective (0.05). This setup was designed to analyze the solution space and better understand the trade-offs involved. Firstly, the run 1 to 9 will be presented and analyzed. The hypotheses on the weights attributed to each objective for these 9 runs are the following:

"The less weight given to the loss space objective, the smaller the number of DS and batteries, and the more sharing of the batteries."

"The more weight given to the "at terminal" times objective, the smaller the total costs."

The first hypotheses stems from the model's strategy to minimize the space occupied by batteries on vessels in order to reduce the associated costs. By assigning less weight to the loss space objective, the model prioritizes minimizing the number of batteries on board, leading to fewer swaps and thus requiring fewer DS. Moreover, with fewer batteries on the vessels, there are more opportunities for swaps, resulting in more frequent sharing of batteries. The second hypothesis is based on the observation that "at terminal" costs are typically lower than investment and loss space costs. By giving more weight to the "at terminal" times objective, the model aims to reduce "at terminal" times, which in turn minimizes overall costs.

	Scenarios		
	Run 1	Run 2	Run 3
w_{invest}[%]	90	90	90
w_{space}[%]	5	2.5	7.5
$w_{atTerminal}$[%]	5	7.5	2.5
Number of vessels	14	14	14
Objective functions	Invest. Lost space "At terminal"	Invest. Lost space "At terminal"	Invest. Lost space "At terminal"
Number of batteries	39	41	40
Number of DS	8	6	8
Locations of the DS	T1, T2, T4, T7, T9, T10 T11, T13	T1, T2, T7, T9, T10, T11	T1, T2, T3, T4, T7, T9 T10, T13
Total costs [€]	52,999,976	48,122,474	58,650,080
Number of batteries per vessel	2.786	2.923	2.857
Number of DS per vessel	0.571	0.429	0.571
Shared batteries	16 by 2 V 2 by 3 V	18 by 2 V 2 by 3 V	19 by 2 V 1 by 3 V
Costs per vessel [€/vessel]	3,785,712	3,437,319	4,189,291
Optimality gap [%]	46.8	47.4	48.0

Table 4.16: Detailed breakdown of the runs with a weight of 90% attributed to the investment objective and various weights for the "at terminal" and loss space objectives.

Table 4.16 represents the results for Runs 1,2 and 3. From this Table, one can observe that the number of batteries remains stable, with slight variations (39 in Run 1, 41 in Run 2, and 40 in Run 3). This stability suggests that the overall battery requirement is relatively consistent across different weight distributions of the objective functions. There is a decrease in the number of DS from 8 in Run 1 and Run 3 to 6 in Run 2. The increase in the number of batteries in Run 2 correlates with the reduction in DS, as more batteries are required to maintain operations with fewer docking stations available. The total costs decreases when more weight is given to the "at terminal" times objective (Run 2) compared to the others. This results in fewer DS, as the model prioritizes reducing "at terminal" times. The space lost costs are very high, so giving them less weight automatically decreases the total costs. Thus, the costs per vessel follow a similar trend, with the lowest costs in Run 2 (3,437,319€) when more weight is given to "at terminal" times. This decrease in costs highlights the efficiency gained by reducing "at terminal" times and the number of DS. Regarding the locations of the DS, there are common DS locations across the runs (T1, T2, T7, T9, T10). This indicate a stable and preferred selection of places, with some additional DS needed in specific scenarios. This consistency suggests that these locations are strategically important for the battery swapping network.

	Scenarios		
	Run 4	Run 5	Run 6
$w_{invest}[\%]$	95	95	95
$w_{space}[\%]$	2.5	1.125	3.635
$w_{atTerminal}[\%]$	2.5	3.635	1.125
Number of vessels	14	14	14
Objective functions	Invest. Lost space "At terminal"	Invest. Lost space "At terminal"	Invest. Lost space "At terminal"
Number of batteries	40	41	39
Number of DS	8	6	9
Locations of the DS	T1, T2, T3, T4, T7, T9 T10, T13	T1, T2, T3, T4, T9, T10	T1, T2, T3, T4, T7, T9 T10, T11, T13
Total costs [€]	51,421,673	47,756,578	53,826,709
Number of batteries per vessel	2.857	2.929	2.786
Number of DS per vessel	0.571	0.429	0.643
Shared batteries	16 by 2 V 1 by 3 V	19 by 2 V 1 by 3 V	17 by 2 V 2 by 3 V
Costs per vessel [€/vessel]	3,672,976	3,411,184	3,844,764
Optimality gap [%]	49.2	49.0	50.3

Table 4.17: Detailed breakdown of the runs with a weight of 95% attributed to the investment objective and various weights for the "at terminal" and loss space objectives.

Table 4.17 represents the results for Runs 4,5 and 6. Similar to the previous runs, there is a stable number of batteries (around 39 to 41). The number of docking stations (DS) shows more variability, decreasing from 8 in Run 4 to 6 in Run 5, and increasing to 9 in Run 6. This variation reflects the model's adjustments based on the different weights assigned to the "at terminal" times and lost space objectives. Common DS locations across these three runs, including T1, T2, T3, T4, T7, T9, and T10, indicate a stable and preferred selection. This consistency suggests these locations are strategically important for the battery swapping network, with additional DS required in specific scenarios to optimize operations. As for the previous runs, the total costs decreases when more weight is given to the "at terminal" times objective, as observed in Run 5 (47,756,578€). This reduction in total costs aligns with fewer DS and an increase in the number of batteries, as the model prioritizes reducing "at terminal" times, but also to less weight given to the space lost costs. Thus, the costs per vessel also follow a similar trend, being lowest in Run 5 (3,411,184€).

Table 4.18 represents the results for Runs 7,8 and 9. The number of DS is higher in these runs, increasing from 8 in Run 8 to 9 in Run 7, and further to 10 in Run 9. This is especially the case when a high weight is given to the space lost objective. This is because the model aims to transport fewer batteries, necessitating more frequent swaps and hence more DS. The stable common DS locations (T1, T2, T4, T7, T9, T10, T11, T13) again reflect a consistent pattern in optimal DS placement. The total costs changes significantly across these runs. Run 8, where more weight is given to the "at terminal" times objective (49,133,575€), has the lowest total costs, indicating that

	Scenarios		
	Run 7	Run 8	Run 9
w_{invest}[%]	85	85	85
w_{space}[%]	7.5	3.75	11.25
$w_{atTerminal}$[%]	7.5	11.25	3.75
Number of vessels	14	14	14
Objective functions	Invest. Lost space "At terminal"	Invest. Lost space "At terminal"	Invest. Lost space "At terminal"
Number of batteries	39	40	39
Number of DS	9	8	10
Locations of the DS	T1, T2, T3, T4, T7, T9, T10, T11, T13	T1, T2, T4, T7, T9, T10, T11, T13	T1, T2, T3, T4, T7, T8, T9, T10, T11, T13
Total costs [€]	55,841,480	49,133,575	63,413,771
Number of batteries per vessel	2.786	2.857	2.786
Number of DS per vessel	0.643	0.571	0.714
Shared batteries	17 by 2 V 1 by 3 V	13 by 2 V 1 by 3 V	15 by 2 V 2 by 3 V
Costs per vessel [€/vessel]	3,988,677	3,509,541	4,529,555
Optimality gap [%]	44.9	48.9	43.1

Table 4.18: Detailed breakdown of the runs with a weight of 85% attributed to the investment objective and various weights for the "at terminal" and loss space objectives.

managing "at terminal" times effectively can reduce overall costs. Conversely, Run 9, with more weight given to the lost space objective (63,413,771€), has the highest total costs, highlighting the high costs associated with managing lost space. Thus, as in the other runs, total costs are influenced by the balance between investment, "at terminal" times, and space lost objectives, with costs generally decreasing as the weight shifts towards "at terminal" times.

Managerial insights: *As evidenced by the results, it is crucial to carefully attribute and choose the weight assigned to each objective. The weights significantly influence the design of the network and the total costs incurred. Therefore, a balanced and well-considered approach to weighting each objective is essential for optimizing the system. Table 4.19 provides more insights and leads to further advice.*

Table 4.19 shows additional results for each run. **#x is the number of 2h time slots where batteries are on terminals ("at terminal" times), and #y is the number of 2h time slots where batteries are on vessels.** The table, as well as its analysis, is divided into three blocks: the basic scenarios, the 9 runs where the investment function is given weights between 85% and 95%, and the three last runs where the weight given to the loss space function is fixed to 5%.

The first block exhibits interesting results and provides the minimal costs for each objective separately. As can be seen in Figure 4.12, the smallest x occurs when all the weight is given to the batteries' "at terminal" times objective. This makes sense because prioritizing "at terminal" times

w1 [%]	w2 [%]	w3 [%]	RUN	Total [€]	#b	DS	Invest. [€]	#x (b at T)	#y (b on V)	Loss sp. [€]	at T. [€]
100	0	0	Base 1	46’881’000	42	5	46’881’000	122	844	-	-
0	100	0	Base 2	164’510’040	44	13	-	446	566	164’510’040	-
0	0	100	Base 3	129’712	56	13	-	25	1263	-	129’712
90	5	5	Run1	52’999’976	39	8	48’064’500	252	645	193’531’018	1’307’502
90	2.5	7.5	Run2	48’122’474	41	6	47’275’500	212	731	219’681’074	1’099’962
90	7.5	2.5	Run3	58’650’080	40	8	49’020’000	263	657	193’306’208	1’364’576
95	2.5	2.5	Run4	51’421’673	40	8	49’020’000	271	649	192’700’837	1’406’084
95	1.1	3.9	Run5	47’756’578	41	6	47’275’500	218	725	249’231’189	1’131’093
95	3.9	1.1	Run6	53’826’709	39	9	49’414’500	276	621	189’429’619	1’432’026
85	7.5	7.5	Run7	55’841’480	39	9	49’414’500	267	630	183’136’737	1’385’330
85	3.7	11.3	Run8	49’133’575	40	8	49’020’000	255	665	197’243’393	1’323’068
85	11.3	3.7	Run9	63’412’771	39	10	50’764’500	288	609	179’622’292	1’494’288
60	5	35	Run10	38’843’165	39	8	48’064’500	262	635	190’573’591	1’359’387
70	5	25	Run11	43’535’295	39	8	48’064’500	255	639	191’187’562	1’323’067
80	5	15	Run12	48’887’450	40	8	49’020’000	279	641	189’086’022	1’447’591

Table 4.19: Detailed breakdown of the summary of the 15 multi-objective runs, with regards to the most relevant output.

reduces the number of batteries that need to be kept on hand, minimizing the inventory at the terminals. The second smallest x is observed when only the investment cost is considered, highlighting the balance between these two objectives. The highest x is seen when all the weight is given to the loss space objective. This is because minimizing the space lost to batteries on vessels leads to a greater number of batteries being stored at the terminals. This scenario is also associated with the smallest Y, which again makes sense because prioritizing the loss space objective means fewer batteries are kept on vessels to maximize cargo space. This results in a lower number of batteries being present on vessels over the 2-day period.

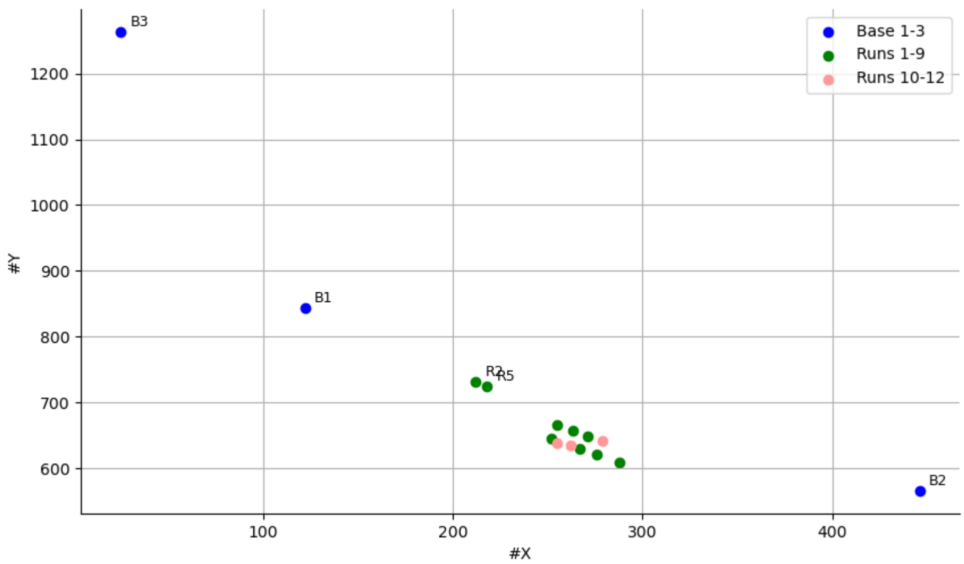

Figure 4.12: Number of 2-hour slots with batteries on terminals vs. vessels, for each run

Regarding the second block, the following overall remarks can be done:

- Stability in battery numbers: Across all scenarios, the number of batteries remains stable, hovering around 40.

- DS: The number of DS varies between 6 and 10, with most scenarios clustering around 8. This variability is influenced by the weights assigned to the investment, "at terminal" times, and space lost objectives. When more weight is given to the investment objective, the number of DS tends to decrease. Conversely, when more weight is given to the loss space objective, the number of DS increases. This is because prioritizing lost space leads to a need for more frequent swaps to minimize "at terminal" times, hence more DS are required.

- Total costs: The total costs remain within a similar range, with variations depending mostly on the weight assigned to the space loss objective. When more weight is assigned to the "at terminal" times objective, The total costs tend to be lower due to reduced "at terminal" times and fewer DS. Conversely, when more weight is assigned to the loss space objective, total costs increase due to the need for more DS and the associated infrastructure costs. This dependency highlights the trade-offs between minimizing "at terminal" times and managing loss space effectively.

- Stability: Investment and "at terminal" costs exhibit relative stability. However, loss space costs demonstrate a wider range. This can be attributed to generally higher costs associated with loss space. As a result, a one-unit increase in loss space could lead to a proportionally larger increase in total costs compared to the other two objectives.

- Pareto optimum: The three best solutions for each costs separately are:

  - Total costs: $Run5 \leq Run2 \leq Run8$
  - Investment costs: $Run5 = Run2 \leq Run1$
  - Loss space costs: $Run9 \leq Run7 \leq Run6$
  - "At terminal" costs: $Run2 \leq Run5 \leq Run1$

  The results indicate that no single scenario dominates across all cost factors. However, Runs 2 and 5 appear to achieve superior outcomes for three out of the four cost categories.

- Interestingly, Runs 2 and 5 exhibit very similar values for x (212 vs. 218) and y (731 vs. 725), as can be seen in Figure 4.12. These values contrast with the other runs in this block, which tend to have lower x and higher Y. This suggests alignment between the "at terminal" cost and investment cost objectives in Runs 2 and 5, indicating they are not conflicting. In contrast, the loss space objective appears to be independent. This is logical because minimizing loss space prioritizes maximizing x while minimizing Y.

The third block (see Table 4.20) achieves significantly lower total costs due to the emphasis placed on the "at terminal" cost objective through higher weights. However, this comes at the expense of a less flexible network design. The network remains very stable, consistently consisting of only 8 DS and 39 or 40 batteries. Furthermore, the other performance metrics for this block fall within the average range observed in block 2.

Managerial insights: *The general advice from this experiment is that, from a purely network optimization perspective, the network is physically more efficient when the weight assigned to loss space costs is minimized. From the perspective of the battery and DS operator, it is anyways more logical to prioritize their own costs, including investment and the expenses associated with renting space to store batteries at terminals.*

This thesis utilizes this weighting sum method. However, two other methods (the *hierarchical* method and the *blended objectives* method) could also be relevant for further studies. Brief descriptions of these two methods are provided below.

	Scenarios		
	Run 10	Run 11	Run 12
$w_{invest}[\%]$	60	70	80
$w_{space}[\%]$	5	5	5
$w_{atTerminal}[\%]$	35	25	15
Number of vessels	14	14	14
Objective functions	Invest. Lost space "At terminal"	Invest. Lost space "At terminal"	Invest. Lost space "At terminal"
Number of batteries	39	39	40
Number of DS	8	8	8
Locations of the DS	T1, T2, T3, T4, T7, T9, T10, T13	T1, T2, T4, T7, T9, T10, T11, T13	T1, T2, T4, T7, T9, T10, T11, T13
Total costs [€]	38,843,165	43,535,295	48,887,450
Number of batteries per vessel	2.786	2.786	2.857
Number of DS per vessel	0.571	0.571	0.571
Shared batteries	20 by 2 V 1 by 3 V	16 by 2 V 2 by 3 V	14 by 2 V 1 by 3 V
Costs per vessel [€/vessel]	2,774,511	3,109,664	3,491,961
Optimality gap [%]	44.9	47.6	48.0

Table 4.20: Detailed breakdown of the runs with a weight of 5% attributed to the loss space objective and various weights for the "at terminal" and investment objectives.

Hierarchical (lexicographic) method

Hierarchical (or lexicographic) optimization involves optimizing multiple objectives in a strict priority order. The first objective is optimized fully before considering the second objective, and so on. This method is suitable when one objective is significantly more important than the others, or when there are strict priorities. It is particularly useful in cases where certain objectives are non-negotiable and must be optimized first. In this case, with three objective functions, the process is composed of the three following steps:

1. **First Objective** $f_1(x)$:

   $$\min f_1(x)$$

   Subject to no constraints initially.

2. **Second Objective** $f_2(x)$:

   $$\min f_2(x)$$

   Subject to:

   $$f_1(x) \leq f_1^* \times (1 + \epsilon_1)$$

   This ensures f_1 stays within the acceptable tolerance.

3. **Third Objective** $f_3(x)$:

   $$\min f_3(x)$$

   Subject to:

   $$f_1(x) \leq f_1^* \times (1 + \epsilon_1)$$

   $$f_2(x) \leq f_2^* \times (1 + \epsilon_2)$$

   This ensures both f_1 and f_2 stay within their respective acceptable tolerances.

Where f_1^* and f_2^* are the optimized values of the first and second objectives, and ϵ_1 and ϵ_2 their respective tolerances.

Blended objectives method

Blended objectives in Gurobi allow for a more advanced combination of multiple objectives. Each objective can be assigned a weight and a priority, and the solver tries to find a balance according to these specifications. This method provides flexibility in handling multiple objectives with varying degrees of importance. It is ideal for complex decision-making scenarios where multiple objectives must be balanced, and each has different levels of importance and urgency. The minimization process becomes:

$$\min \sum_{i=1}^{3} w_i f_i(x) \quad \text{, subject to priorities}$$

where w_i are the weights for the objective functions f_i respectively.

Chapter 5

Conclusions and recommendations

This chapter synthesizes the findings from the previous experiments, providing an overview of the key insights gained from this study. The conclusions drawn highlight the critical factors influencing the design and optimization of maritime battery swapping systems. These insights also inform the recommendations provided, aimed at guiding future research and practical implementation in the field.

5.1 Conclusions

This study aimed to investigate the potential of integrating battery storage into IWT systems. To this end, a computational model was developed to assess the system's performance under various conditions. The analysis encompassed a base case scenario to establish a comparison point and a subsequent sensitivity analysis to determine the impact of key system parameters, including battery capacity, costs, and availability. Recognizing the complex nature of the problem, a multi-objective optimization approach was then employed to simultaneously consider multiple objectives, providing a more realistic understanding of the complex decision making.

Section 4.5.2 shows that the decrease in the number of batteries and DS with increasing battery capacity is primarily due to the higher energy storage capability of each battery. This allows vessels to operate longer without requiring frequent swaps, leading to fewer overall batteries and DS. Consequently, the infrastructure can be more efficiently utilized, reducing investment costs. Furthermore, it also reveals that battery costs influence the financial aspect of maritime battery swapping systems. Higher costs lead to increased Capex and per vessel costs, emphasizing the need for cost-effective battery solutions. While the overall infrastructure requirements remain relatively stable, strategic resource allocation and optimization become more challenging with rising costs. Lastly, this section also exhibits that the number of available spots at DS presents contradictory results: sometimes leading to higher Capex due to increased complexity, as seen in the +2 spots scenario, and sometimes enhancing investment efficiency, as observed in the +4 and +8 spots scenarios. The +4 spots scenario strikes the best balance, achieving lower Capex and optimal resource utilization. Overall, the results of this experiment show instability and a lack of coherence, likely due to dependencies on the initial conditions and inputs provided to the model. Specifically, the initial location of batteries at time p=0 plays a crucial role. As shown in Section 4.5.4, loading conditions significantly influence the operational and financial aspects of maritime battery swapping systems. Fully unloaded vessels require fewer resources and lower costs, while fully loaded vessels necessitate more batteries and docking stations. However, none of these two scenarios is realistic. Thus, mixed loading scenarios provide a more realistic and balanced approach but introduce additional optimization challenges.

Section 4.5.5 analyzes various scenarios to determine the optimal balance between investment and space loss costs. After initial trials, it became evident that the loss costs were excessively high relative to investment costs. To address this, the hourly loss costs were reduced, acknowledging that the initial costs, derived from shipping prices, did not accurately reflect the barge owner's actual profits or losses. A key observation is that reducing the fraction of transport costs attributed to revenue loss results in more balanced outcomes, where the loss costs do not overshadow investment costs. This balance is essential to avoid disproportionately high total costs driven by excessive docking station utilization. Scenarios with higher weights on the investment objective (e.g., 90% in Cases 1.3 and 1.5) tend to reduce the number of docking stations, leading to lower capital expenditures (Capex). In contrast, scenarios with lower weights on the investment objective (e.g., 75% in Cases 1.1, 1.2, and 1.4) utilize more resources, including additional docking stations, resulting in higher Capex. This trend underscores the need to find a balanced approach where both investment costs and loss space are effectively managed. From the analysis, Case 1.5 emerges as the most balanced scenario, providing a practical trade-off between investment costs and operational efficiency. This scenario, with a higher weight on the investment objective, effectively minimizes Capex while maintaining an efficient distribution network. The number of batteries required remains relatively stable across scenarios, ranging from 39 to 41, indicating that battery requirements are not highly sensitive to changes in the weight given to the investment objective function. However, the number of docking stations show a clear decrease as more weight is allocated to investment costs, reflecting a strategic reallocation of resources to minimize expenditures progressively.

After the introduction of a third objective function in Section 4.5.7, representing the costs associated with the batteries times at terminal, 15 different runs were conducted in Section 4.5.8. Overall, the number of batteries remains stable around 40, while the number of DS varies between 6 and 10, mostly clustering around 8. The number of DS decreases when more weight is given to the investment objective and increases with greater emphasis on the loss space objective, due to the need for more frequent battery swaps. Total costs fluctuate mainly based on the weight assigned to the space loss objective, with lower costs observed when prioritizing "at terminal" times due to fewer DS and smaller "at terminal" times costs. Investment and "at terminal" costs show relative stability, whereas loss space costs exhibit a wider range, leading to significant impacts on total costs. The results also highlight that no single scenario dominates across all cost factors. However, two runs (2 & 5) stand out by achieving superior outcomes in three out of the four cost categories. These two runs are the ones where the weights given to the loss space objective are the smallest, indicating alignment between "at terminal" and investment cost objectives. These runs also show similar values for the number of batteries at terminals (X) and on vessels (Y), suggesting a balance that is disrupted when the loss space objective is prioritized. The general advice from this experiment is the following: for optimal network efficiency, minimizing the weight assigned to loss space costs is crucial. From the battery and DS operator's perspective, it is more logical to prioritize investment and rental costs. The importance of carefully assigning weights to each objective is emphasized, as this significantly influences network design and total costs. To determine these appropriate weightings, the BSS system operators should use a collaborative approach, involving all concerned stakeholders. By engaging in open dialogue, diverse perspectives can be considered, and trade-offs between conflicting objectives can be identified. This participatory process promotes transparency and ensures that the model aligns, as much as possible, with the priorities of all parties involved.

5.2 Recommendations

By addressing the following recommendations, future research can build upon the findings of this thesis to develop more refined, efficient, and sustainable battery swapping systems for IWT.

Optimality gaps The optimality gaps observed in this study are high. It is essential to acknowledge that while a large network provides more realistic results and greater opportunities for battery sharing, it also increases the complexity of the optimization process. Future work should focus on reducing these optimality gaps to enhance the applicability of the model.

Expanding the network After getting better optimality gaps, the next step should involve expanding the network even more, in order to include more connections between the Netherlands and the rest of Europe, beyond just Antwerp and Duisburg. This expansion would provide a more comprehensive view of the potential efficiencies and challenges in a broader context, further enhancing the model's realism and utility.

Detailed sailing profiles It would be beneficial to model the sailing profiles with greater detail, but also flexibility. This could include external factors such as wind speed, weather conditions, and varying waterway traffic. Incorporating these elements would provide a more accurate representation of operational conditions, leading to more robust and reliable optimization outcomes.

Energy grid resilience How does the transition to electricity impact the resilience of the energy grid, and what strategies can be implemented to enhance the robustness of logistics operations in case of an overloaded grid network? It is crucial to study the implications of increased electric demand on the energy grid and develop strategies such as smart grid technologies, decentralized energy storage, and demand response mechanisms to ensure the reliability and resilience of logistics operations amidst potential grid overloads. Appendix A, which explores the implications of increased electric demand on the energy grid and proposes potential solutions to ensure reliability and resilience, proposes first answers to this aspect.

Technological advancements Future research should also explore advancements in battery technology and their integration into the optimization model. As battery efficiency and capacity improve, updating the model to reflect these changes will ensure it remains relevant and effective.

Policy and economic factors It is also recommended to consider the impact of policy changes and economic factors on the feasibility and sustainability of battery swapping systems. This includes analyzing subsidies, regulations, and market dynamics that could influence the adoption and operational efficiency of such systems. Notably, this could change the outcome that include the net present values, or revenue losses.

Environmental impact Lastly, a more detailed assessment of the environmental impact of battery swapping systems should be conducted. This includes evaluating the lifecycle emissions of batteries, the potential for renewable energy integration, and the overall reduction in greenhouse gas emissions compared to traditional fuel-based systems.

Appendix A

Impacts on the electricity grid

This appendix explores the implications of increased electric demand on the energy grid and proposes potential solutions to ensure reliability and resilience. Although extensive research has been conducted on the impacts and solutions for EVs, there appears to be a lack of studies focusing on the electrification of IWT. This section leverages the findings and methodologies applied to EVs to propose initial steps towards solutions that could be implemented for IWT.

A.1 Grid pressure concerns for electrified IWT

Although a lot of research has been done on how EVs affect the electricity grid, not as much has been done on the possible pressure that comes with electrifying IWT. According to previous research on EVs, grid stability may be threatened by the growing demand for power brought on by the electrification of transportation [115]. The impact of rising EV use on local power demands has also been evaluated by Su et al. (2012) [116], highlighting the significance of taking into account the effects on power distribution systems and transportation networks. Nevertheless, IWT electrification currently lacks this level of investigation, creating a knowledge gap about its possible effects on the grid.

The Netherlands relies on a nationwide electricity grid (TRL 9) for a stable and continuous supply. This grid is also interconnected with neighboring European countries for added security, such as Belgium, Norway and Germany. Battery electric charging facilities for IWT, typically ranging from 2MVA to 10MVA [117], require a medium voltage grid connection (173kVA to 10MVA), which has a process and development period of 6 months to 3 years [118]. Concerns exist regarding potential network congestion when developing a nationwide charging and bunkering infrastructure for the Netherlands. While Figure A.1 depicts current demand-side congestion on a limited portion of the Dutch grid [5], even seemingly small projects like a 2MVA battery charging facility (requiring medium voltage connection) can necessitate adjustments at higher grid levels [118]. Notably, the impact varies significantly based on location. Integrating renewable energy sources like wind and solar into the national grid presents potential challenges related to grid congestion. Notably, this is not solely due to the variability of these sources, but also increased overall demand for electricity driven by the broader electrification of various sectors.

A.2 Vehicle-to-grid (V2G) for energy storage

V2G technology allows EVs to do more than just receive electricity for charging [26]. EVs can actually feed electricity back into the grid thanks to V2G. A MIT team's recent publication in the journal Energy Advances explores how V2G technology can enable EVs to function as a large-scale energy storage system [119]. By enabling EVs to return power to the grid, costly fixed battery

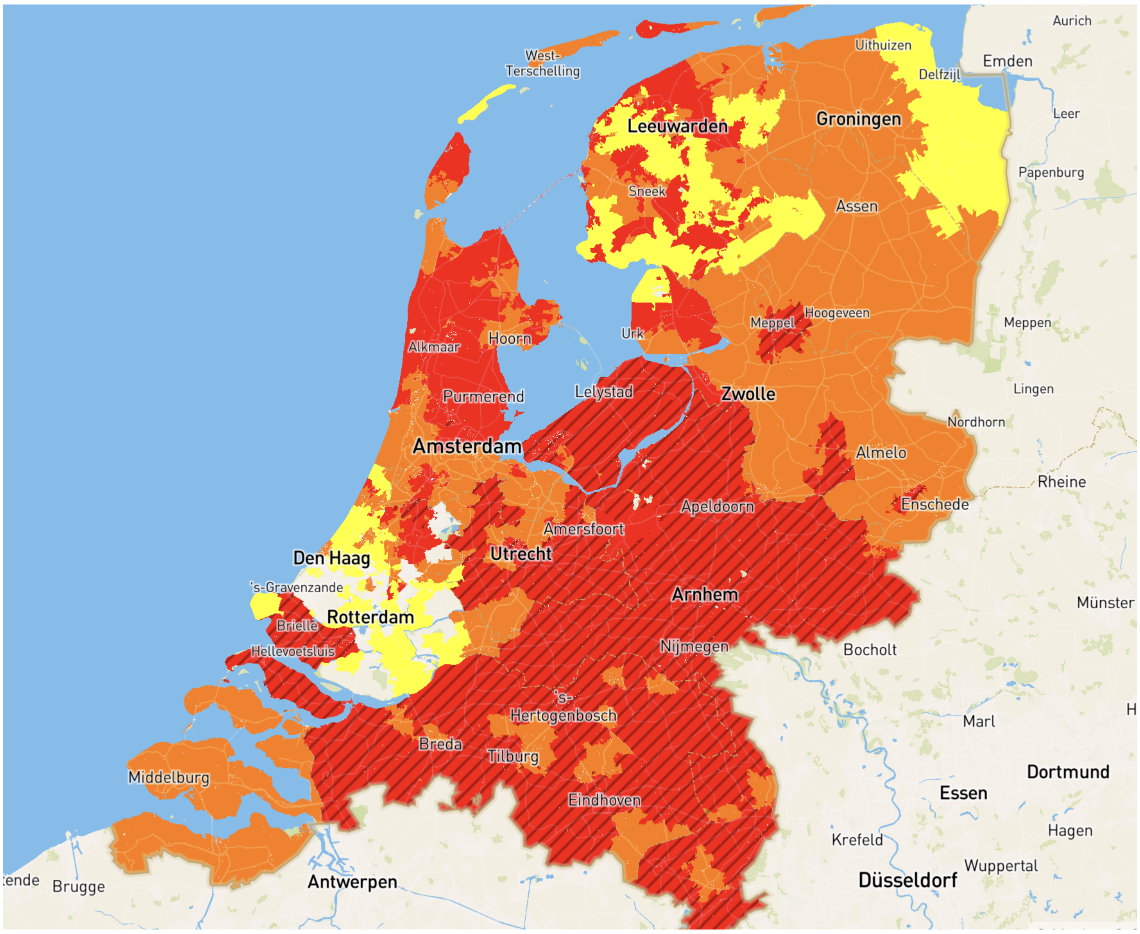

Figure A.1: The current electrical grid congestion from the demand side. Yellow is limited transport capacity available, orange is a pre-announcement of structural congestion, red is current structural congestion, and red shaded means that no transport capacity available (i.e. the limits for the application of congestion management have been reached) [5].

storage and backup generators may become unnecessary. This is especially important when intermittent renewable energy sources like wind and solar power increase in share of the energy mix. This MIT study is the first in-depth examination of the integration of V2G into next-generation power systems. The study team examined variables such carbon emission targets, fluctuating renewable energy generation, and the expenses of constructing conventional energy storage and transmission infrastructure using computational models. According to their research, V2G might considerably lower the price of decarbonising the electricity system.

Within the scope of this study, V2G technology can also be considered as battery-to-grid technology, making it applicable to the IWT sector. This V2G capability offers several advantages, such as a reduced reliance on fossil fuels, grid stability, and economic benefits [120]. Indeed, emissions from power facilities can be reduced by utilising stored renewable energy during peak hours. Moreover, V2G lessens the burden on the grid by balancing out variations in electricity demand. Last but not least, operators may be able to make money by reselling electricity to the grid at busy times. There are, however, a few difficulties to take into account. First off, there is a significant investment in infrastructure. It would be essential to set up a network of exchanging stations with the required bi-directional charging capability. IWT requires network construction regardless of V2G technology. The costs of the investment are therefore inevitable. Second, more research is necessary about the battery's capacity and degradation over time, as these factors will affect V2G's economic viability [121].

A study made by Ke et al. (2020) [122] examined converting the Penghu bus system to battery-swapping electric buses. A genetic algorithm optimized charging schedules to minimize daily costs. They explored using leftover battery capacity for demand response (selling power back to the grid). While reselling electricity increased revenue, it also raised the total cost due to needing more batteries, faster battery degradation, and energy losses. Two scenarios were compared: one with just battery optimization and another that factored in wind and solar power generation. The cost increase for considering renewable energy sources and demand response was 13% to 17%. Interestingly, the revenue from reselling electricity could outweigh this added cost, but only if the resale price was double the standard electricity rate. The research team of MIT [119] is currently investigating the potential impact of heavy-duty EVs on the power grid. They think that electric delivery trucks could be early adopters of V2G technology and have a big impact on grid balancing and decarbonisation efforts because of their predictable routes and charging schedules. The vessels also have a lot of potential and might be considered a useful resource in this regard. It is true that inland vessels usually have dependable routes and operational routines, which facilitates scheduling of V2G charging and discharging cycles. Thus, one of the main benefits of incorporating them into the grid is their predictability. Furthermore, because inland vessels have longer operating ranges than land-based electric vehicles, they have bigger battery capacities. Increased capacity for energy storage and return to the grid results from this. The redeployment of electricity from the charged containers could be envisioned in the following way:

1. Grid signal: The swapping station receives a signal from the grid operator indicating a peak demand period.

2. Power flow reversal: The switching station starts a power draw from the already charged batteries rather than keeping charged batteries in the containers and waiting for a vessel to arrive.

3. Electricity injection: The captured electric current is fed back into the grid, helping to meet the surge in demand and stabilize the overall grid frequency.

4. Battery management: The system is not intended to empty every container to the fullest extent possible. A sufficient number of reserve containers are kept on hand to guarantee that a few upcoming vessels can be fully charged with the required number of containers.

A.3 Renewable energy sources

The paper published by the MIT [119] highlights the increasing demand for electricity as transportation electrification accelerates. Although this is good for cutting emissions, it also makes it more difficult to guarantee that there will be enough renewable energy to power this shift. Achieving clean energy targets requires storing energy from renewable sources. BSS are a well-liked and practical method of connecting solar power to electric vessels. They can smooth out the fluctuations in PV energy production using supercapacitors [123], and they can also shift the load profile and store energy. Reducing operational costs is one of the main advantages of incorporating renewable energy, particularly solar photovoltaic (PV), into the grid through demand response. However, it's imperative to control the inherent uncertainty caused by fluctuating PV output and demand. Energy management systems and charging stations must properly communicate in order to charge depleted batteries as efficiently as feasible using renewable energy sources rather than depending solely on energy storage. Energy storage system integration improves power delivery and is especially important in day-ahead scheduling scenarios with system uncertainty. By using a smart grid, load demand can be shifted to coincide with the production of renewable energy, maximising energy consumption [124]. Moreover, the problem of high peak demand brought on by more charging stations can be handled by utilising renewable energy sources to maximise charging service capacity at a lower cost [125]. In order to send power to loads and store a predetermined quantity of energy in the battery for later charging, a grid-connected PV-wind hybrid system with battery storage systems (BSS) and charging stations is one option [126]. This section has focused a lot of attention on solar energy, but it's crucial to emphasise that the ideas covered here may be applied to any renewable energy source that has the potential to become a significant player in the future.

A.4 Other solutions to network congestion or too high pressure

Besides the V2G technology, addressing network congestion can involve other strategies. One proposed solution is to modify the grid structure itself. The medium voltage grid typically employs radial, annular, or meshed configurations, as illustrated in Figure A.2. In a radial grid, also known as a star-shaped grid, the supply point is connected to the network station through a single connection. Any malfunction in this connection results in a complete grid outage. An annular grid allows the supply point to reach multiple stations via two connections, and a failure in one connection can be rectified by relocating the grid opening. In a meshed grid, the supply point connects to several stations through more than two connections [127]. To enhance the medium voltage grid, additional support points can be introduced, supplied by a meshed-operated medium voltage transport grid. This would result in shorter radial medium voltage grid structures, offering increased flexibility and capacity [127].

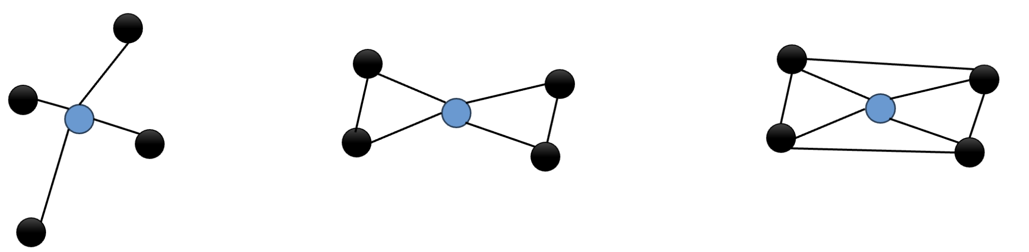

Figure A.2: Three common grid structures used in medium voltage networks: the radial, annular, and meshed configurations.

Making grids that are simpler and shorter is another strategy. A direct connection between a charging facility and a renewable production source, such as a solar field or wind turbine, is possible. It's crucial to remember that renewable energy sources are sporadic, and installing a system like this would require extra financial outlay. Although renewable energy sources with intermittent nature, such as wind and solar, have great potential, their unpredictability calls for creative solutions in order to achieve broad electrification of ships. Luckily, there are more intermittent sources available in the future. Exciting prospects like thermochemical energy storage, white hydrogen, and many more that are independent of the season, solar exposure, etc. are being investigated through ongoing study. Though these solutions remain on the horizon, they represent a promising avenue for overcoming intermittency and ensuring reliable energy access for the maritime industry in the long term. The ongoing pursuit of these technologies carries the potential to revolutionize the industry's decarbonization objective, and their eventual breakthroughs could prove transformative for electrification efforts. While interesting, this topic falls outside the scope of this thesis and won't be explored further.

Appendix B

Inputs

This appendix provides the input data for the model, presented in Excel format.

p	cds	cht	pw	name	maxDS
1	1350000	4	1000	T1	8
2	1350000	4	1000	T2	8
3	1350000	3	1000	T3	6
4	1350000	3	1000	T4	6
5	1350000	3	1000	T5	6
6	1350000	2	1000	T6	4
7	1350000	2	1000	T7	4
8	1350000	2	1000	T8	4
9	1350000	2	1000	T9	4
10	1350000	2	1000	T10	4
11	1350000	2	1000	T11	4
12	1350000	2	1000	T12	4
13	1350000	2	1000	T13	4

Figure B.1: Example of the inputs in excel: the DS inputs

v	chv	L	
1	3	Vessel 0	C3b
2	3	Vessel 1	C3b
3	3	Vessel 2	C3b
4	3	Vessel 3	M8
5	3	Vessel 4	M8
6	3	Vessel 5	M8
7	3	Vessel 6	M8
8	3	Vessel 7	M8
9	3	Vessel 8	M8
10	3	Vessel 9	M11
11	3	Vessel 10	M11
12	3	Vessel 11	M11
13	3	Vessel 12	M8
14	3	Vessel 13	M6

Figure B.2: Example of the inputs in excel: the vessels inputs

	Vessel0		Vessel1		Vessel2		Vessel3		Vessel4		Vessel10		Vessel11	
t	spv	pv	spv	pv	spv	pv	spv	pv	spv	pv	spv	pv	spv	pv
0	0	900	0	900	0	900	4	0	4	0	0	600	6	0
1	0	900	3	0	0	900	0	600	4	0	0	600	6	0
2	0	900	0	900	0	900	0	600	0	600	0	600	0	600
3	0	900	0	900	0	900	0	600	0	600	5	0	0	600
4	0	900	1	0	0	900	0	600	0	600	0	600	7	0
5	0	900	0	900	0	900	0	600	0	600	0	600	7	0
6	1	0	0	900	2	0	1	0	0	600	0	600	0	600
7	1	0	0	900	2	0	1	0	1	0	1	0	0	600
8	0	900	0	900	0	900	0	600	1	0	0	600	6	0
9	0	900	0	900	0	900	0	600	0	600	0	600	6	0
10	0	900	0	900	0	900	0	600	0	600	0	600	0	600
11	0	900	2	0	0	900	0	600	0	600	5	0	0	600
12	0	900	2	0	0	900	0	600	0	600	0	600	7	0
13	0	900	0	900	0	900	4	0	0	600	0	600	7	0
14	2	0	0	900	1	0	4	0	4	0	0	600	0	600
15	2	0	0	900	1	0	0	600	4	0	1	0	0	600
16	0	900	0	900	0	900	0	600	0	600	0	600	6	0
17	0	900	0	900	0	900	0	600	0	600	0	600	6	0
18	0	900	0	900	0	900	0	600	0	600	0	600	0	600
19	0	900	1	0	0	900	0	600	0	600	5	0	0	600
20	0	900	0	900	0	900	1	0	0	600	0	600	7	0
21	0	900	0	900	0	900	1	0	1	0	0	600	7	0
22	1	0	0	900	2	0	1	0	1	0	0	600	7	0
23	1	0	0	900	2	0	1	0	1	0	1	0	7	0
	Vessel12		Vessel13		Vessel5		Vessel6		Vessel7		Vessel8		Vessel9	
t	spv	pv	spv	pv	spv	pv	spv	pv	spv	pv	spv	pv	spv	pv
0	1	0	1	0	0	800	1	0	1	0	0	600	0	500
1	0	600	0	600	0	800	1	0	1	0	0	600	0	500
2	0	600	11	0	0	800	0	800	1	0	12	0	0	500
3	0	600	0	600	0	800	0	800	0	800	0	600	0	500
4	0	600	0	600	0	800	0	800	0	800	0	600	0	500
5	8	0	0	600	0	800	0	800	0	800	9	0	13	0
6	0	600	0	600	0	800	0	800	0	800	0	600	0	500
7	0	600	3	0	0	800	0	800	0	800	0	600	0	500
8	0	600	0	600	0	800	0	800	0	800	12	0	0	500
9	0	600	0	600	1	0	0	800	0	800	0	600	0	500
10	1	0	0	600	1	0	0	800	0	800	0	600	0	500
11	0	600	0	600	1	0	10	0	0	800	9	0	1	0
12	0	600	11	0	0	800	10	0	10	0	0	600	0	500
13	0	600	0	600	0	800	0	800	10	0	0	600	0	500
14	0	600	0	600	0	800	0	800	10	0	12	0	0	500
15	8	0	0	600	0	800	0	800	0	800	0	600	0	500
16	0	600	0	600	0	800	0	800	0	800	0	600	0	500
17	0	600	3	0	0	800	0	800	0	800	9	0	13	0
18	0	600	0	600	0	800	0	800	0	800	9	0	0	500
19	0	600	0	600	0	800	0	800	0	800	0	600	0	500
20	1	0	0	600	0	800	0	800	0	800	7	0	0	500
21	0	600	0	600	10	0	0	800	0	800	0	600	0	500
22	9	0	11	0	10	0	1	0	0	800	9	0	0	500
23	0	600	11	0	10	0	1	0	0	800	0	600	1	0

Figure B.3: Example of the inputs in excel: the sailing profiles

Vessel0	Vessel1	Vessel2	Vessel3	Vessel4	Vessel5
100	500	100	0	0	180
100	0	100	120	0	180
100	250	100	120	120	180
100	250	100	120	120	0
100	0	100	120	120	180
100	100	100	120	120	180
0	100	0	0	120	180
0	100	0	0	0	0
100	100	100	120	0	180
100	100	100	120	120	180
100	100	100	120	120	180
100	0	100	120	120	0
100	0	100	120	120	180
100	100	100	0	120	180
0	100	0	0	0	180
0	100	0	120	0	0
100	100	100	120	120	180
100	100	100	120	120	180
100	100	100	120	120	180
100	0	100	120	120	0
100	100	100	0	120	180
100	100	100	0	0	180
0	100	0	0	0	180
0	100	0	0	0	0

Figure B.4: Example of the inputs in excel: loss costs

			Initial values					
b	**cb**	**cap**	**Lbo**	**Uto x0**	**Uvo y0**	**ko**	**mo**	
1	955500	2900	2900	1	0	0	0	**OK**
2	955500	2900	2900	1	0	0	0	**OK**
3	955500	2900	2900	2	0	0	0	**OK**
4	955500	2900	2900	2	0	0	0	**OK**
5	955500	2900	2900	3	0	0	0	**OK**
6	955500	2900	2900	3	0	0	0	**OK**
7	955500	2900	2900	4	0	0	0	**OK**
8	955500	2900	2900	4	0	0	0	**OK**
9	955500	2900	2900	5	0	0	0	**OK**
10	955500	2900	2900	5	0	0	0	**OK**
11	955500	2900	2900	6	0	0	0	**OK**
12	955500	2900	2900	6	0	0	0	**OK**
13	955500	2900	2900	7	0	0	0	**OK**
14	955500	2900	2900	7	0	0	0	**OK**
15	955500	2900	2900	8	0	0	0	**OK**
16	955500	2900	2900	8	0	0	0	**OK**
17	955500	2900	2900	9	0	0	0	**OK**
18	955500	2900	2900	9	0	0	0	**OK**
19	955500	2900	2900	10	0	0	0	**OK**
20	955500	2900	2900	10	0	0	0	**OK**
21	955500	2900	2900	11	0	0	0	**OK**
22	955500	2900	2900	11	0	0	0	**OK**
23	955500	2900	2900	12	0	0	0	**OK**
24	955500	2900	2900	12	0	0	0	**OK**
25	955500	2900	2900	13	0	0	0	**OK**
26	955500	2900	2900	13	0	0	0	**OK**
27	955500	2900	2900	0	1	0	1	**OK**
28	955500	2900	2900	0	1	0	0	**OK**
29	955500	2900	2900	0	2	0	2	**OK**
30	955500	2900	2900	0	2	0	0	**OK**
31	955500	2900	2900	0	3	0	3	**OK**
32	955500	2900	2900	0	3	0	0	**OK**
33	955500	2900	2900	0	4	0	4	**OK**
34	955500	2900	2900	0	4	0	0	**OK**
35	955500	2900	2900	0	5	0	5	**OK**
36	955500	2900	2900	0	5	0	0	**OK**
37	955500	2900	2900	0	6	0	6	**OK**
38	955500	2900	2900	0	6	0	0	**OK**
39	955500	2900	2900	0	7	0	7	**OK**
40	955500	2900	2900	0	7	0	0	**OK**
41	955500	2900	2900	0	8	0	8	**OK**
42	955500	2900	2900	0	8	0	0	**OK**
43	955500	2900	2900	0	9	0	9	**OK**
44	955500	2900	2900	0	9	0	0	**OK**
45	955500	2900	2900	0	10	0	10	**OK**
46	955500	2900	2900	0	10	0	0	**OK**
47	955500	2900	2900	0	11	0	11	**OK**
48	955500	2900	2900	0	11	0	0	**OK**

Figure B.5: Example of the inputs in excel: part of initial conditions

Appendix C

Python code

```
# %%
#-----------Imports---------------------------------------------------------------
from gurobipy import *
from openpyxl import load_workbook
from tabulate import tabulate
import numpy as np
import csv
import pandas as pd
np.set_printoptions(threshold=np.inf) # to see all extension when printing

# %%
#Create model
BM = Model("Basic_Model")

# %%
#Import data
wb = load_workbook("PinaT14VNUIT1_5_3.xlsx")
ws = wb.active

# %%
#14V13DS
#-----------Sets----------------------------------------------------------------
B = np.array([i[0].value for i in wb.worksheets[0]["A3":"A83"]]) # set of batteries
T = np.array([i[0].value for i in wb.worksheets[1]["A2":"A14"]]) # set of terminals
V = np.array([i[0].value for i in wb.worksheets[2]["A2":"A15"]]) # set of vessels
P = np.array([i[0].value for i in wb.worksheets[3]["A3":"A26"]]) # set of time periods

# %%
#14V13DS
#-----------Parameters --------------------------------------------------------
## Batteries
cb = np.array([i[0].value for i in wb.worksheets[0]["B3":"B83"]]) # Investment cost [
    Euro]
cap = np.array([i[0].value for i in wb.worksheets[0]["C3":"C83"]]) # Capacity [kW]
mbl = 0.1 # Min battery level at all times
Lb0 = np.array([i[0].value for i in wb.worksheets[0]["D3":"D83"]]) # Initial values:
    battery level [kW]

ut_aux = np.array([i[0].value for i in wb.worksheets[0]["E3":"E83"]]) # Initial values:
    battery location at terminal
Ut0 = np.zeros((len(B),len(T)))
for b in range(len(B)):
    if ut_aux[b]>0:
        Ut0[b,ut_aux[b]-1]=1

uv_aux = np.array([i[0].value for i in wb.worksheets[0]["F3":"F83"]]) # Initial values:
    battery location on vessel
```

```
Uv0 = np.zeros((len(B),len(V)))
for b in range(len(B)):
    if uv_aux[b]>0:
        Uv0[b,uv_aux[b]-1]=1

k_aux = np.array([i[0].value for i in wb.worksheets[0]["G3":"G83"]]) # Initial values: battery usage on terminal
k0 = np.zeros((len(B),len(T)))
for b in range(len(B)):
    if k_aux[b]>0:
        k0[b,k_aux[b]-1]=1

m_aux = np.array([i[0].value for i in wb.worksheets[0]["H3":"H83"]]) # Initial values: battery usage on vessel
m0 = np.zeros((len(B),len(V)))
for b in range(len(B)):
    if m_aux[b]>0:
        m0[b,m_aux[b]-1]=1

## Vessels
chv = np.array([i[0].value for i in wb.worksheets[2]["B2":"B15"]]) # Total number of charging points in vessel
sp_aux = [np.array([i[0].value for i in wb.worksheets[3]["B3":"B26"]]), # Sailing profile of vessels
          np.array([i[0].value for i in wb.worksheets[3]["D3":"D26"]]),
          np.array([i[0].value for i in wb.worksheets[3]["F3":"F26"]]),
          np.array([i[0].value for i in wb.worksheets[3]["H3":"H26"]]),
          np.array([i[0].value for i in wb.worksheets[3]["J3":"J26"]]),
          np.array([i[0].value for i in wb.worksheets[3]["L3":"L26"]]),
          np.array([i[0].value for i in wb.worksheets[3]["N3":"N26"]]),
          np.array([i[0].value for i in wb.worksheets[3]["P3":"P26"]]),
          np.array([i[0].value for i in wb.worksheets[3]["R3":"R26"]]),
          np.array([i[0].value for i in wb.worksheets[3]["T3":"T26"]]),
          np.array([i[0].value for i in wb.worksheets[3]["V3":"V26"]]),
          np.array([i[0].value for i in wb.worksheets[3]["X3":"X26"]]),
          np.array([i[0].value for i in wb.worksheets[3]["Z3":"Z26"]]),
          np.array([i[0].value for i in wb.worksheets[3]["AB3":"AB26"]])]

sp_aux = np.array(sp_aux)

sp = np.zeros((len(V),len(T),len(P)))
for v in range(len(V)):
    for p in range (len(P)):
        if sp_aux[v,p]>0:
            sp[v,sp_aux[v,p]-1,p]=1

pv_aux = [np.array([i[0].value for i in wb.worksheets[3]["C3":"C26"]], dtype=float), # Power requirement per time step
            np.array([i[0].value for i in wb.worksheets[3]["E3":"E26"]], dtype=float),
            np.array([i[0].value for i in wb.worksheets[3]["G3":"G26"]], dtype=float),
            np.array([i[0].value for i in wb.worksheets[3]["I3":"I26"]], dtype=float),
            np.array([i[0].value for i in wb.worksheets[3]["K3":"K26"]], dtype=float),
            np.array([i[0].value for i in wb.worksheets[3]["M3":"M26"]], dtype=float),
            np.array([i[0].value for i in wb.worksheets[3]["O3":"O26"]], dtype=float),
            np.array([i[0].value for i in wb.worksheets[3]["Q3":"Q26"]], dtype=float),
            np.array([i[0].value for i in wb.worksheets[3]["S3":"S26"]], dtype=float),
            np.array([i[0].value for i in wb.worksheets[3]["U3":"U26"]], dtype=float),
            np.array([i[0].value for i in wb.worksheets[3]["W3":"W26"]], dtype=float),
            np.array([i[0].value for i in wb.worksheets[3]["Y3":"Y26"]], dtype=float),
            np.array([i[0].value for i in wb.worksheets[3]["AA3":"AA26"]], dtype=float),
            np.array([i[0].value for i in wb.worksheets[3]["AC3":"AC26"]], dtype=float)]

pv = np.array(pv_aux)
pc = np.zeros((len(V),len(P)))
for v in range(len(V)):
    for p in range (len(P)):
        if pv[v,p]>0:
            pc[v,p]=1
```

```
penalty_aux = [np.array([i[0].value for i in wb.worksheets[3]["C30":"C53"]], dtype=float
    ), # Power requirement per time step
    np.array([i[0].value for i in wb.worksheets[3]["E30":"E53"]], dtype=float),
    np.array([i[0].value for i in wb.worksheets[3]["G30":"G53"]], dtype=float),
    np.array([i[0].value for i in wb.worksheets[3]["I30":"I53"]], dtype=float),
    np.array([i[0].value for i in wb.worksheets[3]["K30":"K53"]], dtype=float),
    np.array([i[0].value for i in wb.worksheets[3]["M30":"M53"]], dtype=float),
    np.array([i[0].value for i in wb.worksheets[3]["O30":"O53"]], dtype=float),
    np.array([i[0].value for i in wb.worksheets[3]["Q30":"Q53"]], dtype=float),
    np.array([i[0].value for i in wb.worksheets[3]["S30":"S53"]], dtype=float),
    np.array([i[0].value for i in wb.worksheets[3]["U30":"U53"]], dtype=float),
    np.array([i[0].value for i in wb.worksheets[3]["W30":"W53"]], dtype=float),
    np.array([i[0].value for i in wb.worksheets[3]["Y30":"Y53"]], dtype=float),
    np.array([i[0].value for i in wb.worksheets[3]["AA30":"AA53"]], dtype=float),
    np.array([i[0].value for i in wb.worksheets[3]["AC30":"AC53"]], dtype=float)]

penalty = np.array(penalty_aux)
penalty *= 5
pen = np.zeros((len(V), len(P)))
for v in range(len(V)):
    for p in range(len(P)):
        if penalty[v, p] > 0:
            pen[v, p] = penalty[v, p]

mlv = 1 # Min battery level to be placed on vessel


## Docking Stations
cds = np.array([i[0].value for i in wb.worksheets[1]["B2":"B14"]]) # Investment cost [
    Euro]
cht = np.array([i[0].value for i in wb.worksheets[1]["C2":"C14"]]) # Total number of
    charging points at terminal
pw = np.array([i[0].value for i in wb.worksheets[1]["D2":"D14"]]) # Power grids provide
    the DS [kWh]
maxDS = np.array([i[0].value for i in wb.worksheets[1]["F2":"F14"]]) # Maximum number of
     batteries that can be at the port at the same time

## Others
M1 = 2*len(P) # Large number
M2 = 0.001 # Small number
M3 = cap[0] # Large number
lost = 691.8 # Loss of space




# %%
#-----------Variables -------------------------------------------------------------
# x[b,t,p]: Binary variable if battery is at ds
x = {}
for b in range(len(B)):
    for t in range(len(T)):
        for p in range(len(P)):
            x[b,t,p]=BM.addVar (lb=0, vtype=GRB.BINARY , name="x["+str(b)+","+str(t)+","
    +str(p)+"]")

# y[b,v,p]: Binary variable if battery is at a vessel
y = {}
for b in range(len(B)):
    for v in range(len(V)):
        for p in range(len(P)):
            y[b,v,p]=BM.addVar (lb=0, vtype=GRB.BINARY , name="y["+str(b)+","+str(v)+","
    +str(p)+"]")

# n[b]: Binary variable if a battery is used
n = {}
for b in range(len(B)):
```

```
    n[b]=BM.addVar (lb=0, vtype=GRB.BINARY , name="n["+str(b)+"]")

# u[t]: Binary variable if a terminal is used as DS
u = {}
for t in range(len(T)):
    u[t]=BM.addVar (lb=0, vtype=GRB.BINARY , name="u["+str(t)+"]")

# l[b,p]: Continuous variable for battery level
l = {}
for b in range(len(B)):
    for p in range(len(P)):
        l[b,p]=BM.addVar (lb=0, vtype=GRB.CONTINUOUS , name="l["+str(b)+","+str(p)+"]")

# m[b,v,p]: Binary variable if battery being used on a vessel
m = {}
for b in range(len(B)):
    for v in range(len(V)):
        for p in range(len(P)):
            m[b,v,p]=BM.addVar (lb=0, vtype=GRB.BINARY , name="m["+str(b)+","+str(v)+","
    +str(p)+"]")

# k[b,t,p]: Binary variable if battery being charged at a terminal
k = {}
for b in range(len(B)):
    for t in range(len(T)):
        for p in range(len(P)):
            k[b,t,p]=BM.addVar (lb=0, vtype=GRB.BINARY , name="k["+str(b)+","+str(t)+","
    +str(p)+"]")

BM.update()

# %%
#----------Objective ----------------------------------------------------------
obj1 = quicksum(u[t]*cds[t] for t in range(len(T))) + quicksum(n[b]*cb[b] for b in range
    (len(B )))
obj2 = quicksum(quicksum(quicksum(lost*7.5*x[b,t,p]*n[b] for b in range (len(B))) for p
    in range (1,len(P))) for t in range (len(T)))
obj3 = quicksum(quicksum(quicksum(lost*pen[v,p]*y[b,v,p] for b in range (len(B))) for p
    in range (1, len(P))) for v in range (len(V)))

#Weights given to each objective
w1 = 0.9 #Investment costs
w2 = 0.05 #Idle times
w3 = 1-w1-w2 #Loss of space

BM.setObjective(w1*obj1+w2*obj2+w3*obj3, GRB.MINIMIZE)

BM.update()

# %%
#-----------Constraints -------------------------------------------------------

#Constraint 1 - Used batteries
con1 = {}
for b in range(len(B)):
    BM.addConstr(n[b]*M1, GRB.GREATER_EQUAL, quicksum(quicksum(m[b,v,p] for v in range(
    len(V))) for p in range(1,len(P))))


#Constraint 2 - Used terminals
con2 = {}
for t in range(len(T)):
    BM.addConstr(u[t]*M1, GRB.GREATER_EQUAL, quicksum(quicksum(x[b,t,p] for b in range(
    len(B))) for p in range(1,len(P))))


#Constraint 3 - Maximum number of used batteries in vessel
con3a = {}
```

```
for v in range(len(V)):
    for p in range(1,len(P)):
        BM.addConstr(quicksum(m[b,v,p] for b in range(len(B))), GRB.LESS_EQUAL, 1)
con3b = {}
for v in range(len(V)):
    for p in range(1,len(P)):
        BM.addConstr(quicksum(m[b,v,p] for b in range(len(B))), GRB.GREATER_EQUAL, pv[v,
    p]*M2)

#Constraint 301 - Maximum number of charging batteries at terminal
con301a = {}
for t in range(len(T)):
    for p in range(1,len(P)):
        BM.addConstr(quicksum(k[b,t,p] for b in range(len(B))), GRB.LESS_EQUAL, cht[t])
con301b = {}
for t in range(len(T)):
    for p in range(1,len(P)):
        BM.addConstr(quicksum(k[b,t,p] for b in range(len(B))), GRB.GREATER_EQUAL, 0)

#Constraint 4 - Battery level
con4 = {}
for b in range(len(B)):
    for p in range(1,len(P)):
        BM.addConstr(l[b,p], GRB.LESS_EQUAL, l[b,p-1]+(quicksum(pw[t]*k[b,t,p] for t in
    range(len(T))) - quicksum(m[b,v,p]*pv[v,p] for v in range(len(V)))))

#Constraint 5 - Maximum & minimum battery level
con5a = {}
for b in range(len(B)):
    for p in range(1,len(P)):
        BM.addConstr(l[b,p], GRB.LESS_EQUAL , cap[b])
con5b = {}
for b in range(len(B)):
    for p in range(1,len(P)):
        BM.addConstr(l[b,p], GRB.GREATER_EQUAL , cap[b]*mbl)

#Constraint 6 - Minimum battery level to be placed on a ship
con6 = {}
for b in range(len(B)):
    for v in range(len(V)):
        for p in range(1,len(P)):
            BM.addConstr((y[b,v,p]-y[b,v,p-1])*mlv*cap[b], GRB.LESS_EQUAL , l[b,p])

#Constraint 7 - Battery location
con7 = {}
for b in range(len(B)):
    for p in range(1,len(P)):
        BM.addConstr(quicksum(y[b,v,p] for v in range(len(V))) + quicksum(x[b,t,p] for t
     in range(len(T))), GRB.EQUAL , n[b])

#Constraint 8 - Batteries & vessels routes
con8a = {}
for b in range(len(B)):
    for t in range(len(T)):
        for p in range(1,len(P)):
            BM.addConstr(x[b,t,p], GRB.LESS_EQUAL, x[b,t,p-1]+quicksum(y[b,v,p-1]*sp[v,t
    ,p] for v in range(len(V))))
con8b = {}
for b in range(len(B)):
    for v in range(len(V)):
        for p in range(1,len(P)):
            BM.addConstr(y[b,v,p], GRB.LESS_EQUAL, y[b,v,p-1]+quicksum(x[b,t,p-1]*sp[v,t
    ,p-1] for t in range(len(T))))

#Constraint 9 - Maximum number of batteries at DS
con9 = {}
for t in range(len(T)):
    for p in range(1,len(P)):
```

```
        BM.addConstr(quicksum(x[b,t,p] for b in range(len(B))), GRB.LESS_EQUAL, maxDS[t
    ])

#Constraint 10 - Maximum number of batteries on vessel
con10 = {}
for t in range(len(T)):
    for p in range(1,len(P)):
        BM.addConstr(quicksum(y[b,v,p] for b in range(len(B))), GRB.LESS_EQUAL, chv[v])

#Constraint 11 - Battery charging at DS only if it is at DS
con11 = {}
for b in range(len(B)):
    for t in range(len(T)):
        for p in range(1,len(P)):
            BM.addConstr(k[b,t,p], GRB.LESS_EQUAL , x[b,t,p])

#Constraint 12 - Battery used in vessel only if it is on vessel
con12 = {}
for b in range(len(B)):
    for v in range(len(V)):
        for p in range(1,len(P)):
            BM.addConstr(m[b,v,p], GRB.LESS_EQUAL , y[b,v,p])

#Constraint 13 - Initial battery location & battery usage (on vessel and terminal)
con13a = {}
for b in range(len(B)):
    for t in range(len(T)):
        BM.addConstr(x[b,t,0], GRB.EQUAL, Ut0[b,t])
con13b = {}
for b in range(len(B)):
    for v in range(len(V)):
        BM.addConstr(y[b,v,0], GRB.EQUAL, Uv0[b,v])
con13c = {}
for b in range(len(B)):
    for t in range(len(T)):
        BM.addConstr(k[b,t,0], GRB.EQUAL, k0[b,t])
con13d = {}
for b in range(len(B)):
    for v in range(len(V)):
        BM.addConstr(m[b,v,0], GRB.EQUAL, m0[b,v])

#Constraint 14 - Initial battery levels
con14 = {}
for b in range(len(B)):
    BM.addConstr(l[b,0], GRB.EQUAL , Lb0[b])


# %%
#-----------Solve------------------------------------------------------------

# Set optimality tolerance
BM.params.MIPGap = 0.2
#Running time
BM.params.TimeLimit = 14400 #3.5 hours

BM.params.MIPFocus = 3 #blocked at 21%
BM.params.Cuts = 1 #-1,0,1,2,3 (very aggressive so higher comp. time)
BM.params.VarBranch = 1 #blocked at 23.6%
BM.params.Heuristics =1 #-1,0,this: 1,2,3 (higher comp. time)


BM.setParam ("OutputFlag", True) # show the gurobi output BM.setParam (â MIPGapâ , 0);
     # find the optimal solution

BM.write ("output_MO_run1.lp") # print the model in .lp format file

BM.optimize ()
```

```
# %%
#----------Print------------------------------------------------------------

## Batteries
batteries =0
for i0 in n.values():
    if i0.X > 0:
        batteries = batteries +1

v_names = np.array([i[0].value for i in wb.worksheets[2]["C2":"C15"]])
batt_vessel = []
for b in range(len(B)):
    for v in range(len(V)):
        usage= sum(m[b,v,p].X for p in range(1,len(P)))
        if usage >0:
            batt_vessel.append([b,v_names[v]])


## Docking stations
ds_names = np.array([i[0].value for i in wb.worksheets[1]["E2":"E14"]])
DS = 0
uL = []
Aux1 = []
for i2 in u.values():
    if i2.X > 0:
        DS= DS +1
        Aux1.append(1)
    else:
        Aux1.append(0)
for i3 in range(len(Aux1)):
    if Aux1[i3] > 0:
        uL.append(ds_names[i3])

## KPIs
Aux2 = 0
for i3 in n.values():
    if i3.X>0:
        Aux2=Aux2+1

bv = Aux2/len(V)

Aux3 = 0
for i4 in u.values():
    if i4.X>0:
        Aux3=Aux3+1

dsv = Aux3/len(V)

Aux4 = []
for i5 in n.values():
    if i5.X>0:
        Aux4.append(1)
    else:
        Aux4.append(0)

Aux5 = []
for i6 in u.values():
    if i6.X>0:
        Aux5.append(1)
    else:
        Aux5.append(0)

cxv = (sum(Aux4*cb) + sum(Aux5*cds))/len(V)

print ("\n---------------------------------------------------------------------\n")
print ("OBTAINED RESULTS\n")
print (" ")
print ("Used terminals as docking stations:",DS)
```

```
print ("")
print ("Docking stations locations:",uL)
print (" ")
print (" ")
print ("Used batteries:",batteries)
print (" ")
print ("Shared batteries:\n")
print(tabulate(batt_vessel , headers=["Battery #","Vessel"]))
print (" ")
print (" ")
print ("KPIs:\n")
print (" * Batteries/vessel:",bv)
print (" ")
print (" * DS/vessel:",dsv)
print (" ")
print (" * Capex/vessel:",cxv)
print ("\n---------------------------------------------------------------------\n")


#-----------Save outputs in Excel file----------------------------------------
nInfo = []
for a1 in n.values():
    if a1.X > 0:
        nInfo.append(a1.varName)

uInfo = []
for a2 in u.values():
    if a2.X > 0:
        uInfo.append(a2.varName)

xInfo = []
for a3 in x.values():
    if a3.X > 0:
        xInfo.append(a3.varName)

yInfo = []
for a4 in y.values():
    if a4.X > 0:
        yInfo.append(a4.varName)

lName = []
lValue = []
for a5 in l.values():
    if a5.X > 0:
        lName.append(a5.varName)
        lValue.append(a5.X)

kInfo = []
for a6 in k.values():
    if a6.X > 0:
        kInfo.append(a6.varName)

mInfo = []
for a7 in m.values():
    if a7.X > 0:
        mInfo.append(a7.varName)


# Create dataframes for each variable
df1 = pd.DataFrame({"n[b]": nInfo})
df2 = pd.DataFrame({"u[p]": uInfo})
df3 = pd.DataFrame({"x[b,t,p]": xInfo})
df4 = pd.DataFrame({"y[b,v,p]": yInfo})
df5 = pd.DataFrame({"l[b,p]": lName,"Level": lValue})
df6 = pd.DataFrame({"k[b,t,p]": kInfo})
df7 = pd.DataFrame({"m[b,v,p]": mInfo})
writer = pd.ExcelWriter("Output_MO_run1.xlsx", engine="xlsxwriter")

```

```
# Write each dataframe to a different worksheet
df1.to_excel(writer , sheet_name="Batteries n(b)")
df2.to_excel(writer , sheet_name="Docking stations u(t)")
df3.to_excel(writer , sheet_name="Batt. loc. terminal x(b,t,p)")
df4.to_excel(writer , sheet_name="Batt. loc. vessel y(b,v,p)")
df5.to_excel(writer , sheet_name="Batt. level (b,p)")
df6.to_excel(writer , sheet_name="Batt. ch. terminal k(b,t,p)")
df7.to_excel(writer , sheet_name="Batt. used vessel m(b,v,p)")
writer.close()
```

Listing C.1: Example of Python code for one of the multi-objective run ("Run 1")

Bibliography

[1] International Renewable Energy Agency (IRENA). A pathway to decarbonise the shipping sector by 2050. Report, 2021.

[2] Fabian Driessen. A method for optimal charging station placement for ships: Combining a flow-refueling location model and an agent-based simulation. Master's thesis, TU Delft, 2022.

[3] Carrie Hampel. Fleetzero develops battery-swapping for ships. https://www.electrive.com/2022/03/17/fleetzero-develops-battery-swapping-for-ships/, 2022. Accessed on February 7, 2024.

[4] Mariana Piña Rodriguez. Optimal exchangeable battery distribution and docking station location for electric sailing in iww shipping: The case study of zes. 2021.

[5] Netbeheer Nederland. Capaciteitskaart afname elektriciteitsnet, 2022.

[6] Container-xChange. Terminal handling charges: A comprehensive guide, 2022. Accessed: 2024-06-24.

[7] Paul Balcombe et al. How to decarbonise international shipping: Options for fuels, technologies, and policies. *Energy Conversion and Management*, 182:72–88, 2019.

[8] International Maritime Organization (IMO). Fourth imo ghg study 2020, 2020. Report.

[9] Statista Research Department. Transport volume of worldwide maritime trade 1990-2020. Webpage, 2021. Accessed Feb. 23, 2022, https://www.statista.com/statistics/264117/tonnage-of-worldwide-maritime-trade-since-1990/.

[10] International Chamber of Shipping (ICS). Environmental performance - international chamber of shipping. https://www.ics-shipping.org/shipping-fact/environmental-performance-environmental-performance/, 2024. Accessed on January 5, 2024.

[11] European Comission. Inland waterways. https://transport.ec.europa.eu/transport-modes/inland-waterways$_e n. Accessed on February 7$, 2024.

[12] 2030 climate target plan, 2023.

[13] M.G. Prina, D. Groppi, B. Nastasi, and D.A. Garcia. Bottom-up energy system models applied to sustainable islands. *Renewable and Sustainable Energy Reviews*, 152:111625, 2021.

[14] Name of Funding Organization. Project title. https://www.nwo.nl/en/projects/nwa143920001, 2024. Accessed on January 15, 2024.

[15] Alexander Kirichek, Jeroen Pruyn, Bilgehan Atasoy, Rudy Negenborn, Rob Zuidwijk, J. H. R. van Duin, Kiyoshi Tachi, and Mark van Koningsveld. Paving the way towards zero-emission and robust inland shipping. *Modelling and Optimisation of Ship Energy Systems 2023*, 2024.

[16] European IWT plateform. Eurostat data on inland waterway freight transport. https://www.inlandwaterwaytransport.eu/eurostat-data-on-inland-waterway-freight-transport/. Accessed on February 7, 2024.

[17] K. Gillingham and P. Huang. Long-run environmental and economic impacts of electrifying waterborne shipping in the united states. *Environmental Science Amp; Technology*, 54:9824–9833, 2020.

[18] N.N.A. Bakar, N. Bazmohammadi, H. Ãimen, T. Uyanik, J.C. Vasquez, and J.M. Guerrero. Data-driven ship berthing forecasting for cold ironing in maritime transportation. *Applied Energy*, 326:119947, Nov. 2022.

[19] M. Gu, S. Wen, M. Zhu, C. Chen, and Y. Huang. Voyage optimization for all-electric vessels integrated with swappable containerized battery. In *2021 11th International Conference on Power and Energy Systems (ICPES)*, pages 586–91, Shanghai, China, Dec. 2021. IEEE.

[20] H. Daniel, J.P.F. Trovao, and D. Williams. Shore power as a first step toward shipping decarbonization and related policy impact on a dry bulk cargo carrier. *eTransportation*, 11:100150, Feb. 2022.

[21] S. Karimi, M. Zadeh, and J. Suul. Shore charging for plug-in battery-powered ships: power system architecture, infrastructure, and control. *IEEE Electr. Mag.*, 8:47–61, Sep. 2020.

[22] Sohaib Qazi, Prasanth Venugopal, Gert Rietveld, Thiago Batista Soeiro, Udai Shipurkar, Alex Grasman, Alan J. Watson, and Patrick Wheeler. Powering maritime: Challenges and prospects in ship electrification. *IEEE Electrification Magazine*, 11(2):74–87, 2023.

[23] James Kersey, Neil D. Popovich, and Amol A. Phadke. Rapid battery cost declines accelerate the prospects of all-electric interregional container shipping. *Nat Energy*, 7:664–674, 2022.

[24] H. Wu, G.K.H. Pang, K.L. Choy, and H.Y. Lam. An optimization model for electric vehicle battery charging at a battery swapping station. *IEEE Transactions on Vehicular Technology*, 67(2):881–895, 2018.

[25] S. Schmidt. Use of battery swapping for improving environmental balance and price-performance ratio of electric vehicles. *eTransportation*, 9:100128, August 2021.

[26] Hao Wu. A survey of battery swapping stations for electric vehicles: Operation modes and decision scenarios. *IEEE Transactions on Intelligent Transportation Systems*, 23(8):10163–10185, 2022.

[27] F. Adegbohun, A. von Jouanne, and K.Y. Lee. Autonomous battery swapping system and methodologies of electric vehicles. *Energies*, 12(4):Art. no. 4, January 2019.

[28] J. Hu, G. Yang, C. Ziras, and K. Kok. Aggregator operation in the balancing market through network-constrained transactive energy. *IEEE Transactions on Power Systems*, 34(5):4071–4080, September 2019.

[29] P. You. Chapter 8 - scheduling of ev battery swapping in microgrids. In W. Meng, X. Wang, and S. Liu, editors, *Distributed Control Methods and Cyber Security Issues in Microgrids*, pages 203–241. Academic Press, 2020.

[30] J.G. Jia et al. Technical requirements and economic benefit evaluation of interaction between vessel charging and battery swapping stations and power grid. *E3S Web Conf.*, 256:01011, 2021.

[31] World shipping council - our work, 2024.

[32] European community shipowners' associations, 2024.

[33] Society of naval architects and marine engineers, 2024.

[34] European sea ports organisation, 2024.

[35] International association of ports and harbors, 2024.

[36] Wartsila corporation, 2024.

[37] Man energy solutions, 2024.

[38] Contemporary amperex technology co. limited, 2024.

[39] Sk innovation, 2024.

[40] Ocean conservancy, 2024.

[41] Environmental defense fund, 2024.

[42] Ministerie van Economische Zaken en Klimaat. Zero emissie binnenvaart, batterij-elektrisch (zero emission services) - projecten ronde 2 - nationaal groeifonds. Retrieved November 9, 2022, July 8 2022. Last Modified: 2022-07-08T17:51.

[43] Hanna Bach, Anna Bergek, Teis Hansen, Assiya Kenzhegaliyeva, and Markus Steen. Implementing maritime battery-electric and hydrogen solutions: A technological innovation systems analysis. *Transportation Research Part D: Transport and Environment*, 87:102492, 2020.

[44] Nathan Gray, Shane McDonagh, Richard O'Shea, Beatrice Smyth, and Jerry D Murphy. Decarbonising ships, planes and trucks: An analysis of suitable low-carbon fuels for the maritime, aviation and haulage sectors. *Advances in Applied Energy*, 1:100008, 2021.

[45] Carlos A. Reusser and Joel R. PâÂ©rez Osses. Challenges for zero-emissions ship. *Journal of Marine Science and Engineering*, 9(10), 2021.

[46] Charles John McKinlay, Stephen Turnock, and Dominic Hudson. A comparison of hydrogen and ammonia for future long distance shipping fuels. In *LNG/LPG and Alternative Fuel Ships (29/01/20 - 30/01/20)*, pages 53–65, January 2020. Publisher Copyright: © 2020: The Royal Institution of Naval Architects.

[47] Selma Atilhan, Sunhwa Park, Mahmoud M El-Halwagi, Mert Atilhan, Margaux Moore, and Rasmus B Nielsen. Green hydrogen as an alternative fuel for the shipping industry. *Current Opinion in Chemical Engineering*, 31:100668, 2021.

[48] DNV GL. Comparison of alternative marine fuels. Report, Det Norske Veritas Germanischer Lloyd AS Maritim, Høvik, Norway, 2019.

[49] GOV.UK. Transport. Greater London Authority, 2020.

[50] Kevin Kendall et al. Hydrogen vehicles in china: Replacing the western model. *International Journal of Hydrogen Energy*, 42(51):30179–30185, 2017.

[51] Shell Deutschland Oil GmbH. Shell hydrogen study. Technical report, Shell Deutschland Oil GmbH, Hamburg, 2017.

[52] R.T. Madsen, L.E. Klebanoff, S.A.M. Caughlan, J.W. Pratt, T.S. Leach, T.B. Appelgate, S.Z. Kelety, H.-C. Wintervoll, G.P. Haugom, A.T.Y. Teo, and S. Ghosh. Feasibility of the zero-v: A zero-emissions hydrogen fuel-cell coastal research vessel. *International Journal of Hydrogen Energy*, 45(46):25328–25343, 2020.

[53] Hui Xing, Charles Stuart, Stephen Spence, and Hua Chen. Fuel cell power systems for maritime applications: Progress and perspectives. *Sustainability*, 13(3), 2021.

[54] Manfred Wanner. Transformation of electrical energy into hydrogen and its storage. *The European Physical Journal Plus*, 136(5):593, 5 2021.

[55] Electrive. Explosion at fuel cell filling station in norway. Webpage, June 2019. https://www.electrive.com/2019/06/11/norway-explosion-at-fuel-cell-filling-station/.

[56] David Chiaramonti and Lorenzo Testa. Deploying eu biomethane potential for transports: Centralized/decentralized biogasrefinery schemes to saf and maritime fuels. *Applied Energy*, 366:123306, 2024.

[57] George Mallouppas, Elias Ar. Yfantis, Constantina Ioannou, Andreas Paradeisiotis, and Angelos Ktoris. Application of biogas and biomethane as maritime fuels: A review of research, technology development, innovation proposals, and market potentials. *Energies*, 16(4), 2023.

[58] Methanex. Methanol as a marine fuel, 2020.

[59] K. Machaj, J. Kupecki, Z. Malecha, A.W. Morawski, M. Skrzypkiewicz, M. Stanclik, and M. Chorowski. Ammonia as a potential marine fuel: A review. *Energy Strategy Reviews*, 44:100926, 2022.

[60] S Crolius, DG Pugh, S Morris, and A Valera-Medina. Safety aspects. *Techno-Economic Challenges of Green Ammonia as an Energy Vector*, pages 221–257, 2021.

[61] Seung Yeon Jeong, Daejin Jang, and Min Chul Lee. Property-based quantitative risk assessment of hydrogen, ammonia, methane, and propane considering explosion, combustion, toxicity, and environmental impacts. *Journal of Energy Storage*, 54:105344, 2022.

[62] Siemens Gas and Power GmbH & Co. KG. Power-to-x: The crucial business on the way to a carbon-free world. Technical report, Siemens Gas and Power GmbH & Co. KG, Munich, 2020.

[63] T.S. Ash. Sailing on solar: Could green ammonia decarbonise international shipping? Technical report, Environmental Defense Fund, London, 2019.

[64] Trevor Brown. Maritime ammonia engines in japan; ammonia shipbuilding in south korea, 2019. Accessed February 9, 2024.

[65] Hellenic Shipping. Korea's 3 shipbuilders stepping up efforts to develop ammonia-powered vessels, 2020. Accessed February 9, 2024.

[66] Janos Lucian Breuer, Juri Scholten, Jan Christian Koj, Felix Schorn, Marc Fiebrandt, Remzi Can Samsun, Rolf Albus, Klaus Gâârner, Detlef Stolten, and Ralf Peters. An overview of promising alternative fuels for road, rail, air, and inland waterway transport in germany. *Energies*, 15(4), 2022.

[67] RH2INE. RH2INE Awarded Co-Funding of the EU Connecting Europe Facility! `https://www.rh2ine.eu/latest-news/253/`. Accessed: 2024-05-30.

[68] Xiaohui Xu, Liangzhong Yao, Pingliang Zeng, Yujun Liu, and Tingting Cai. Architecture and performance analysis of a smart battery charging and swapping operation service network for electric vehicles in china. *Journal of Modern Power Systems and Clean Energy*, 3(2):259–268, 2015.

[69] Bo Sun, Xiaoqi Tan, and Danny H. K. Tsang. Optimal charging operation of battery swapping stations with qos guarantee. In *2014 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pages 13–18, 2014.

[70] Mushfiqur R. Sarker, Hrvoje PandÅ¾iÄ, and Miguel A. Ortega-Vazquez. Optimal operation and services scheduling for an electric vehicle battery swapping station. *IEEE Transactions on Power Systems*, 30(2):901–910, 2015.

[71] Wenjin (Jason) Li, Xiaoqi Tan, Bo Sun, and Danny H. K. Tsang. Optimal power dispatch of a centralised electric vehicle battery charging station with renewables. *IET Communications*, 12(5):579–585, 2018.

[72] Yiqun Miao, Quanyuan Jiang, and Yijia Cao. Battery switch station modeling and its economic evaluation in microgrid. In *2012 IEEE Power and Energy Society General Meeting*, pages 1–7, 2012.

[73] Masaaki Takagi, Yumiko Iwafune, Kenji Yamaji, Hiromi Yamamoto, Kunihiko Okano, Ryoji Hiwatari, and Tomohiko Ikeya. Economic value of pv energy storage using batteries of battery-switch stations. *IEEE Transactions on Sustainable Energy*, 4(1):164–173, 2013.

[74] Eirik Eikeland Haahjem. Optimal location of energy replenishment stations for zero-emission vessels. Master's thesis, NTNU, 2022.

[75] Elias Ødegaard. Decision support for the optimal placement of battery swapping stations for high speed passenger vessels. Master's thesis, NTNU, 2022.

[76] Weipeng Zhan, Zhenpo Wang, Lei Zhang, Peng Liu, Dingsong Cui, and David G. Dorrell. A review of siting, sizing, optimal scheduling, and cost-benefit analysis for battery swapping stations. *Energy*, 258:124723, 2022.

[77] Yu Feng and Xiaochun Lu. Construction planning and operation of battery swapping stations for electric vehicles: A literature review. *Energies*, 14(24), 2021.

[78] Yanru Chen, Decheng Li, Zongcheng Zhang, M.I.M. Wahab, and Yangsheng Jiang. Solving the battery swap station location-routing problem with a mixed fleet of electric and conventional vehicles using a heuristic branch-and-price algorithm with an adaptive selection scheme. *Expert Systems with Applications*, 186:115683, 2021.

[79] Julian Hof, Michael Schneider, and Dominik Goeke. Solving the battery swap station location-routing problem with capacitated electric vehicles using an avns algorithm for vehicle-routing problems with intermediate stops. *Transportation Research Part B: Methodological*, 97:102–112, 2017.

[80] Hong Liu, Yuhan Zhang, Shaoyun Ge, Chenghong Gu, and Furong Li. Day-ahead scheduling for an electric vehicle pv-based battery swapping station considering the dual uncertainties. *IEEE Access*, 7:115625–115636, 2019.

[81] BrÃ¡ulio M.O. Portela, Heder S. Bernardino, Luciana B. GonÃ§alves, and StÃªnio S. R. F. Soares. Cheapest insertion and disruption of routes operators for solving multi-depot electric vehicle location routing problem with time windows and battery swapping via grasp and rvnd. In *2021 IEEE Congress on Evolutionary Computation (CEC)*, pages 2133–2140, 2021.

[82] Christopher Upchurch and Michael Kuby. Comparing the p-median and flow-refueling models for locating alternative-fuel stations. *Journal of Transport Geography*, 18(6):750–758, 2010. Special Section on Alternative Fuels and Vehicles.

[83] Zuo-Jun Max Shen, Bo Feng, Chao Mao, and Lun Ran. Optimization models for electric vehicle service operations: A literature review. *Transportation Research Part B: Methodological*, 128:462–477, 2019.

[84] Bo Sun, Xiaoqi Tan, and Danny H. K. Tsang. Optimal charging operation of battery swapping stations with qos guarantee. In *2014 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pages 13–18, 2014.

[85] Xiaoqi Tan, Bo Sun, and Danny H. K. Tsang. Queueing network models for electric vehicle charging station with battery swapping. In *2014 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pages 1–6, 2014.

[86] Wentao Jing, Inhi Kim, and Kun An. The uncapacitated battery swapping facility location problem with localized charging system serving electric bus fleet. *Transportation Research Procedia*, 34:227–234, 2018. International Symposium of Transport Simulation (ISTSâÃÃ´18) and the International Workshop on Traffic Data Collection and its Standardization (IWTDCSâÃÃ´18)Emerging Transport Technologies for Next Generation Mobility.

[87] Lu Xinyi, Liu Nian, Huang Yangqi, Zhang Jianhua, and Zhou Nan. Optimal configuration of ev battery swapping station considering service availability. In *2014 International Conference on Intelligent Green Building and Smart Grid (IGBSG)*, pages 1–5, 2014.

[88] Furkan Ahmad, Mohammad Saad Alam, Ibrahim Saad Alsaidan, and Samir M. Shariff. Battery swapping station for electric vehicles: opportunities and challenges. *IET Smart Grid*, 3(3):280–286, 2020.

[89] Wentao Jing Kun An and Inhi Kim. Battery-swapping facility planning for electric buses with local charging systems. *International Journal of Sustainable Transportation*, 14(7):489–502, 2020.

[90] Abdelrahman Ayad, Nader A. El-Taweel, and Hany E. Z. Farag. Optimal design of battery swapping-based electrified public bus transit systems. *IEEE Transactions on Transportation Electrification*, 7(4):2390–2401, 2021.

[91] Nader A. El-Taweel, Abdelrahman Ayad, Hany E. Z. Farag, and Moataz Mohamed. Optimal energy management for battery swapping based electric bus fleets with consideration of grid ancillary services provision. *IEEE Transactions on Sustainable Energy*, 14(2):1024–1036, 2023.

[92] Mustafa Cagatay Kocer, Ahmet Onen, Jaesung Jung, Hakan Gultekin, and Sahin Albayrak. Optimal location and sizing of electric bus battery swapping station in microgrid systems by considering revenue maximization. *IEEE Access*, 11:41084–41095, 2023.

[93] Yanling Deng, Zhibin Chen, Pengyu Yan, and Renxin Zhong. Battery swapping and management system design for electric trucks considering battery degradation. *Transportation Research Part D: Transport and Environment*, 122:103860, 2023.

[94] Bin Liu, Jie Chen, Nan Zhang, Jun Liu, Yuchao Zhang, Hongyin Bao, Lili Liu, and Kang Chen. Optimized scheduling of an integrated energy system with an electric truck battery swapping station. *Processes*, 12(1), 2024.

[95] Lu Bai, Hongmin Li, Bo Zeng, and Xiaojia Huang. Design of a combined system based on multi-objective optimization for fine particulate matter (pm2.5) prediction. *Frontiers in Environmental Science*, 10, 2022.

[96]

[97] XiaoXiao Niu, Zhengxiang Wang, Yinyan Wang, and Yang Song. Multi-objective optimization of a crdi assisted diesel engine with predictive regression model developed by uniform design. In *Proceedings of the 2016 2nd Workshop on Advanced Research and Technology in Industry Applications*, pages 992–1000. Atlantis Press, 2016/05.

[98] Kalyanmoy Deb and Ankur Sinha. Solving bilevel multi-objective optimization problems using evolutionary algorithms. In Matthias Ehrgott, Carlos M. Fonseca, Xavier Gandibleux, Jin-Kao Hao, and Marc Sevaux, editors, *Evolutionary Multi-Criterion Optimization*, pages 110–124, Berlin, Heidelberg, 2009. Springer Berlin Heidelberg.

[99] Kenneth Sörensen and Johan Springael. Progressive multi-objective optimization. *International Journal of Information Technology & Decision Making*, 13(05):917–936, 2014.

[100] Namjung Kim, Ishan Bhalerao, Daehoon Han, Chen Yang, and Howon Lee. Improving surface roughness of additively manufactured parts using a photopolymerization model and multi-objective particle swarm optimization. *Applied Sciences*, 9(1), 2019.

[101] Qing Song Ai, Zhou Liu, and Yan Wang. Genetic algorithm for the multi-objective optimization of product gene. In *Information Technology for Manufacturing Systems III*, volume 6 of *Advanced Engineering Forum*, pages 116–121. Trans Tech Publications Ltd, 12 2012.

[102] Thomas Monks. Operational research as implementation science: definitions, challenges and research priorities. *Implementation Science*, 11(1), june 2016.

[103] Martin Utley, Sonya Crowe, and Christina Pagel. *Operational research approaches.* Cambridge University Press, 2022.

[104] Acha Chigozie Kelechi and Nduaguibe Ugochukwu Joe. Entrepreneurial success and operations research techniques. *American Journal of Operational Research*, 2(5):45–50, 2012.

[105] Kuodi Jian. Introductory chapter-operations research. In *Operations Research-the Art of Making Good Decisions*. IntechOpen, 2016.

[106] Paul M Emerson, Matthew Burton, Anthony W Solomon, Robin Bailey, and David Mabey. The safe strategy for trachoma control: using operational research for policy, planning and implementation. *Bulletin of the World Health Organization*, 84:613–619, 2006.

[107] Frederick S Hillier and Gerald J Liebermann. *Operations Research: Einführung.* Walter de Gruyter GmbH & Co KG, 2014.

[108] Dingsong Cui, Zhenpo Wang, Peng Liu, Shuo Wang, David G. Dorrell, Xiaohui Li, and Weipeng Zhan. Operation optimization approaches of electric vehicle battery swapping and charging station: A literature review. *Energy*, 263:126095, 2023.

[109] Ruotong Wang, Xingmei Li, Chuanbo Xu, and Fengyun Li. Study on location decision framework of electric vehicle battery swapping station: Using a hybrid mcdm method. *Sustainable Cities and Society*, 61:102149, 2020.

[110] Hao Wu, Grantham Kwok-Hung Pang, King Lun Choy, and Hoi Yan Lam. A charging-scheme decision model for electric vehicle battery swapping station using varied population evolutionary algorithms. *Applied Soft Computing*, 61:905–920, 2017.

[111] Xu Zhang, Yue Cao, Linyu Peng, Naveed Ahmad, and Lexi Xu. Towards efficient battery swapping service operation under battery heterogeneity. *IEEE Transactions on Vehicular Technology*, 69(6):6107–6118, 2020.

[112] Xinan Wang, Jianhui Wang, and Jianzhe Liu. Vehicle to grid frequency regulation capacity optimal scheduling for battery swapping station using deep q-network. *IEEE Transactions on Industrial Informatics*, 17(2):1342–1351, 2021.

[113] Qian Dai, Tao Cai, Shanxu Duan, and Feng Zhao. Stochastic modeling and forecasting of load demand for electric bus battery-swap station. *IEEE Transactions on Power Delivery*, 29(4):1909–1917, 2014.

[114] FBAZoom. Port storage guide: Everything you need to know, 2022. Accessed: 2024-06-24.

[115] P. Dharmakeerthi. *Electric Vehicle Integration - Grid Stability Concerns and Countermeasures.* PhD thesis, 2015.

[116] W. Su, J. Wang, K. Zhang, and M. Chow. Framework for investigating the impact of phev charging on power distribution system and transportation network. In *Proceedings of the 38th Annual Conference on IEEE Industrial Electronics Society (IECON)*, 2012.

[117] Ruben Damwijk. Towards the implementation of bunkering infrastructure for new energy carriers for inland navigation in the netherlands: A techno-economic feasibility study. Master's thesis, Utrecht University, 2022.

[118] Netbeheer Nederland. Basisinformatie over energie-infrastructuur, 2019.

[119] James Owens, Ian Miller, and Emre GenâÃer. Can vehicle-to-grid facilitate the transition to low carbon energy systems? *Energy Adv.*, 1:984–998, 2022.

[120] Sagar Hossain, Md. Rokonuzzaman, Kazi Sajedur Rahman, A. K. M. Ahasan Habib, Wen-Shan Tan, Md Mahmud, Shahariar Chowdhury, and Sittiporn Channumsin. Grid-vehicle-grid (g2v2g) efficient power transmission: An overview of concept, operations, benefits, concerns, and future challenges. *Sustainability*, 15(7), 2023.

[121] Muhammad Shahid Mastoi, Shengxian Zhuang, Hafiz Mudassir Munir, Malik Haris, Mannan Hassan, Mohammed Alqarni, and Basem Alamri. A study of charging-dispatch strategies and vehicle-to-grid technologies for electric vehicles in distribution networks. *Energy Reports*, 9:1777–1806, 2023.

[122] Bwo-Ren Ke, Yu-Hsun Lin, Hong-Zhang Chen, and Shyang-Chyuan Fang. Battery charging and discharging scheduling with demand response for an electric bus public transportation system. *Sustainable Energy Technologies and Assessments*, 40:100741, 2020.

[123] Hasan Mehrjerdi. Resilience oriented vehicle-to-home operation based on battery swapping mechanism. *Energy*, 218:119528, 2021.

[124] Xiaodong Liang. Emerging power quality challenges due to integration of renewable energy sources. *IEEE Transactions on Industry Applications*, 53(2):855–866, 2017.

[125] Liang Zhang, Sihang Zhou, Jing An, and Qi Kang. Demand-side management optimization in electric vehicles battery swapping service. *IEEE Access*, 7:95224–95232, 2019.

[126] Somudeep Bhattacharjee and Champa Nandi. Design of an industrial internet of things-enabled energy management system of a grid-connected solar–wind hybrid system-based battery swapping charging station for electric vehicle. In Jyotsna K. Mandal, Somnath Mukhopadhyay, and Alak Roy, editors, *Applications of Internet of Things*, pages 1–14, Singapore, 2021. Springer Singapore.

[127] P. van Oirsouw and J. F. G. Cobben. *Netten voor Distributie van Elektriciteit*. Phase to Phase, 2011.

Multi-objective optimization for the design of electrified IWT network

S. Blanc

Delft University of Technology, The Netherlands

Abstract. The global push towards energy transformation and decarbonisation highlights the urgent need to reduce greenhouse gas emissions, particularly in the maritime sector, which contributes significantly to global trade and emissions. This study examines inland waterway transportation (IWT) as a key area for implementing zero-emission solutions. With the transition to zero-carbon ships being critical for climate neutrality by 2050, immediate action is essential. This research delves into the optimization of battery swapping systems within the Dutch IWT sector, focusing on multi-objective optimization that balances investment costs, operational efficiencies, and other factors.

The findings indicate that higher battery capacities reduce the number of required batteries and docking stations, enhancing network efficiency and lowering investment costs. Vessel loading conditions significantly affect the network design, with unloaded vessels requiring fewer batteries and docking stations. The study also examines the impact of varying weights assigned to three objectives: investment, "at terminal" times, and space loss. Results confirm that less weight on the loss space objective reduces the number of DS and batteries, while prioritizing the "at terminal" times objective lowers total costs. The research demonstrates that no single scenario dominates across all cost factors, though two scenarios achieve superior outcomes in most categories, indicating alignment between "at terminal" cost and investment cost objectives. In conclusion, the study emphasizes the importance of carefully balancing weights assigned to each cost objective to optimize network design and total costs.

Keywords: IWT · Battery swapping · Optimization · Zero-emission

1 Introduction

Energy transformation and decarbonization of the economy are critical global priorities, focusing on shifting from fossil fuel-based energy sources to renewable and low-carbon alternatives. The maritime sector, a significant contributor to global greenhouse gas emissions, requires immediate action. Maritime transport, which facilitates 80-90% of global trade, accounts for approximately 3% of yearly GHG emissions. If this sector was a country, it would rank as the sixth or seventh highest emitter of CO_2 [1]. Currently, around 99% of the energy in the maritime industry is derived from fossil fuels, with diesel and marine fuel oil making up 95% of the total demand [2]. Without corrective action, GHG emissions from the maritime sector could rise by 50% to 250% by 2050 compared to 2008 levels, driven by the growth in maritime commerce, which has nearly tripled in volume from 1990 to 2020 [3]. Despite its significant GHG contribution, international shipping remains an efficient and environmentally friendly mode of transport compared to air and land transportation. Opportunities for regional progress exist, particularly in inland waterway transportation (IWT). IWT plays an important role for the transport of goods in Europe, with an approximate 6.3% share of the total freight volumes. More than 41,000 kilometres of waterways connect hundreds of cities and industrial regions, with 13 European member states having an interconnected waterway network [4]. IWT is distinguished by its shorter routes, specific vessel types, and established infrastructure, making it an attractive alternative for reducing greenhouse gas emissions. Given the average age and technical lifespan of vessels in the IWT sector, new ship and engine designs should be developed between 2025 and 2035 to ensure a significant impact on energy consumption and carbon emissions by 2050.

Several studies suggest that a systematic shift from fossil fuels to alternative energy sources is necessary for complete decarbonisation [5]. Hydrogen, liquefied bio-methane (LBM), methanol, and ammonia are among the potential solutions, each offering unique benefits and facing specific challenges (see Figure 1). Compared to traditional marine diesel fuel, the potential alternatives suffer from significantly lower energy density, and sometimes necessitating complex storage solutions. Additionally, their production often relies on electricity. In facts, these alternative fuels require 2 to 3 times the renewable electricity reference (direct use). Thus, as long as the power demand induced by electric vessels isn't too high, electricity is the best option. The electrification of IWT, especially through battery swapping technology, presents a promising solution. Battery swapping allows for rapid energy replenishment and reduces the operational downtime of vessels, enhancing efficiency and sustainability. However, while directly utilizing renewable electricity seems attractive, a large-scale shift to electric vessels could strain the power grid. Thus, a combination of electricity with other alternative energy sources appears to be the best solution in the long term.

Several shipping firms operating multiple ships and a large number of independent contractors, each owning a single ship, define the Dutch IWT network. As

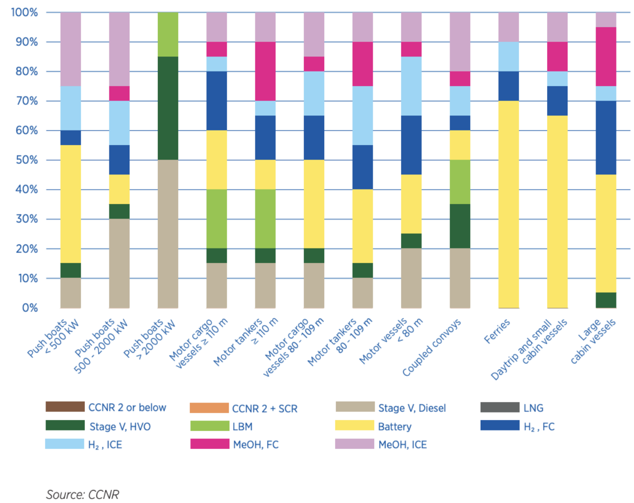

Fig. 1: Innovative transition pathway: technology share for each fleet family in 2050

such, it is unlikely that individual shipowners will spend a lot of money on stations and costly battery swapping systems. This poses a serious dilemma, sometimes known as a "chicken-and-egg" scenario: shipowners are reluctant to switch to a battery-electric system in the absence of conveniently accessible swapping stations [6]. However, businesses are hesitant to make investments in the absence of a sizable fleet of fully functional battery-electric ships. To further complicate matters, this industry often has a deeply rooted familial aspect. Many ships are handed down through the generations, fostering strong emotional bonds among families who see their ships as treasured legacy as much as equipment. The nostalgic tie that certain generations have to diesel-powered vessels may make the switch to electric systems more difficult. Even while shipowners are aware of the environmental advantages of electrification, breaking away from the engine's familiar noise and the routines they have developed around conventional fuel sources can be a big obstacle. To encourage a seamless transition in the business and attaining widespread adoption of electric ships, this study delves into the optimization of battery swapping systems within the Dutch IWT sector. It aims to identify the most effective logistics design for battery distribution and the placement of docking stations, considering factors such as the number of required batteries, docking station locations, and battery distribution plans. The optimization process incorporates multiple objective functions to model real-world scenarios and complex decision-making processes.

2 Literature Review

This section explores various models proposed in recent studies to optimize the design and operation of BSS in the maritime sector. Interestingly, all four models identified originated from master thesis researches (2021-2022), highlighting the nascent stage of this field.

Models based on static optimization: the first three studies present static optimization models, analyzing factors like infrastructure placement and operational costs without explicitly considering time-based dynamics.

– Energy replenishment location model (Haahjem, 2022 [7]): This model builds upon existing location and network optimization frameworks. It considers factors like energy storage capacity, facility location, and network optimization for scenarios with multiple vessels, energy hubs, and charging stations. The objective function minimizes total costs, encompassing voyage expenses, lost opportunity cost due to onboard battery storage space, and service costs associated with replenishing energy. Haahjem further adapts this model for hydrogen fuel, incorporating insulation factors and hydrogen replenishment costs.
– Flow-refueling location with path-based optimization (Driessen, 2022 [8]): This model combines flow-refueling location and path-based static optimization approaches to determine optimal placement of charging stations. Its objective function maximizes the total energy utilized by battery-electric ships within a defined network.
– Battery swapping as a minimum cost flow problem (Odegaard, 2022 [9]): This work proposes a model that views battery swapping as a variant of the minimum cost flow problem. It aims to identify the most cost-effective route through a network by pinpointing ports suitable for battery swapping technology and determining the number of battery modules required for each leg between established stations. The objective function minimizes the combined cost of establishing battery swapping stations and supplying batteries to vessels throughout their trips.

Model with discrete time integration: the fourth study incorporates a time dimension into the analysis.

– Mixed-integer linear programming (MILP) model with discrete time (Pina, 2021 [10]): This model utilizes a MILP framework with discrete time steps. Its objective is to determine the optimal number and locations of docking stations, alongside the required number of batteries. The model minimizes the total investment cost associated with batteries and docking stations.

While the previously mentioned models provide valuable insights, further research is necessary to develop comprehensive BSS optimization frameworks. In this study, the developed model integrates the following new factors:

- Expanding model scope: While existing studies on IWT have focused on relatively small networks, this study expands the model to cover a more extensive and realistic network. This broader scope ensures that outputs are more reliable and applicable to actual marine operations.
- Multi-objective mixed-integer linear programming (MILP): Multi-objective optimization is employed to simultaneously optimize several goals, many of which may conflict. This method seeks to reflect trade-offs between multiple objectives, rather than a single ideal solution. Integrating multi-objective optimization into MILP enhances the model's relevance. Objectives include minimizing upfront investment costs, optimizing long-term operational costs, and reducing battery "at terminal" times. This approach balances investment in infrastructure with operational efficiency, making it cost-effective for BSS operators and beneficial for the barge owners.

3 Methodology

This study formulates a deterministic optimization problem to manage battery locations and charge levels effectively, given the well-defined nature of vessel demand. A discrete time representation with bi-hourly time steps models vessel locations, power requirements, battery locations, and charge levels. This approach simplifies the network representation, allowing for flexibility and scalability. The MILP model uses discrete time steps to determine the optimal number of batteries, docking station locations, and battery capacity to meet vessels' electrical power consumption. In order to effectively match batteries with the pre-planned sailing paths of the vessels, the model takes a battery-centric approach, tracking battery location and charge level. To ensure flexibility and scalability, the network representation is simplified. Numbers are used to identify terminals, and at each time step, vessel sailing profiles are modified to reflect the position of the vessel (sailing or at terminals). Because of this, a particular node-arc network topology is no longer necessary, making it easier to modify and expand the model to accommodate various network topologies. In Figure 2, a general overview of the model with the inputs and outputs is shown. The model contains three objective functions. They are developed from the perspective of a battery and swapping station operators (such as ZES). The three objective functions are the following:

1. Minimizing costs: This involves reducing the initial investment (capital expenditure) required for batteries and DS at each terminal.
2. Minimizing the loss space (thus profit loss) of the barge operators: This objective function is designed for ZES to minimize their impact on their clients, the barge operators, to prevent losing them as customers. A scaler is applied to the operational costs to reflect a long-term vision, ensuring that this objective function accounts for long-term expenditure, such as the investment costs in the first objective function.
3. Minimizing time at terminal ("at terminal"): This objective aims to minimize the total time batteries spend at terminals, encompassing both charging and

storage periods. By reducing terminal dwell time, this objective contributes to optimizing battery usage and overall system efficiency.

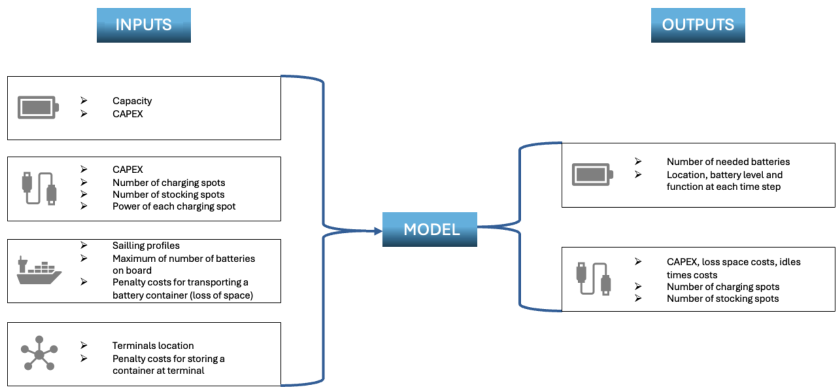

Fig. 2: Model overview

4 Case Study and Numerical Experiments

This section dives into the chosen network and input, presenting the results obtained through the conducted numerical experiments. Python is the programming language used, and Gurobi is chosen as the optimisation problem's commercial solver. The organization of the results is the following: first, a sensitivity analysis is conducted on the model with only the investment costs objective. The aim is to assess the influence of three key input parameters: battery capacity, battery costs, and the number of battery storage spots available at terminals. Thereafter, the impact of loaded or unloaded vessels on the model's outputs is studied. Following this, the space inefficiency caused by transporting batteries on board vessels is taken into account and studied, via the introduction of a second objective. Finally, the results section is concluded with an analysis considering the multi-objective perspective of the study, analysing three objectives together. To ensure consistency in the analysis, a ***hypothesis*** is formulated for each experiment. This hypothesis is then tested against the results. Finally, an ***advice*** (recommendation) is provided, summarizing the key takeaways of each experiment. This recommendation is written to be comprehensible and practical for a DS and battery operator, such as ZES.

4.1 Network

This research focuses on a specific section of the Dutch IWT network. The data used to define this network section is derived from Rijkswaterstaat, the executive agency of the dutch ministry of infrastructure and water management. The data analysis period covers a timeframe from March 1st to April 12th, 2024.

Network Scope:

- *Routes*: The network focuses on the twelve most frequently used direct routes (both directions) within the designated section. These routes represent A-to-B journeys without intermediate stops.
- *Terminals*: The network encompasses thirteen ports, eleven located within the Netherlands, one in Germany, and one in Belgium. This inclusion ensures the network reflects cargo flow entering and exiting the Netherlands through its bordering countries.

A visual representation of the final network structure is provided in Figure 4.1. As evident from the visualization, the network captures a significant portion of the Dutch IWT network, highlighting the most heavily utilized waterways.

Rotterdam	T1
Antwerp	T2
Moerdijk	T3
Amsterdam	T4
Alphen	T5
Wanssum	T6
Nijmegen	T7
Bergen	T8
Alblasserdam	T9
Duisburg	T10
Oosterhout	T11
Tilburg	T12
Veghel	T13

Fig. 3: Graphical representation of the selected network

4.2 Sailing profiles and vessels types

The route data for this network section is also derived from Rijkswaterstaat, covering the same period from March 1st to April 12th. This data includes the daily number of trips for each route, considering both directions. To obtain realistic sailing times and distances for each route, data was sourced from Eurisportal, a platform that provides live sailing information on chosen routes. The vessel type assigned to each route reflects the most commonly used vessel type on that specific route within the analyzed timeframe. These types are differentiated by their time-dependent power requirements while sailing. To estimate the power consumption for each vessel type, an interpolation method was employed, based on the literature [10]. This interpolation leverages the maximum load capacity of each vessel type to determine its power requirements at each time step during its journey. The power consumption is per time step (i.e. two hours of sailing). To represent vessel activity within the network, sailing profiles were constructed for each route. These profiles encompass a two-day timeframe, effectively doubling the frequency of the actual routes identified in the data. Due to limitations in computational resources, vessel selection during route construction aimed to minimize the total number of vessels required to service all routes. The optimization process identified a fleet of 14 vessels to efficiently cover the designated network section.

4.3 Influence of battery capacity, battery costs, and the number of battery storage spots available at terminals

Influence of battery capacities The hypothesis on the impact of battery capacities is the following:

"Higher battery capacity leads to a reduction in the number of batteries and DS used."

The rationale behind this hypothesis is that higher capacity batteries can store more energy, allowing vessels to travel longer distances without needing frequent recharges. Consequently, fewer batteries are required to meet the energy demands of the fleet. Additionally, with longer travel capabilities, vessels can rely on fewer, strategically located DS. These docking stations are typically situated at key terminals within the network, which act as hubs. By centralizing recharging points at these critical locations, the system can operate efficiently with a reduced number of DS, optimizing both the infrastructure and operational costs.

Battery costs The hypothesis on the impact of battery costs is the following:

"Lower battery costs would lead to a higher number of used batteries and fewer DS."

This hypothesis can be explained by the fact that once battery costs are sufficiently low, it becomes more cost-effective to transport a larger number of batteries and minimize the use of DS. By carrying more batteries, vessels can reduce the need for frequent recharges and thereby decrease the necessity for extensive DS infrastructure. This shift allows for lower investment in DS, as the network relies more on the availability of low-cost batteries to maintain operations efficiently.

Number of spots available at DS The hypothesis on the impact of the number of spots available at DS is the following:

"More spots available at DS would decrease the number of used DS and increase the sharing of batteries."

This hypothesis is based on the idea that central terminals, where many vessels pass through, can function as "swapping" hubs. These hubs would be capable of storing and handling a large number of batteries, allowing most battery swaps to occur there. As a result, fewer DS would be needed elsewhere in the network. By concentrating the battery swapping activities at central hubs, the overall network can operate more efficiently with a reduced number of DS while maximizing the sharing of batteries.

Sensitivity analysis main results

The key results of this section are:

- As anticipated by the hypothesis, as battery capacity increases, the number of batteries required decreases significantly. For instance, with a capacity of 2,700 kWh, 49 batteries are needed, whereas only 22 batteries are required for a capacity of 10,000 kWh. Because each higher-capacity battery can store more energy, fewer batteries are needed to meet the same total energy demand. Thus, vessels equipped with higher capacity batteries can operate for longer periods before needing to swap or recharge their batteries. This reduces the frequency with which they need to visit DS.
- Furthermore, because vessels need to swap batteries less frequently, the total number of DS required to support the fleet decreases when the battery capacity increases. With fewer batteries and less frequent swaps, the docking station infrastructure can be consolidated into fewer, more strategically located stations. One can observe that a critical shift occurs between batteries with capacities of 3200 kWh and 4000 kWh. Within this range, the number of required DS decreases significantly. The DS that remain in use are the ones that are key nodes or far away (such as Antwerp and Duisburg) in the network. Ultimately, with even higher battery capacities, only a single docking station in Rotterdam is sufficient. This aligns with Rotterdam's central role in the network, as it's a major port with a high volume of vessel traffic. This reduces the overall infrastructure cost and simplifies the logistics.

– Battery costs have an important impact on total Capex. Higher battery costs lead to increased total expenditures, reflecting the critical role of battery pricing in the economic viability of the system.
– Slight variations in the number of batteries and DS required suggest that while battery costs affect total costs, they do not drastically alter the infrastructure needs. However, with fewer batteries, more DS are needed to answer the demand.
– The results of the experiment with the number of spots avilable at DS show instability and a lack of coherence, likely due to dependencies on the initial conditions and inputs provided to the model. Specifically, the initial location of batteries at time p=0 plays a crucial role. If the hypothesis holds, the batteries need to be transported to the hubs initially, which can take more than the 48-hour simulation period used in this study. Additionally, the process of moving batteries to hubs necessitates the use of multiple DS, increasing the overall number of DS needed. Despite these inconsistencies, observable trends still emerge from the results. Notably, as the number of DS decreases, the number of batteries increases. This trend suggests a shift towards fewer DS with more centralized battery handling, ultimately leading to a decrease in total costs per vessel.

To sum up, as shown in Figure 4, despite some variations, the number of DS and batteries per vessel remains relatively stable across the different experiments. The cost of batteries primarily influences the number of batteries per vessel, while both battery capacity and the availability of spots at terminals impact the number of DS and batteries used.

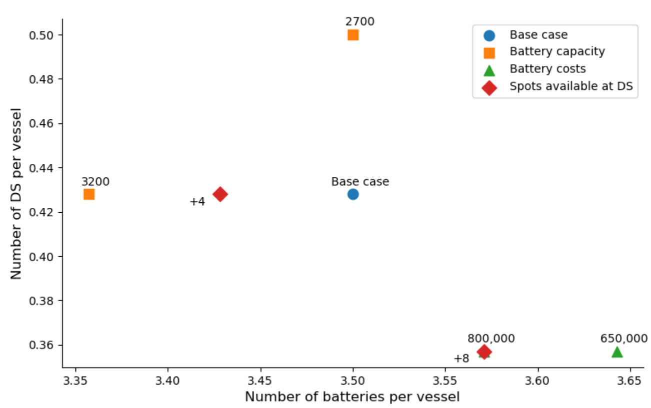

Fig. 4: Battery and DS requirements for the most relevant runs

Managerial insights:

- **Battery capacities:** Although a capacity of 10,000 kWh may not be feasible in the near term, even intermediate capacities such as 3,200 or 4,000 kWh demonstrate substantial changes in network design. These capacities lead to lower investment costs, highlighting the importance of pursuing higher battery capacities. Therefore, it is advisable to continue efforts in developing and improving battery technologies to achieve these benefits.
- **Battery costs:** To achieve a significant shift as mentioned in the hypothesis, battery costs would need to decrease more substantially than the range used in this research. Given the current technological landscape, such a significant reduction in battery costs does not seem feasible or realistic. Therefore, the current battery costs, whether slightly increased or decreased, do not significantly alter the network design. The primary impact is on the total costs, which are influenced by changes in battery costs rather than adjustments in the network design. As a result, it is crucial to focus on other factors that can optimize the network, as substantial changes in battery costs alone are unlikely to provide significant improvements.
- **Number of spots available at DS:** Given the trends observed, the availability of more spots at DS could significantly impact network design. Therefore, this variable warrants further study. Investigating the optimal number of spots at central DS could lead to a more efficient network configuration, reducing overall costs and improving operational efficiency.

4.4 Loaded vs unloaded

This section examines the implications of considering that vessels are not always fully loaded. This parameter induces changes in speed, affecting the sailing profiles. When vessels move faster, they reach their next destination earlier.

The hypothesis on the impact of vessels loading is the following:

"The less loaded the vessels are, the fewer batteries and DS are used."

This hypothesis assumes that, for the same period of time and the same number of trips, less loaded vessels will operate more efficiently. When vessels are less loaded, they can travel at higher speeds. This increased speed results in shorter travel times and reduced overall energy consumption for the same number of trips. Consequently, vessels require fewer batteries and, therefore, fewer battery swaps. As a result, the overall need for DS is reduced, optimizing the network by minimizing the infrastructure required to support the operations.

The results show that the number of batteries required decreases significantly in the 100% unloaded scenario (32 batteries) compared to the 100% loaded scenario (49 batteries). This reduction is due to fewer vessels, but also to the faster travel speeds of unloaded vessels, which together reduces the overall energy demand. Thus, the number of docking stations also decreases in the 100% unloaded scenario (4 DS) compared to the 100% loaded scenario (6 DS). In the mixed loading scenarios, the number of batteries required falls between the two extremes, with 40 batteries in the 50%-50% fully loaded at p=0 scenario and 42 batteries in the 50%-50% half loaded at p=0 scenario. This reduction is due to the faster travel speeds of the vessels when they are unloaded. Thus, it also reduces the overall energy demand. The locations of the DS vary slightly across scenarios, reflecting the adjusted sailing profiles and optimized routes based on loading conditions.

Managerial insights: This experiment highlights the critical importance of realistic modeling in capturing the true impacts of vessel loading conditions on network design and costs. The significant differences observed in total investment costs, sometimes exceeding 20%, emphasize the need for accurate and detailed simulation of real-world conditions. Therefore, it is crucial to incorporate realistic loading scenarios in future studies to ensure the network design is realistic, efficient and cost-effective.

4.5 Lost space

To optimize the use of space on vessels, it is essential to consider the trade-offs between carrying battery containers versus goods containers. This implies a revenue loss for the barge operators when opting to carry battery containers. Since the BSS operators should aim to keep its clients, they have to minimize their impacts on them. In this scenario, they should aim to minimize the revenue loss of the barge operators. Thus, a second objective function is introduced.

The hypothesis on the impact of the weights attributed to each of the two objectives is the following:

"The more importance given to the investment objective, the fewer DS are used. Additionally, due to fewer DS and less emphasis on loss costs, the total costs also decrease."

This hypothesis is grounded in the understanding that prioritizing the investment objective leads to a reduction in the number of DS required. By focusing more on investment costs, the network design aims to minimize initial expenditures, which in turn reduces the infrastructure needed, such as DS. Additionally, with less weight given to loss costs, the total costs are further lowered, as these costs have less influence on the overall optimization. This results in a more cost-effective network configuration, balancing investment efficiency with operational needs.

The results suggest that the battery requirements are not highly sensitive to the variations in the weight given to the investment objective function. However, the number of DS decreases as the weight given to the investment objective function increases. This makes sense because prioritizing investment costs leads to a reduction in the number of DS to lower overall expenditures. Contrarily, when less weight is attributed to the investment objective function, there are more DS because the model prioritizes operational efficiency and convenience. More DS mean that vessels can access battery swapping services more frequently and conveniently, reducing downtime and improving overall efficiency. However, this comes at the cost of higher investments in infrastructure. There is no single shifting point in this trend. Instead, the number of DS decreases gradually as more weight is given to the investment objective function. This indicates a steady reallocation of resources to minimize investment costs progressively.

Managerial insights: The weights assigned to each objective can significantly affect the design of the network and the total costs incurred. It is crucial to prioritize the objectives appropriately and assign well-reflected weights to achieve a balanced and efficient network configuration. Therefore, careful consideration should be given to the weighting process to optimize both investment and operational outcomes effectively.

4.6 Multi-objective analysis

In this section, a third objective function that considers the difference between the number of designated charging spaces for battery containers at the terminal and the available storage space, is introduced. In other words, once fully charged, batteries can be stored at the terminals. However, storing containers at the terminals incurs costs per square meter. Therefore, this third objective function aims to minimize the time batteries spend at the terminal ("at terminal" times), effectively maximizing their utilization. To ensure consistent comparison with the other two objective functions, these "at terminal" times need to be converted into monetary costs.

This section focuses on exploring the impact of varying the weights attributed to each of the three objective functions on the optimal solutions. Multi-objective optimization is a critical aspect of decision-making in complex systems, where different criteria must be balanced to achieve the best overall outcome. By adjusting the weights assigned to each objective, one can observe how the optimal solutions shift in response to these changes. This approach allows to understand the trade-offs between different objectives and how they affect the overall system performance, and identify the most balanced and effective solutions that achieve a desirable compromise between investment costs, space lost, and "at terminal" times. In order to do so, the weighting sum method is used [11]. This method involves combining multiple objective functions into a single composite objective function. Each objective function is assigned a weight that reflects its relative importance. The solver then optimizes this single weighted objective function. It is useful in scenarios where there is a clear understanding of the relative importance of each objective. The equation of the objective function is:

$$F = \sum_{i=1}^{3} w_i f_i(x) \quad = w_1 \cdot f_1 + w_2 \cdot f_2 + w_3 \cdot f_3$$

Where w_1, w_2, w_3 are the weights for the objective functions f_1, f_2, f_3 respectively. f_1 is the investment costs objective, f_2 the loss space and f_3 the "at terminal" times.

To understand the impacts of different priorities in multi-objective optimization, 15 scenarios are analyzed where each objective function is given a varying weight (see Table 1). The Table, as well as its analysis, is divided into three blocks: the basic scenarios, the 9 runs where the investment function is given weights between 85% and 95%, and the three last runs where the weight given to the loss space function is fixed to 5%. X is the number of 2h time slots where batteries are on terminals ("at terminal" times), and Y is the number of 2h time slots where batteries are on vessels. The two main hypotheses are the following:

"The less weight given to the loss space objective, the smaller the number of DS and batteries, and the more sharing of the batteries."

"The more weight given to the "at terminal" times objective, the smaller the total costs."

The first hypotheses stems from the model's strategy to minimize the space occupied by batteries on vessels in order to reduce the associated costs. By assigning less weight to the loss space objective, the model prioritizes minimizing the number of batteries on board, leading to fewer swaps and thus requiring fewer DS. Moreover, with fewer batteries on the vessels, there are more opportunities for swaps, resulting in more frequent sharing of batteries. The second hypothesis is based on the observation that "at terminal" costs are typically lower than investment and loss space costs. By giving more weight to the "at terminal" times objective, the model aims to reduce "at terminal" times, which in turn minimizes overall costs. Table 1 contains the main results of each run.

The first block exhibits interesting results and provides the minimal costs for each objective separately. #X is the number of 2h time slots where batteries are on terminals ("at terminal" times), and #Y is the number of 2h time slots where batteries are on vessels. As can be observed in Figure 5, the smallest X occurs when all the weight is given to the batteries' "at terminal" times objective (B3). This makes sense because prioritizing "at terminal" times reduces the number of batteries that need to be kept on hand, minimizing the inventory at the terminals. The second smallest X is observed when only the investment cost is considered, highlighting the balance between these two objectives. The highest X is seen when all the weight is given to the loss space objective. This is because minimizing the space lost to batteries on vessels leads to a greater number of batteries being stored at the terminals. This scenario is also associated with the smallest Y, which again makes sense because prioritizing the loss space objective means fewer batteries are kept on vessels to maximize cargo space. This results in a lower number of batteries being present on vessels over the 2-day period.

w1 [%]	w2 [%]	w3 [%]	RUN	Total [€]	#b	DS	Invest. [€]	#X (b at T)	#Y (b on V)	Loss space [€]	"at term." [€]
100	0	0	Base 1	46'881'000	42	5	46'881'000	122	844	-	-
0	100	0	Base 2	164'510'040	44	13	-	446	566	164'510'040	-
0	0	100	Base 3	129'712	56	13	-	25	1263	-	129'712
90	5	5	Run1	52'999'976	39	8	48'064'500	252	645	193'531'018	1'307'502
90	2.5	7.5	Run2	48'122'474	41	6	47'275'500	212	731	219'681'074	1'099'962
90	7.5	2.5	Run3	58'650'080	40	8	49'020'000	263	657	193'306'208	1'364'576
95	2.5	2.5	Run4	51'421'673	40	8	49'020'000	271	649	192'700'837	1'406'084
95	1.1	3.9	Run5	47'756'578	41	6	47'275'500	218	725	249'231'189	1'131'093
95	3.9	1.1	Run6	53'826'709	39	9	49'414'500	276	621	189'429'619	1'432'026
85	7.5	7.5	Run7	55'841'480	39	9	49'414'500	267	630	183'136'737	1'385'330
85	3.7	11.3	Run8	49'133'575	40	8	49'020'000	255	665	197'243'393	1'323'068
85	11.3	3.7	Run9	63'412'771	39	10	50'764'500	288	609	179'622'292	1'494'288
60	5	35	Run10	38'843'165	39	8	48'064'500	262	635	190'573'591	1'359'387
70	5	25	Run11	43'535'295	39	8	48'064'500	255	639	191'187'562	1'323'067
80	5	15	Run12	48'887'450	40	8	49'020'000	279	641	189'086'022	1'447'591

Table 1: Detailed breakdown of the summary of the 15 multi-objective runs, with regards to the most relevant output.

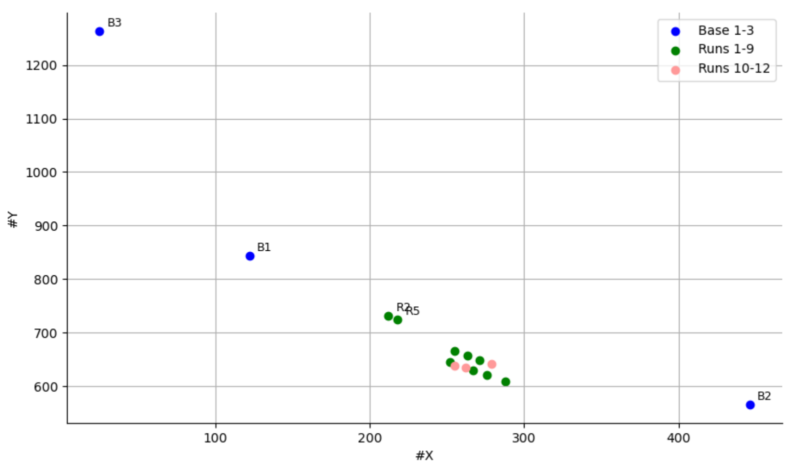

Fig. 5: Number of 2-hour slots with batteries on terminals vs. vessels, for each run

Regarding the second block, the following overall remarks can be done:

– Stability in battery numbers: Across all scenarios, the number of batteries remains stable, hovering around 40.

– DS: The number of DS varies between 6 and 10, with most scenarios clustering around 8. This variability is influenced by the weights assigned to the investment, "at terminal" times, and space lost objectives. When more weight is given to the investment objective, the number of DS tends to decrease. Conversely, when more weight is given to the space loss objective (w2), the number of DS increases, as can be seen in Figure 6. This is because prioritizing lost space leads to a need for more frequent swaps to minimize "at terminal" times, hence more DS are required.

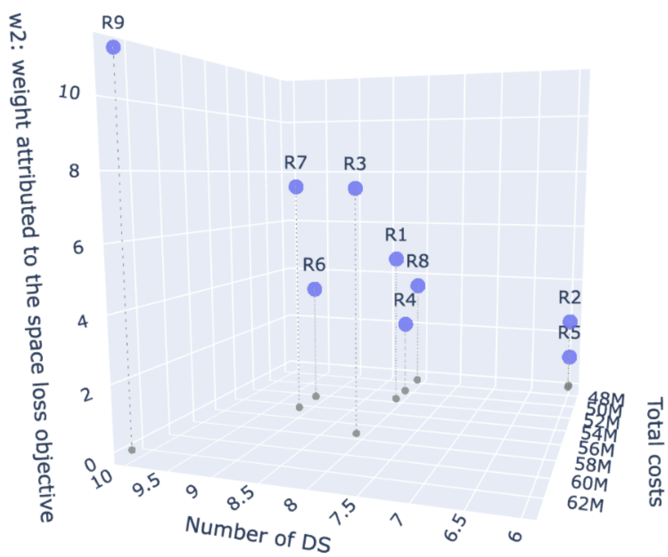

Fig. 6: Results of runs 1-9: comparing total costs, DS count, and space loss weighting

– Total costs: The total costs remain within a similar range, with variations depending mostly on the weight assigned to the space loss objective, see Figure 6. When more weight is assigned to the "at terminal" times objective, the total costs tend to be lower due to reduced "at terminal" times and fewer DS. Conversely, when more weight is assigned to the loss space objective, total costs increase due to the need for more DS and the associated infrastructure costs. This dependency highlights the trade-offs between minimizing "at terminal" times and managing loss space effectively.
– Stability: Investment and "at terminal" costs exhibit relative stability. However, loss space costs demonstrate a wider range. This can be attributed to generally higher costs associated with loss space. As a result, a one-unit

increase in loss space could lead to a proportionally larger increase in total costs compared to the other two objectives.

– Pareto optimum: The three best solutions for each costs separately are:
  - Total costs: $Run5 \leq Run2 \leq Run8$
  - Investment costs: $Run5 = Run2 \leq Run1$
  - Loss space costs: $Run9 \leq Run7 \leq Run6$
  - "At terminal" costs: $Run2 \leq Run5 \leq Run1$

  The results indicate that no single scenario dominates across all cost factors. However, Runs 2 and 5 appear to achieve superior outcomes for three out of the four cost categories, as shown in Figure 7.

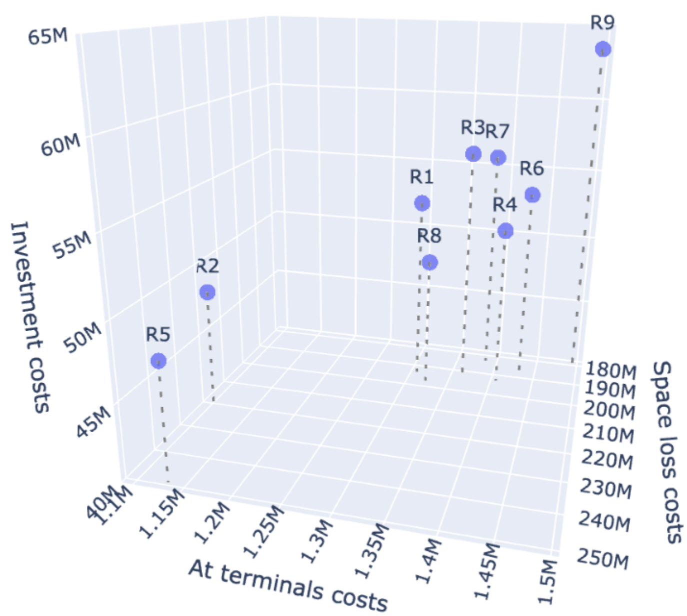

Fig. 7: Investment, space lost and at terminal costs for runs 1 to 9

– Interestingly, as can be observed in Figure 5, Runs 2 and 5 exhibit very similar values for X (212 vs. 218) and Y (731 vs. 725). These values contrast with the other runs in this block, which tend to have lower X and higher Y. This suggests alignment between the "at terminal" cost and investment cost objectives in Runs 2 and 5, indicating they are not conflicting. In contrast, the loss space objective appears to be independent. This is logical because minimizing loss space prioritizes maximizing X while minimizing Y.

The third block achieves significantly lower total costs due to the emphasis placed on the "at terminal" cost objective through higher weights. However, this comes at the expense of a less flexible network design. The network remains very stable, consistently consisting of only 8 DS and 39 or 40 batteries. Furthermore, the other performance metrics for this block fall within the average range observed in block 2.

Managerial insight: The general advice from this experiment is that, from a purely network optimization perspective, the network is physically more efficient when the weight assigned to loss space costs is minimized. From the perspective of the battery and DS operator, it is anyways more logical to prioritize their own costs, including investment and the expenses associated with renting space to store batteries at terminals.

5 Conclusion and Future Research

This study aimed to investigate the potential of integrating battery storage into IWT systems. To this end, a computational model was developed to assess the system's performance under various conditions. The analysis encompassed a base case scenario to establish a comparison point and a subsequent sensitivity analysis to determine the impact of key system parameters, including battery capacity, costs, and availability. Recognizing the complex nature of the problem, a multi-objective optimization approach was then employed to simultaneously consider multiple objectives, providing a more realistic understanding of the complex decision making.

The results show that the decrease in the number of batteries and DS with increasing battery capacity is primarily due to the higher energy storage capability of each battery. This allows vessels to operate longer without requiring frequent swaps, leading to fewer overall batteries and DS. Consequently, the infrastructure can be more efficiently utilized, reducing investment costs. Furthermore, it also reveals that battery costs influence the financial aspect of maritime battery swapping systems. Higher costs lead to increased Capex and per vessel costs, emphasizing the need for cost-effective battery solutions. While the overall infrastructure requirements remain relatively stable, costs optimization become more challenging with rising costs. Moreover, the number of available spots at DS presents contradictory results. It shows instability and a lack of coherence, likely due to dependencies on the initial conditions and inputs provided to the model. Specifically, the initial location of batteries at time p=0 plays a crucial role. Loading conditions significantly influence the operational and financial aspects of maritime battery swapping systems. Fully unloaded vessels require fewer resources and lower costs, while fully loaded vessels necessitate more batteries and docking stations. However, none of these two scenarios is realistic. Thus, mixed loading scenarios provide a more realistic and balanced approach. The analysis of the space loss costs underscores the need to find a balanced approach where both investment costs and loss space are effectively managed. A higher weight on the investment objective, effectively minimizes Capex while maintaining an efficient distribution network. The number of docking stations shows a clear decrease as more weight is allocated to investment costs, reflecting a strategic reallocation of resources to minimize expenditures progressively.

After the introduction of a third objective function, representing the costs associated with the batteries "at terminal" times, 15 different runs are conducted. Overall, the number of batteries remains stable around 40, while the number of DS varies between 6 and 10, mostly clustering around 8. The number of DS decreases when more weight is given to the investment objective and increases with greater emphasis on the loss space objective, due to the need for more frequent battery swaps. Total costs fluctuate mainly based on the weight assigned to the space loss objective, with lower costs observed when prioritizing "at terminal" times due to fewer DS and smaller "at terminal" times costs. Investment and "at terminal" costs show relative stability, whereas loss space costs exhibit a wider range, leading to significant impacts on total costs. The results also highlight that no single scenario dominates across all cost factors. However, two runs stand out by achieving superior outcomes in three out of the four cost categories. These two runs are the ones where the weights given to the loss space objective are the smallest, indicating alignment between "at terminal" and investment cost objectives. These runs also show similar values for the number of batteries at terminals (X) and on vessels (Y), suggesting a balance that is disrupted when the loss space objective is prioritized. The general insight from this experiment is the following: for optimal network efficiency, minimizing the weight assigned to loss space costs is crucial. From the battery and DS operator's perspective, it is more logical to prioritize investment and rental costs. The importance of carefully assigning weights to each objective is emphasized, as this significantly influences network design and total costs. To determine these appropriate weightings, the BSS system operators should use a collaborative approach, involving all concerned stakeholders. By engaging in open dialogue, diverse perspectives can be considered, and trade-offs between conflicting objectives can be identified. This participatory process promotes transparency and ensures that the model aligns, as much as possible, with the priorities of all parties involved.

Yet there are various limitations of this study and future research can build upon the findings of this thesis to develop more refined, efficient, and sustainable battery swapping systems for IWT.

Optimality gaps The optimality gaps observed in this study are high. It is essential to acknowledge that while a large network provides more realistic results and greater opportunities for battery sharing, it also increases the complexity of the optimization process. Future work should focus on reducing these optimality gaps to enhance the applicability of the model.

Detailed sailing profiles It would be beneficial to model the sailing profiles with greater detail, but also flexibility. This could include external factors such as wind speed, weather conditions, and varying waterway traffic. Incorporating these elements would provide a more accurate representation of operational conditions, leading to more robust and reliable optimization outcomes.

Energy grid resilience How does the transition to electricity impact the resilience of the energy grid, and what strategies can be implemented to enhance the robustness of logistics operations in case of an overloaded grid network? It is crucial to study the implications of increased electric demand on the energy grid and develop strategies such as smart grid technologies, decentralized energy storage, and demand response mechanisms to ensure the reliability and resilience of logistics operations amidst potential grid overloads.

References

[1] P. Balcombe *et al.*, “How to decarbonise international shipping: Options for fuels, technologies, and policies,” *Energy Conversion and Management*, vol. 182, pp. 72–88, 2019. DOI: 10.1016/j.enconman.2018.12.080.

[2] I. M. O. (IMO), *Fourth imo ghg study 2020*, Report, 2020.

[3] S. R. Department, *Transport volume of worldwide maritime trade 1990-2020*, Webpage, Accessed Feb. 23, 2022, https://www.statista.com/statistics/264117/tonnage-of-worldwide-maritime-trade-since-1990/, 2021.

[4] E. Comission, *Inland waterways*, https://transport.ec.europa.eu/transport-modes/inland-waterways$_e n$, Accessed on February 7, 2024.

[5] H. Bach, A. Bergek, Bjrgum, T. Hansen, A. Kenzhegaliyeva, and M. Steen, “Implementing maritime battery-electric and hydrogen solutions: A technological innovation systems analysis,” *Transportation Research Part D: Transport and Environment*, vol. 87, p. 102 492, 2020, ISSN: 1361-9209. DOI: https://doi.org/10.1016/j.trd.2020.102492. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1361920920306799.

[6] M. T. Brozynski and B. D. Leibowicz, “A multi-level optimization model of infrastructure-dependent technology adoption: Overcoming the chicken-and-egg problem,” *European Journal of Operational Research*, vol. 300, no. 2, pp. 755–770, 2022, ISSN: 0377-2217. DOI: https://doi.org/10.1016/j.ejor.2021.10.026. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0377221721008754.

[7] E. E. Haahjem, “Optimal location of energy replenishment stations for zero-emission vessels,” M.S. thesis, NTNU, 2022.

[8] F. Driessen, “A method for optimal charging station placement for ships: Combining a flow-refueling location model and an agent-based simulation,” M.S. thesis, TU Delft, 2022.

[9] E. Ødegaard, “Decision support for the optimal placement of battery swapping stations for high speed passenger vessels,” M.S. thesis, NTNU, 2022.

[10] M. Piña Rodriguez, “Optimal exchangeable battery distribution and docking station location for electric sailing in iww shipping: The case study of zes,” 2021.

[11] L. Ng, N. Chemmangattuvalappil, V. Dev, and M. Eden, “Chapter 1 - mathematical principles of chemical product design and strategies,” in *Tools For Chemical Product Design*, ser. Computer Aided Chemical Engineering, M. Martn, M. R. Eden, and N. G. Chemmangattuvalappil, Eds., vol. 39, Elsevier, 2016, pp. 3–43. DOI: https://doi.org/10.1016/B978-0-444-63683-6.00001-0. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780444636836000010.