Delft University of Technology

Energy Price Setting in Optimal Routing, Scheduling and Battery Swapping for Electric Barges

An e-barge operator-centric model to identify cost-efficient energy price designs through optimal planning

Maarten Wijn

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An e-barge operator-centric model to identify cost-efficient energy price designs through optimal planning

by

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Summary

The inland waterway transportation sector in The Netherlands must, just like many sectors, reduce greenhouse gases emissions. One of the methods that is currently explored to reduce the emission of these gases, is by letting barges sail on electric energy, instead of traditional fuel. This system works with battery containers that are placed on the vessel with general container cranes. These containers are filled with large battery packs of 2600 kWh in total, providing the energy for propulsion. With this battery container, the vessel can sail for a couple of hours. Once the battery is depleted, the skipper can moor the barge at a battery swapping facility to replace the depleted battery and continue its journey. Meanwhile, the depleted battery is replenished on shore so it can be used by another vessel.

The market for electric inland vessels is still very immature, with only a limited number of electric sailing vessels. Accordingly, battery providers are assumed here to prioritise market share growth over direct profit. Pricing and service must therefore first make electric operation financially and operationally attractive to skippers to encourage uptake. This research aims to understand inland skippers' requests for containerised energy so the battery provider can design an appealing price setting.

The study seeks which price setting, from flat rates to various forms of dynamic tariffs, most reduces skippers' operational energy costs by modelling their routing, scheduling and battery-swap decisions under each regime. The optimisation model is built from the skipper's decision-making perspective. The model output includes cost minimising routes, departure times and swap decisions for e-barges, and will be used to test which price setting results in the lowest operational costs for the skippers. These cost outcomes will inform the battery container provider to determine the most favourable pricing design for skippers.

In this research, a price setting denotes how the provider's fluctuating grid costs are passed on to the skipper (fixed price or flexible tariffs). The analysis excludes the provider's profit level as absolute prices can be adjusted later on. Moreover, the study focuses solely on energy related costs for the skippers.

Four different price settings are examined. These settings are based on the fluctuation of the energy price per kWh, that are visible in historical data. The hourly price profiles for each price setting are shown in Figure 1. This figure shows the difference in price at each hour for the variable setting, which follows the energy price that the battery provider pays to the grid, on-/off-peak setting, fixed price setting, which is the current strategy, and finally the flexible setting.

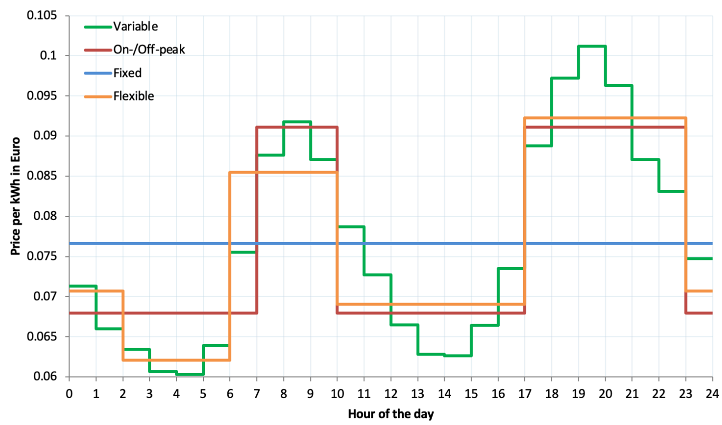

Figure 1: Price per hour for all price setting

After determining different potential price settings, the requirements for the model are found using a system analysis. These requirements specify the necessary capabilities of the model.

A mixed-integer linear programming model is constructed using these requirements. This model minimises the energy costs for a specified fleet of vessels. The model does so in 24 discrete time steps of one hour, and determines the optimal solution by assigning each vessel to swapping locations, if swapping is needed. This is done in such a way that in the hour the swap takes place, energy prices are as low as possible within the operational constraints. Optimal arrival times at swapping locations are achieved by determining a route from origin to destination and assigning a speed to each trip for every vessel. Furthermore, the timing can be influenced by giving the vessels the possibility to wait at a swapping station before continuing their journey. The constructed model is implemented in Python, in order to obtain numerical results. The implementation of the mathematical model was successfully verified and validated.

Ultimately, different price settings are tested under varying scenarios. Based on these tests, an advice can be formulated for the battery provider on which price setting to implement. The different test circumstances for which the price settings are tested, are shown in Table 1.

Table 1: Different tested scenarios

Scenarios	Vessels in fleet	# batteries / facility	# swapping facilities	Battery capacity (kWh)
Base	10	2	9	2600
Battery capacity +15%	10	2	9	2990
3 batteries per facility	10	3	9	2600
Extra locations	10	2	13	2600
3 batteries, extra locations	10	3	13	2600
Extra vessels	15	2	9	2600
Extra locations and extra vessels	15	2	13	2600

After running these scenarios for all price settings, the minimal energy cost is reported per setting and scenario in Table 2. This table shows the favourable results of the variable price settings over the other potential settings. This setting scores consequently about 15% better than the current fixed-price setting on all scenarios included in this study. The flexible setting scores approximately 12% better than the fixed setting and the on-/off-peak price setting results in around 10% lower energy costs.

Table 2: Experimental plan results in Euros

Scenarios	Costs per price setting in Euros			
	Variable	On-/Off-peak	Fixed	Flexible
Base	5976.18	6296.39	7092.27	6138.83
Battery capacity +15%	5931.79	6135.56	6895.98	6052.43
3 batteries per facility	5939.52	6257.58	7091.72	6121.34
Extra locations	5865.58	6170.47	6882.83	6035.95
3 batteries per facility, extra locations	5835.09	6129.15	6882.83	6000.52
Extra vessels	8325.63	8780.77	9745.54	8595.20
Extra locations and extra vessels	8223.93	8666.66	9536.66	8478.62

From these results, the variable price settings appears to be the most suitable setting. To confirm this, end users of the system are interviewed to obtain their perspectives on the various price settings and the results they produce. To explore how skippers could respond to such price settings, four e-barge skippers in The Netherlands were interviewed as well as three freight forwarders and one terminal operator. From these conversations, the general conclusion is that a price setting with an hourly variable price is not desirable for various reasons. From the skippers' perspective, the policy significantly restricts their autonomy, preventing them from choosing how to allocate their rest periods throughout the day. From the freight forwarders' perspective, the requirement complicates the construction of e-barge schedules due to hourly price fluctuations. The interviewed terminal operator also expresses concerns that an hourly variable pricing scheme would concentrate swapping operations into the single cheapest hour. Because most inland terminals have a rather limited number of container cranes and crane operators, such demand concentration could create processing issues: not all vessels would be serviced in time, increasing waiting times, and the potential risk of higher operational costs. When discussed with the stakeholders, the most appealing price setting is the on-/off-peak setting. A 10% reduction in energy costs is large enough to trigger plan adjustments while widening the allowable rest window for skippers instead of fixing a single hour. This shows the trade-off between increased profitability and greater scheduling complexity for freight forwarders and skippers. Finally, there is not one cheapest hour any more thus less concentration of vessels on one hour is expected.

Although considerations have to be made about the limitations of this research, based on this research the on-/off-peak price setting can be recommended as most promising price setting for the deployment of the battery containers. It should, however, be considered that this research focused on one single objective: minimising operational energy costs. Including multiple objectives such as client satisfaction or time minimisation could shift the solution towards a different price setting. Furthermore, the consequences of implementing dynamic energy prices should be considered on a greater scale than just on barge level. Dynamic pricing could on one side impact the whole hinterland transportation chain, as the moment of arrival of a barge, also determines when the connecting transport mode must be available. Therefore, dynamic prices can not only impact the working hours of barge operators, but also the schedule of terminal operators and truck drivers. On the other side, also the impact on the energy grid should be considered. A fully charged battery container with which a barge can sail for about 5 hours, provides 2600 kWh, that is comparable with the annual energy demand of a standard household in The Netherlands. One can imagine the impact this can have if all 8000 barges active in The Netherlands were to switch to electric sailing, especially if the dynamic pricing redirects the moment of demand for energy to one concentrated hour each day.

Further research is needed in two main directions. On one side, future research could help to overcome some limitations of this work, for example by including river currents or by including uncertainty in travel time and energy consumption in the model. On the other hand, more research is needed to fully understand the impact that dynamic pricing of energy can have on the whole hinterland transportation chain. Research in these two directions would help to optimally advise the battery container provider on a price setting.

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1 Introduction

Day in and day out, enormous container ships arrive at the Port of Rotterdam, bringing thousands of containers to The Netherlands. However, the Port of Rotterdam is not the final destination for these containers. Once unloaded from the container ship, these containers are mostly loaded into individual trucks for further distribution to the hinterland (57%). A smaller part is transported by barge over inland waterways (33%) and another commonly used option, being the train, is chosen the least (10%)(Konings et al., 2013). In order to reduce the emissions caused by cargo transport, as was agreed up on in the Paris Agreement (EURLEX, 2016), shifting a large part from freight transport by truck to transport by barge is important. As transportation by barge is a cleaner way of transport in terms of emissions per tonne-kilometer, this shift can greatly improve the amount of greenhouse gases emitted by the transport sector (Port of Rotterdam, 2021). This way, the hinterland transportation can become greener and comply with the Paris Agreement.

The Alphenaar is the first fully electric operating barge with interchangeable batteries in The Netherlands (Port of Rotterdam, 2021). This ship carries containers within The Netherlands between Moerdijk and Alphen aan den Rijn. The Alphenaar shows that the difference in the emissions of gases can be even bigger than just the gain from shifting from truck to barge (Port of Rotterdam, 2021). Two of the containers on board of the Alphenaar do not contain cargo, but are fully loaded with batteries. These batteries provide the propulsion power for the ship. Once the batteries are empty, the container-batteries are unloaded from the vessel and replaced with loaded batteries, so the ship can continue its journey. With this battery technology, depending on the origin of the energy with which the batteries are reloaded, the barge can sail without emitting greenhouse gases.

This is, however, just one ship on one trajectory and thus not making a large impact on the emission numbers of the transport sector. This research aims to contribute to an optimal roll-out plan for e-barges. This roll-out plan should provide insights in how the theory of battery swapping can be developed to an actual activate large scale system. How can this principle of changing battery-containers be applied at large scale, throughout the inland waterways of the hinterland of the Port of Rotterdam? And what would it look like? Is it applicable for all different kind of barges? Could this new way of transportation stimulate the use of barges for the transport of containers and lower the number of containers distributed by the polluting trucks? These questions describe the current research gap, which this project aims to explore.

To try to fill the knowledge void, a literature review is conducted to investigate the existing literature about the e-barges. This literature review also reveals what has not been researched before. Based on the revealed knowledge gap, the research questions are constructed and discussed in chapter three. In chapter four, the method that is used to find answers to the research questions is explained. Chapters five until ten discuss the sub-questions one by one. Part of this is an analysis of the opinions of experts in the field. Their input is valuable in determining the practical viability of any solutions formed in this research. In the last chapter, the research is concluded with a discussion and conclusion.

2
Literature review

As the Alphenaar has already proven, it is technically possible to power an inland vessel with swappable batteries. However, this works for one ship, but to make a real impact, many more barges should become electric over time. Key to the success is not only the e-barge itself, but also the functioning of rotating batteries between barges and the recharging and swapping infrastructure. This research proposal will therefore take also the batteries in consideration, resulting in the following focus for the literature research:

What are the key strategic, tactical and operational factors influencing the optimal deployment of battery-electric barges in the inland waterways of the Port of Rotterdam and how can these be scaled?

With this broad initial research question, the literature review is started in order to find gaps in the academical knowledge on e-barges and their functioning in a network. This research question leaves room for investigating different aspects of the project. In the following section, the research question is divided in smaller components as proposed by various studies as ((Misni and Lee, 2017), (Schmidt and Wilhelm, 2000) & (Seifi, 2011)). For these different parts, academical information is searched for to obtain knowledge about the topic, but also to see which parts of the research focus is not yet investigated sufficiently in previous research. Combining the findings should result in a comprehensive overview of what is already known and what should be looked further into. The strategic, tactical and operational levels are investigated via the following aspects:

1. Strategic level
   - Rotterdam inland waterways network & network potential
   - E-barge overview
   - Facility locations
   - Market dynamics in EV market
   - Implementation challenges
2. Tactical level
   - Routing, scheduling & fleet optimization
   - Energy grid
   - KPI management
3. Operational level
   - Optimization models for routing
   - Battery distribution
   - Technical optimization
   - Battery repositioning

For each part, various search engines and different search terms were used to find the information needed, but also to see what aspects are not yet investigated. The papers that provided useful information are listed in the table below, Table 2.1. In order to improve the repeatability of the review, also the search terms and the search engines that were used are listed per source. If a paper was found via the citations of another paper, this is listed in the last column, 'Snowball from'.

Table 2.1: Literature review table

Literature	Search engine	Search term	Snowball from
Adler et al. (2014)			Optimal Exchangeable Battery Distribution & Docking Station Location for Electric Sailing in IWW Shipping
Amoros et al. (2023)	Google Scholar	"Electric barges"	
Bi et al. (2015)	Google Scholar	"Upscaling EV charging points"	"The role of charging technologies in upscaling"
Blanc et al. (2024)		Forwarded by supervisor	
De Bok et al. (2018)	Scopus	modal AND freight AND transport AND netherlands	
Guo and Dai (2023)		Forwarded by supervisor	
Hir et al. (2024)		Forwarded by supervisor	
Hopkins et al. (2023)	Scopus	"Battery AND roll-out AND plan AND EV"	
Konings et al. (2013)	Scopus	inland AND shipping AND port AND of AND rotterdam AND hinterland	
Konings (2007)			Developing a Hub-and-Spoke Network for Container Barge Transport in the Hinterland
Kotowska et al. (2018)	Scopus	inland AND shipping AND port AND of AND rotterdam	
Lebrouhi et al. (2021)	Scopus	large AND scale AND electric AND vehicle AND development	
Li et al. (2025)	Scopus	battery AND swapping AND station AND routing	
Meherishi et al. (2025)		Forwarded by supervisor	
Nicolet et al. (2023)	Scopus	container AND barging AND rotterdam	
Perčić et al. (2021)	Scopus	electric AND inland AND waterway AND ships	

Literature	Search engine	Search term	Snowball from
Port of Rotterdam (2021)	Google Scholar	”Electric barges”	”Electrification of River Freight: Current Status and Future Trends in Europe”
Port of Rotterdam (2025)	Google	Port of Rotterdam inland shipping	
Rodríguez et al. (2021)		Forwarded by supervisor	
Ryghaug et al. (2019)	Google Scholar	”Upscaling EV charging points”	
Verma (2018)	Scopus	electric AND vehicles AND battery AND swapping AND routing	
Vinke et al. (2024)	Scopus	inland AND shipping AND freight AND transport AND rotterdam	
Zero Emission Services (2025)	Google	Zero Emission Services	
Zhang et al. (2016)	Scopus	”Hinterland AND Rotterdam”	

2.1. Strategic level literature

The strategic level handles the bigger picture. It keeps in mind the long-term vision of the project. Decisions that will impact the system over the years are part of the strategic level, but also obtaining an overall understanding of the project is part of the strategic scope.

2.1.1. Rotterdam inland waterways network & network potential

The Port of Rotterdam is famous for handling large amounts of containers every day. The port processes up to 500 million tonnes of cargo annually (Vinke et al., 2024). Large part of these containers need to be further transported to the mainland of Europe. Nicolet et al. (2023) points out that using a barge for this transportation offers a more sustainable and cheaper option compared to other modes of transport. However, the majority is transported by trucks (Konings et al., 2013). For a large part this is due to the relatively short distance between the destinations of the cargo and the Port of Rotterdam. Most cargo is delivered within 300 km from the port (M. Zhang & Pel, 2016). At this shorter distance the economies of scale of larger modes of transport as rail and barge are not yet exploited to the fullest (M. Zhang & Pel, 2016). Furthermore, on a shorter distance, the cost saving of the cheaper mode of transport does not always outweigh the additional cost of unloading the train/barge and loading the cargo on trucks for the last part of the delivery, which is commonly not accessible by train or barge (De Bok et al., 2018).

The hinterland that is connected to the Port of Rotterdam via navigable inland waterways is depicted in the image here below, Figure 2.1 (Port of Rotterdam, 2025). This image gives an overview of all the reachable destinations. However, as this research focuses on e-barges, which at least in the initial phase will sail closer to the Port of Rotterdam due to the smaller range of e-barges, also a second image, Figure 2.2, that depicts the routes closer to the port, is shown in more detail (Port of Rotterdam, 2025).

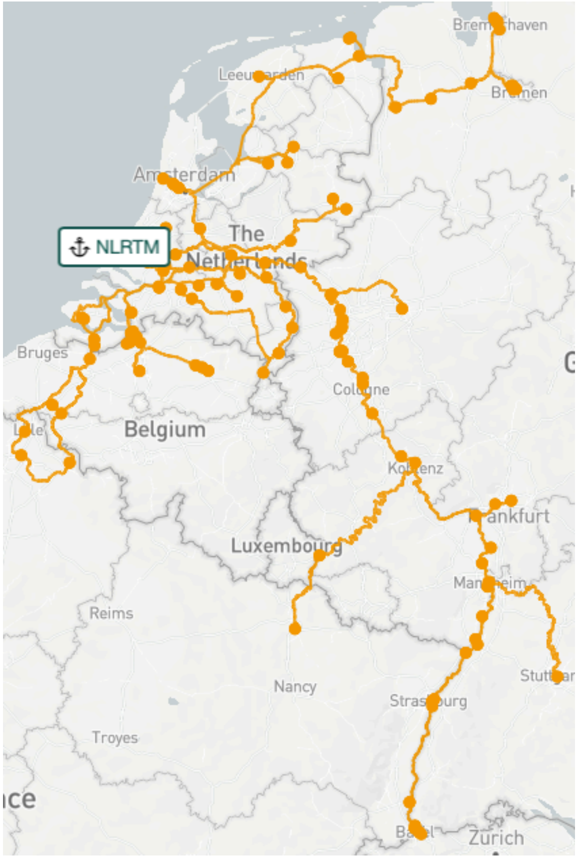

Figure 2.1: Inland waterways connected with the Port of Rotterdam

Figure 2.2: Inland waterways in close connection to the Port of Rotterdam

Figure 2.1 shows an important advantage of the Port of Rotterdam over some other Northern-European ports. The port is namely located in the estuary of the river Rhine, making it accessible for barges with many different destinations (Konings, 2007). Hinterland transportation by barge over the inland waterways from the Port of Rotterdam entails 38.2% of all containers transported further to the hinterland (Kotowska et al., 2018). 110.000 barges were handled in the Port of Rotterdam in 2018 to complete this transport demand and Kotowska et al. expects the demand volume to rise over the coming years (Port of Rotterdam, 2025), (Kotowska et al., 2018).

Hinterland transportation via inland waterways is well described in the academical literature. A clear understanding of what hinterland transport and inland waterways are, can be found and the current situation in terms of routes and transportation amounts is discussed in various papers. Some articles here discussed even provided expectations for future states of hinterland transport by barge.

2.1.2. E-Barge overview

The first electrical barges are currently operational. As indicated by Hir et al. (2024), such electric vehicles with exchangeable power packs can offer some important benefits compared to other forms of energy for the propulsion. Exchanging battery packs is especially convenient compared to regular charging, as it saves a lot of time. Simply swapping a depleted battery for a fully charged one is way faster than charging a fixed onboard battery. Exchanging battery packs can save time, reduce the potential loss of revenue as it takes up less space and incur lower initial investment costs for the skipper when the performance is compared to recharging fixed internal batteries in an electric vehicle (Hir et al., 2024). These e-barges with exchangeable batteries typically consist of a dedicated space for cargo containers and one or two locations for container batteries (Meherishi et al., 2025). At those locations for battery containers, one of the batteries can be connected to the engine. This way, the barge sails on electrical energy provided by a battery in a container. Once the state of charge of the connected battery is not sufficient to sail any further, the second battery can be connected to provide the required power. The advantage of having the battery in a shipping container is that these containers are the standard in cargo transportation. All infrastructure designed for handling normal containers can also handle and process the battery-containers. For example, if the battery is empty and needs to be taken off the ship, a commonly used crane can do so. For now, the containers use lithium-ion batteries, but similar infrastructure could be used for other propulsion methods as well, such as hydrogen fuel cells (Zero Emission Services, 2025).

2.1.3. Facility locations

In order to swap batteries, the e-barges make use of battery swapping stations. At these stations, skippers can rapidly exchange their depleted battery for a new fully charged one (Lebrouhi et al., 2021). This exchange of batteries takes about 15 minutes, with which a vessel can sail about 4 hours, making the loss of time reasonable (Zero Emission Services, 2025). Downside of this infrastructure, like all infrastructure, is the cost that comes with setting up the stations. Especially at the start of the project, as a limited number of ships use the stations, economies of scale are hardly applicable and the costs of developing a completely new infrastructure are high (Hir et al., 2024). Another difficulty of the battery swapping stations is their location. What is the ideal location for these stations to be optimally suitable for the system? The investment cost of these swapping stations is high, thus limiting the number of stations needed is desired, and the stations that are built, should be located in such a way that they are most useful, also over time, when capacity of the containers might increase (Hir et al., 2024). For the location of these swapping stations, a recent study by Li et al. advised to consider a number of factors, among which the type of use (Y. Li et al., 2025). Li considered two types of use, individual swapping stations, for companies private use and a participation mode. In the participation mode, any e-barge can make use of the facility, regardless of the operator of the barge. Opting for either of the two strategies should depend on the locations of the service customers (Y. Li et al., 2025). If potential destinations are located in each other's proximity, a participation mode can reduce the cost for infrastructure as less locations are needed. However, if the potential users are spread over a large area, the company responsible for the infrastructure is advised to choose the locations based on their budget and cost of construction at different locations (Y. Li et al., 2025).

2.1.4. Market dynamics in EV market

As the e-barge market is not yet well developed, a closer look is taken into the more mature market of more common electric vehicles. Market dynamics from this market could provide insights in the market dynamics of the e-barges. Hopkins et al. (2023) studied the relationships that played a role in the upscaling of the electric car system. Upscaling the charging infrastructure is dependent on the adoption of electric vehicles by users and vice versa. When looking at the dynamic relationship diagram for electric vehicles constructed by Hopkins et al., it is clear that some parts are not directly applicable for the case of e-barges, such as the influence of 'Home charging subsidy for renters and landlords' (Hopkins et al., 2023). However, other parts could work the same way for the case of the e-barges. The outer lanes of the diagram are a clear example of the logic that still holds for the e-barges. Following this path, an increase of either the charging demand (effectively more e-barges that need electrical power) or expansion of the charging infrastructure (more locations where a barge can swap batteries) would result in the improvement of the adoption rate of the e-barges. This, in turn, will improve the affordability of the system, creating a positive impulse for both the charging demand and charging infrastructure. A positive loop in the adoption rate is thus visible once the start is triggered. However, following the diagram it becomes clear that exactly this trigger is the problem, there is no external factor working on any of the factors that need to be triggered. So, although there are similar projects that are already implemented successfully in day to day life, no clear step by step route to success is found in the literature.

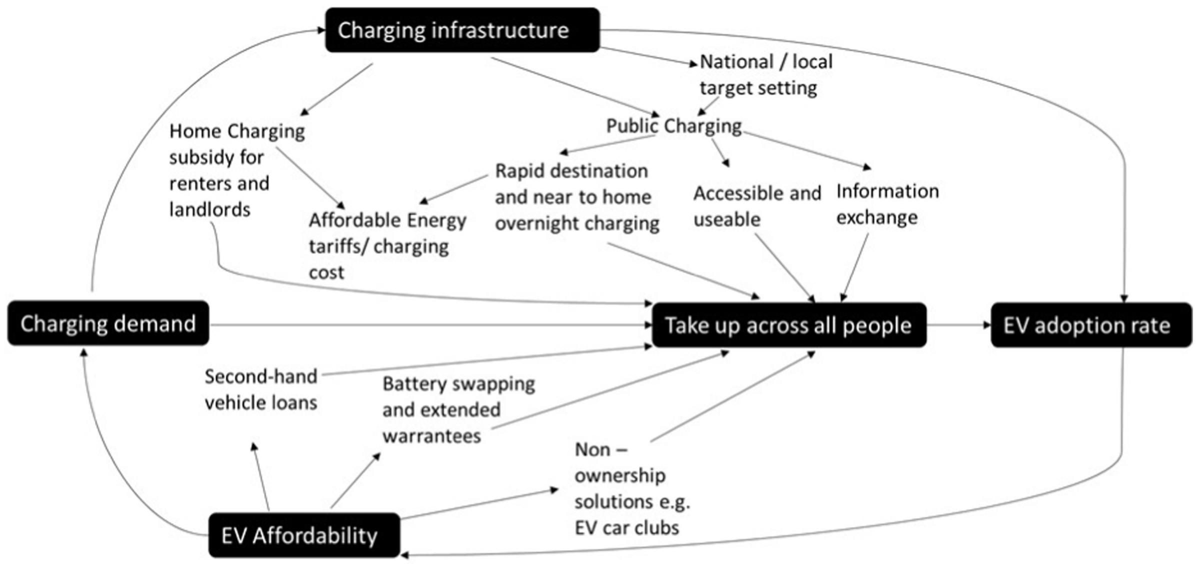

Figure 2.3: Dynamic relationships of EV adaptation diagram by Hopkins et al. (Hopkins et al., 2023)

An important opening for the scaling up of the container batteries for e-barges project lies in the kick start of the feedback loop discussed above. ZESpack sees this opportunity as well. This organisation is willing to make the initial purchase of the container-batteries (Port of Rotterdam, 2021). With this, the barge operators do not have to buy their own battery-containers which makes the electrical barges much more affordable. Now the operators only pay per use of the energy of the containers to ZESpack as new intermediate player. This could help the electrification of the barges to get started. If the diagram shown before in Figure 2.3 is now followed again, an increase in both the charging infrastructure and affordability can be seen, resulting in an increase in charging demand and an increased adoption rate.

2.1.5. Implementation challenges

Although electric vehicles such as electric cars and buses are already a common part of our day to day life, electric barges are still very rare. According to Amoros et al. this is mainly due to two aspects. On one hand is the long lifetime of a barge (Amoros et al., 2023). Due to the absence of waves in inland waterways, inland vessels are quite durable. The engine lifetime is about 20 years (Perčić et al., 2021). This makes that barge operators firstly do not often have the choice for a new barge with different types of powering systems (electric or not). Secondly, the chosen option needs to be reliable over a long period of time. This results operators choosing traditional propulsion engines for their new barges as it is proven to be trustworthy. On the other hand, Amoros et al. pointed out that weak regulation evolution over the past decades has not accelerated the development of e-barges (Amoros et al., 2023). The most barges are sailing with older engines, given their long lifetime. The performance of these old engines corresponds with the legislation on emissions from the time these engines were constructed (Amoros et al., 2023). This lack of progressive legislation does not make the electric barge more appealing.

A final and more general side note on the scaling problem is made by Ryghaug et al.. She warned of the political opposition towards any path-breaking innovation (Ryghaug et al., 2019). This is, according to Ryghaug, because the political power mainly wants to maintain the status quo. Also, new regulations and differences in economies due to the project might enhance political opposition. For this project, this doesn't seem like a serious potential risk, but is always good to keep in the back of one's mind.

2.1.6. Conclusion strategic level literature

In summary, although the literature provides valuable insights into e-barges and their supporting infrastructure, several gaps on the strategic level remain unanswered. Firstly, the optimal sizing and placement of battery swapping facilities are under-explored. Although studies discuss different location strategies (Y. Li et al., 2025), there is little clarity on the economic thresholds and capacity requirements necessary for optimal performance. Secondly, research has yet to thoroughly quantify the long-term sustainability and financial implications of integrating battery exchange systems, particularly regarding battery lifespan and charging cycles (Hir et al., 2024). Thirdly, despite drawing parallels with the broader EV market, the literature does not identify a clear external trigger to initiate the scaling of e-barge operations, leaving the role of regulatory and policy interventions ambiguous (Hopkins et al., 2023). Addressing these gaps is essential for developing robust decision frameworks that can accommodate both operational constraints and evolving market conditions in the Port of Rotterdam's inland waterway network.

2.2. Tactical level literature

The tactical level consists of handling routine decisions that keeps the system running smoothly. Mainly weekly to monthly tasks are included in the tactical level. Also managing the performance is part of the tactical activities. In this section, a closer look is taken into the academic literature on these topics.

2.2.1. Routing, scheduling & fleet optimisation

Efficient deployment of e-barges requires well-planned routing and scheduling to minimise delays and optimise fleet utilisation. Two studies conducted by Adler and Mirchandani (2014) and Verma (2018) analysed how e-barges could be routed efficiently within a battery-swapping network. The study by Adler et al. focused on minimising total delays in the system by implementing online scheduling and battery reservations along the route (Adler & Mirchandani, 2014). This approach ensured that barges could anticipate battery availability in advance, preventing congestion at swapping stations. However, it required some vessels to take small detours in favour of overall network efficiency. This makes Adler's approach more applicable for network-wide coordination, where a central system oversees and adjusts routes dynamically. On the other hand, Verma's study concentrated on reducing operational costs for individual barges. It compared the costs of using battery-swapping stations versus traditional recharging, emphasising cost efficiency in scheduling. Verma's approach is particularly relevant for barge operators who must decide on the most cost-effective routing strategies based on energy costs and availability of swapping stations. The study suggests that optimising individual routes can significantly reduce the financial burden on operators, and with that increase the attractiveness of electric barges in commercial logistics.

To further improve routing efficiency for e-barges, Verma suggests studying the impact of non-fully recharged batteries on network performance. If partially charged batteries could still be used effectively, the system would become more flexible and could reduce waiting times at charging stations. Additionally, integrating real-time data such as terminal congestion and battery availability into fleet scheduling could improve overall network performance.

2.2.2. Energy grid

The container-batteries are comparable with the batteries of 36 electric cars combined (Zero Emission Services, 2025). This emphasises the importance of considering the electricity grid when recharging the batteries. Bi et al. indicated that the usage of such large batteries can cause problems on the electricity grid (Bi et al., 2015). Charging these batteries can increase the pressure on an already tense electricity network. However, the timing of reloading could also be fine-tuned to moments of energy overflow on the network, these containers can then be a relief for the overfull network. It could be interesting to determine the right time to reload the numerous containers, while keeping in mind the desires of the barge operators, as no previous literature was found on this topic.

2.2.3. KPI management

Keeping track of the efficiency of the operations is an important aspect of the tactical level planning. To keep track of the operations, key performance indicators can be closely monitored. Besides the earlier discussed time needed to swap a battery and how long a barge normally can sail on one battery, other key elements of the system include the number of available batteries per location, the tracking of the e-barges in the system, and the energy consumption of the vessels. Where tracking of the vessels is currently done relatively simply with GPS data, the number of available batteries at swapping locations is already more complicated to keep track of. This is because the dropped off batteries need to be recharged which takes a different amount of time for each battery as the state of charge at the drop-off moment varies. It is especially difficult to track the energy consumption per vessel. However, it can be very relevant to know the energy consumption per vessel upfront in order to advise the barge operator on where to swap batteries. In a case study for an e-barge operating in Shanghai, Ling et al. were able to find specific numbers on energy consumption of an e-barge, but these numbers differ per vessel due to the differences in for example, size, weight and amount of cargo (Ling et al., 2025).

2.2.4. Conclusion tactical level literature

While the tactical level literature provides knowledge into efficient routing, scheduling, and energy management for e-barge operations, other aspects are not yet academically explored. For instance, although Adler et al. and Verma have researched both network wide coordination and individual cost efficiency, there is insufficient exploration into the impact of partially charged batteries on overall network performance. Energy demand management is another critical area. There is little research on aligning battery recharging times with grid overflow periods to ease network pressure. Additionally, KPI management presents challenges, especially in tracking variable energy consumption and dynamic battery availability across different vessels and locations. Addressing these gaps through detailed empirical studies and advanced simulation models is essential for refining tactical decision-making processes, ultimately leading to more robust, resilient, and cost-effective e-barge operations.

2.3. Operational level literature

The operational level has the most detailed scope of the three levels. On this level, optimality decisions and actions can be taken as it focuses on the detailed implementation of tactical level planning, with consideration of real time information of internal and external system condition.

Table 2.2 shows the different studies that fit in the operational level. These will be discussed in this chapter. This table gives a quick overview of what the objective of each study is, and how the authors tried to achieve that specific goal.

Table 2.2: Studies of operational level planning of e-barges, with their objectives and approaches

Literature	Objective	Decisions	Approach
Adler et al. (2014)	Minimizing average delay	Online routing with battery reservations,	Markov chance-decision process + Temporal differencing
Verma (2018)	Minimize total cost	Routing solution for recharging and swapping stations	Integer Programming
Rodriguez et al. (2021)	Optimal logistic design	Battery distribution and docking station location	Mixed Integer Linear Programming
Guo et al. (2023)	Minimize energy-related cost	Speed and battery swapping decisions	Mixed Integer Linear Programming
Blanc et al. (2024)	Identify most effective design	Battery distribution and placement of docking stations	Mixed Integer Linear Programming
Meherishi et al. (2025)	Minimal battery investment cost	Battery replenishment and repositioning	Integer Linear Programming

2.3.1. Optimisation models for routing

At the operational level, optimisation models play a crucial role in refining route planning and improving overall network efficiency. Adler and Mirchandani (2014) developed a model that minimised total network delay by implementing a Markov decision process with online scheduling and battery reservations. This model prioritised efficiency across the entire system, making routing decisions dynamically based on network conditions. The trade-off in Adler's model is that individual barges may need to take longer routes to benefit the system as a whole, making it more suitable for centralised logistics planning rather than individual operator decision-making.

Verma (2018) approached route optimisation from a cost minimisation perspective, utilising Integer Programming to compare the expenses of battery-swapping stations with traditional recharging methods. The study found that in certain scenarios, hybrid strategies combining partial recharging with swapping could further reduce costs. Additionally, Verma (2018) proposed integrating variable electricity pricing into the optimisation framework, ensuring that barges could be scheduled to charge when electricity rates are lower.

Future research directions identified in both studies include optimising the number of batteries required in the network to maintain efficiency while minimising capital investment. This is particularly important when considering findings by Blanc and Atasoy (2024) that battery capacity and swapping station size heavily impact the system costs. Increasing battery capacity can lower running costs by reducing the total number of battery swaps required, but excessive capacity can lead to higher initial investments.

2.3.2. Battery distribution

Research done by Blanc and Atasoy (2024) and Rodríguez (2021) investigated the ideal locations of battery swapping stations. The model developed by Rodriguez added to this also the task to determine the optimal number of batteries and facilities in the system. This work touches upon the suggestion of Adler and Mirchandani (2014) to further research the amount of batteries needed in the network. Blanc did not try to find an optimal number of batteries in the system; instead, the study investigated the balance between investment costs and operational efficiency in the e-barge system. In this multi-objective study, the impact of battery capacity, investment costs for batteries and the availability of docking station locations are taken into account. Blanc suggested research to further improve the model build in the study by expanding the network. By adding new ports to the network, the model can provide a broader context of both the potential and challenges of the e-barge system in Europe. Rodriguez' model had some issues with run times, but was at least for smaller numbers of vessels capable of providing valuable insights. Rodriguez suggested further model development to overcome these long model runtimes. Other suggestions, were to dive deeper into including repositioning of batteries in the system by already sailing barges that have space available. Finally, Rodríguez (2021) advised, similarly to Verma (2018), to include the pricing of electricity purchased from the grid in a decision making model.

2.3.3. Technical optimisation

Not only routing and battery distribution problems are dominant, also electricity price related problems are rising. Guo and Dai (2023) are one of the first authors to consider electricity pricing in their optimisation model. They tried to tackle the problem of determining the optimal vessel speed, at which locations to swap batteries and the number of battery swaps. With the model it was intended to provide decision makers with upfront information regarding the costs of the service. Although this model incorporated the price of electricity, the price of a unit electricity is static in the model. This model could be improved by applying both Verma's (Verma, 2018) and Rodriguez' (Rodríguez, 2021) suggestion of including variable pricing.

2.3.4. Battery repositioning

Finally, battery repositioning solves the logistics of the batteries, which is important to the network balance. Meherishi et al. investigated the consequences of replacing the swapped batteries back in the network on different locations than where they were swapped. This was done on two different manners, firstly by truck and later a combination of trucks and barges (Meherishi et al., 2025). The study found that repositioning the batteries over the network is an effective strategy. Furthermore, the paper also combined the repositioning activity with the amount of batteries that are needed in the system. The study showed that, as Adler and Mirchandani (2014) already expected but not investigated, the number of batteries needed in the system is not for each system constant. Meherishi et al. (2025) found that the repositioning of batteries by either truck or barge can lower the number of batteries needed in the network. In the final remarks of the paper, it suggested further research in joint optimisation of routing replenishment and repositioning in the network (Meherishi et al., 2025).

2.3.5. Conclusion operational level literature

The operational level literature offers robust optimisation models for e-barge operations, yet several research gaps persist. Although different studies have developed models that could reduce delays and costs, the understanding of integrating dynamic electricity pricing remains underdeveloped. Additionally, although optimal battery distribution and docking station placement have been explored, issues of computational efficiency and network scalability require further investigation. Furthermore, preliminary studies on battery repositioning indicate potential reductions in required battery numbers; however, a joint optimisation of routing, replenishment, and repositioning is still lacking.

2.4. Literature review conclusion

In this literature review, the e-barge system was discussed on strategic, tactical and operational level to gain insights from various viewpoints. On strategic level, the network potential, facility locations, market dynamics, and implementation challenges were discussed. On the tactical level, a closer look into weekly to monthly functioning was taken. Routing and scheduling of the barges and their energy demand impact was described. Furthermore, key performance indicators were identified. On the operational level, the different optimisation models were investigated. Many different combinations of factors exist in these models, such as optimisation for routing and facility location, and determining the optimal number of batteries in combination with battery relocation strategies. These optimisation models have their own objectives as shown in Table 2.2, but all contribute to an optimal functioning of the e-barge system. When all the individual optimisations are combined, the graphical representation of the sailing e-barge system can be constructed, as shown in Figure 2.4. In this figure the different optimisation objectives are illustrated. The green battery symbol represents battery replacement in the network with different numbers of batteries at different swapping stations. The charging level optimisation is depicted with the three levels of battery charge. The dotted line corresponds with the search for the optimal route. The illustration of the vessel represents the research to ideal vessel speed over the trajectory. The cranes, finally, depict the ideal locations for swapping stations.

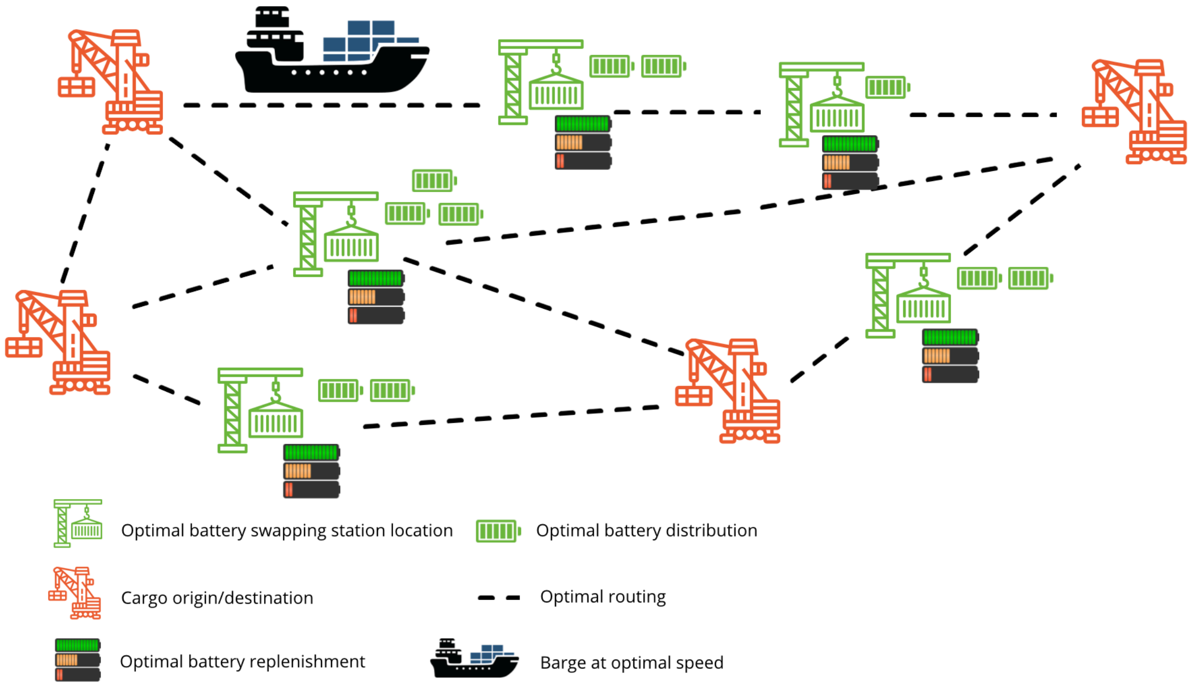

Figure 2.4: Sailing e-barge system

Although a number of different optimisation objectives have already been researched in the light of e-barges, one factor is scarcely addressed in the literature: variable pricing of electricity over the day. This is also not visible in the sailing e-barge system figure. As the price of green electricity can fluctuate significantly, it is of interest to investigate the impact of battery swap timing on the energy cost of battery service for e-barges. This research area has been recommended for further study by Verma (2018) and Rodríguez (2021). Guo and Dai (2023) incorporated electricity pricing into their model, but used static pricing, so the time of day did not affect the system.

To address the research gap, it is crucial to explore the effects of fluctuating electricity prices on e-barges, and to investigate when skippers should start sailing, in order to arrive at swapping locations at moments when battery-containers are cheaper. The cost of the battery that is picked up is dependent on the time of the day, as the energy prices fluctuate during the day. Thus, an ideal sailing time to arrive at swapping stations at moments of cheaper battery-containers could potentially lower the operational cost of the e-barges. Studying this direction can be relevant, as Hopkins et al. showed in their framework that affordability can be one of the triggers the system needs to scale up over time.

Based on the findings in this literature review, a main research question will be formed in the next chapter. With the research question and with help of the sub-questions, the research will try to fill the described knowledge gap. The fulfilment of the of this gap is a first step in setting up a roll-out plan for e-barges. With this information on the operational level, a plan can be created to optimally schedule the fleet on the tactical level.

3
Objective & research questions

3.1. Research objective

This study targets the emerging market for electrically powered inland shipping. This market is still immature: infrastructure and technical standards are limited, business models are evolving, and the current fleet of electric vessels is very limited. Because of this developing phase, battery providers are assumed to be prioritising expanding market share over immediate profit maximisation in this research. Consequently, pricing and service designs must first make electric operation financially and operationally attractive for skippers to stimulate uptake.

The objective of this research is therefore to understand the request from inland skippers for containerised energy, such that the battery provider can design appropriate pricing. It aims to identify which pattern of energy pricing (from a fixed price to different levels of dynamic pricing) best reduces skippers' operational energy costs by modelling skippers' routing, scheduling and battery-swap decisions under each pattern. The study builds the model from the skipper's decision-making perspective and uses the resulting cost outcomes to inform the battery container provider's pricing design.

The pricing pattern, or price setting, refers to the way the fluctuating energy price paid by the container battery provider to the grid is accounted for in the price the skipper pays to the battery provider. This can be done at a flat price rate, as is currently the case, or at different flexible tariffs. The study does not evaluate the battery provider's profit level, as the absolute price in each price mechanism can be shifted up or down in a later stadium, but focuses on which pattern of pricing best reduces skippers' operational energy costs.

An optimisation model determines skippers' cost minimising decisions under different price settings to identify which setting is most favourable to skippers. For the costs, only the energy related cost is taken into account, which is mainly determined by the electricity prices. The model will provide ideal routes between inland terminals for skippers of e-barges to minimise their energy costs. This includes not only the best routes between origin and destination, but also the ideal starting time of each journey and the decision on where and when to swap batteries. Based on this model, different price settings can be tested to determine the optimal setting. In a for skippers optimal price setting, costs are as low as possible for the barge operators.

However, it is important that the proposed price setting is not only cost efficient but also practically viable. Therefore, this research is divided in two parts. In the upcoming chapters, first the theoretical most cost efficient price setting is searched for. Secondly, the practical viability of these different settings is tested by interviewing professionals in the field to determine the possibilities and challenges for the different price settings discussed in this research.

3.2. Research question

In order to achieve the objective of this study, a main research question is formulated. The main research question for this study is as follows:

How can a routing and scheduling optimisation model for electric barges be developed to identify which price setting for battery containers minimises operational costs?

To answer the main research question, the following sub-questions have been formulated:

1. How volatile are green electricity prices over the day at the different loading stations and what historical trends in the pricing can be observed?
2. Which infrastructural, environmental and operational factors must be represented to model inland (e-)barge performance?
3. What theoretical concepts underpin the design and construction of routing, scheduling and battery swap planning systems?
4. How can a model be developed that minimises operational energy costs for skippers while respecting operational constraints such as delivery deadlines?
5. How does the current price setting perform, compared to other price settings determined, according to the developed model?
6. How do stakeholders in the inland shipping industry assess barriers and enablers to implement different price settings in a practical context?

4 Method selection

4.1. Different potential approaches

In this chapter, different potential approaches to answer the main research question, as determined in chapter 3, are discussed. The aim of this chapter is to find the approach that best suits the research question, given the characteristics of the different techniques. Different related modelling techniques are first discussed one by one to find promising approaches based on their functioning. Later, a conclusion is formed based on the description of each approach. The technique that appears to be most suitable to answer the main research question will be used. Finally, for each sub-question, a method is selected and the reasoning is briefly explained

Agent based modelling
In agent based modelling, a real-world situation is simulated, or a new scenario is created in a model. With this computer simulation, the interactions between different elements of the model can be investigated (Schank, 2025). With this, it is possible to see individual decision-making by, for example, skippers on different energy prices. Using agent based modelling also makes it possible to include real-world behavioural aspects. Delays and occupation of docking places can be included in this way. These features make agent based modelling suitable for the job, however, there are some difficulties with this technique. First, validating the model behaviour against the real-world behaviour is difficult for this approach. Secondly, agent based modelling does not have an optimisation focus. The model's attention is more on the behaviour in the model, rather than numerical output. This could potentially result in difficulties in determining optimal actions.

System dynamics
System dynamics is a way of simulating and modelling complex systems that consists of feedback-loops. From a macro-level point of view, system dynamics can be a great way to investigate the e-barge system. Using system dynamics can give valuable insight in the influence on different energy prices on the usage of the system. Higher level connections become clear with help of system dynamics as it shows feedback loops throughout the system. However, this higher level focus becomes problematic as the objective is to advise individual skippers on their routing and scheduling. This makes system dynamics not a suitable technique to tackle the problem. However, it might be a great addition to another approach that meet the requirements, but lacks an overall understanding of the system.

Game theory
Game theory studies the interdependencies from one player's actions to another player's potential actions. In this case, players can be barge operators and energy suppliers. Based on their role, players choose a strategy as they think is best for them given their information. The different players are competing over the best outcomes for their personal role. The way they behave can give insight in how the decision-makers would act in real-life. With the use of game theory, human behaviour does not need to be modelled. This is of great advantage as this is often difficult to grasp in a model. However, also this approach struggles with consistent optimal value finding, making it not ideal for this research.

Reinforcement learning
Reinforcement learning can be a very powerful tool to determine the optimal departure times and routes. When enough data is provided, this approach can continuously provide an optimal schedule. However, this needed data is exactly the problem. Current data on traditional barges is available, but as hardly any e-barges have started sailing, limited data on their performance is available. This makes it difficult to successfully train a reinforcement learning model. Once the deployment of e-barges is abundant, sufficient data will be available and a reinforcement model might give better results than other approaches, but for now, correctly training a reinforcement model is not feasible.

Mixed integer linear programming
Mixed integer linear programming (MILP) is an optimization technique which takes into account the factors to be considered by means of constraints. That way, for example the maximum battery capacity can be indicated. The approach is furthermore capable of including time-dependent cost factors, with that it can handle the dynamic pricing part of the research. It is furthermore capable of providing an optimal solution. As long as the problem is well defined, MILP appears to be a promising technique. However, as soon as there are loose ends, the technique will not work. Besides, real-time updates are more complex to incorporate in the model, making last-minute changes in routing and scheduling challenging to include. Finally, the MILP approach requires very specific data in order to formulate an answer. Depending on the availability of this data, this potentially can give problems.

4.2. Research approach

As discussed above, all different techniques have their own advantages and disadvantages. These findings are displayed in Table 4.1. Each method is scored on their capabilities on the important aspects as discussed above. To select the right approach, the impact of these pros and cons on the research are considered. A method is searched for that makes optimal use of the advantages and limits the drawbacks of the disadvantages for this specific research.

Mixed integer linear programming is chosen as, first of all, it is very well capable of finding optimal solutions. With this characteristic, the research question can potentially be answered. MILP allows for including a time element, which is very likely to be needed. Finally, the restrictions of the system can also be included in the model, making the MILP a promising approach. On the downside, MILP requires precise input data, all information must be known upfront in order to make the model work. As not many e-barges are sailing yet, collecting the needed information might be difficult. However, if no data is available dummy data could be used to overcome this problem. Once more e-barges start sailing, this dummy data can be replaced with real values.

Table 4.1: A summary of possible methods to this research

Method	**Capability of numerical solution**	**Real-world behaviour aspects**	**Dependency on data**	**Suitability**
Agent-Based Modelling	Medium	High	Medium	Medium
System Dynamics	Low	Medium	Low	Low
Game Theory	Low	High	Low	Medium
Reinforcement Learning	High	Medium	High	High
MILP	High	Medium	High	High

4.2.1. Method sub-question 1

How volatile are green electricity prices over the day at the different loading stations and what historical trends in the pricing can be observed?

This first sub-question is necessary to get an idea of the differences in price over the day. The difference in price of green electricity determines the maximal benefit of adjusting departure times to ideal moments. If a great difference in price exists, then more costs can be saved. To investigate the cost differences, data will be gathered and analysed. Multiple open sources with historical energy price datasets are available, this data will be analysed and handled so it is suitable as input for the to be created model.

4.2.2. Method sub-question 2

Which infrastructural, environmental and operational factors must be represented to model inland (e-)barge performance?

It is important to determine how the barge system currently works and how the future e-barge system might look like, in order to formulate a model that best represents the real world. To do so, a combination of two approaches is used. First and foremost, a literature study is conducted to determine what is known about the system and what should be considered in the model. Then afterwards, the results of the literature study are extended with information of barge operators. An expert interview is conducted to find information that was not to be found in the literature. Combining these two approaches should lead to a strong basis of requirements for the model.

4.2.3. Method sub-question 3

What theoretical concepts underpin the design and construction of routing, scheduling and battery swap planning systems?

In order to provide a route and schedule for the different barges, one must understand how these tasks are generally completed. Therefore, the theoretical background of solving routing and scheduling problems is investigated. By studying classic routing and scheduling problems, a better understanding is created. With this understanding, ultimately, the classical problems can be expended to include all necessary elements needed to answer the research question. As a foundation for the to be constructed model in this research, a base model with a similar approach is selected from the literature. This model is then later modified to the needed model for this research.

4.2.4. Method sub-question 4

How can a model be developed that minimises operational energy costs for skippers while respecting operational constraints such as delivery deadlines?

This sub-question is closer related to the main research question. To answer this question, the previous sub-questions need to be solved, in order to have the required input information available. With this knowledge, a Mixed integer linear programming model can be constructed based on the selected model from the literature to solve this sub-question. This new model, in turn, can form the basis to build an answer for the main research question upon.

4.2.5. Method sub-question 5

How does the current price setting perform, compared to other price settings determined, according to the developed model?

After constructing and implementing an optimal routing and scheduling model in the previous sub-question, in this sub-question the different price settings are tested with the help of the constructed model. Both the current price setting and the newly developed price settings are tested in order to see which setting performs best. Based on these results, a conclusion can be drawn on which price setting works in theory the best.

4.2.6. Method sub-question 6

How do stakeholders in the inland shipping industry assess barriers and enablers to implement different price settings in a practical context?

After determining the model results for the different price setting, the different settings and their results are proposed to the actors involved in inland shipping. Through interviews, respondents are asked their view on the price settings and their results. Here, extra focus is on the practical viability of the different settings; as the respondents are experts in this field, they are likely to know what is possible in reality and what could only work in theory.

5
Volatile energy prices

How volatile are green electricity prices over the day at the different loading stations and what historical trends in the pricing can be observed?

In the upcoming chapters, input data is gathered that later will be used to base the outcomes of the research upon. The aim of this first chapter in data gathering, is to find a basis for the input data about the energy prices and their fluctuation over the day. Furthermore, different price setting strategies are explored.

In Figure 5.1, the actors involved in the energy pricing system are depicted. The red line around all actors indicates the system boundaries of the system as a whole. The green line shows the intermediate actor selling charged batteries to the e-barge operator. In this example, via a greatly fluctuating variable price over time, but other potential selling scenarios are shown below. The current pricing system is visible in the second pricing scenario as a flat line. Energy is currently sold at a fixed price. However, when the e-barge market matures over time, the intermediate player is expected to adjust their pricing system to any of these other depicted scenarios, as this could potentially lower the cost of the service and therefore attract more clients.

This chapter first handles the left hand side of the figure, the part that describes the fluctuation in price as determined by the energy supplier from the grid. Later, this chapter also dives deeper into the potential price settings that could be used to potentially lower the operational costs for skippers.

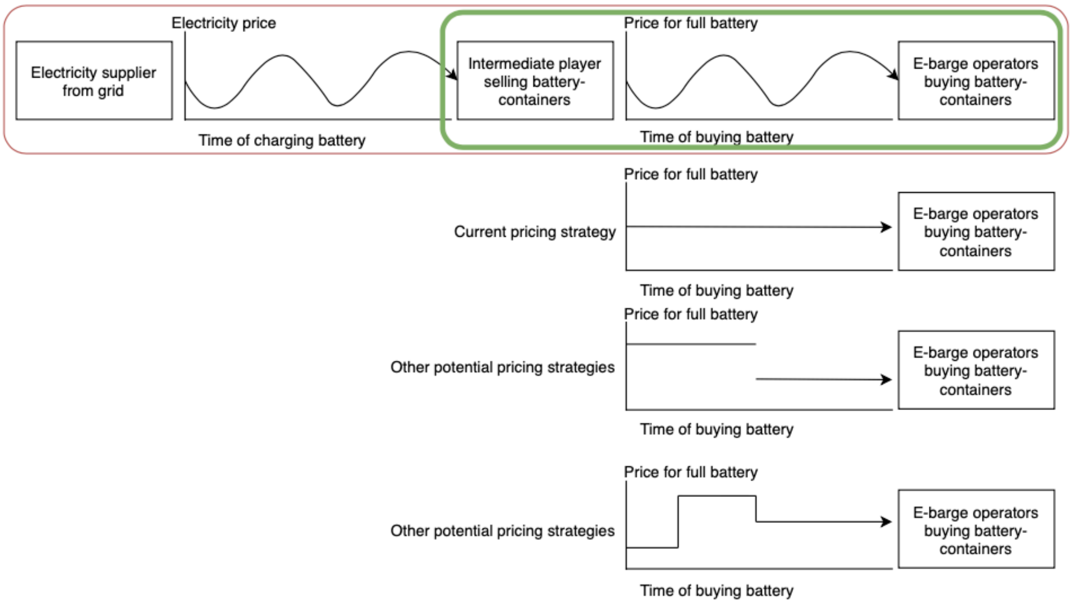

Figure 5.1: Energy system boundaries

5.1. Fluctuations in energy prices

The historical energy prices for each hour of the day in recent years are well documented. However, this extensive documentation does not account for the location of the energy price, more specific than in The Netherlands.

In order to determine the volatility in electricity pricing, a data analysis is made over ten years of hourly energy prices in The Netherlands. For this analysis, a dataset with raw energy price data is used. Raw pricing only covers the buy price per kWh. As a consumer, one normally pays more than the raw price. For consumers the price per kWh is a combination of the raw price, cost for energy storage, profit for supplier and taxes. This makes the energy used in this data analysis cheaper than it would be in a real case scenario. However, using this raw pricing makes the hour by hour comparison more reliable, as the all-inclusive price heavily depends on the energy suppliers behaviour over time. Using the raw price can give a great impression of the fluctuation of the price, without the disruption of changing profits for energy suppliers over time.

In appendix A, an idea is given of the analysed data set. Based on this data set a heatmap is created. This heatmap consists of the energy price for every hour for each day in the year 2024. Although information on prices is known for a longer period of time than just one year, 2024 is chosen as it is most representative for the current energy prices, given the changing geopolitical landscape over the last few years and its impact on the energy market. In Table 5.1 the average prices for a kWh of energy are shown per hour. This is the year-round average for each hour, meaning that for each individual hour from 00:00 to 23:00 the average for all days in the year is shown. The hours of the day are colour-coded for the price at that time, more expensive hours in dark red and cheaper hours in bright green.

Table 5.1: Average price per kWh for each hour.

Hour:	00:00–01:00	01:00–02:00	02:00–03:00	03:00–04:00	04:00–05:00	05:00–06:00	06:00–07:00	07:00–08:00
Price:	0.07132	0.06605	0.06343	0.06067	0.06032	0.06391	0.07551	0.08758

Hour:	08:00–09:00	09:00–10:00	10:00–11:00	11:00–12:00	12:00–13:00	13:00–14:00	14:00–15:00	15:00–16:00
Price:	0.09184	0.08706	0.07874	0.07267	0.06647	0.06278	0.06257	0.06642

Hour:	16:00–17:00	17:00–18:00	18:00–19:00	19:00–20:00	20:00–21:00	21:00–22:00	22:00–23:00	23:00–00:00
Price:	0.07351	0.08876	0.09719	0.10123	0.09626	0.08707	0.08307	0.07470

This figure shows what one might already expect. There are two distinctive time periods during the day during which the price of a kWh is significantly higher; from 07:00 until 10:00 in the morning and from 17:00 to 22:00 in the evening. In the hours around noon, the prices are rather low, almost as cheap as during the night, despite the higher demand for energy during the day than at night. This is most likely because of the availability of solar energy during the day. As can be seen in Table 5.1, the difference between electricity prices can be rather large. Compared to the most expensive hour (19:00 - 20:00) the cheapest hour (14:00 - 15:00) is almost twice as cheap. Although the difference of almost 4 Euro cents per kWh may not seem very relevant, it becomes significant when one considers a fully loaded battery container of 2600 kWh. On a full battery, it can save about 100 Euros. Expanding that further to a whole day, in which the barge might need to swap batteries every couple of hours, one can imagine the large cost differentiation.

With this knowledge, multiple price settings implemented by the intermediate player towards its customers can be considered. One could set the fluctuating price from the energy supplier from the grid through to the end-user, or charge an on- and off-peak hours price. Among the options are also a somewhat more flexible pricing than simply on- and off-peak or the current strategy, or a fixed price.

In this research, different pricing scenarios will be tested to see if one price setting can be preferred over the others. For the variable pricing scenario, the prices as shown in Table 5.1 will be used. In this scenario the variable price of the grid energy supplier is also charged for the vessel operators by the intermediate party. This player is compensated for its efforts as each swap has a fixed cost. In the peak pricing scenario, two prices are applicable. One price during the on-peak hours, which is equal to the average price during all peak hours and one price for off-peak hours, the average of all remaining hours. For the somewhat flexible price setting, five different prices are implemented, each corresponding with a block of similar prices per hour in the hour by hour comparison. One block-price is active from 02:00 until 05:00, the next is from 06:00 up until 09:00. The third price-block starts at 10:00 and is active to 17:00 and is the block with lowest cost. The evening price is implemented between 17:00 and 22:00 and finally a night tariff is applicable from 23:00 to 02:00. For all these price-blocks the electricity price charged by the intermediate player consist of the average hourly price of all hours within that window. Furthermore, each swap has a fixed charge, independent of the hour in which the swap takes place. These different pricing scenarios result in the following prices per hour, visible in Table 5.2.The figures show the price at hour 00:00 at the top, all the way to hour 23:00 at the bottom. These are the price settings used in this research. In Figure 5.2 the price per hour for all settings is combined in one graph to show the differences among them.

Table 5.2: Hourly prices per price setting

Hour of the day	Price per hour per price setting			
	Variable	On-/Off-peak	Fixed	Flexible
00:00 - 01:00	0.0713	0.0679	0.0766	0.0707
01:00 - 02:00	0.0660	0.0679	0.0766	0.0707
02:00 - 03:00	0.0634	0.0679	0.0766	0.0621
03:00 - 04:00	0.0607	0.0679	0.0766	0.0621
04:00 - 05:00	0.0603	0.0679	0.0766	0.0621
05:00 - 06:00	0.0639	0.0679	0.0766	0.0621
06:00 - 07:00	0.0755	0.0679	0.0766	0.0855
07:00 - 08:00	0.0876	0.0911	0.0766	0.0855
08:00 - 09:00	0.0918	0.0911	0.0766	0.0855
09:00 - 10:00	0.0871	0.0911	0.0766	0.0855
10:00 - 11:00	0.0787	0.0679	0.0766	0.0690
11:00 - 12:00	0.0727	0.0679	0.0766	0.0690
12:00 - 13:00	0.0665	0.0679	0.0766	0.0690
13:00 - 14:00	0.0628	0.0679	0.0766	0.0690
14:00 - 15:00	0.0626	0.0679	0.0766	0.0690
15:00 - 16:00	0.0664	0.0679	0.0766	0.0690
16:00 - 17:00	0.0735	0.0679	0.0766	0.0690
17:00 - 18:00	0.0888	0.0911	0.0766	0.0923
18:00 - 19:00	0.0972	0.0911	0.0766	0.0923
19:00 - 20:00	0.1012	0.0911	0.0766	0.0923
20:00 - 21:00	0.0963	0.0911	0.0766	0.0923
21:00 - 22:00	0.0871	0.0911	0.0766	0.0923
22:00 - 23:00	0.0831	0.0911	0.0766	0.0923
23:00 - 00:00	0.0747	0.0679	0.0766	0.0707

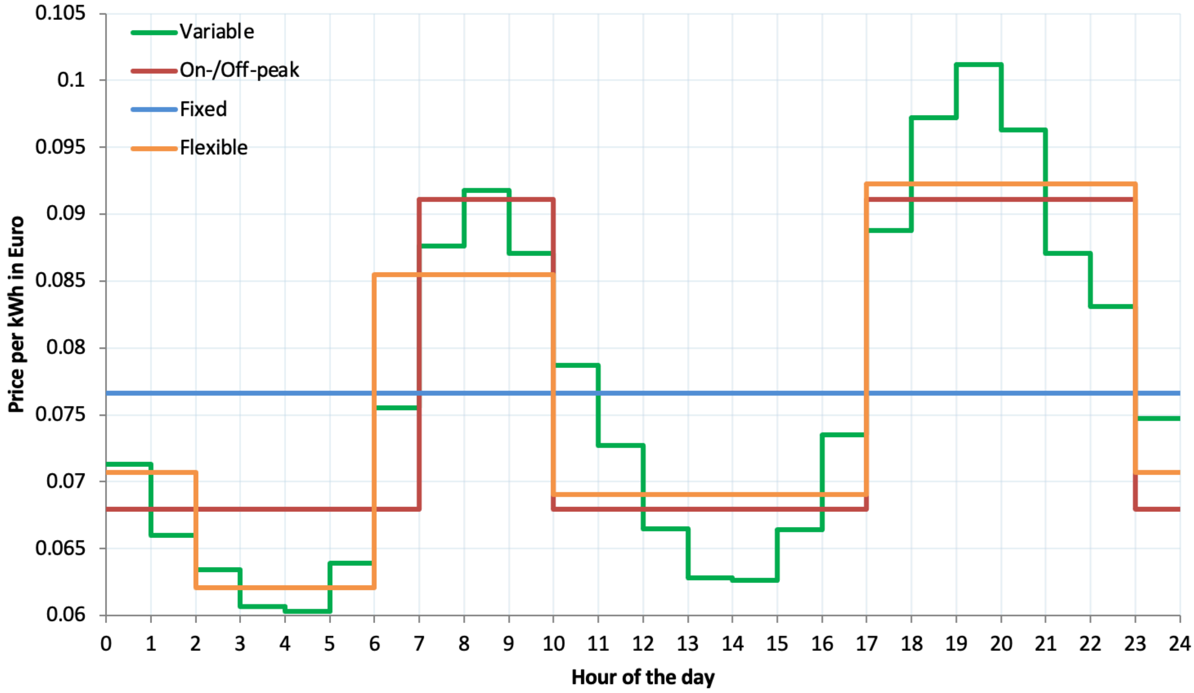

Figure 5.2: Price per hour for all price settings

5.2. Conclusion volatility energy price

This chapter tried to formulate an answer on the first sub-question. To answer the question about volatility in electricity prices over the hours of the day, historical data was analysed. The hourly data of the energy prices per day in The Netherlands, showed a clear distinction in price at different hours. The analysis found that the prices are highest during the late afternoon and the beginning of the evening. Also the from seven to ten in the morning price is relatively high, compared to for example the price early in the night or on the middle of the day. The difference in price can reach up to 4 Euro cents per kWh, which can have a serious impact on the operation costs, considering one battery contains 2600 kWh and about every two hours a new battery is needed. Although detailed data was available for the time of the day, no data was to be found on differences in electricity prices at different locations. Therefore, the price per kWh is assumed to be independent of the location.

The hourly prices found in this analysis resulted in the formation of four different price settings. These settings will be tested after the model formulation in the upcoming chapters. With the testing of the price settings, ultimately an advice on which pricing design is favourable for the skippers, can be formulated for the battery provider.

6 System analysis

Which infrastructural, environmental and operational factors must be represented to model inland (e-)barge performance?

The Dutch inland shipping market is characterised by its unique structure: predominantly family-run businesses operating a single vessel. Their decisions are not solely driven by logistical efficiency but also shaped by considerations of life on board. Moreover, the sector is known for its conservative nature. For these reasons, the study is divided into two parts. The first part develops an optimisation model and compares its outcomes to the current situation. The second part examines the practical feasibility through interviews with stakeholders in the inland shipping sector. The upcoming chapters focus on the model development, after which Chapter 10 addresses the practical viability through stakeholder interviews.

In order to formulate a model in the upcoming chapters, it must first be clear what factors should be included in the model. By looking deeper into the world of the inland waterway transportation these factors can be determined. A system analysis is made to cover all important aspects of the barge transportation in The Netherlands. In this system analysis, first a more zoomed out system description is given. Afterwards, the functioning of individual barges is elaborated on. To conclude the system analysis, the future e-barge system is explored. As the e-barges are a relatively new concept in the inland waterway transportation in both The Netherlands and worldwide, no fully up and running system can be described. However, as ultimately large parts of the traditional barges should be replaced with the e-barges, it is important to look ahead and see what is, or will be, important in the e-barge system. This chapter concludes with the findings of the system analysis, as these findings form the requirements for what the to be developed model should include.

The system analysis of the barge transportation is divided in multiple sections based on the aspects that together describe the inland transportation system, according to Henrickson et al. (2005). In the first part, the system is discussed from a zoomed-out perspective. Here the focus is not on one barge, but on how barge transportation is organised. After the organisation of barge transport is analysed, the focus shifts towards a single barge and its functioning. Here a more detailed look is taken at single barge performance and factors that influence this performance. The system analysis concludes with the requirements for the to be developed model. These requirements follow from the learnings of the system analysis and determine what the model should include.

6.1. General system description of the transport chain by barge

Inland waterway transportation handles the movement of cargo from origin to destination by barge over rivers. Although 40% of the container transportation by barge is international transport, in this research, the focus lies on the 60% of the container transport that has an origin and destination in The Netherlands, as the research is aimed at e-barges. These electric barges have a limited range, making them, at least for now, most suitable for shorter-haul transport. Below, the barge system is divided in subtopics that together give a more complete overview of the functioning of the system.

Flow patterns and cargo volumes

Within The Netherlands, one in three containers are transported by barge, most of these containers travel either to or from Rotterdam or Amsterdam, the major seaports in The Netherlands (van der Geest et al., 2023, de Leeuw van Weenen et al., 2023). From seaports, the containers are transported over the inland waterways to mainly the province of Noord-Brabant, in the south of The Netherlands (de Leeuw van Weenen et al., 2023). However, all provinces with an extensive waterway network are well supplied by barges. For example, the provinces of Utrecht and Gelderland are also well connected, with cities such as Utrecht and Nijmegen directly reachable from the waterways. A few main corridors for domestic transportation can be identified. These routes form the heart of the container transportation by barge. The first corridor is between the Maasvlakte via Rotterdam towards Utrecht (van der Geest & Kindt, 2018). From Utrecht, some smaller waterways lead cargo towards the northern parts of The Netherlands. Another main corridor is between the Maasvlakte towards the inland terminal in Moerdijk (van der Geest & Kindt, 2018). At this location, many containers are handled for further transportation by truck. The corridor towards Moerdijk continues to Antwerpen and connects two of the largest seaports of Europe. Finally, the most used corridor is the river Waal corridor (van der Geest and Kindt, 2018). This corridor connects Nijmegen with the Port of Rotterdam. Over this corridor, 2.7 million TEU are transported annually, compared to 1.6 million TEU on the Rotterdam - Moerdijk corridor and 750 thousand TEU travelling towards Utrecht (van der Geest and Kindt, 2018). Side note to these volumes is that not all of these containers have both their origin and destination in The Netherlands.

Not only are these main corridors sailed by barges, but shipping lines also exist between inland terminals not on one of the main corridors or directly connected with a seaport. Alphen aan den Rijn and Bergambacht are examples of such larger terminals without direct seaport connection. These terminals are well used options for logistics service suppliers in the surroundings. The inland terminal of Alphen aan den Rijn, for example, handles 162 thousand TEU a year (van der Geest and Kindt, 2018).

Resulting model requirements:

- More movement over the inland waterways of the three corridors.
- Routes between both small and larger terminals via inland waterways.
- Model directional flows mainly from seaport into provinces such as Noord-Brabant and Gelderland.

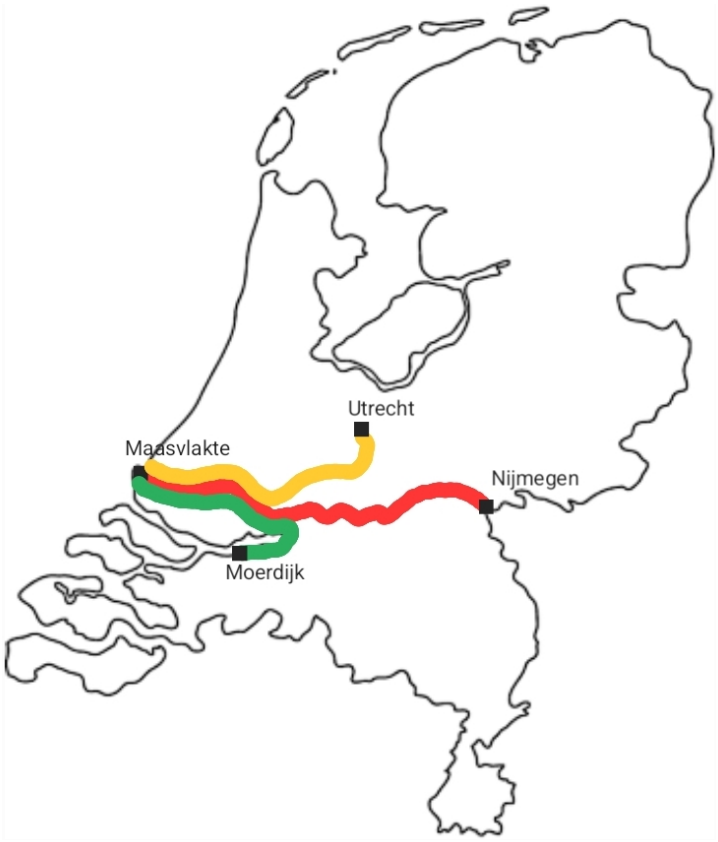

Figure 6.1: Three main corridors for container transport by barge in The Netherlands.

Barge fleet characteristics

To satisfy all these transport movements, a large fleet of barges is needed. The containers are transported with a number of different vessels. For the transportation of containers, two main types of vessels are used. One type of vessel is motorised, while the other is a coupled combination of a push barge that propels an unmotorised vessel. Rijkswaterstaat, the Dutch ministry of Infrastructure and Water Management has divided the inland barges into different categories. The dominant motorised vessels transporting cargo via the Dutch inland waterways are of type M6, M7, M8, M9, M10, M11, M12 (Vinke et al., 2024). With M6 being the smallest and M11 the largest (M12 has a larger beam, but is in length much shorter), these vessels range up to 135 meters in length and 17 meters in width. At most, such a large vessel can carry nearly 400 TEU, but more commonly, these vessels carry 150 TEU per trip (Vinke et al., 2024).

The coupled units work somewhat differently: a push barge propels a large unmotorised floating box. This box on its own cannot do anything other than floating and carrying cargo. However, combined with a push barge, the combination is able to transport large amounts of cargo. In the Dutch waterways, three different kinds of coupled units are mainly used. The combination units of type C3b, C3l and C4 can transport in one trip what would take up to 660 trips by truck (BureauVoorlichtingBinnenvaart, 2013). Table 6.1 shows the different vessel categories active in container transport in The Netherlands and their dimensions. Mainly the beam of a vessel can be a limiting factor in the navigation of larger vessels over inland waterways, due to the presence of locks. Larger vessels commonly only sail over the Rhine corridor as there are no locks in the way and the demand over this waterway is large enough to actually fill the larger ships.

Table 6.1: Vessel classes and size

Category	RWS class	Beam [m]	Length [m]
Coupled units	C3l	11.4	180
	C3b	22.8	105
	C4	22.8	185
Motorised vessels	M0	5.0	28
	M1	5.1	39
	M2	6.6	55
	M3	7.2	70
	M4	8.2	73
	M5	8.2	85
	M6	9.5	85
	M7	9.5	105
	M8	11.4	110
	M9	11.4	135
	M10	13.6	110
	M11	14.2	185
	M12	17.0	135

Resulting model requirements:

- Different types of vessels travel the Dutch waterways. The model must allow for different types of vessels.
- Enforce navigation constraints based on vessel beam versus lock dimensions.

Inland terminal

An inland terminal is a site at an inland waterway where barges can moor to load and unload their cargo using cargo handling facilities (Wiegmans et al., 2015). Normally, one inland terminal is the starting terminal for container transport by barge and another terminal marks the destination for the vessel (van der Geest et al., 2023). From here, the transport of the cargo is continued by truck or train to reach its true final destination. Within The Netherlands, 135 of such terminals can be found (Wiegmans et al., 2015).

Barges arriving at these terminals spend, depending on their size and fill-rate, generally two hours loading and one hour unloading for vessels of type M6/M7 (Zero Emission Services, 2025). For vessels, this typically means a delay of three hours, as most barges arriving at a terminal first spend two hours unloading and afterwards one hour loading. For barges, the capacity at the inland terminals is under standard conditions not the source of additional waiting times, however, the terminals at seaports can be causing issues (van der Geest et al., 2023). As sea-terminals prioritise seagoing vessels over inland barges, idle times at these terminals can add up for the barges (van der Geest et al., 2023). This makes mainly the terminal located in the Maasvlakte prone to additional idle times, whereas inland terminals normally do not experience significant delays due to queuing. Currently, swapping stations exist or are under development at nine different terminals (Zero Emission Services, 2025). The figure below shows the development plans for potential swapping facility locations.

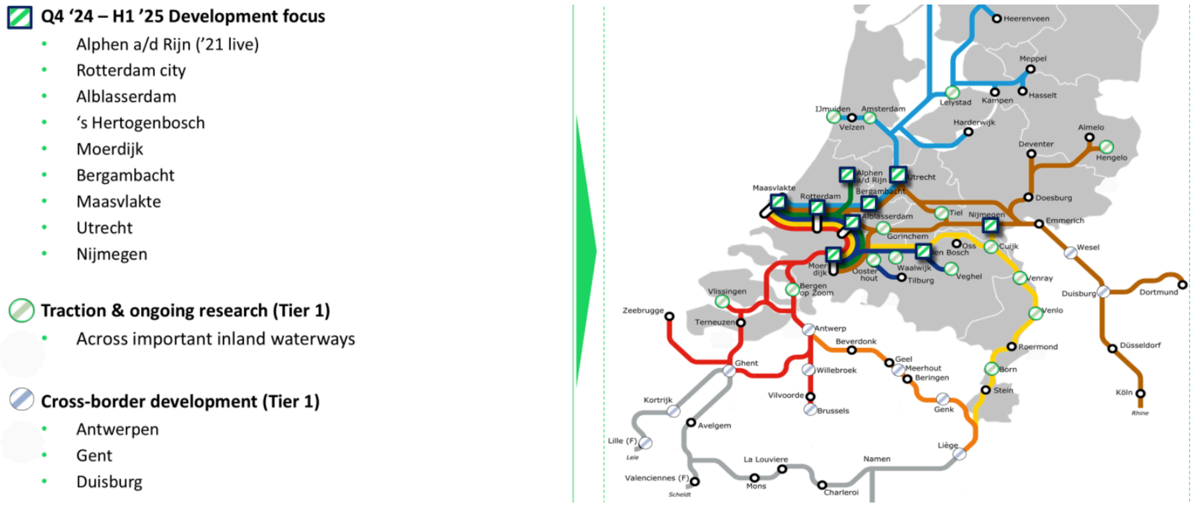

Figure 6.2: Development plans for swapping facilities (Zero Emission Services, 2025).

Resulting model requirements:

- Swapping batteries need to happen at a terminal.
- 9 terminals in the development focus, these locations should be included in the model.
- Two hours unloading, one hour loading time.
- Idle times for barges at seaports can be longer.
- Inland terminal capacity under standard conditions does not add additional waiting time

Inland waterways

As described in section 2.1.1, The Netherlands has an extensive waterway network. All these waterways are formed by many different rivers, all with different characteristics. The rivers vary in width, depth and current, not only between rivers, but also on different parts of the same river. These factors can have a significant impact on the energy consumption, but as data on these river characteristics are lacking, the influence it might have, is not considered in the model. In this research, the rivers that are navigable based on their depth and width and are connecting the different locations mentioned in the paragraph about inland terminals above, are included. On the rivers that link the different terminals, four locks are to be found. One of these locks, the Princes Beatrix locks in Nieuwegein, very close to Utrecht, was recently renovated. With this renovation, waiting times for commercial shipping have been eliminated. For the remaining locks, waiting times can still occur. As mentioned by Centraal Landelijk Overleg Binnenvaart (CLO) (2018), the official target for maximum wait time is 30 minutes, which is met in 80% of the passages. However, skippers interviewed for this research indicated that a simple phone call to the lock operator can secure an unobstructed passage. Therefore, waiting times for locks are not modelled in this research.

Resulting model requirements:

- All connected inland waterways that are navigable based on width and depth should be included.
- Four locks on the waterways of interest, no waiting time implied by these locks.

Scheduling of barges

The right scheduling of barges is very important for the barge system as delivery deadlines are strict and storage costs for containers at terminals can be high (Zweers et al., 2019). To meet delivery deadlines and avoid unnecessary storage costs, barges must time their arrival and departure optimally. However, timing the vessel's arrival perfectly is not so simple, as the freight forwarder commonly has to make an appointment with the terminal well before the arrival of the barge, making the system less flexible (Zweers et al., 2019). The appointments made with the terminals determine the delivery moment of the containers, usually, these appointments are non-negotiable and imply a route for the barge operator

(Zweers et al., 2019). The schedule of the barge operator is thus determined by the appointments with terminals. Also delivering containers long before the the delivery deadline is commonly not appreciated by terminals, as the storage costs in that case can become unnecessary high. Finally, the appointments are commonly recurring events, meaning that if a barge operator and terminal have an appointment, it is likely that this barge travels to and from this terminal at regular intervals (van der Geest et al., 2023).

In short, the schedule of barge operators is normally determined within a planning horizon of up to a day in advance by appointments with terminals that set delivery deadlines for the cargo (Zweers et al., 2019). Recurring trips, however, make the routing schedule of the barge operators more predictable. This determines the main part of the schedules, but it leaves room for the operators to determine their own route and speed. An operator can choose to sail the minimum speed to arrive just in time at the terminal or sail faster and wait somewhere along the route for the delivery deadline to approach.

Resulting model requirements:

- Origin and destination terminals are known upfront.
- Starting time and delivery deadline are given and fixed.
- Early arrival at the destination terminal is not wanted.
- Barge operators determine their own route and speed between the terminal visits.
- Appointments with terminals are typically made up to a day in advance.

Contractual and economic environment

Typically, all economic activities in the barge system start with the consignee. This is the party that owns the cargo to be transported and requests its transportation (van der Geest et al., 2023). The consignee has bought products in another location and needs it shipped to the consignee's facility. Therefore, they can make use of a freight forwarder. The freight forwarder is not physically moving products, but is involved in the process of finding the right operator that can move the products under the best circumstances for the consignee (Tufano et al., 2023). In the situation of inland waterway transportation, the freight forwarder contracts a barge operator that can provide the physical movement of the containers from an origin inland terminal to a destination inland terminal. The last delivery part, from the inland terminal to the final destination, is generally done by truck (van der Geest et al., 2023). Although contracts vary, normally the freight forwarder is responsible for both organising the route of the containers as well as the cargo itself during transportation (van der Geest et al., 2023).

The freight forwarder acts as the intermediary between the different actors. On one side the freight forwarder has a contract with the consignee that orders the freight forwarder to get the goods delivered to the consignee. This forms the primary market: the consignee and freight forwarder must first reach an agreement before the forwarder seeks a transport solution. On the other side, the freight forwarder has a contract with the terminals, indicating a pick up and delivery time at each terminal. Finally, the freight forwarder has a barge operator working that makes sure the actual movement of the cargo takes place. This market is schematically depicted in Figure 6.3 here below.

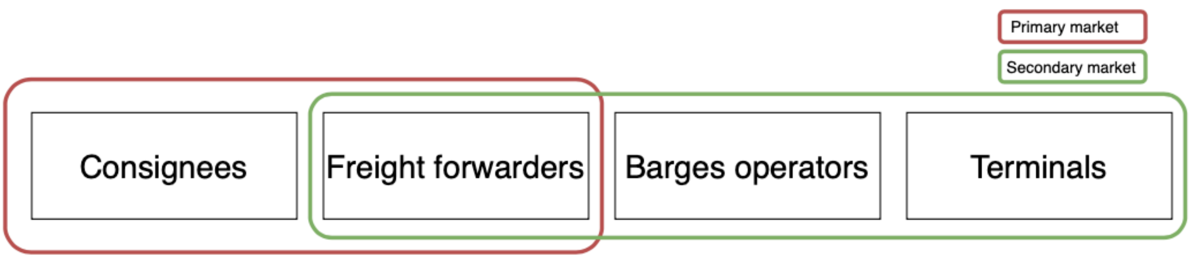

Figure 6.3: Primary and secondary inland transportation market (van der Geest et al., 2023).

The contract between the barge operators and the freight forwarders can vary strongly, mainly in duration. Commonly, freight forwarders set up their contracts with barge operators in such a way that they have a group of long term transporters (van der Geest et al., 2023). This group is used for the majority of the, mostly well predictable, trips. On the other hand, freight forwarders also contract skippers and their barges for shorter periods of times. With contracts varying in duration between a month and on trip basis, the forwarders can still satisfy the transport demand, if more vessels are needed than usual (van der Geest et al., 2023). With this structure, the freight forwarders can guarantee transportation in normal demand scenarios, still satisfy the demand for transportation in higher demand scenarios and prevent idle contracted vessels during low demand scenarios.

According to van der Geest et al. (2023), the transportation demand scenarios are also a determining factor in the profit margin of the skippers. The differences in profit margins are so large, that they run from a small negative margin in low transport demand, to over 20% of the total transportation costs during high demand. In order to translate these percentages in to monetary terms, a closer look is taken on the total transportation costs. van der Geest et al. (2023) show in their analysis of the cost build up of large inland container vessel a total cost of 18.47 Euro per kilometer. This number includes not only the vessel specific costs as personnel costs and fuel, but also fixed costs as depreciations and insurances and general company operating costs. After the personnel costs and fixed costs, the fuel costs are the most important factor. Almost a fifth of the costs, 3.64 Euro, per kilometer is determined by fuel consumption. If the cost build up remains the same in the case of an electric barge, this can become an decisive number for the comparison between traditional fuel barges and e-barges. If the price for the electricity needed to sail one kilometer is lower than this 3.64 Euro, then the e-barge can get competitive with traditional barges. Especially, the vessels operating under a short-term contract can then be moved towards the use of an e-barge. The transition for long-term contracted vessel is expected to be slower, as they are already ensured of work regardless of their competitiveness.

Resulting model requirements:

- Allow for electric versus traditional fuel price comparison. Price per kilometer must be calculable.

6.2. Barge level operation

After inspecting the system from the perspective of the transport chain as a whole, a more detailed look is taken on the individual barges. How do these barges perform individually, as an element in the system just discussed? Therefore, on one hand different performance metrics on barge level and on the other hand, factors that limit this performance, are investigated. First, however, the swapping process of the battery containers is explained in more detail.

When the batteries on board of a vessel are running low, the vessel can sail to a swapping facility. Here, the battery containers can be unloaded from the vessel after mooring at the terminal. While the vessel lies still on the quay, just like it would for unloading cargo, a terminal operator can pick up the battery container with a common container crane and lift it off the vessel. Once the battery is on land, another crane can bring it to a charging facility where the battery is reloaded so it can be used by another vessel later on. The current vessel can get a charged new battery on the vacant slot of the unloaded battery container with which it can continue its journey.

Performance metrics

As discussed in the general description of the barge system, the barges sail a route between an origin and destination terminal as instructed by a freight forwarder. This route can be determined well ahead of departure in the case of a long lasting contract between barge operator and freight forwarder, or on short notice in case of a short term contract. In many cases, not all freight that must be delivered to the indicated terminal is located at the same terminal, therefore, a barge operator can be summoned to collect part of the containers at a different terminal (van der Geest and Kindt, 2018). As many consignees place orders smaller than the full capacity of a barge, freight forwarders also try to consolidate orders in one sending (van der Geest and Kindt, 2018). Because of this, barge operators must often visit more than two terminals for the pick up and delivery of the containers. It is then the responsibility of the skipper of the barge to determine a route between the terminals that must be visited. The skipper makes, of course, use of the available inland waterways but takes into consideration the water levels, length and duration of each possible route as these factors can have an impact on the economic results of the selected route (van der Meulen et al., 2009). Finally, the chosen route must either be possible with the amount of energy onboard from the start, or the route must have the option to tank fuel along the route.

Besides these operational factors, also legal limitations must be considered in the process of route and schedule determination. Although many rules apply to the inland barge navigation, such as requirements on the training and experience for the crew, two laws with a large impact on the routing and scheduling are discussed here. The first rule is rather straight forward. According to the Dutch inland waterway act, the general maximum speed for commercial shipping over inland waterways is 20 km/h measured against the shore (Wettenbank, 2025). This is a general maximum, ports and terminals can imply stricter rules for their harbours. Furthermore, on different zones of the waterways, other speed restrictions are active, indicated by a traffic sign.
The second rule deals with the working hours of the vessel crew. The employees on board are defended by the Dutch government with a law that dictates the maximum allowable working hours. Within every 24 hour period, each employee onboard must have a resting time of at least 10 hours, 6 of these 10 hours must be uninterrupted by any form of labour (Rijksoverheid, 2018). This leaves 4 hours of resting time that can be divided into smaller breaks. It is depending on the manner of exploitation of the vessel whether the ship lies still during these rest periods. If the vessel is operated by a single captain, the barge must remain in place as the captain needs its mandatory rest. However, if the vessel is exploited via a (semi)continuous mode, with more than one captain onboard, then a second captain can take over the control of the barge, while the first captain takes its rest.

The difference in the crew size has a major impact on the performance of the vessels. First of all, vessels with more than one captain onboard can sail many more hours compared to single captain barges. According to van der Geest et al. (2023), a typical continuous operating container vessel sails the inland waterways for 6823 hours per year, meaning that the vessel is effectively operating for almost 78% of all the hours in a year. Smaller vessels, that usually do not have this dual occupancy are operating on average 4679 hours per year, or 53% of all available hours. The second captain onboard also impacts the operating cost of the vessel. Here, the waiting time is compared, as this indicates the additional costs for an extra skipper onboard, separated from the additional cost coming with a larger vessel such as higher fuel consumption costs. With an second skipper onboard, the costs of waiting one hour are 105.23 Euro, a significant increase compared to the waiting cost of 68.19 Euro when the vessel is staffed with just one captain. The difference in expenses should be covered by the additional kilometers and thus extra deliveries, that can be travelled due to the extra captain. A general container barge with two captains can average 50565 kilometers per year, whereas a single captain can only cover 34002 kilometers per year (van der Geest et al., 2023).

Resulting model requirements:

- Support more than two terminal visits per trip.
- Include route selection factors as length, duration and energy feasibility.
- Impose speed limit of 20km/h.
- Enforce crew hours regulations

Energy consumption

As the fuel costs are a large factor in the price structure of inland barges, roughly 20% of total cost per kilometer, also the energy consumption of the barges is investigated (van der Geest et al., 2023). This is mainly done for the impact the sailing speed has on the energy consumption. It is namely not expected that travelling one kilometer with for example, 10 km/h requires the same amount of energy as travelling that same kilometer with 5 km/h. This hypothesis was confirmed by Backer van Ommeren (2011). He showed in his study that loaded inland barges consume more energy over the same distance if they travel with greater speed. The study was conducted for 9 different, but common, inland vessel types and all showed more or less the same relation between speed and energy consumption. All vessels showed a linear increasing relation between energy consumption and speed; travelling the same distance at double the speed requires double the amount of energy. It is important to take into consideration that the energy consumption is dependent on many aspects, such as the river size and the hull dimensions of the vessel, making this an important uncertainty.

Resulting model requirements:

- Treat energy consumption per km as a linear function of speed in km/h.

Specific for e-barges

After analysing the system of the traditional inland transportation, a more detailed look in the requirements for the electric barge system is needed to formulate the model. E-barges differ on some aspects strongly from the traditional powered barges, which must be considered in the model. First and foremost is the electric energy requirement. E-barges need a container battery onboard to power the engine. These container batteries have a capacity of 2600 kWh, with which an e-barge can, depending on the circumstances, sail round 90 kilometers (Zero Emission Services, 2025). As discussed earlier, the energy consumption of different types of barges is shown to be more or less linear by Backer van Ommeren (2011). A vessel operator that was spoken to, but who preferred not to be named, also recognised this more or less linearity in energy consumption compared to the speed. In the case of his vessel, the engine consumed 450 kWh at 16 km/h. Linearising this would show a consumption of 28.125 kWh/km at the speed of 1 km/h. This number compares rather well with the kWh per kilometer if the capacity of the battery (2600) is divided with the distance it can cover (90km) as this results in 28.88 kWh per kilometer.

Furthermore, the time it takes to swap a battery should also be considered. It takes about 15 minutes for a vessel to swap one battery for another, and each battery needs about 2.5 hours to recharge, which can happen simultaneously for multiple batteries (Zero Emission Services, 2025). The time it takes for a battery to become available is important to consider, as the swapping stations have just a limited number of batteries available, if all batteries are rented out and still a vessel arrives at the swapping location for a new battery, it must wait on the charging battery. Finally, swapping a depleted battery for a fully charged one, costs money as this energy needs to be paid for. Currently, this happens according to a fixed fee per kWh. However, this research will explore potential different price settings.

Resulting model requirements:

- E-barges battery containers have a capacity of 2600 kWh.
- Battery swapping time equals 15 minutes, recharging time is 3 hours.
- Enforce limited battery inventory at each facility.
- Charge per kWh as fixed fee, allow exploration of different price settings.

6.3. Example use case

In this section, an example of a typical transport movement is closely followed. All important elements discussed in the system analysis are put in perspective here. In the use case both the flow of the containers as well as the flow of information and money is tracked, as illustrated in Figure 6.4.

In this example, a consignee in the surroundings of Nijmegen wants to get 80 TEU shipped to its facility from a terminal in the Maasvlakte. To make this happen, it contracts a freight forwarder. The freight forwarder organises the transport movement by making an appointment with the both the terminals for the collection of the goods and the delivery terminal. Once those appointments are made, the freight forwarder informs one of the barge operators it has under contract with the instructions for pick up and delivery terminals and times. The skipper of the, in this example, single captained e-barge, can now start planning its trip. By determining the right speed and route over the waterways, the skipper makes sure that the delivery deadline is met at minimal cost. During the process of determining the route, the skipper must make sure that over the whole route from Maasvlakte to Nijmegen, sufficient energy is available. Therefore, stops are determined where batteries can be swapped, for example at the terminal of Bergambacht must be considered. However, these stops should ideally be minimised as they costs both time and money.

With a route in mind, the skipper sets sail from the origin terminal at the starting time indicated by the freight forwarder towards the first stop. On its way, the skipper must respect some regulations. This means that the vessel speed cannot exceed 20 km/h and the crew must take their mandatory rest. After a certain amount of kilometers, the battery onboard needs to be replaced. In this example, this exchange takes place in Bergambacht. Here, the skipper makes the decision on how much new batteries to get, in order to make it in time to the final destination. If the deadline is close, the vessel might need an additional battery as sailing faster requires more energy than when the vessel has time for a slower travel speed. However, collecting an extra battery also implies additional costs, this trade-off needs to be considered.

After the stop at Bergambacht, the barge continues its journey towards the final destination. The vessel should arrive in Nijmegen, the final destination, before the deadline set by the freight forwarder. Once in Nijmegen the barge is unloaded, and the final delivery to the consignee is done by truck from the terminal to the facility of the consignee.

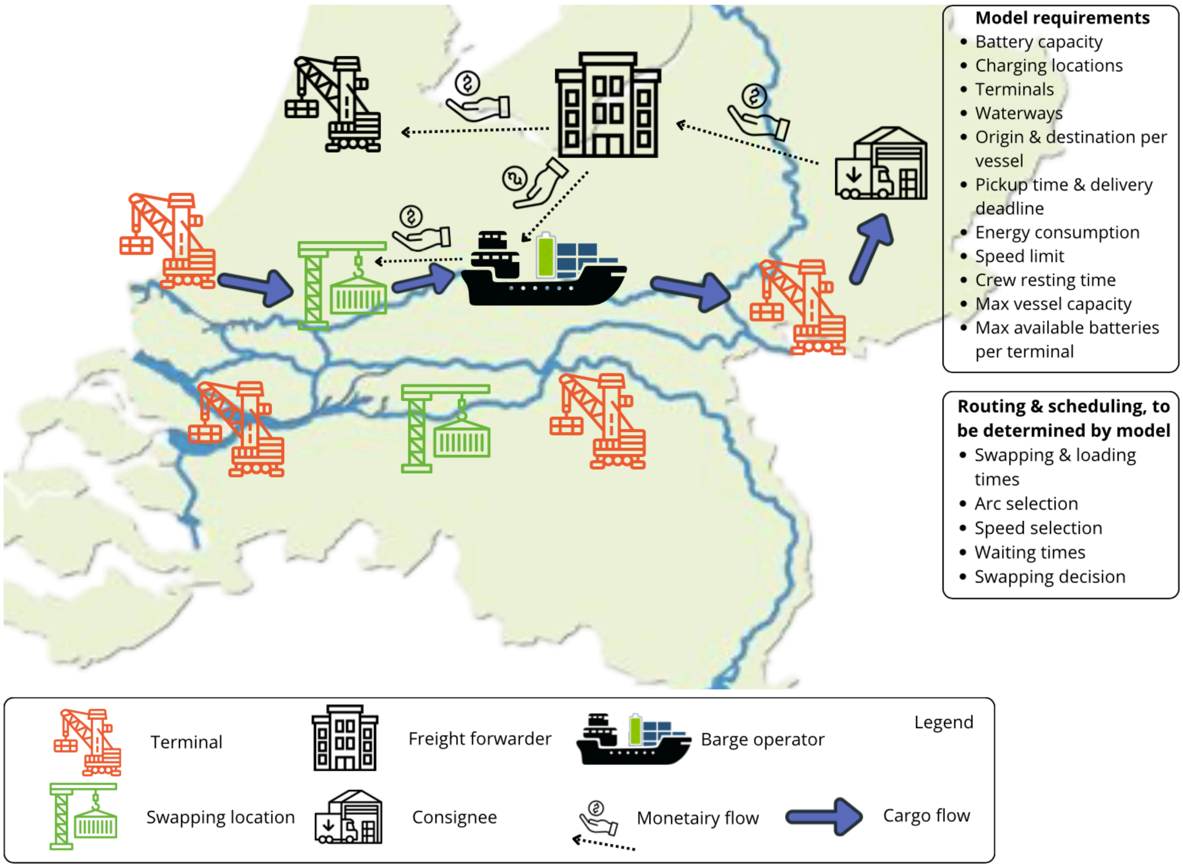

Figure 6.4: Example of a use case scenario.

6.4. Conclusion model requirements

After analysing the inland waterway transportation system in The Netherlands, requirements for the model that will be developed are found. These requirements on many different aspects of the system, must ensure that the model correctly captures the functioning of the transport over the Dutch waterways. The requirements found in the analysis in this chapter are listed here below one by one.

List of model requirements:

1. More movement over the inland waterways of the three corridors.
2. Routes between a combination of small and larger terminals via inland waterways.
3. Model directional flows mainly from seaport into provinces such as Noord-Brabant and Gelderland.
4. Different types of vessels travel the Dutch waterways (model must allow for different vessel types).
5. Enforce navigation constraints based on vessel beam versus lock dimensions.
6. Swapping batteries need to happen at a terminal.

7. Include the 9 terminals in the development focus (these locations should be in the model).
8. Two hours unloading, one hour loading time at terminals if they must load and/or unload.
9. Idle times for barges at seaports can be longer than at inland terminals.
10. Inland terminal capacity under standard conditions does not add additional waiting time.
11. All connected inland waterways that are navigable, based on their width and depth, and are connecting the different included terminals, should be included.
12. Four locks on the waterways of interest, no waiting time implied by these locks.
13. Origin and destination terminals are known upfront.
14. Starting time and delivery deadline are given and fixed.
15. Early arrival at the destination terminal is not appreciated.
16. Barge operators determine their own route and speed between terminal visits.
17. Appointments with terminals are typically made up to a day in advance. So maximum of day ahead planning.
18. Allow for electric versus traditional fuel price comparison.
19. Support more than two terminal visits per trip.
20. Include route-selection factors such as route length, duration and energy feasibility.
21. No vessel can sail faster than 20 km/h.
22. Enforce crew hours regulations (10 h rest per 24 h, of which 6 h uninterrupted).
23. Treat energy consumption per km as a linear function of speed in km/h.
24. E-barge battery containers have a capacity of 2600 kWh.
25. Battery swapping time equals 15 minutes; recharging time is 3 hours.
26. Enforce limited battery inventory at each swapping facility.
27. Charge per kWh as fixed fee, allow exploration of different price settings.

7

Modelling theory

What theoretical concepts underpin the design and construction of routing, scheduling and battery swap planning systems?

The aim of this chapter is to find a strong theoretical foundation for the formulation of the mathematical model to be developed. With the help of a literature review, it is intended to search for models that can provide insight in the functioning of the mathematical model for vehicle routing and scheduling problems as well as energy propagation over routes. Key elements in those formulations are searched for in different types of these models. Common structures and constraints are determined. Ultimately, a base model for the development of the problem at hand is selected. Useful elements of this model are discussed in the closing of this chapter. The newly required knowledge is then used in the next chapter to formulate the mathematical model for the research question central in this research.

7.1. Components mathematical model formulation

In this section, multiple recurring aspects in mixed-integer linear programming models are shown. This is divided in routing, timing, and energy propagation elements.

7.1.1. Routing literature

The base of the problem at hand is a vehicle routing problem. Without the correct formation of individual routes, the model can never find a feasible optimal solution. Therefore, the first group of constraints investigated, handle the formulation of the routing problem. As expected, a number of routing constraints is present in many different vehicle routing problems. Three common constraints in such models are: Flow balancing, Subtour elimination and a maximum fleet size. These constraints are discussed here below.

Flow balancing:

In many cases for vehicle routing problems, a flow balance constraint is needed. Functional requirement 16 of the previous chapter, stating that the model must allow vessels to travel between multiple terminals, indicates that a flow balance constraint is needed here as well. This constraint ensures the flow logic throughout a network. If a vehicle enters a node, this same vehicle must leave this node as well, unless this node is a source or sink. In that case the number of incoming arcs per vehicle does not match the outgoing number of arcs. In many papers this is the way of formulating the flow logic, resulting in the following mathematical representation (Yan et al., 2025, Schiffer and Walther, 2017, Y. Li et al., 2025):

$$\sum_{(i,j)\in A} x_{ij} - \sum_{(j,i)\in A} x_{ji} = \begin{cases} 1 & \text{if } j = \text{origin node} \\ 0 & \text{if } j \in \text{hub} \\ -1 & \text{if } j = \text{destination node} \end{cases} \qquad \forall j \in N \tag{7.1}$$

Subtour elimination:
Other reoccurring element in the literature is the need to eliminate subtours from the solution. These subtours are smaller loops within the route of a vehicle that does satisfy the flow balancing constraint, but interferes with an optimal model result when the route to be sailed, is a round trip. There are multiple ways to prevent subtours from forming in the literature, but a common and relatively simple way to eliminate subtours is via the MTZ approach as shown here (Bazrafshan et al., 2021, Malandraki and Daskin, 1992, Luo et al., 2025):

$$u_i - u_j + n\,x_{ij} \leq n - 1 \quad \forall\, i, j \in C,\ i \neq j, \tag{7.2}$$

$$1 \;\leq\; u_i \;\leq\; n \quad \forall\, i \in C, \tag{7.3}$$

This forces the order of visiting the node in such a way that subtours cannot be formed anymore. The MTZ is simple and direct, but can result in longer runtimes in larger models, compared to other approaches (Bazrafshan et al., 2021). The impact on the runtime should be tested after formulating the model to see if a different, more complex, subtour elimination approach is needed.

Maximum fleet size:
In many optimisation models, the fleet size is limited to mirror real-life situations. This is commonly done with a simple constraint like (Zhou et al., 2024):

$$\sum_{j\in C} x_{0j} \;\leq\; K \tag{7.4}$$

However, in the case of this research objective, the fleet size is not a limiting factor and therefore also not found as a model requirement. The model should, for each vessel that has specified its origin and destination, find an optimal solution as specified in functional requirement (13), (14), (16)). This constraint is therefore not applicable in this research and will not be part of the mathematical model in the next chapter. Also other common constraints in the routing problem formulation are not applicable in this case. In many models, for example, constraints on vehicle capacity are needed. However, for the model in this research, vehicle capacity does not play a role.

7.1.2. Timing literature

With a first impression on the routing constraints in place, now the timing of these routes is looked into. In order to satisfy arrival deadlines, the timing of the active vehicles must be tracked as given by functional requirements (14), (20), (22). In this section, the literature is studied in which models closely monitor the timing of vehicle activities. The lessons from these models are described below.

Window bounds:
One of the common constraints that regulates the timing of the model is the service window for each node. This entails that service at a certain node is only allowed between some time and some other time later. This is commonly formulated as follows (Malandraki and Daskin, 1992, Ha et al., 2021):

$$a_i \;\leq\; t_i \;\leq\; b_i \quad \forall\, i \in N \tag{7.5}$$

In constraint 7.5, this window is applicable for all nodes in the network. However, a common adjustment in this formulation is to only let this window be applicable for the origin or destination. This can be done as follows:

$$t_0 \;\geq\; a_0 \quad , \quad t_0 \;\leq\; b_0 \tag{7.6}$$

Time propagation:
The next standard timing constraint is in 7.7. Here it shows the logical propagation of time. The arrival

time at the next node must be greater than the arrival time at the previous node plus the service time at this node and the travel time between the two nodes. However, this is only necessary if the arc between the two nodes is actually used. The last term with Big M makes sure that the constraint is only applied if the arc between the two nodes is actually travelled.

$$t_j \geq t_i + s_i + \tau_{ij} - M\left(1 - x_{ij}\right) \quad \forall (i,j) \in A \tag{7.7}$$

7.1.3. Energy propagation literature

Tracking the state of charge is done in numerous different ways throughout the literature. That is mostly because of the different factors that are included in the determination of the energy levels. Zhou et al., 2024, for example, includes the speed, curb weight and load of the vehicle to determine the energy consumption. Other models include also factors as wind or, for vessels, current. This can make it difficult to determine one standard constraint, but most models follow the energy levels in a similar way as the time propagation:

$$\mathrm{SoC}_j \leq \mathrm{SoC}_i - e_{ij} + M\left(1 - x_{ij}\right) \quad \forall (i,j) \in A \tag{7.8}$$

The difference in the models is in the determination of e_{ij}, as this can, as discussed, consist of many different factors. Despite this difference, most models agree on using two different variables to follow the state of charge of an electric vehicle. One for the state of charge on the moment of arrival, and one for the state of charge upon departure. This allows for tracking the battery recharges at nodes.

7.2. Base model selection

In order to formulate a mathematical formulation for the problem of this research, no completely new approach is needed. Therefore, a base model that already captures the foundation of the problem has been searched for. This model should preferable have addressed the constraints discussed above. The core function of the constraints above is to formulate a routing and scheduling problem for electric vehicles. The foundation model should thus be of that type. A model that has implemented the features described above for a routing and scheduling of electric vehicles problem, was created by Verma (2018). Although many more models of this type are created, the work by Verma was chosen as foundation for the to be developed model, as this model also includes the battery swapping stations logic.

The flow balance logic is in Verma's model not combined into one formulation, but in three separate equations. In constraints (9), (10) and (11) by Verma the same logic is described as in the generic formulation in (7.1). Verma's constraint (14) has the exact same functioning for the time propagation as the before described time propagation constraint (7.7). The presence of this time propagation constraint means that the subtour elimination constraints as shown in (7.2) and (7.3) is no longer needed, as the time propagation constraint forces a positive time increase meaning that going back to an already visited node is no longer possible. Finally, also the energy propagation in (19) for Verma, uses the same big M approach as the constraint above (7.8). Here below the full mathematical by Verma can be found. This base model will be updated in the next chapter according to the requirements found in the previous chapter.

Mathematical model as described by Verma:

Sets and Indices

K	Set of vehicles ($k \in K$)
C	Set of customer nodes ($i, j \in C$)
F	Set of battery swap/recharge stations ($i \in F$)
O, O'	Start and end depots
A	Set of directed arcs ($(i,j) \in A$)

Parameters

c^f	Fixed cost per vehicle
c^t	Transit cost rate (per time unit)
c^r	Recharge cost per kWh
c^s	Battery swap cost
$c^e,\ c^d$	Early/late arrival penalty rates
t_{ijk}	Travel time on arc (i,j) for vehicle k
s_i	Service time at node i
$D^{\max}$	Maximum battery capacity (kWh)
t^s	Full swap duration (h)
g	Recharge rate (kWh/h)
h	Energy consumption rate (kWh per travel-h)
$T_i^{\text{early}},\ T_i^{\text{delay}}$	Earliest/latest service times at node i
M	Big-M constant, a sufficiently large positive number

Decision Variables

$x_{ij}^k \in \{0,1\}$	1 if vehicle k travels from i to j, else 0
$y_{ik} \in \{0,1\}$	1 if k swaps battery at station i, else 0
$u_{ik} \in \{0,1\}$	1 if k recharges at station i, else 0
$T_{ik} \geq 0$	Departure time of vehicle k from node i
$D_{ik} \geq 0$	State-of-charge upon departure from i
$l_{ik} \geq 0,\ m_{ik} \geq 0$	Slack for early/late arrival at customer i
$p_{ik} \geq 0$	Auxiliary for $D_{ik}u_{ik}$
$z_{ijk} \geq 0$	Auxiliary for $t_{ijk}x_{ij}^k$
Co	Total cost (objective)

Objective:

$$\min\ \mathrm{Co} = \sum_{k\in K}(C_k^f + C_k^t + C_k^r + C_k^s + C_k^p) \tag{1}$$

$$C_k^f = c^f \sum_{i\in C} x_{iO'}^k \tag{2}$$

$$C_k^t = c^t\Big(\sum_{i\in O'} T_{ik} - \sum_{i\in O} T_{ik} - t^s \sum_{i\in F} y_{ik} - \sum_{i\in F} u_{ik} - \sum_{i\in C} s_i\Big) \tag{3}$$

$$C_k^r = c^r \sum_{i\in F} u_{ik}(D^{\max} - D_{ik}) \tag{4}$$

$$C_k^s = c^s \sum_{i\in F} y_{ik} \tag{5}$$

$$C_k^p = \sum_{i\in C}(c^e\, l_{ik} + c^d\, m_{ik}) \tag{6}$$

Subject to:

$$\sum_{i\in C\cup F\cup O} x_{ij}^k = 1 \qquad \forall\, j \in C,\ k \in K \tag{7}$$

$$\sum_{j\in C\cup F\cup O'} x_{ij}^k = 1 \qquad \forall\, i \in C,\ k \in K \tag{8}$$

$$\sum_{i\in C\cup F\cup O} x_{ij}^k - \sum_{m\in C\cup F\cup O'} x_{jm}^k = 0 \qquad \forall\, j \in C\cup F,\ k \in K \tag{9}$$

$$\sum_{j\in C\cup F\cup O'} x_{Oj}^k = 1 \qquad \forall\, k \in K \tag{10}$$

$$\sum_{i \in C \cup F \cup O} x^k_{iO'} = 1 \qquad \forall k \in K \tag{11}$$

$$l_{ik} \geq T_i^{\text{early}} - T_{ik}, \quad l_{ik} \geq 0 \qquad \forall i \in C,\ k \in K \tag{12}$$

$$m_{ik} \geq T_{ik} - T_i^{\text{delay}}, \quad m_{ik} \geq 0 \qquad \forall i \in C,\ k \in K \tag{13}$$

$$T_{jk} \geq T_{ik} + t_{ijk} + s_i + y_{ik}\, t^s + u_{ik}\, \frac{D^{\max} - D_{ik}}{g} - M\,(1 - x^k_{ij}) \qquad \forall i, j \in C, k \in K \tag{14}$$

$$z_{ijk} \leq t_{ijk}\, x^k_{ij} \qquad \forall i, j \in C, k \in K \tag{15}$$

$$z_{ijk} \leq t_{ijk} \qquad \forall i, j \in C, k \in K \tag{16}$$

$$z_{ijk} \geq t_{ijk} - M\,(1 - x^k_{ij}) \qquad \forall i, j \in C, k \in K \tag{17}$$

$$z_{ijk} \geq 0 \qquad \forall i, j \in C, k \in K \tag{18}$$

$$D_{jk} \geq (1 - y_{ik} - u_{ik})\, D_{ik} + (y_{ik} + u_{ik})\, D^{\max} - h\, d_{ij} - M\,(1 - x^k_{ij}) \qquad \forall i, j \in C, k \in K \tag{19}$$

$$D_{jk} \geq 0 \qquad \forall j \in C, k \in K \tag{20}$$

$$D_{jk} \leq D^{\max} \qquad \forall j \in C, k \in K \tag{21}$$

$$p_{ik} \leq D^{\max}\, u_{ik} \qquad \forall i \in C, k \in K \tag{22}$$

$$p_{ik} \leq D_{ik} \qquad \forall i \in C, k \in K \tag{23}$$

$$p_{ik} \geq D_{ik} - M\,(1 - u_{ik}) \qquad \forall i \in C, k \in K \tag{24}$$

$$p_{ik} \geq 0 \qquad \forall i \in C, k \in K \tag{25}$$

$$y_{ik} \leq z_i \qquad \forall i \in C, k \in K \tag{26}$$

$$u_{ik} \leq v_i \qquad \forall i \in C, k \in K \tag{27}$$

$$z_i + v_i \leq 1 \qquad \forall i \in C \tag{28}$$

$$y_{ik} + u_{ik} \leq 1 \qquad \forall i \in C, k \in K \tag{29}$$

$$\sum_{i \in C \cup F \cup O} \sum_{j \in C} w_i\, x^k_{ij} \leq W^{\max} \qquad \forall k \in K \tag{30}$$

$$D_{Ok} = D^{\max} \qquad \forall k \in K \tag{31}$$

$$T_{Ok} \geq T_O^{\text{early}} \qquad \forall k \in K \tag{32}$$

$$T_{O'k} \leq T_{O'}^{\text{delay}} \qquad \forall k \in K \tag{33}$$

$$x^k_{ij} \in \{0, 1\},\ y_{ik}, u_{ik}, z_i, v_i \in \{0, 1\} \tag{34}$$

7.3. Conclusion modelling theory

Investigating previous studies learned that many models are quite similar in their structure, especially for the routing and timing constraints. Studies that can be useful for the implementation of these constraints are Yan et al. (2025), Y. Li et al. (2025), Bazrafshan et al. (2021) for routing constraints and Ha et al. (2021), Malandraki and Daskin (1992) for timing constraints. Energy propagation constraints are shown in research by, for example, Zhou et al. (2024) and Verma (2018). As these models have already proven their functionality, learning from these studies should enhance the chances for the to be created model in the next chapter. Constraints as flow balancing and time propagation are thoroughly tested throughout all the different models that have had success with these constraints as part of the mathematical formulation. This can take away uncertainties from the to be developed model. Furthermore, the lesson of including two variables to track the state of charge at two different moments, on arrival and departure, is likely to be very useful as battery swaps in research happen at the nodes. The study by Verma (2018) will be used in the next chapter as a starting point. From this model, the useful elements will be conserved, while other parts that do not align with the model requirements will be dropped. The model will be extended with constraints found in the literature that correctly mimic the requirements as listed in 6.4. Taking this information towards the development of the mathematical formulation, should make the problem both easier and more reliable, due to the proven concept of these commonly used constraints.

8

Model development

How can a model be developed that minimises operational energy costs for skippers while respecting operational constraints such as delivery deadlines?

In this chapter, sub-question number four is answered. To do so, a mathematical model is formulated that later on will be implemented in Python code to find an answer to the question asked above. In this chapter, the model objective is discussed, the constraints as formulated in the mathematical notation by Verma are reconsidered, the assumptions of the model are described and a model formulation for the problem is given. Afterwards, the implementation of the model into Python code is discussed. Ultimately, the constructed model is verified and validated.

8.1. Model description

The sub-question that stands central in this chapter is tried to be answered with the help of an optimisation model. This model should find the minimal cost for a fleet of vessels while respecting their operational constraints. These operational constraints can consist of factors such as delivery deadlines, time needed for swapping and the vessels maximum speed, as seen in the requirements.

The model is built for the locations that are either already in use or identified as development focus locations for the near future by the provider of the battery containers. These locations are fully connected via inland waterways. The full connectivity ensures that between all combinations of locations one or more paths are available. Each path is exactly as long as the navigable route between the two locations. This avoids the use of too narrow and shallow waterways, so all routes can actually be sailed by the barges.

The model is defined in hourly time steps, as electricity prices are determined in hourly intervals on the day-ahead market. Using a finer resolution, such as minutes, would significantly increase computational complexity and therefore computation times. Conversely, using coarser intervals, such as two-hour steps, would reduce accuracy and limit the ability to capture the timing of operations relative to hourly prices. Although electricity prices are only known for the next 24 hours, the optimisation horizon is extended to 48 hours, with the same hourly prices as the day before. This ensures that operations starting late in the day, for example, a vessel departing at 22:00 and finishing after midnight, are handled correctly, and avoids edge effects that would otherwise occur if the model stopped strictly at 24 hours.

Within the window, the MILP model is searching for the lowest energy costs for the fleet of vessels in the model. This means that one vessel might be forced to make a little detour in order to minimise the cost for another vessel, but the optimisation makes sure that the final solution is optimal for the fleet as a whole. Individual ships can optimise their operations within the same model, once that vessel is implemented as only vessel of a fleet.

The model determines the optimal solution by assigning each vessel to swapping locations, if swapping is needed. This is done in such a way that in the hour the swap takes place, energy prices are as low as possible within the operational constraints. Ensuring optimal arrival times at swapping location is done by determining a route from the origin to destination and assigning a speed over every arc for each vessel. Furthermore, the timing can be influenced by giving the vessels the possibility to wait at a swapping station before continuing their journey.

In conclusion, within 24 discrete hourly time steps, the MILP model tries to optimise the costs of swapping batteries for a specified fleet. This is done by determining ideal routes, swapping locations, speed on each arc and waiting times for all vessels in a fleet, all while accounting for the operational constraints. Ultimately, with a fully functioning model, different price settings can be tested. Based on these tests, an advice can be formulated for the battery provider on which price setting to implement. In the following sections, the development of a mathematical model that supports the construction of such an MILP model is discussed.

8.2. Model assumptions

Before the model can be formulated, some assumptions have to be made. These assumptions are needed to correctly mimic the model's behaviour according to the requirements determined in 6.4. These assumptions are likely to impact the results that will be discussed later on, the expected impact is discussed individually in Table 11.1. The assumptions are organised per category:

Routing assumptions:

- The network graph includes only the waterways (three main corridors plus feeder links) that connect the nine focus terminals. Only these waterways are considered as navigable.
- Origin and destination terminals are known and fixed at model start, as are the starting times and delivery deadlines (start before 24:00, deadline before 48:00).
- Travel time on each arc depends solely on chosen speed, from 8 km/h up to 20 km/h and arc length.
- Vessels choose their own route and speed to arrive just-in-time.
- Beam/lock-dimension do not form problems, all included waterways are navigable for each vessel.
- Crew-hours: in any 24 hour window, one uninterrupted rest block of 6 hour and a total of 4 hours interrupted rest is included.

Battery swapping assumptions:

- Each e-barge carries exactly one container battery at full capacity of 2600 kWh at the model start.
- Energy consumption per km is a linear function of speed.
- Swapping is allowed only at the nine focus terminals. Each location holds a limited number of charged batteries in stock.
- Swap duration is 15 minutes. Recharging the returned battery to full takes 3 hours, during which that specific battery can not be swapped.
- If no charged battery is available upon arrival, the vessel must wait until the recharge finishes or choose a different swapping location.
- The full battery capacity may be used. Any state of charge value between 0 and battery capacity B is acceptable.
- Every swap replaces the depleted battery with a 100% state-of-charge unit.

Market assumptions:

- Prices for a kWh of energy are fully based on historical data. The price in each hour is depending on the active price setting.
- The price for a battery swap is battery capacity times the price for one kWh in the hour of the swap. Although the battery might be charged over multiple hours, the price at the time of swapping the battery is leading.
- If a battery is swapped, the remaining state-of-charge of the swapped battery determines the discount for the new battery. The price for one kWh at the time of swapping the battery multiplied with the remaining kWh in the battery, determine the monetary discount for the vessel operator.

Other assumptions:

- Battery performance is always equal, regardless of the temperature, matureness of the battery or other factors that might have an impact on battery performance.

8.3. Changes to base model

As seen in the previous chapter, the foundation for the problem at hand, was found in the model by Verma (2018). After determining the exact model goal and assumptions, now changes to this model will be made, so the problem in this research can be tackled. The right aspects of the model by Verma need to be changed, therefore an additional look is taken into the modelling goals of Verma to see any deviations from the problem that should be solved in this research.

Some clear differences in model setup can be found. First of all, in Verma's work, all vehicles are required to start and end in the depot, which is not the case in this problem. Furthermore, Verma does take capacity of the vehicles into consideration, something that is not required in this problem. A more subtle difference but potentially with a big impact on the model outcome is the soft time windows Verma implemented. The soft windows mean that one can act outside of the windows, just at extra costs. In this research, the time windows are fixed, so one can, for example, not start before a certain time. Finally, a key difference lies in the possibility for recharging. In Vermas model, each electric vehicle has the option at a facility to either swap the battery for a fully charged one, or recharge the current battery. Recharging the battery is not included in this research as in the case of recharging large container batteries, it would take too long for the vessel to wait for.

Despite the clear differences, the work by Verma remains very much in line with what needs to happen in this situation. Verma's work correctly makes use of a fleet of electric vehicles, applies a maximum battery capacity and the vehicles can visit any swapping facility in the network. Furthermore, a battery swap includes a cost and takes time, just like the requirements in 6.4 implied. Also the fact that multiple swaps are allowed at the same time at the same swapping station, correctly handles the requirements set for this model. The flow conservation in Verma's model can be used in the new model, as the flow of the batteries over the arcs must be conserved. Furthermore, the time propagation from one node to another can be reused in this model. Finally, Verma's constraints that only lets vehicles swap batteries at facilities that are actually open, can be used in the to be developed model.

After eliminating the constraints from Verma's model that are not usefull in the new model, the constraints specific for this problem can be added. The constraints added are for example, the constraint that if a battery is dropped off at a station, this specific battery is not available for the coming 3 hours, as it needs to be charged. Based on the previously determined requirements, constraints are added until the requirements are satisfied, which results in the model described in the next section.

8.4. Mathematical model

Here below, the mathematical notation of the problem is given. This mathematical model contains all constraints that restricts the model and the objective function for the problem. First, in a table, Table 8.1, the symbols and abbreviations used in the formulation are shown and enlightened. Afterwards, the objective and constraints that form the model are explained.

Table 8.1: Notation for battery swapping model

Sets and Indices		
$\mathcal{L}$	Set of all legs	$\ell \in \mathcal{L}$
$R(\ell)$	Candidate routes for leg ℓ	$r \in R(\ell) = \{0, \ldots, K_\ell - 1\}$
$A^{\ell r}$	Arcs on route r of leg ℓ	$(i, j) \in A^{\ell r}$
$N^{\ell r}$	Nodes on route r of leg ℓ	$n \in N^{\ell r}$
D	Calendar-day indices	$d \in D = \{0, \ldots, D_{\max} - 1\}$
H	Hourly time slots	$k \in H = \{0, \ldots, H_{\max} - 1\}$
H_{start}	Feasible rest-block start times	$s \in H_{\text{start}} = \{0, \ldots, H_{\max} - L\}$
V	Set of all vessels	$v \in V$
S	Set of discrete speeds	$s \in S$
R_{all}	Swap-station nodes	$n \in R_{\text{all}} \subseteq V$
Parameters		
B_{cap}	Battery capacity per battery pack	[kWh]
$N_{\max}$	Max batteries per vessel	[–]
T_{swap}	Time needed per swap	[h]
L	Rest-block length (hours)	[h]
SF	Fee per swap	[€]
TC	Fraction lost on resale	[–]
C	Time needed to recharge a battery	[h]
d_{ij}	Distance of arc (i, j)	[km]
e_s	Energy per km at speed s	[kWh/km]
p_k	Price at hour k	[€/kWh]
I_n	Initial packs at station n	[–]
START^ℓ	Start time of leg ℓ	[h]
DEAD^ℓ	Deadline of leg ℓ	[h]
$orig(\ell)$	Starting location of leg ℓ	[-]
$M_t, M_{\text{soc}}, M_{\text{sell}}$	Big-M constants	[-],[-],[-]
Decision Variables		
$X^{\ell r}$	1 if route r chosen for leg ℓ	$\{0, 1\}$
$z^{\ell r}_{ij,s}$	1 if arc (i, j) on route (ℓ, r) at speed s	$\{0, 1\}$
$y^{\ell r}_{nk}$	1 if swap at node n time k	$\{0, 1\}$
$\text{pick}^{\ell r}_{nk}$	Packs picked up	$[0, N_{\max}]$
$\text{drop}^{\ell r}_{nk}$	Packs dropped	$[0, N_{\max}]$
$\text{sell}^{\ell r}_{nk}$	kWh sold back	$[0, B_{\text{cap}} N_{\max}]$
$\text{sbin}^{\ell r}_{nk}$	1 if selling activated	$\{0, 1\}$
$t^{\ell r}_n$	Arrival time at node n	$[0, \infty)$
$\text{dep}^{\ell r}_n$	Departure time at node n	$[0, \infty)$
$w^{\ell r}_{nd}$	Waiting hours at n on day d	$[0, \infty)$
$\text{BA}^{\ell r}_n$	Packs on board upon arrival	$[0, N_{\max}]$
$\text{BD}^{\ell r}_n$	Packs on board upon departure	$[0, N_{\max}]$
$E^{\ell r,\text{arr}}_n$	Energy upon arrival	$[0, B_{\text{cap}} N_{\max}]$
$E^{\ell r,\text{dep}}_n$	Energy upon departure	$[0, B_{\text{cap}} N_{\max}]$
$b^{\ell r}_{ns}$	1 if rest-block starts at s at n	$\{0, 1\}$
$v^{v}_{\text{rest},k}$	1 if vessel v rests in hour k	$\{0, 1\}$

Objective:

$$\min \sum_{\ell \in \mathcal{L}} \sum_{r \in R(\ell)} B_{\text{cap}}\, p_{t^{\ell r}_{\text{orig}(\ell)}}\, \text{BA}^{\ell r}_{\text{orig}(\ell)} + \sum_{\ell \in \mathcal{L}} \sum_{r \in R(\ell)} \sum_{n \in R_{\text{all}}} \sum_{k \in H} B_{\text{cap}}\, p_k\, \text{pick}^{\ell r}_{nk} \tag{8.1}$$

$$+\ \mathrm{SF}\left(\sum_{\ell\in\mathcal{L}}\sum_{r\in R(\ell)}\mathrm{BA}^{\ell r}_{\mathrm{orig}(\ell)}+\sum_{\ell\in\mathcal{L}}\sum_{r\in R(\ell)}\sum_{n\in R_{\mathrm{all}}}\sum_{k\in H}y^{\ell r}_{nk}\right)$$
$$-\sum_{\ell\in\mathcal{L}}\sum_{r\in R(\ell)}\sum_{n\in R_{\mathrm{all}}}\sum_{k\in H}(1-\mathrm{TC})\,p_k\,\mathrm{sell}^{\ell r}_{nk}$$

Subject to:

$\sum_{r\in R(\ell)} X^{\ell r}=1$	$\forall\,\ell\in\mathcal{L}$	(8.2)
$\sum_{s\in S} z^{\ell r}_{ij,s}=X^{\ell r}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ (i,j)\in A^{\ell r}$	(8.3)
$E^{\ell r,\mathrm{arr}}_{\mathrm{orig}(\ell)}=B_{\mathrm{cap}}\,\mathrm{BA}^{\ell r}_{\mathrm{orig}(\ell)}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell)$	(8.4)
$E^{\ell r,\mathrm{dep}}_{\mathrm{orig}(\ell)}=B_{\mathrm{cap}}\,\mathrm{BD}^{\ell r}_{\mathrm{orig}(\ell)}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell)$	(8.5)
$\mathrm{BA}^{\ell r}_i\geq X^{\ell r}$	$\forall\,\ell,r,\ (i,j)\in A^{\ell r}$	(8.6)
$y^{\ell r}_{nk}\leq X^{\ell r}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(8.7)
$\mathrm{pick}^{\ell r}_{nk}+\mathrm{drop}^{\ell r}_{nk}\geq y^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(8.8)
$\mathrm{pick}^{\ell r}_{nk}\leq N_{\max}\,y^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(8.9)
$\mathrm{drop}^{\ell r}_{nk}\leq N_{\max}\,y^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(8.10)
$\mathrm{sell}^{\ell r}_{nk}\leq B_{\mathrm{cap}}\,\mathrm{drop}^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(8.11)
$\mathrm{sell}^{\ell r}_{nk}\leq (B_{\mathrm{cap}}-\epsilon)\,\mathrm{sbin}^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(8.12)
$y^{\ell r}_{nk}\geq \frac{1}{N_{\max}}\,\mathrm{pick}^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(8.13)
$y^{\ell r}_{nk}\geq \frac{1}{N_{\max}}\,\mathrm{drop}^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(8.14)
$t^{\ell r}_n\leq k+M_t\,(1-y^{\ell r}_{nk})$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(8.15)
$t^{\ell r}_n\geq k-M_t\,(1-y^{\ell r}_{nk})$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(8.16)
$\mathrm{sbin}^{\ell r}_{nk}\leq y^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(8.17)
$\mathrm{drop}^{\ell r}_{nk}\geq \mathrm{sbin}^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(8.18)
$\mathrm{sell}^{\ell r}_{nk}\leq E^{\ell r,\mathrm{arr}}_n$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(8.19)
$\mathrm{sell}^{\ell r}_{nk}\geq E^{\ell r,\mathrm{arr}}_n-M_{\mathrm{sell}}\,(1-\mathrm{sbin}^{\ell r}_{nk})$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(8.20)
$E^{\ell r,\mathrm{arr}}_n\leq B_{\mathrm{cap}}\,\mathrm{BA}^{\ell r}_n$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}}$	(8.21)
$E^{\ell r,\mathrm{dep}}_n\leq B_{\mathrm{cap}}\,\mathrm{BD}^{\ell r}_n$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}}$	(8.22)
$t^{\ell r}_j\geq \mathrm{dep}^{\ell r}_i+\sum_{s\in S}\frac{\mathrm{d}_{ij}}{s}\,z^{\ell r}_{ij,s}-M_t\,(1-X^{\ell r})$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ (i,j)\in A^{\ell r}$	(8.23)
$t^{\ell r}_j\leq \mathrm{dep}^{\ell r}_i+\sum_{s\in S}\frac{\mathrm{d}_{ij}}{s}\,z^{\ell r}_{ij,s}+M_t\,(1-X^{\ell r})$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ (i,j)\in A^{\ell r}$	(8.24)
$\mathrm{dep}^{\ell r}_n=t^{\ell r}_n+T_{\mathrm{swap}}\sum_{k\in H}y^{\ell r}_{nk}+\sum_{d\in D}w^{\ell r}_{nd}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in N^{\ell r}$	(8.25)
$\mathrm{BA}^{\ell r}_j=\mathrm{BD}^{\ell r}_i$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ (i,j)\in A^{\ell r}$	(8.26)
$E^{\ell r,\mathrm{arr}}_j\leq E^{\ell r,\mathrm{dep}}_i-\sum_{s\in S}(\mathrm{d}_{ij}e_s)\,z^{\ell r}_{ij,s}+M_{\mathrm{soc}}(1-\sum_s z^{\ell r}_{ij,s})$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell)\ (i,j)\in A^{\ell r}$	(8.27)
$E^{\ell r,\mathrm{arr}}_j\geq E^{\ell r,\mathrm{dep}}_i-\sum_{s\in S}(\mathrm{d}_{ij}e_s)\,z^{\ell r}_{ij,s}-M_{\mathrm{soc}}(1-\sum_s z^{\ell r}_{ij,s})$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ (i,j)\in A^{\ell r}$	(8.28)
$\sum_{k\in H}\mathrm{pick}^{\ell r}_{nk}\leq I_n+\sum_{h\in H}^{h+C\leq k}\sum_{\ell',r'}\mathrm{drop}^{\ell' r'}_{nh}-\sum_{h<k}\sum_{\ell',r'}\mathrm{pick}^{\ell' r'}_{nh}$	$\forall\,n\in R_{\mathrm{all}},\ k\in H$	(8.29)

$$t^{\ell r}_{\text{orig}(\ell)} \geq \text{START}^{\ell} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell) \tag{8.30}$$

$$t^{\ell r}_{\text{dest}(\ell)} \leq \text{DEAD}^{\ell} + M_t(1 - X^{\ell r}) \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell) \tag{8.31}$$

$$\text{dep}^{\ell r}_{\text{dest}(\ell)} \leq t^{\ell' r'}_{\text{orig}(\ell')} \qquad \forall\, (\ell \in \mathcal{L},\ r \in R(\ell)), (\ell' \in \mathcal{L},\ r' \in R(\ell)) \tag{8.32}$$

$$\sum_{\ell \in \mathcal{L}(v)} \sum_{r \in R(\ell)} \sum_{n \in R_{\text{all}}} \sum_{s=24\,d}^{24\,d+24-L} b^{\ell r}_{ns} = 1 \qquad \forall\, v \in V,\ d \in D \tag{8.33}$$

$$b^{\ell r}_{ns} \leq X^{\ell r} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\text{all}},\ s \in H_{\text{start}} \tag{8.34}$$

$$t^{\ell r}_{n} \leq s + M_t\left(1 - b^{\ell r}_{ns}\right) \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in N^{\ell r},\ s \in H_{\text{start}} \tag{8.35}$$

$$\text{dep}^{\ell r}_{n} \geq s + L - M_t\left(1 - b^{\ell r}_{ns}\right) \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in N^{\ell r},\ s \in H_{\text{start}} \tag{8.36}$$

$$w^{\ell r}_{nd} \leq (24 - L)\left(1 - \sum_{s=24d}^{24d+24-L} b^{\ell r}_{ns}\right) \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\text{all}},\ d \in D \tag{8.37}$$

$$\sum_{\ell \in \mathcal{L}(v)} \sum_{r \in R(\ell)} \sum_{n \in R_{\text{all}}} w^{\ell r}_{nd} \geq 4 \qquad \forall\, v \in V,\ d \in D \tag{8.38}$$

$$w^{\ell r}_{nd} \leq X^{\ell r} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\text{all}},\ k \in H \tag{8.39}$$

$$v^{v}_{\text{rest},k} \geq \sum_{\ell \in \mathcal{L}} \sum_{r \in R(\ell)} \sum_{n \in R_{\text{all}}} \sum_{\substack{s \leq k \leq s+L-1 \\ s \in H_{\text{start}}}} b^{\ell r}_{ns} \qquad \forall\, v \in V,\ k \in H \tag{8.40}$$

$$v^{v}_{\text{rest},k} \leq 1 \qquad \forall\, v \in V,\ k \in H \tag{8.41}$$

Non negativity and binary domain constraints:

$$X^{\ell r} \in \{0,1\} \qquad \forall\, \ell \in \mathcal{L}, r \in R(\ell) \tag{8.42}$$

$$z^{\ell r}_{ij,s} \in \{0,1\} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ (i,j) \in A^{\ell r},\ s \in S \tag{8.43}$$

$$y^{\ell r}_{nk} \in \{0,1\} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\text{all}},\ k \in H \tag{8.44}$$

$$\text{sbin}^{\ell r}_{nk} \in \{0,1\} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\text{all}},\ k \in H \tag{8.45}$$

$$\text{pick}^{\ell r}_{nk},\quad \text{drop}^{\ell r}_{nk},\quad \text{sell}^{\ell r}_{nk} \geq 0 \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\text{all}},\ k \in H \tag{8.46}$$

$$\text{BA}^{\ell r}_{n},\quad \text{BD}^{\ell r}_{n},\quad E^{\ell r,\text{arr}}_{n},\quad E^{\ell r,\text{dep}}_{n} \geq 0 \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\text{all}} \tag{8.47}$$

$$t^{\ell r}_{n},\quad \text{dep}^{\ell r}_{n} \geq 0 \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in N^{\ell r} \tag{8.48}$$

$$w^{\ell r}_{nd} \geq 0 \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\text{all}},\ d \in D \tag{8.49}$$

$$v^{v}_{\text{rest},k} \in \{0,1\} \qquad \forall\, v \in V,\ k \in H \tag{8.50}$$

$$b^{\ell r}_{ns} \in \{0,1\} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\text{all}},\ s \in H_{\text{start}} \tag{8.51}$$

Objective and constraints explanation

The model starts with the objective function (8.1).The objective function intends to minimise the operational cost of the battery swapping system. The first two summations charge the energy initially on board at each leg's origin and any batteries picked up at stations at the prevailing hourly electricity prices (each multiplied by the battery capacity), while the SF term adds fixed swap fees for initial packs and for every executed swap. The final negative summation credits revenue from remaining energy that is sold back to the battery provider by the skipper, reduced by the transaction TC, so the objective trades off purchasing energy, paying swap fees, and recovering value from sold back energy.

The constraints section begins by enforcing that exactly one route is selected per leg (8.2), and for each used route, exactly one speed is chosen for every arc (8.3). To ensure full battery deployment at each leg's origin, the arrival and departure energy at each start is tied to the number of packs multiplied by the battery capacity (8.4), (8.5), and any active arc must carry at least one battery pack (8.6).

Battery exchanges can only happen on legs that are chosen (8.7), and if a swap occurs then the sum of packs picked up and dropped off must be at least one (8.8). The pickup and drop quantities are limited by vessel capacity and linked to the swap decision via binary variables (8.9), (8.10), (8.13), (8.14).

Energy selling is enabled only when packs are dropped: the sold energy cannot exceed the dropped pack capacity (8.11), (8.12), and the sell-binary is tied to the swap event and drop action (8.17), (8.18). The amount of energy sold cannot exceed the energy on board upon arrival (8.19), and if selling is activated then all available arrival energy must be sold (8.20).

Temporal constraints ensure consistency: if a swap event occurs at hour k, the arrival time must match this hour (8.15), (8.16). The general travel-time constraints enforce that arrival at node j equals departure from i plus travel time (distance over speed) (8.23), (8.24), and each node's departure time equals its arrival time plus swap duration plus any waiting (8.25).

Flow constraints link battery packs and energy: packs on board carry over from arc start to arc end (8.26), and arrival energy equals departure energy minus consumption from travel (8.27), (8.28). Both arrival and departure energy are bounded by the pack capacity (8.21), (8.22).

Station inventory is balanced by ensuring that cumulative pickups at a node do not exceed the initial inventory plus all previously dropped packs that have recharged (8.29).

Scheduling constraints enforce that each leg departs no earlier than its start time (8.30) and arrives by its deadline (8.31); the next constraint guarantees that if one leg follows another, its departure occurs after the predecessor's arrival (8.32).

Mandatory waiting and rest are modelled via daily rest blocks of fixed length L: exactly one rest block per vessel per day (8.33). Rest blocks are tied to chosen legs (8.34) and enforced by requiring arrival and departure times to bracket the rest interval (8.35), (8.36). No waiting hours occur during a scheduled rest (8.37). Each vessel must accumulate at least four waiting hours per day (8.38), and waiting hours can only occur on active legs (8.39). The hourly rest indicator ensures consistent scheduling: if a rest block starts at hour s, the vessel is in rest for hours s through $s + L - 1$ (8.40), and at most one rest indicator can be active at any time (8.41).

Finally, all decision variables are restricted to appropriate domains: selection and event variables are binary (8.42), (8.51), while pack, energy, time, and waiting variables are non-negative (constraints (8.46), (8.49).

8.5. Implementation

The mathematical model described above, has been implemented in a programming language in order to get numerical results from the model. For this, Python was used. The mathematical model was implemented to Python code in the program Spyder. Spyder is very well capable of running Mixed integer programming problems as the one above. To solve the optimisation problem, Gurobi was chosen as solver.

The implementation of the mathematical model in the solver happens in two phases. In the first phase, a set of optimal routes for each vessel is created. This set contains per vessel and per leg the three shortest routes from its origin to destination. As most of the input vessels have in the two day horizon of the model, two different legs (origin to destination), this first phase results in a list of 6 routes per vessel. The three shortest routes for the first leg of a vessel and the three shortest routes of the second leg. However, for vessels with only one leg, three routes are created and vessel with three legs get nine routes assigned. These routes and then used in the second phase of the implementation to determine the optimal solution upon.

In the second phase of the model, the solver is determining the optimal solution for the objective as formulated in the mathematical model. Therefore it uses the set of routes per vessel as determined in the first phase. For each of the vessels in the model, the sailing speed on each arc, where to swap at which time, where to plan the required 6 hours of rest and when to wait for four hours in total are determined in such a way that the cost of sailing is minimised. Per vessel, the route that minimises the total cost for the whole fleet is selected. This can lead to a sub-optimal solution for individual barges but guarantees the best solution for the fleet as a whole. A small detour for one vessel, can result in a large cost saving for another vessel, for example if that allows the second vessel to pick-up the battery that was also on the optimal route of the first vessel.

By splitting the model in two phases, the problem size is strongly decreased as instead of all possible routes, only a set of three routes have to be explored for the optimal speed, rest- and waiting time and swapping moments by the solver. By first determining the three shortest routes, the most optimal routes are very likely to be included in the set, as a large detour in distance is not likely to be part of the best solution. This separation in the optimisation makes the run time of the model much more manageable as the runtime is now decreased from several hours of running to just under 25 minutes in the base scenario. These runtimes were a result of running the code with standard input settings as will be shown later in the scenario analysis base function on a basic computer with 4 cores.

8.6. Verification

After implementing the model, the next step is to verify the model. The verification is done to ensure the right implementation of the model in the code. Although verification is an iterative process during the implementation of the model in the programming language to identify mistakes in the implementation, a final verification is shown in Table 8.2 her below. In the table, the functioning of the key constraints is tested on their functioning according to the mathematical model. On the left hand side of the table, the constraint, or group of constraints, to be tested is shown, while the right side indicates if the constraint passes the verification test.

Table 8.2: Verification of subsystems

Constraint(s)	Confirmation
One route per leg	Each leg gets assigned one route from the set of shortest routes
One speed per arc, multiple speeds per route possible	Each arc gets an individual speed assigned, can differ within the same route
Battery-container flow conservation	Vessels arrive with the same amount of battery-containers onboard at the next node as the have left the previous node with
Energy recursion	The energy upon arrival equals the energy at departure, minus the consumed energy. Consumed energy is based the distance and the energy-rate at different speeds
Inventory battery balance	No swapping station hands out a battery that it doesn't have, no negative amounts of batteries at any moment at any swapping station
Swap action	No pick-ups or drop off of batteries without a swap session and energy is only sold if a battery is actually dropped off
Swap location	Each battery pick-up or drop off happens at the station where that vessel currently is. In other words, a vessel does not swap batteries at a location or time it not currently is
Swapping time	Each swap costs exactly 15 minutes
Time recursion	The arrival of a vessel at its destination is before the departure of that same vessel from the same location
Rest and wait time	Each vessel does indeed not move for exactly 6 consecutive hours per day and spends at least 4 more hours per day laying still. Each hour only counts for either the 6 hour block, or the wait time
Minimal energy on board	Each vessel arrives with a positive amount of energy remaining in the battery
Start time and arrival deadline	Each vessel starts upon the indicated starting time and arrives before its deadline

In the following table, Table 8.3, variations in parameter values are shown against their expected impact and the actual impact on the model outcomes. Changes are made for each subsystem in the model that are part of the overall system. As suggested by Salado and Kannan (2018), testing these individual subsystems can verify the model as a whole. In the left column the change in the subsystem is indicated, the middle column shows the expected impact of the change and the right column shows whether the hypothesis is confirmed by the model results. With this form of black box validating, the focus is on the reaction of the outcome of the model as a result of a change in the input.

Table 8.3: Verification of subsystems

Adjustment	Hypothesis	Hypothesis result
Set of 5 potential best routes per vessel instead of 3	Only impacting the model results at large numbers of vessels in the model	Confirmed
Only the shortest route per vessel, no detour possible	Depending on the strictness in the delivery schedule if the model is still feasible. If feasible then likely at higher cost	Confirmed
Low price per kWh	Lower model outcome, no additional battery pick-ups	Confirmed
High price per kWh	Higher model outcome, no decrease in number of battery pick-ups	Confirmed
No revenue for selling remaining energy back	No kWh sold back, batteries will still be dropped off when depleted	Confirmed
High energy consumption	Lower speeds over the arcs, higher total costs	Confirmed
High amount of batteries in stock per swapping facility	Lower costs, as detours are eliminated. Model collapses to individual optimisation per vessel	Confirmed
No 6 hour rest period and 4 hours of waiting, same schedule	Lower costs, as more freedom in the schedule let the model choose better timing for battery swaps	Confirmed

To further verify the implemented model, the output of a vessel in the optimal solution found by the model, was tracked over a full route. This was done in order to potentially spot any violations of the constraints and simultaneously check the numerical values manually to ensure the correctness of the model results.

As all the hypothesis of the checks visible in Table 8.2 were consequently confirmed by the model outputs and no issues both in constraint violation and numerical output could be found, the model implementation is considered as successfully verified.

8.7. Validation

After the verification above, the model needs to be validated. This is done via multiple steps. First, the input data is validated by an expert in the field of inland waterway transportation with electric barges. Afterwards, the model is subject to a white box validation, with this, the internal logic is validated. Finally, a performance validation is used to examine the output of the model.

The input used in the model is discussed with the skipper of one of the few currently sailing e-barges in The Netherlands. During this conversation, individual elements of the input values were discussed. The table below shows each input value that is discussed with the skipper, the value assigned in the model and the skippers opinion on the model input value.

Table 8.4: Input validation

Input element	Value in model	Skippers reflection
Battery capacity	2600 kWh	Comfirmed by the skipper, all currently used battery-containers have a capacity of 2600 kWh under normal conditions
Swapping time	15 minutes	Difficult to determine exactly, as it is often part of the process of handling more containers, but if also mooring and departuring is included, might take a bit longer and if it is part of the usual loading/unloading somewhat shorter
Energy consumption at different speeds	Exponential relationship	Higher speeds consume more energy per kilometer, but very dependent on the river current
Vessel routes	Routes based on most used corridors. Locations on this corridors are dominant	Many different locations possible. The skipper sails a standard route on the most used corridor
Recharging time batteries	3 hours, regardless of the state of charge	Takes 2.5 hours to recharge a fully depleted battery, but it takes a variable amount of up to hours between unloading the battery and the start of charging
Price per kWh	Base model uses a fixed price per kWh	You pay a fixed connection fee to be able to use the batteries, then you pay for the kWh you use

Although some elements of the input values are difficult to determine exactly, according to the expert, the input values are realistic.

In the last part of this validation process, the model is validated by comparing its outputs against historical operational data from an electric barge in The Netherlands. The available records from VesselFinder (2025) include the vessel's routes, average speeds, and stop locations, but do not specify battery-swap events. Although one cannot directly observe where and when the barge actually swapped batteries, one can assess feasibility by checking whether the model's recommended routes, travel speeds, and stopping points align with the historic data. A close match in these dimensions increases the confidence that the model captures the right operational behaviour. In the tables below, both a real route sailed by a currently operating e-barge, Table 8.5, and an example of the output from the model for a vessel travelling from the same origin to destination is shown, Table 8.6. The two routes compared, both start in the port of Den Bosch and finish at the Maasvlakte. Comparing the route formed by the model and the actual route shows great similarity. Both routes make a stop at Alblasserdam, before ending in the Maasvlakte. The real life route, however, also makes a stop in Zwijndrecht, only a few kilometers from Alblasserdam. As no swapping station is located there, it presumably visited this location to pick up or drop off cargo. Right after visiting Zwijndrecht, the vessel stops again in Alblasserdam, now presumably to get a new battery, just like in the model.

Also the travelled distances are in line between the two models. Due to the extra stop in Zwijndrecht the real life route sailed an additional 4.8 kilometer. As Zwijndrecht is more or less on the route to the Maasvlakte, the small number of extra kilometers for an extra stop seems possible. When comparing the speeds, it can be observed the real life average speed is higher over the whole route than the models speed. This is due to the fact that the model tries to optimise its energy consumption which is lowest at lower speeds. One can see that the model finds an optimal route that just satisfies the resting limitations of 6 consecutive hours and 4 additional hours and arrives just on time. The real life vessel travels somewhat faster and spends an extra 3 hours and 15 minutes in downtime.

Table 8.5: Real life route

Time	Location	Distance & avg. speed
00:00	Den Bosch	
07:30	Den Bosch - departure	
13:00	Zwijndrecht - arrival	52 km at 9.5 km/h
13:45	Zwijndrecht - departure	
14:15	Alblasserdam - arrival	6.8 km at 13.6 km/h
16:30	Alblasserdam - departure	
20:00	Maasvlakte - arrival	50 km at 14.3 km/h
23:00	Maasvlakte	
13:15 h	Total rest time	

Table 8.6: Model output route

Time	Location	Distance & avg. speed
00:00	Den Bosch	
03:15	Den Bosch - departure	
10:00	Alblasserdam - arrival	54 km at 8 km/h
16:45	Alblasserdam - departure	
23:00	Maasvlakte - arrival	50 km at 8 km/h
10:00 h	Total rest time	

8.8. Conclusion model development

This chapter aimed to develop a model that could balance the cost savings of timing the pick up and drop off of batteries with all operation constraints. Therefore, the model as developed by Verma is revised, adjusting all suitable constraints to the problem at hand and replacing the unrelated constraints with new formulations. After formulating the model, the model was implemented in Python code. To check if this was done correctly the model was verified, by confirming the functioning of the constraints and testing various hypothesis for adjustments in the model. After successfully verifying the model, the validation took place. First, an expert in the field, in this case a e-barge skipper, validated the input data. Then, by comparing the model output with historical routing data of an e-barge, the performance of the model was validated. After confirming the similarities in schedule, the validation step is completed.

In conclusion, the model developed based on the model as formulated in Verma (2018), was correctly implemented according to the verification. The validation ensured that the right model was constructed. Considering all this, the question on how a model can be developed that balances cost savings with operational constraints can be considered as answered.

In the next chapter, the model is subjected to an experimental plan in order to formulate an answer on the question: how does the current price setting perform, compared to other price settings determined?

9 Experimental plan and results

How does the current price setting perform, compared to other price settings determined, according to the developed model?

The aim of this chapter is to answer sub-question number five. In this sub-question, the current pricing mechanism is compared to the other potential price settings. With this sub-question it is intended to find if there is a price setting that results in better overall model outcomes. We speak about better model results, if the total operational costs for the fleet of vessel are lower. This is appealing for the barge operators as well as the company providing the battery-containers. Lower total costs indicate a lower propulsion costs for the barge operators, and these lower costs make the electric sailing system more attractive for other barge operators, and with that attracting more customers renting a battery-container.
In order to test if any of the price settings outperform the other settings, the model developed in the previous chapter is tested for the different pricing mechanisms as determined in chapter 5. The different price settings are tested twice for different circumstances. The first test round is in an experimental setup with the current model as shown above, the second test round is done with the same model but instead of optimising for the fleet, each individual barge searches for its own optimal path. In this chapter, the results are shown for both approaches. Afterwards, the results are interpreted and discussed.

9.1. Experimental plan

In order to determine the optimal price setting, not only is it important to investigate what works best for the current circumstances, an open view towards possible developments in the future is required. Therefore, besides a scenario that best describes the current situation of the system, also scenarios that hold future possibilities are looked into.

Table 9.1 summarises the environment per scenario in a short overview. In the next section, the results of the experimental plan are shown and discussed.

Table 9.1: Different scenarios to test

Scenarios	Vessels in fleet	# batteries / facility	# swapping facilities	Battery capacity (kWh)
Base	10	2	9	2600
Battery capacity +15%	10	2	9	2990
3 batteries per facility	10	3	9	2600
Extra locations	10	2	13	2600
3 batteries, extra locations	10	3	13	2600
Extra vessels	15	2	9	2600
Extra locations and extra vessels	15	2	13	2600

First, for the base scenario, the model is tested for the four different pricing mechanisms developed earlier. The base scenario with the fixed price strategy compares best with the current actual situation. The base scenario entails a battery capacity of 2600 kWh per battery-container, place for maximum two battery-containers per vessel at the same time on board and two batteries at each swapping facility available. Furthermore, the routes that need to be sailed in the model are formed according to the corridors identified, each vessel pays for the energy it actually uses and a small fee has to be paid for each time a battery is loaded and unloaded of a vessel.

Besides this base situation, six possible future situations are developed and tested. These scenarios are the same as the base scenario for most aspects, but one or two elements have been changed to see their impact on the model results in comparison with the base scenario. The first future scenario looks into the impact that battery development can have on the performance of the system. Therefore, the capacity of each battery in the system is upgraded by 15%. In the second scenario, the impact of additional batteries in the system is investigated. If at each swapping facility three batteries are available, instead of the two normally, the individual barges get less dependent on each other, potentially improving the model result. In the next scenario, four new swapping facilities are included in the model. These swapping facilities are not part of the development focus as determined by ZES, but are part of ongoing research before opening up, as can be seen in Figure 6.2. These four locations make two already included swapping locations more accessible as the new locations are decreasing the distance to the facilities of Den Bosch and Nijmegen, which are the furthest away from the other locations. In the next scenario, a combination of factors will be tested. In the fourth future scenario, both the additional locations are included as well as three batteries per swapping facility. This is an interesting scenario in combination with results of the same individual aspects as ZES can have an impact on both elements. The results of these scenarios could indicate on what aspect the focus towards the future must lie.

The last two scenario tests a situation where the system is developed somewhat further. In scenario five, 50% more vessels are added to the base model, to see the impact of additional vessel becoming part of the system. Finally, in the last scenario, these additional vessels are also considered but now in combination with the four extra locations as determined earlier. In Table 9.2 and 9.4, these two scenarios are colour-code separately, as the additional vessels make their costs incomparable with the other scenarios.

Results experimental plan

In Table 9.2, the results of the experimental plan are shown and colour-coded per row. The values in the table are the numerical outputs of the model in Euros. At first glance, a clear favourable price setting is visible. The variable price setting scores best under all circumstances tested. Another immediate lesson can be seen in the fixed price setting. When judging purely on numerical outcomes and not taking subjective aspects such as convenience in consideration, the fixed price setting scores the worst. Furthermore, a flexible price outperforms a two peak setting. The results for the scenarios tested, show that the more variable the price is, the better the outcomes are. This is due to the fact that this gives the model more space to find a better solution. Table 9.3 shows how much higher the solutions get for other pricing mechanisms compared to the best scoring setting. This table clearly shows the relative small difference between the variable price setting and the peak and flexible setting. Compared to the variable setting, the flexible price adds about 2% to the solution and the two-peak setting adds around 4% to the best solution. However, the current price setting with a fixed price, adds around 15%. Translating these percentages to Euros, results in an increase of almost 200 Euro on average for the flexible setting scenarios, a little over 300 Euro for the peak setting and more than 1100 Euro on average for the fixed pricing strategy. The impact of the fixed setting is thus much greater on the final solution compared to the other solutions.

Table 9.2: Experimental plan results in Euros

Scenarios	**Total energy costs per price setting in Euros**			
	Variable	**On-/Off-peak**	**Fixed**	**Flexible**
Base	5976.18	6296.39	7092.27	6138.83
Battery capacity +15%	5931.79	6135.56	6895.98	6052.43
3 batteries per facility	5939.52	6257.58	7091.72	6121.34
Extra locations	5865.58	6170.47	6882.83	6035.95
3 batteries per facility, extra locations	5835.09	6129.15	6882.83	6000.52
Extra vessels	8325.63	8780.77	9745.54	8595.20
Extra locations and extra vessels	8223.93	8666.66	9536.66	8478.62

Table 9.3: Difference in percentage relative to fixed price setting (fixed = 1)

Scenarios	**Variable**	**On-/Off-peak**	**Fixed**	**Flexible**
Base	−15.74%	−11.22%	1	−13.44%
Battery capacity +15%	−13.98%	−11.03%	1	−12.23%
3 batteries per facility	−16.25%	−11.76%	1	−13.68%
Extra locations	−14.78%	−10.35%	1	−12.30%
3 batteries, extra locations	−15.22%	−10.95%	1	−12.82%
Extra vessels	−14.57%	−9.90%	1	−11.80%
Extra locations and extra vessels	−13.77%	−9.12%	1	−11.09%

After comparing the results mainly within the rows in Table 9.2 and 9.3, also the impact of the different scenarios is looked into. This means looking at the table column per column, the influence of the different scenarios can be seen. When comparing the numerical outputs of Table 9.2 per scenario within the same pricing mechanism, the relative small impact of the different scenarios can be seen. For example, the gain in optimal outcome for a battery with 15% more capacity is only three-quarters of a percentage compared to the base scenario. The largest impact is in the scenario where each facility has an extra battery available at the start and four additional locations are open. This results in a decrease of total costs of 2.4 to 3%, depending on the price setting. While the different scenarios appear not to have a large impact on the solution, it is further investigated what the impact is of the current fleet optimisation model compared a model in which each vessel can sail its own optimal route. In the next section it is explained how this is done, what results this model provides and how the results relate to the fleet optimisation model.

9.2. Variance analysis

The model used until now tried to minimise the total cost of all vessels combined. It might thus occur that one vessel is forced to take a less favourable route in order to let another vessel minimise its costs if that would result in a lower combined cost. Although this could be a realistic situation for vessels sailing for the same organisation, competitors are not likely to give up their best route for one other. Therefore, it is also looked into what would change if all vessels can determine their own optimal route. In order to do so, the number of batteries available at each swapping facility is assumed to be sufficient. This means that each vessel can sail it optimal route, without other vessels interfering. The results for the individual vessels are combined so the results can be compared to the optimisation for the whole fleet.

The results of this variance analysis show a similar pattern as the results discussed earlier. Again, the variable setting scores best, while the fixed price setting shows the least favourable results. Furthermore, it is visible that the more room for adjustments the model has, the better the solutions become, just as was the case in the fleet optimisation model.

Also Table 9.5 shows a similar pattern as its fleet optimal equivalent. A small difference between the three settings with fluctuating prices and a larger difference with the fixed price setting.

Table 9.4: Variant analysis results in Euros

Scenarios	Variable	On-/Off-peak	Fixed	Flexible
Base	5938.61	6257.58	7091.72	6121.34
Battery capacity +15%	5884.45	6126.88	6895.98	6027.58
Extra locations	5835.09	6129.14	6882.83	6000.52
Extra vessels	8322.10	8780.77	9745.54	8592.06
Extra locations and extra vessels	8207.65	8652.34	9536.65	8471.53

Table 9.5: Difference in percentage relative to fixed pricing setting (fixed = 1)

Scenarios	Variable	On-/Off-peak	Fixed	Flexible
Base	−16.26%	−11.76%	1	−13.68%
Battery capacity +15%	−14.67%	−11.15%	1	−12.59%
Extra locations	−15.22%	−10.95%	1	−12.82%
Extra vessels	−14.61%	−9.90%	1	−11.84%
Extra locations and extra vessels	−13.94%	−9.27%	1	−11.17%

In order to determine the cause of the differences between the fleet optimal and individual barge optimum, a closer look is taken into the cost build up of both models. This is interesting as this can tell whether one vessel is taking up all the additional costs in order to let the other vessels choose their best route. This couldn't be determined based on the previous results as, although they showed only a small difference between both approaches, it was not clear if one vessel took the majority of the cost so the others could sail the preferred route. Table 9.6 shows the cost associated with each vessel. Here, it can be observed in the fleet optimal solution, most vessels can sail their preferred route. Only two vessels need to adjust their schedule to find the best results for the fleet as a whole. With this adjustment of their schedule, their routes do not get much more expensive compared to their optimal routes, for vessel 3 it means an increase of 7.8% and for vessel 10 a very small increase of 0.19%. These results demonstrate that a fleet optimal routing strategy can be adopted within a single organisation where a freight forwarder can instruct its skippers to sail according to a certain schedule, without imposing large detours on any single vessel, preserving both overall cost efficiency and operational equity.

Table 9.6: Cost comparison per vessel for fleet and individual barge optimality in Euros

Vessels	Fleet optimal sc1	Barge optimal sc1	Difference (percentage of barge optimum)
Vessel 1	356.13	356.13	0.00
Vessel 2	560.85	560.85	0.00
Vessel 3	499.37	463.24	7.80
Vessel 4	660.08	660.08	0.00
Vessel 5	908.29	908.29	0.00
Vessel 6	556.18	556.18	0.00
Vessel 7	749.21	749.21	0.00
Vessel 8	520.74	520.74	0.00
Vessel 9	385.28	385.28	0.00
Vessel 10	780.06	778.61	0.19
Total cost	5976.18	5938.61	0.63

9.3. Sensitivity analysis

Now that the model has executed and results are shown, a sensitivity analysis is conducted. The aim of this analysis is to determine how sensitive the model is to small changes in input value. This is important, as, despite that the input is validated by an expert, there are certainly changes possible in the input values. With this analysis the impact these small changes have on the model is investigated. Models with hardly changing outcomes for varying inputs are robust and less dependent on the exact input values. On the other hand, if the model outcomes relatively changes more than the change in input, the model is very vulnerable for for changes in the input values. For these sensitive models, it is of great importance to either determine the input values with precision, or experiment with a wide variety of input ranges.

Table 9.7 shows the results for small changes in input values for the developed model, tested for a smaller set of vessels. A group of 5 input variables were chosen based on either their uncertainty and/or their expected impact on the model. For these input parameters, the values were adjusted with 5%, both added and subtracted. The impact of these adjustments were tested one by one to see the sole impact of the individual change on the model results. In the figure below, the results are shown, first for the numerical output for each change, but more importantly in the second half of the figure, the relative differences are shown.

A closer look at how output changes respond to the 5% input fluctuation provides a clear message: the model is largely robust. For four out of five input variables the percentage change in the model's output is smaller than the 5% change applied to the input. The lone exception is the energy consumption per kilometer at different speeds; when energy consumption is reduced, the model's output changes by more than the input reduction. This is likely driven by one vessel: with the lower energy-consumption assumption it can reach its destination without an additional battery, which would be needed in the original settings, causing a relatively large drop in total cost.

The results show that it is important to determine the energy consumption accurately in order to find reliable results. However, for example the exact amount of time needed to recharge a depleted battery is not as relevant. This means that less effort needs to be put into determining recharge times compared to determining exact energy consumptions at different speeds.

Table 9.7: Sensitivity of total cost to key parameters

Parameter	-5%	Base	+5%
Price per kWh	3397.22	3528.65	3660.52
Energy consumption	3267.41	3528.65	3670.09
Recharge time per battery	3528.65	3528.65	3528.65
Battery capacity	3550.19	3528.65	3393.23
Transaction cost	3497.59	3528.65	3576.87
Relative change (%):			
Price per kWh	3.72		3.74
Energy consumption	7.40		4.01
Recharge time per battery	0.00		0.00
Battery capacity	0.61		3.84
Transaction cost	0.88		1.37

9.4. Conclusion experiments

The aim of this chapter is to compare the current price system, a fixed price per kWh regardless of the time of the purchase, with other potential price settings to determine if any setting outperforms the others. In order to answer this question, an experimental plan was set up. This plan included a base scenario, similar to the current situation and six other potential future states of the system. After testing all scenarios, it became clear that the variable price setting always outperforms the other settings. However, the difference with the flexible and peak settings was respectively ±2% and 4% more, whereas the difference with the current mechanism of a fixed price was in around 15%.

Afterwards, a variant of the same model was tested. In this variance analysis, the number of batteries per facility was considered to be sufficiently large. That way, the vessels are no longer dependent on each other and each vessel can sail its own optimal route. This analysis showed a similar pattern in this results, with again the variable setting being the best and the fixed setting resulted in the highest costs. Also the differences between the different settings remained similar, with the flexible setting being around 3% more expensive, the peak setting 4% and the fixed setting in the range of 14 to 16%.

Finally, this chapter discussed the cost build up for both variants of the model, in order to determine if one vessel was paying the price to make all other vessels optimal route possible. Here it was found that although one vessel was forced to deviate from its optimal route, its total cost was affected by this detour with less than 8%. These results demonstrate that a fleet optimal routing strategy can be adopted within a single organisation where a freight forwarder can instruct its skippers to sail according to a certain schedule, without imposing large detours on any single vessel, preserving both overall cost efficiency and operational equity.

In this chapter it was found that all previously divined price settings outperform the current fixed pricing mechanism. The variable setting showed the best results closely followed by the flexible and on-/off-peak setting. In the next chapter, the practical feasibility of implementing one of these settings will be discussed before a final verdict can be given on which price setting is favourable for skippers.

10

Practical viability

How do stakeholders in the inland shipping industry assess barriers and enablers to implement different price settings in a practical context?

After constructing and testing the optimisation model, now with this sub-question, a closer look is taken into the practical viability of the model results. The goal of this sub-question is to further investigate the potential of the different price settings. This chapter tries to find an answer to what extent the pricing options find support from those who are ultimately working with the system. Do they see problems with implementing any of the options or is there a clear industry favourite? To do so, interviews were conducted. First, potential respondents from the industry were approached and afterwards, those willing to participate were interviewed. In this chapter, the set up of the interviews and the lessons learned from the interviews are discussed.

10.1. Respondents

In order to find the right respondents, first it was determined who might be affected by the implementation of one of the price settings. This was done in consultation with the skipper who also validated the input values of the model. Based on this conversation, 3 different functions were selected as desired respondents for the interviews. The first group of participants are the skippers. Secondly, the ones that make the planning for the barges, can have interesting views on the price settings. Finally, terminal operators are approached as they are the ones that needs to work with the results of the price settings. Table 10.1 shows the participants of the interviews. The interviews were conducted in different atmospheres. The interview with skipper A was conducted on board of the vessel operated by skipper A, the interviews with skipper B and the terminal operator were conducted in an informal setting over a coffee while the rest of the interviews were conducted via (extensive) phone calls.

Despite the different surroundings in which the interviews took place, a fixed plan was followed for each interview. This was done to gather comparable results. The structured interview enables the respondents to answer in their own way, but ensured that all different respondents also answered the same questions, while still leaving room for side tracks to discuss aspects initiated by the respondent. To create a uniform interview for all participants, each interview was conducted via a structured set of interview sections. In total six sections were included in the interview. These sections include the start of the interview, in which the purpose of the interview is explained and permission is asked to record. In the introduction section, the respondent is asked to elaborate on their job description and their experience. Afterwards, in the third section, the current situation is discussed to increase understanding in how the system is currently functioning. In section four the principle of electric sailing is introduced and discussed, before in the next section, the results of the model are discussed. It is in this section that the participants are asked on their view on the different price settings. In this part questions are asked that aim to determine where the respondents see problems for the different strategies, but also their willingness to adapt to any of the price settings. Finally, the interview is concluded in the last section. In this section the interview is summarised on the main take-aways while the respondent has the option to add any missing insights that could be relevant for the research. The above described protocol that was developed and followed for each interview, is visible in the appendix in Table B.1.

Table 10.1: Overview of participants

Respondent	Function characteristics
Skipper A	Battery electric, 132 TEU, under a fixed-term contract (with the same vessel assigned throughout)
Skipper B	Diesel, 909 tonnage, on a time-charter basis (hire of a private vessel and skipper)
Skipper C	Diesel, 726 tonnage, on a voyage-charter basis (charterer using their own vessel)
Skipper D	Diesel electric, 104 TEU, on a skipper-only hire basis (hire of a skipper without a vessel)
Planner freight forwarder 1	Fleet of 4 vessels, network of ships and skippers available, operating in The Netherlands, Belgium and Germany
Planner freight forwarder 2	Partial owner of a fleet of 10 vessels, hiring charters for other transport movements, operating in The Netherlands, Belgium, Germany and France
Planner freight forwarder 3	Fleet of 81 vessels, operating in The Netherlands and Belgium
Terminal operator	Crane operator and supervisor at a large inland terminal in The Netherlands (160.000 TEU capacity, two cranes)

After interviewing all the participants, the results of the interviews are here below discussed per profession. Afterwards, the general perception per price setting is touched upon.

10.1.1. Skippers

Although skippers with different types of vessels and contracts were interviewed, three main themes could be observed in the interviews. The first of these themes is the cost awareness, this considers to what extent skippers are aware of their operating cost and also discusses the indifference of skippers to these costs. The second recurring theme during the interviews with the skippers was the operational challenges that come with the different price settings. Finally, the willingness to adapt to the different price settings is also commonly brought up by the skippers. Here below, each theme is discussed in the light of the skippers' visions.

Cost awareness - *"There are still skippers sailing with engines from '95, not because it is efficient or cheap, but just because they like the old engine."* - Skipper A

The interviewed skippers indicate a major difference in behaviour for skippers with different contracts. On one side you have the skippers that run their own business and are paying for their own fuel while on the other side skippers are under contract of a freight forwarding company that pays the fuel cost for the skippers. This leads to a clear difference in their sailing behaviour, according to skipper A, B and C. Skippers that are not financially responsible for their own expenses are sailing way faster than skippers who are paying for their own energy sources, says skipper B. This is because skippers who are not paying for their own fuel do not mind the extra energy consumed when sailing faster, whereas skippers that do need to pay for their own energy are far more concerned with their energy consumption. Skipper B then gives an interesting example to prove this point. He says that skippers who pay their own fuel expenses adjust their planning according to the tides if that is relevant at their location. Take, for example, a route from The Maasvlakte to Rotterdam for example. On this route, tides can play a significant role in energy consumption on this trip. Skipper B indicates that skippers who are responsible for their own energy cost are, if possible, adjusting their planning to sail on high tide to Rotterdam, as then the movement of the water is pushing the vessel towards Rotterdam, minimising the energy consumption on that trip. Vice versa, on the opposite trip, skippers are willing to wait for lowering tide to let the water drag the vessel towards the Maasvlakte, as long as the schedule allows the waiting time. This example provided by skipper B shows that skippers are not indifferent for their operating cost and that they are willing to adjust their planning if that leads to lower costs. However, this behaviour was only indicated for shipowners, those who are not responsible for their fuel costs, need to be instructed by their freight forwarder in order to change their behaviour. Finally, skipper B, who is paying for his own fuel, states that he does monitor the fuel prices as they can differ over time, again showing that the skippers paying for the fuel are not indifferent to the operational cost. However, important to consider here is that the vessel operated by skipper B only needs to refuel once a month whereas a new battery is needed every couple of hours.

For the skippers that are not paying for their fuel, much less awareness could be observed in their attempts to limit operational costs. For example, skipper D, who is not responsible for fuel costs tries to sail always the same speed measured against the shore, regardless of the current or tide, whereas skipper B explained to try to maintain a consistent fuel consumption of around 40 litre per hour instead of focussing on the speed. Finally, skipper A mentioned that for many skippers, they simply sail as they used to do regardless of any development in energy price or motor technique, just because they love the old system and want to keep sailing exactly like their parents or even grandparents did. For that reason, even engines from the past century are still being used.

All together, the cost awareness or at least the indifference towards the operational cost varies a lot among skippers. Where skippers paying for their own expenses show that they are trying to minimise the cost and are even willing to adjust their schedule to do so, for example by making use of the tides. On the other side are skippers that pay less attention to their sailing costs as they are not financially responsible for this part. For this group, the interviewed skippers indicate a clear indifference to operational cost.

Operational challenge - *"Many vessels are already delayed by missing containers and overly rigid schedules - let alone when I must call at additional terminals at the right time and pray the right container is waiting."* - Skipper D

After establishing who is aware of and consciously working on the operational cost, it is now discussed what problems the skippers foresee in using any of the price settings. Here, the skippers assume that they are operating a vessel that already makes use of the battery containers. Their problems with the implementation of the battery electric barges are thus not part of this overview.

Again, a division among the skippers is needed to determine their issues with the different price settings. On one hand there are the skippers that operate according to a planning developed by a freight forwarder. On the other side are skippers that sail charter routes, they do not know for which organisation they are transporting goods after their current trip. These charters are working on finding a new transport job while still executing the previous one. The charterers normally normally manage their own planning, which is relatively simple as it usually consist of just one vessel that needs to go from one terminal to the other. The interviewed skipper that sails with this type of contracts, does not see many problems with any of the price settings, as long as it can continue sailing as many hours as possible, stating the importance of not just adjusting the timing of the trip, but, like the model does, reschedule the rest times to ensure optimal departure moments without touching the hours sailed. As none of the proposed price settings incline problems for the skipper sailing these charter trips, he opts for the option with the most costs savings, being the Variable price settings.

For skippers who are dependent on the schedule developed by a freight forwarding company, the opinions are stronger. Skipper D, for example, complained that already in the current planning often containers were missing and schedules are so tight that he misses the deadlines. Skipper D is therefore afraid that adding even more detail to the already difficult schedule makes the schedule unmanageable. Skipper A shares a similar opinion, but adds that vessels often have to wait on each other, so the delay of one vessel determines the delay of the next. When hours are priced differently, that could result in a higher cost for the second vessel as it now has to charge at suboptimal hours due to the delay. Then the question arises of who is responsible for that cost. although that might be a valid point, in the current situation, this cost implied by other vessels is already present. As due to a delay from a previous vessel, the second vessel has to lie still, which costs this vessel opportunity costs. With this in mind, it is determined whether skippers are actually willing to adapt to any of the pricing strategies.

Willingness to adapt - *"I only took this job so I could spend more time with my family, so I'm not willing to adjust my hours to a schedule that forces me into odd shifts"* - Skipper C

The last of the reoccurring themes during the interviews is the willingness to adapt to changes in the schedules. Basically all interviewees stated that skippers are not keen on changes. As explained by skipper A, B and C, most skippers prefer to do things the way they have always done it. About electric sailing in general, regardless of the adjusted schedule, skipper D said: "I have been sailing on diesel for 30 years and it works perfectly; why should we change a working system?". This indicates the resilience for change among the skippers. Other comments made by skippers are more in line with the topic of adjusting the schedule. Skipper C for example states that he is working on an inland vessel as this job allows him to spend more time with his family. If the schedule forces him to rearrange his waiting time in such a way that he can spend less time with his family, then he is not to sure whether he would comply to the new schedule. Also skipper A warns about the stubbornness in the shipping industry. Skippers are used to plan their own hours, and the prospect of a planning taking control not only over the trips they sail, but also on where and when to rest, makes that skipper A suggest that this change might not be well received by the skippers. Normally, in the skippers are sailing between 06:00 in the morning and 23:00 in the evening, unless the vessel has more than one captain, in which case the vessel can sail the clock round. Skippers normally prefer to remain operating in that standard time frame, rescheduling the mandatory six hour break for example towards 19:00 the job becomes less family friendly, as the skipper is likely needing sleep during this hours, so he can sail through the night. Finally, skipper C argues the freight forwarding companies are not willing to make an effort for a 15% improved result. Skipper C bases the comment on an example. For a longer period of time, he has asked the forwarding company he is working for to help him finance an anti-fouling film to the outside of his vessel, as this could reduce the fuel cost with a similar percentage. However, the company has not been willing to help him apply this anti-fouling film to reduce the fuel costs for the freight forwarding company.

10.1.2. Planners

After speaking to the skippers, also the ones that usually make their schedule are interviewed. Employees from freight forwarding companies that are occupied with the task of setting up the planning for inland vessels are searched for and contacted. In total, three planners from different companies have been found willing to participate in an interview. Despite the difference in size of the organisation they are working for and mainly the fleet size they are working with, all planners indicate that on the planning side, all pricing mechanisms are technically very well possible to incorporate in the currently used planning tool. However, both planner 1 and 3 warn about the complexity of the schedule, adding too many elements to the schedule makes the planning too complex and can lead to more mistakes, which can cause disruptions and impacts the whole planning. Therefore, they see a variable price setting as more difficult to incorporate as it requires more elements to be included in the model, compared to a fixed or even an on/off peak setting. Before further discussing which price settings has most potential, first the planners where asked if a decrease in fuel cost of 10 to 15% would even be worth the extra work to adjust the schedule. Despite the experience of skipper C, who did not find his freight forwarder willing to undertake action to minimise operational costs, the interviewed planners all indicate that this margin would be large enough to consider adjusting the planning wherever possible. With that set, now the planners are asked their preferences for the price settings. Here, planner 1 and 3 indicate that the maximum decrease of cost is appealing, although the added complexity is a potential deal breaker. These two planners warn again about the complication of every added bit of complexity. Planner 2 looks further than just the planning and skipper side of the story. Planner 2 has concerns about the capacity of the terminals, on quay length, on sufficient staff on the terminal to handle all incoming vessels and on physical space to move in and out of the terminal when many vessels try to collect a battery container on the cheapest hour. This could result in delays and therefore extra cost, diminishing the effects of the adjusted price setting. He states that therefore the variable setting might not be the best alternative, despite the highest decrease in operational costs according to the model.

Planner 2 prefers the on/off peak price setting because it is relatively simple but still manages to reduce the fuel costs significantly. Only remaining concern for this setting for planner 2 is that vessels might be pushed towards the hours just before, or just after the peak prices. That can result in stress moments in the terminals at these hours.

Finally, the planners have emphasised their concerns on imposing rest and waiting times on the vessels crew. Although they all state that it is very well possible to tell skippers exactly where and when to rest, they are afraid that skippers do not take it very well. For chartered trips, planners can generally not impose rest moments on skippers. If this is desired, then this must be indicated when a transport job goes to the market, a skipper can then decide whether to take the task or not, if he does, he then has to comply to the desire of the planner. For skippers under contract, the planning can impose a time and place to rest for the skippers, but they usually don't as, as long the goods are delivered on time, it is not of their interest where and when the crew rests. Imposing rest times can imply difficulties for skippers as they for example need to pick up their children from school or do groceries at certain hours, say both skipper C and planner 3. If simple things like these are no longer possible, planner 3 warns that a raise of the price skippers are going to ask for their services, potentially cancelling out the margin created by the adjusted price setting.

10.1.3. Terminal operators

To conclude the interviews, a terminal operator is spoken to. This terminal operator is working on a large inland terminal in The Netherlands, mainly as crane operator, but also has some supervisor responsibilities on the location. Although the different price settings do not apply directly to his job, he might have to work with the consequences of the chosen setting.

The operator indeed indicated that he does not care too much which setting is chosen as long as the arrival of vessels is distributed more or less evenly. The terminal operator states that every vessel arriving, needs about 15 minutes to moor and sail out again if only one battery container needs to be replaced. However, staff needs to be available for each vessel that comes in to help with the mooring process, unload a depleted battery and get a new battery on board with the crane. Therefore, depending on the number of employees in the terminal, only a limited number of vessels can be helped at the time. Furthermore, the number of vessels that can be supported simultaneously is limited by the number of cranes available per location and the size of the quay.

Finally, the cheapest hours for both the variable and the flexible price setting, are in the middle of the night. The terminal operator sees this as potentially problematic as during this time, usually less staff is available and if this low price attracts more vessels during these hours, delays can be formed. Looking back on figures 5.2 and 5.2, one can see that indeed the hours between 02:00 and 06:00 include the hours with the lower prices. The on- and off-peak setting and the fixed price setting do not have this problem as their lowest prices are not necessarily concentrated in the night. For these reasons, if it were up to the terminal operator, the current fixed price settings is the easiest as this does not push the arrival of vessels towards certain hours, resulting in the best distribution of vessel arrival.

10.2. Conclusion practical viability

After all interviews have been conducted, an overview of the perceptions of the involved actors as described above is given in table 10.2. This table shows which profession is, according to the interviewed representatives, positive (+), negative (-) or indifferent (±) towards each price setting. Based on the interviews with the different stakeholders, a few lessons are learned. First, a cost reduction of 10 to 15% is so appealing for the freight forwarding companies, that they are willing to adjust their schedules. Secondly, freight forwarding companies can impose resting moments for skippers, but planners are hesitant to do so, as they know it can be important for skippers to plan it themselves according to their own needs. Furthermore, also for skippers, a cost reduction of up to 15% for energy costs can be significant, but only interesting for those paying for their own expenses. Next is the aversion many skippers have against change in general. During the interviews, it became clear that skippers prefer to continue working as they are used to do. On the scheduling side, planners are trying to keep the planning as lean as possible, each added element makes the planning more complex, that is why the planners prefer a two peaks price setting over a variable price, despite the somewhat smaller cost decrease. Finally, it became clear that it is technically very well possible to incorporate different prices per hour in the planning tool used by the planners of the freight forwarding companies.

These learnings result the table as shown in 10.2. In the determination of the optimal price setting, the concerns of the stakeholders should be considered seriously as the expressed concerns can have an important impact on the performance of the chosen price setting.

Table 10.2: Perceptions of different professions on the pricing strategies

Function	**Variable**	**On-/Off-peak**	**Fixed**	**Flexible**
Skippers, paying own expenses	+	+	±	+
Skippers, under contract, company pays expenses	-	-	±	-
Planners	-	+	±	±
Terminal operators	-	±	±	-

11

Discussion and conclusion

In this chapter, the research is reviewed. Part of this review is a discussion of the results and how the results of this research compare to the results of similar previous research. The limitations are discussed for both the setup of the research, the limitations of the model used to derive the results, and the limitations of the interviews conducted. Furthermore, in this chapter, a broader perspective is taken to investigate the consequences the implementation of dynamic pricing may have on the larger system. The discussion part of this chapter concludes with recommendations for both the suppliers of the battery electric containers as well as future researches in this field. Finally, at the end of the chapter, a concluding answer is given on the individual sub-questions as well as the main research question.

11.1. Discussion of results

The purpose of this research was to determine a for skippers favourable price settings for containerised energy based on an optimal scheduling and routing model for electric barges. After the development of the mathematical model and the implementation of this model in Python code, the model was executed for the four previously defined pricing mechanisms. The results showed that each added step in complexity for the price setting improved the outcomes of the model. It is striking that the first step of added complexity, so two blocks of peak prices instead of one fixed price, had the most impact compared to each next step of price volatility. Each added volatility improved the model result, but the improvement is much smaller than the improvement imposed by the first step in volatility. Where the first step, the on/off peak price setting, improved the results by around 10%, the flexible setting only further improved the results by another 2 percentage points. The next step where each hour has a different price tag, the results are improved with another 3 percentage points. Although it was expected upfront that the strategy with the most fluctuating prices would result in the best outcomes, given that this setting gives the optimisation model the most freedom, the proximity of the three settings is notable.

During the interviews with key stakeholders involved in the system, two main concerns on the real-world implications became clear. On the skipper side, the reduced freedom in determining their own downtime hours was an important factor to consider when determining which setting is most preferable. On the freight forwarding planner side, while enticed by potential savings in the 10–15% range, worries exist that each tier of price complexity would drastically increase planning effort, complexity and error risk.

This shows the trade-off between additional cost reduction and added complexity in the price setting and therefore the more difficult planning. An extra complicating factor is that the price setting is chosen by a different organisation than for the party for which the added complication is. The battery container provider must set a pricing mechanism and with that, it sets the complexity for the freight forwarding companies. A more sophisticated pricing scheme may attract cost-sensitive customers, but risks alienating companies unwilling or unable to shoulder the extra scheduling burden.

11.2. Positioning in the literature

In this research, a mixed integer linear programming model was constructed to find out to what extent the cost of energy can be reduced. The developed model found a reduction of 10 to 15% possible, depending on the chosen price setting. In this section, this reduction is compared to other research that looked into the cost reductions of different pricing strategies for electric vehicle routing and scheduling models. Therefore, research papers are searched for on this topic. As not much research has been done on dynamic pricing for electric barges, also literature about general electric vehicles is considered, these vehicles are mainly electric cars and buses. The energy cost saving of 10 to 15% is thus benchmarked against cost savings in other electric vehicle fields.

Although Sun et al. (2023) did include dynamic energy pricing in their mixed integer linear programming model to determine optimal routing and scheduling for electric barges, they did not test their model against a fixed, or any other, price setting. So, from this research no comparison between different pricing mechanisms could be made. This work by Sun et al. (2023) seems to be, at this moment, the only research to include dynamic pricing in an optimal routing and scheduling for electric barges. Therefore, the step towards other electric vehicles is taken to still be able to compare the outcomes of this model with previous research. L. Zhang et al. (2024) used a similar method as used in this research to determine how much cost reduction is possible when instead of a fixed pricing mechanism, a dynamic price is implemented. Although this research was focused on optimising the cost of a fleet of electric buses instead of vessels, a similar drop in cost for a variable cost per hour is visible. In this research, the variable pricing allows for a cost reduction of 7 to 22%, depending on the model settings (L. Zhang et al., 2024). These numbers correspond rather well with the findings in the research at hand. Also when a closer look is taken, the similarities are clear. For example, (L. Zhang et al., 2024) found that cost savings gets even higher with more charging points and so is the case in this research, as can be seen in table 9.2.

In a study with a similar method, Ham and Park (2021) found significantly lower cost savings for implementing dynamic pricing than the previously discussed research. At 3.1% reduction in operating cost, the number found in Ham and Park (2021) is also much lower than the study described in this research. This difference can be explained by the fact that Ham and Park (2021) was not only optimising for the operational cost, but also trying to minimise the number of used vehicles.

Finally, when searching for papers that investigate the same topic, but with a different approach, two researches arise. In the first one, a deep neural network was used to schedule the optimal charging of electric cars. Making use of a dynamic price, the study found a decrease of 18.45% for electricity costs (Aljafari et al., 2023). In the second research, a sorting genetic algorithm was used to determine the costs savings of dynamic pricing in comparison to fixed pricing. In this second research, the dynamic price consists of three different prices over the whole day. Comparing this pricing to the strategies in this work, in terms of volatility it would be between the on/off peak strategy and the flexible strategy. In their research J. Li et al. (2025), found a cost reduction of 20.82%.

Comparing all model results, shows a clear range of cost reductions. All researches indicate a cost reduction of up to about 20%, slightly higher than this research. Also the work by (Ham & Park, 2021) does not show this large cost savings, although explained by the multi objective nature of that research. The reason why this research found a comparable, but smaller operational cost savings, might be in the fact that here, results for barges are compared to land vehicles. As barges are less mobile, they have fewer options to profit from lower prices in dynamic pricing.

11.3. Limitations

The model results are likely to be impacted by some limitations of this research. Therefore, it is important to discuss which limitations are acting on the model and what their expected impact on the model is. For overview purposes, all relevant limitations that might have an impact on the model and its outcome are listed in table 11.1. This table provides insights into opportunities to improve the model by adding aspects that can narrow down the gap between the model and reality, as these limitations stand between the model and reality.

Table 11.1: List of limitations and their potential impact on the results

Limitation	Potential impact on model results
Model limitations	
Single objective	The model only optimises for the cost of energy, no other factors are taken into account in the objective function. Factors as crew or client satisfaction are not included. This lets the model focus on minimising the costs, resulting in lower costs.
Dynamic requirements	No changes in routing and deadlines of vessels after model start.
Deterministic travel times	No delay due to unforeseen circumstances.
River conditions	The possibility that river conditions such as the current could impact model outcomes is not included. The effect of this is difficult to determine, as for example the current could both improve or worsen the outcome. However, if the optimisation model makes use of the current to determine the optimal departure time so energy consumption is minimised, in that case it is likely to improve the model solution.
Electricity price forecasting	All prices are determined from historical data. Forecasting could make the model more reliable.
(Un)loading times	Loading and unloading times at intermediate hubs are not part of the model, although they likely impact the optimal solution.
Skippers' preferences	Each hour is treated equally; ignores that crews may refuse night shifts or prefer certain time windows, which can alter feasible schedules.
Known origin, destination, and deadlines	Enables full preplanning and route optimization. However, any ad hoc or unscheduled trips cannot be captured.
Swapping station capacity constraint	Each location holds exactly two charged batteries at the start of the model.
Uniform recharge time	All batteries take 3 h to recharge regardless of remaining state of charge; this simplification may overestimate turnaround time for partially depleted batteries.
Full battery capacity usage	Allows any state of charge between full capacity and 0. No minimum SoC thresholds are enforced, which might not reflect operator preferences or safety margins.
Swap pricing at moment of exchange	Cost is calculated as battery capacity × hourly price at swap time. Charging over multiple hours is ignored, so the model cannot spread charging cost over the actual recharge interval.
No uncertainty in travel time or energy consumption	Vessels cannot over- or underestimate travel time and energy consumption, meaning no safety margin in both time and SoC is needed. This is likely to improve the model results, as in reality these values are not known without any uncertainty.
Constant battery performance	Assumes capacity and efficiency do not vary with temperature, battery age, or usage history. Overlooks degradation and environmental effects, which can reduce range.
Max three-stop route (origin, hub, destination)	Real-world routes can include multiple intermediate stops; limiting to three locations may oversimplify network complexity and mask bottlenecks.
Interview limitations	
Limited number of participants	During the interviews, 4 skippers, 3 freight planners and 1 terminal operator were interviewed. These sample sizes are all quite small, especially for the terminal operators. This limits the representativeness of all actors and therefore limits the reliability of the conclusions of the interviews.
Mixed interview modes	While some respondents were only spoken to over the phone, others were met in person. This could have led to discrepancies in the information entrusted to the interviewer.
Structured but flexible protocol	Although an interview protocol was followed, the protocol left room for side tracks in discussions with respondents. This could have impacted the comparability between interviews.

11.4. Broader impact of dynamic pricing in electric sailing

After determining in what ways the research circumstances differ from the reality, a close look is taken on what impact the implementation of dynamic pricing might have on the real world. In this section, a broader perspective is chosen to determine what the consequences of these implementations mean for actors not directly linked to the e-barge.

11.4.1. Electricity network

First, the consequences for the electricity grid are discussed. In an already tense electricity network in The Netherlands, the exploitation of electric barges can have a very large impact. In The Netherlands, there are about 8000 barges active (BureauVoorlichtingBinnenvaart, 2013). To sail electric, they all would use one battery at the time. The energy in one battery container compares to the energy needs of a regular household of four persons for one year (Milieu Centraal, 2023). With this one battery container, a vessel can sail for up to 5 hours (Zero Emission Services, 2025). This means that if all 8000 vessels sail simultaneously, in 5 hours, the vessels have consumed an amount of energy that could satisfy 8000 households for a whole year. This shows the scale of the energy consumption of the inland vessels and gives an idea of the impact this operation must have on the electricity grid. However, implementing dynamic pricing can actually be a relief for the electricity network. With dynamic pricing, all those vessels get the incentive to move their time of buying energy to lower cost moment. On those moments, the demand for electricity is lower, enabling the grid to supply the power towards the containers. On the other side, there is also an incentive to send remaining state of charge back to the grid at times of high prices, in other words, at times of high demand. This way, the large battery containers can actually help stabilise the energy system as they are incentivised to withdraw energy at times of low demand and send energy back at peak demand hours. In conclusion, although the impact of battery electric sailing on the energy grid is likely to be great, the implementation of dynamic pricing can help relieve some of the stress on the grid, as the batteries can serve as depot to store energy at moments of high volume and release at moments of shortage. It is therefore important that this is a static research, the impact of electric sailing on the energy price is not considered, while with a large e-barge fleet, the price of energy per hour might shift.

11.4.2. Hinterland transportation

Not only does dynamic energy pricing reshape the barge operator's schedule, it ripples all the way through the multimodal transport chain that uses inland waterways as just one link. Barges rarely carry goods from their true origin to their final destination; instead, barge terminals serve as transshipment hubs in a hinterland network that also can include seagoing vessels, rail, and road haulage. When we shift barge departure and arrival times to chase low-price charging windows, we inevitably force downstream modes to adjust as well:

- **Connecting transport:**
  If due to a dynamic price setting a vessel adjusts its schedule to cheaper hours, it also adjusts the loading and unloading moments. With cheap hours potentially being odd working hours, now also the connecting transportation of the cargo has to adjust its schedule to the shift of the vessel. This could imply that due to cheaper sailing hour for a vessel, a, for example, trucker has to adjust to these odd hours to either deliver the cargo on time for the barge to load, or pick up the delivered cargo from the vessel to make space on the terminal. The dynamic pricing thus not only influences the barge and its skipper but also other transport movements in the hinterland transportation.
- **Terminal handling and warehousing:**
  Not only those actually transporting cargo are impacted, also crane operators, warehouse staff, and forklift drivers must realign their work schedules to match barge calls. Nighttime or early morning handling may demand extra labour cost.
- **Terminal and yard planning:**
  If barges bunch into a narrow low price window, terminals can get crowded with vessels and yards can become congested with containers.

- **Equipment utilization:**
  To overcome the peak hours, potentially extra equipment such as cranes and straddle carriers are needed just for handling the peak hours. In an even distribution of vessel arrivals, these additional equipment might not have been necessary. Dynamic pricing then impacts the terminal cost at the profit of the operational cost for the barges.

In short, dynamic pricing doesn't simply tweak when vessels swap batteries, it transforms the tempo of the entire hinterland transportation system. To fully capture its benefits and avoid unintended bottlenecks, any scheduling model must be embedded within a broader system view that coordinates across modes, terminals, and labour regimes.

11.5. Recommendations

After discussing the results and establishing the impact of dynamic pricing on the electricity grid and the consequences for the hinterland transportation system, recommendations can be formed on the implementation of dynamic pricing. The recommendations are separated in two different sections. In the practical recommendations sections, an advice is formed on what to do with the implementation of dynamic pricing for battery containers. In the theoretical recommendations, the lessons learned from constructing the model developed in this research are discussed. The theoretical recommendations section is concluded with recommendations for future research.

11.5.1. Practical recommendations

In this research an optimal price setting for battery containers was searched for. With the development of a routing and scheduling model for electric barges, different price settings were tested. Although a price mechanism that sets a different price for each hour of the day results in the best outcomes, with 15% lower costs than a fixed price, this variable setting is not directly recommended as best solution. This is due to the concerns expressed by the interviewed stakeholders. Concerns for this setting were expressed throughout all professional fields; by skippers, freight forwarding planners, and even by a terminal operator. They all warned for a shift in working hours to undesirable hours, for example at night when prices are lower. Furthermore, skippers are afraid that with this dynamic planning, they will not be in charge of their own resting hours any more. That would be a serious problem for the skippers, who are attached to the time they spend with their families. Not being able to choose their own resting hours, could imply for example that they can no longer get their children from school or plan their evenings as they are used to. Finally, the planners active for freight forwarding companies warned for the added complexity of the schedule implied by this strategy.

However, the cost reduction of 10 to 15% on energy costs that was found in this research was mentioned by freight forwarders to be significant, thus although variable pricing might not be ideal, other price settings with slightly lower cost reductions should be considered. Remaining candidates are a flexible pricing, with a different price every couple of hours and an on/off peak price setting, that has one fixed price for all off peak hours and one fixed price for all peak hours. The results in cost reductions are quite similar, although the flexible strategy has the edge with a 2 percentage point higher cost reduction. Despite the favourable cost reduction for the flexible setting, the on/off peak price setting is recommended. This because the difference in cost reduction is limited, but the on/off peak has some major advantages. First, unlike the flexible mechanism, this price setting does not have its lowest priced hour during the night, which might push vessels to operate more during the night, which is not desired as indicated during the interviews and could also imply additional cost for working the odd hours at terminals. Secondly, as apart from the peak hour price, prices are all equal in this price setting, the need for the resting time to be at specific hours is thus smaller. In contrast to the flexible setting, in the on/off peak setting the exact timing of the rest hours is less rigid due to the same pricing in nearby hours. This can lead to an imposed rest window of a couple of hours during which for example one hour must be spent resting. This can help compromise between the skippers and freight forwarders, as it still reduces the cost of energy significantly but also leaves some room for the skippers to determine their own rest hours.

The on/off peak price setting appears to have the most potential, but before this setting can be implemented both limitations of this research and the consequences of this setting for the electricity grid and the hinterland transportation network must be considered. How this can be done, will be discussed in the theoretical recommendations section.

11.5.2. Theoretical recommendations

Before looking into how the limitations of the research and consequences of dynamic pricing can be overcome by future studies, first the lessons learned from the development process of the model used in this research is discussed.

During this research the used model was developed for a small starting model, with a base similar to the discussed work by Verma. This small model was implemented in Python code to check the functioning of the small model, before extending the model with additional constraints. This way a model was constructed by constantly adding new constraints, with each adding reality to the model. However, after setting up the whole model, it was found that the model became too large to run within a reasonable time. The model needed several hours to find a solution. In the case of this model there was a way to work around this problem by dividing the model in two separate parts without impacting the model outcomes, but this might not always be possible. It is therefore strongly recommended for future research to make an estimation on model runtime of the final model before developing a large model. The models runtime can be roughly estimated by determining the number of variables, binaries, constraints and the use of big M.

Besides the recommendation on runtime estimation, also some recommendations for future work are formed. With these recommendations, on one side the most important limitations of this research could be overcome and on the other side, the consequences of dynamic pricing for battery containers on the hinterland transportation can be further investigated. First, incorporating not only the cost for energy in a model like this, but also different cost factors as labour cost could provide great insight in what the performance of dynamic pricing in a more realistic scenario, especially if the labour cost in this model also depends on the hour of the day. Other directions to further develop this research is to include river conditions such as the current and tide, as this can have great impact on the scheduling of the vessels. On the interview side of this research, it would be interesting to see if extending the number of interviewees leads to new insights.
To investigate the impact on the hinterland transportation network, a study on the logistic chain with dynamic pricing for battery containers would be valuable to gain insight into the consequences of dynamic pricing on the entire chain. If research in these directions is concluded, an optimal price setting can be chosen with greater certainty.

11.6. Conclusion

The aim of this research was to develop a model with which different price settings for battery electric containers could be tested to ultimately determine which strategy would perform best. Therefore, in this research, the question: *"How can a routing and scheduling optimisation model for electric barges be developed to identify which price setting for battery containers minimises operational costs?"* was central.

In order to answer this research question, it was divided into smaller sub-questions. Combining the answers to each sub-question should result in an answer for the main research question. Here below, the sub-questions are answered one by one, before a final answer is given on the main research question.

How volatile are green electricity prices over the day at the different loading stations and what historical trends in the pricing can be observed?

The first sub-question looked into the volatility of energy prices in The Netherlands at different locations. Although no data was available on the price of energy at different locations, a clear impact of the time of the day on the price of a kWh of energy was visible in the available data. Historical data over all hours of all days in 2024 showed a clear fluctuating price over the day. During the night and early morning, the energy prices are relatively low, before they spike in the morning. During the day prices drop again to more or less the same level as at nighttime. From six o'clock in the evening, the price rises again to a maximum between 19:00 and 20:00. After this peak, the price comes down to the nighttime price. Based on this price fluctuation, four different price settings have been formed. A variable price, with every hour a different price, a flexible setting with every couple of hours a new price, an on/off peak strategy in which the peak hours are charged more than the off peak hours and the current fixed price setting. These four settings have been used throughout this research.

Which infrastructural, environmental and operational factors must be represented to model inland (e-)barge performance?

Sub-question 2 looked into the functioning of the barge system in The Netherlands. A system analysis was conducted to gain understanding in what the to be developed model must include in order to realistically represent barge operations in The Netherlands. This gained understanding led to the formulation of many requirements for the model. The model must for example respect the minimal rest hours for the crew of a vessel and the start and deadline for cargo movements. Furthermore, the model must correctly include swapping time per battery and allow for multi-stop routes. These requirements determine what the model should be capable of and will be included upon model development.

What theoretical concepts underpin the design and construction of routing, scheduling and battery swap planning systems?

In the third sub-question, the theory for the development of a routing and scheduling model was investigated. The aim of this sub-question is to establish a foundation for the formulation of the routing and scheduling model. This sub-question found a base for the model in the literature in routing, time window and energy propagation constraints. Furthermore, a mathematical model was found in Verma (2018) that could be used as a starting point for the model in this research. With this sub-question, a strong start for the forthcoming model was found.

How can a model be developed that minimises operational energy costs for skippers while respecting operational constraints such as delivery deadlines?

In sub-question number four, the actual model was developed. The mixed integer linear programming model as seen in Verma (2018), was stripped so that only the useful base with relevant constraints remained. From there, the mathematical model for this problem was constructed according to the in sub-question two establish requirements. The flow of the batteries, energy consumption, crew regulations, deadlines and battery capacity constraints were, amongst others included.

After the construction of the mathematical model, the model was implemented in Python and successfully verified and validated. With this, a model that minimises the cost savings while respecting operational constraints is constructed.

How does the current price setting perform, compared to other price settings determined, according to the developed model?

Sub-question number five tested how the different price settings performed in the developed model. An experimental plan was constructed to rigorously test the settings under different potential future circumstances. The variable setting, where each hour is priced differently, continuously outperforms the other dynamic price settings by a few percentage points. The alternative with a fixed price scores significantly lower than the other strategies. Cost reductions are approximately 10% for the on/off-peak setting, 12% for the flexible setting and 15% for the variable price setting. Furthermore, a variant of the model is analysed. In this variance analysis, the model instead of a fleet optimal, is now optimised for the optimum of each individual barge. Also in this individual-barge analysis, the relative performance of the settings remained the same, again showing 10%, 12% and 15% cost of energy reductions respectively.

How do stakeholders in the inland shipping industry assess barriers and enablers to implement different price settings in a practical context?

In the final sub-question, the practical viability of the different price settings was discussed with the stakeholders involved. Interviews with skippers, freight forwarding planners and a terminal operator were conducted. During these interviews, respondents were asked about what kind of problems and opportunities they saw for the different strategies. Different concerns were expressed during these interviews; the skippers are afraid to lose their autonomy over the planning of their rest hours, whereas the planners expressed concerns about the added complexity of a variable price setting with every hour a different price. On the other hand, the potential energy cost reduction of 10 to 15% was stated as significant and worth some extra work.

Taken together, these findings per sub-question demonstrate that the developed MILP model can robustly evaluate competing pricing schemes under real world constraints. Although the fully variable pricing yields the greatest theoretical savings, stakeholder feedback highlights its complexity. Consequently, an on/off-peak tariff emerges as the optimal compromise, achieving most of the cost reduction (±10%) while preserving crew autonomy and scheduling simplicity. This directly answers the research question by showing that the model not only identifies the lowest cost setting but also ensures its practical viability in inland e-barge operations.

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A

Historical energy data

In figure A.1, a preview of the used historical data for electricity pricing is shown. This is a list of the energy price in The Netherlands for every day and every hour the price of 1 kWh energy in Euros. Full heatmap with the full dataset is available upon request.

Day/Hour	00:00	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00
01/01/2024	0.0001	0.00001	0	-0.00001	-0.00003	-0.00002	-0.00005	-0.00002	0	0.00004	0.00006	0.00054	0.00224	0.00197	0.00113	0.00319	0.04	0.08446	0.06174	0.06127	0.05997	0.05492	0.04765	0.03555
02/01/2024	0.02939	0.0196	0.02733	0.0162	0.0095	0.0112	0.04443	0.05656	0.06428	0.06612	0.0706	0.0788	0.0999	0.1025	0.1106	0.1057	0.1007	0.11893	0.0813	0.0701	0.0667	0.0549	0.05318	0.0549
03/01/2024	-0.00039	-0.00161	-0.00139	-0.00131	-0.00139	-0.00195	0.00105	0.04063	0.0683	0.0759	0.0732	0.0692	0.06	0.05886	0.06086	0.076	0.079	0.101	0.1146	0.1	0.07323	0.06741	0.065	0.05812
04/01/2024	0.0573	0.05046	0.04	0.02548	0.035	0.05773	0.07265	0.08502	0.09147	0.0942	0.09161	0.09003	0.08628	0.08596	0.09211	0.09862	0.10445	0.13021	0.14067	0.1231	0.10165	0.09677	0.09304	0.08861
05/01/2024	0.08608	0.08051	0.07701	0.07288	0.07212	0.07452	0.08011	0.08717	0.08978	0.095	0.09629	0.09822	0.09229	0.09165	0.0965	0.10013	0.10303	0.10743	0.10847	0.104	0.10013	0.09421	0.09492	0.0868
06/01/2024	0.08225	0.0802	0.07613	0.07301	0.07301	0.07459	0.0751	0.08139	0.0884	0.09223	0.0973	0.10043	0.09916	0.09452	0.09245	0.09418	0.09922	0.10469	0.10363	0.099	0.09214	0.088	0.08657	0.07987
07/01/2024	0.08408	0.07982	0.07676	0.07346	0.07186	0.07208	0.0749	0.07769	0.08179	0.08486	0.08714	0.08913	0.08866	0.08481	0.08434	0.08801	0.09342	0.10177	0.10485	0.10355	0.1005	0.09331	0.09117	0.08386
08/01/2024	0.08702	0.08435	0.08171	0.079	0.07847	0.0821	0.0943	0.11109	0.12111	0.11783	0.11058	0.103	0.0849	0.08956	0.1	0.10798	0.11639	0.12915	0.12508	0.1119	0.1001	0.091	0.092	0.09149
09/01/2024	0.08095	0.07998	0.085	0.08342	0.08057	0.0858	0.0839	0.09112	0.1257	0.11996	0.098	0.09	0.0788	0.07778	0.085	0.0999	0.11267	0.13569	0.12925	0.1263	0.10882	0.09366	0.0849	0.088
10/01/2024	0.07554	0.08676	0.08673	0.08122	0.08048	0.0779	0.0793	0.096	0.13252	0.13039	0.11121	0.10913	0.0891	0.08745	0.0849	0.10634	0.12794	0.14379	0.14	0.13215	0.12	0.0973	0.0913	0.08231
11/01/2024	0.09175	0.08859	0.08725	0.08238	0.0812	0.0796	0.09	0.11687	0.141	0.12916	0.11365	0.10648	0.09938	0.099	0.10598	0.11731	0.13262	0.14706	0.1367	0.13231	0.11788	0.10719	0.1	0.081
12/01/2024	0.08212	0.08063	0.08313	0.07729	0.078	0.07918	0.08132	0.1182	0.14074	0.13496	0.12201	0.11473	0.10698	0.10308	0.10454	0.11	0.12	0.1275	0.126	0.11947	0.10713	0.0917	0.08502	0.08249
13/01/2024	0.09	0.08543	0.082	0.07847	0.075	0.07494	0.07816	0.0779	0.07492	0.0854	0.0884	0.0861	0.0797	0.08082	0.0815	0.087	0.0973	0.1146	0.1028	0.0846	0.07547	0.081	0.085	0.08
14/01/2024	0.0749	0.07401	0.0699	0.06824	0.07192	0.08	0.07103	0.07592	0.07927	0.093	0.09711	0.0872	0.08039	0.07704	0.07915	0.08232	0.08662	0.09186	0.0949	0.085	0.07906	0.0786	0.07539	0.06719
15/01/2024	0.0679	0.065	0.06394	0.06204	0.06204	0.06925	0.08018	0.0844	0.09934	0.1003	0.09489	0.0902	0.08118	0.0822	0.0846	0.08957	0.09762	0.10651	0.11281	0.10513	0.0944	0.07904	0.07776	0.0785
16/01/2024	0.068	0.07651	0.07743	0.07682	0.07305	0.07261	0.0924	0.1158	0.14411	0.1386	0.122	0.11	0.088	0.0881	0.084	0.11029	0.11169	0.1283	0.1221	0.102	0.08997	0.084	0.08221	0.0752
17/01/2024	0.0718	0.07165	0.07073	0.06979	0.06954	0.07131	0.07557	0.08494	0.09674	0.10618	0.11033	0.1111	0.11374	0.11673	0.118	0.12262	0.12655	0.13691	0.12251	0.1131	0.09916	0.09373	0.0891	0.08321
18/01/2024	0.0803	0.07699	0.07467	0.07418	0.07609	0.0776	0.08909	0.10923	0.12198	0.11826	0.1104	0.08	0.08395	0.07064	0.08661	0.0858	0.09868	0.10375	0.10335	0.08785	0.081	0.08314	0.07663	0.07361
19/01/2024	0.06914	0.06626	0.063	0.06276	0.06332	0.0669	0.07649	0.086	0.10427	0.09991	0.08753	0.084	0.07221	0.07336	0.07522	0.07304	0.0849	0.09375	0.0879	0.0749	0.07295	0.07112	0.06864	0.06475
20/01/2024	0.066	0.06751	0.06354	0.06182	0.06185	0.06175	0.06259	0.0669	0.07482	0.0779	0.0718	0.0696	0.06489	0.0669	0.07337	0.07914	0.08786	0.09498	0.09989	0.09157	0.08	0.07572	0.07042	0.06913
21/01/2024	0.0625	0.057	0.05515	0.05089	0.04831	0.04694	0.045	0.04217	0.051	0.06	0.05909	0.05624	0.0599	0.05274	0.05584	0.05721	0.05553	0.06879	0.082	0.064	0.0602	0.057	0.05426	0.05327
22/01/2024	0.04408	0.04999	0.045	0.02792	0.018	0.0205	0.04227	0.0685	0.13	0.0896	0.07434	0.0606	0.05701	0.05652	0.05855	0.06047	0.067	0.08877	0.1103	0.0981	0.06743	0.06441	0.05622	0.05035
23/01/2024	0.01684	0.01099	0.01	0.005	0.01084	0.03951	0.06151	0.08825	0.1158	0.09668	0.0809	0.065	0.06413	0.06336	0.07002	0.0743	0.07719	0.08181	0.08489	0.07535	0.065	0.0632	0.0534	0.035
24/01/2024	0.00485	0.00212	0	-0.00389	-0.005	0	0.01665	0.0675	0.095	0.09333	0.068	0.05221	0.03932	0.0383	0.0465	0.06843	0.08	0.098	0.09272	0.1001	0.084	0.08199	0.0718	0.0818
25/01/2024	0.0649	0.0561	0.0672	0.075	0.07531	0.0759	0.07858	0.0921	0.10302	0.094	0.08396	0.07866	0.07495	0.07655	0.08422	0.08861	0.09698	0.116	0.1124	0.09853	0.07991	0.08428	0.0794	0.07417
26/01/2024	0.0628	0.062	0.05849	0.05479	0.0474	0.05087	0.05815	0.07198	0.07745	0.0801	0.07134	0.05894	0.05208	0.0463	0.05	0.05117	0.075	0.095	0.13557	0.11112	0.0958	0.082	0.0842	0.07936
27/01/2024	0.0745	0.0689	0.0659	0.059	0.05649	0.05858	0.05998	0.0669	0.08676	0.0862	0.08017	0.06033	0.05584	0.05388	0.05973	0.0782	0.0824	0.09122	0.09597	0.09262	0.08443	0.07596	0.07597	0.0727
28/01/2024	0.06677	0.0607	0.0591	0.05889	0.05997	0.06241	0.05932	0.05898	0.0592	0.05522	0.05135	0.04551	0.04124	0.04025	0.04971	0.0549	0.06629	0.07642	0.0747	0.07016	0.06861	0.05757	0.05966	0.056
29/01/2024	0.04997	0.04726	0.04812	0.04797	0.05158	0.06006	0.08015	0.09269	0.0992	0.08839	0.0789	0.07127	0.07024	0.07487	0.08199	0.09567	0.10479	0.1202	0.11592	0.10752	0.09095	0.08566	0.08325	0.08029
30/01/2024	0.07194	0.06876	0.06937	0.06709	0.06663	0.06937	0.07861	0.09077	0.09594	0.08493	0.07715	0.0701	0.0681	0.06823	0.07193	0.0786	0.08197	0.08836	0.09938	0.11041	0.0899	0.08012	0.08245	0.0773
31/01/2024	0.0789	0.07403	0.07089	0.06982	0.06917	0.07386	0.08477	0.10517	0.12	0.09353	0.08298	0.07709	0.07491	0.0675	0.0668	0.07394	0.07855	0.08565	0.0855	0.0692	0.06278	0.05818	0.054	0.04057
01/02/2024	0.048	0.04237	0.04304	0.04394	0.04763	0.05606	0.0692	0.08637	0.09976	0.09277	0.08371	0.0755	0.0676	0.05726	0.0712	0.0875	0.084	0.11262	0.113	0.09803	0.09081	0.08334	0.08191	0.07342
02/02/2024	0.06432	0.05995	0.058	0.05469	0.05314	0.05513	0.06649	0.07791	0.08961	0.08621	0.0808	0.07517	0.06489	0.06256	0.0637	0.0677	0.08	0.08847	0.09997	0.082	0.0733	0.07	0.06315	0.05484
03/02/2024	0.04968	0.04308	0.0349	0.014	0.01098	0.0114	0.01648	0.03643	0.04691	0.06748	0.066	0.05802	0.051	0.0479	0.04253	0.04471	0.05058	0.0674	0.106	0.096	0.07245	0.0631	0.05141	0.04
04/02/2024	0.0425	0.03222	0.0069	0.00072	0	0	0	0.0044	0.01188	0.0275	0.04	0.02667	0.01979	0.00507	0.014	0.03168	0.0412	0.0635	0.08581	0.0709	0.0536	0.05489	0.04974	0.03498
05/02/2024	0.00163	0.0001	0.0001	0.00022	0.00008	0.00165	0.04123	0.085	0.1066	0.0787	0.0552	0.04489	0.0348	0.0455	0.054	0.05579	0.065	0.08621	0.09755	0.0801	0.06996	0.05991	0.05604	0.04741
06/02/2024	0.03546	0.0282	0.01	0.00498	0.00311	0.02009	0.05	0.06922	0.0882	0.0873	0.0871	0.0765	0.0649	0.05994	0.06386	0.0639	0.0647	0.08	0.09926	0.09489	0.071	0.06262	0.05711	0.0533
07/02/2024	0.04117	0.0448	0.0499	0.06098	0.061	0.0656	0.0759	0.0886	0.0949	0.0969	0.08188	0.07866	0.075	0.0738	0.07538	0.0853	0.09303	0.11964	0.1358	0.11032	0.098	0.08356	0.07901	0.07921
08/02/2024	0.0737	0.0732	0.07215	0.06863	0.06669	0.07171	0.08206	0.10449	0.13191	0.11237	0.09802	0.08955	0.08401	0.08552	0.08332	0.084	0.07681	0.0772	0.084	0.0815	0.07757	0.075	0.07082	0.06164
09/02/2024	0.06036	0.05216	0.04715	0.0421	0.0413	0.04488	0.05288	0.0637	0.06789	0.06783	0.06882	0.06761	0.06455	0.0637	0.06868	0.07546	0.08238	0.09249	0.09429	0.0871	0.08054	0.07522	0.07491	0.07094
10/02/2024	0.0631	0.06408	0.0644	0.06439	0.06441	0.06582	0.07091	0.07486	0.0777	0.08038	0.0754	0.07042	0.0685	0.06672	0.06953	0.07717	0.08505	0.0899	0.1136	0.089	0.0744	0.07	0.07721	0.06432
11/02/2024	0.0688	0.0593	0.0526	0.04683	0.04651	0.04625	0.0564	0.06303	0.071	0.0661	0.0684	0.06546	0.06434	0.06338	0.06406	0.06822	0.07224	0.07972	0.112	0.0968	0.07703	0.07072	0.06839	0.06401
12/02/2024	0.06435	0.06165	0.06073	0.05947	0.05921	0.065	0.076	0.08541	0.104	0.0965	0.08547	0.07909	0.06742	0.06386	0.06413	0.06665	0.0771	0.09069	0.096	0.08908	0.07915	0.07154	0.06587	0.0619
13/02/2024	0.06859	0.06537	0.06341	0.06049	0.06006	0.06359	0.0707	0.08232	0.0891	0.07512	0.06921	0.06387	0.06053	0.06026	0.0631	0.0707	0.07792	0.09179	0.0992	0.09113	0.0782	0.07218	0.06853	0.06478
14/02/2024	0.06063	0.05934	0.05576	0.05479	0.05506	0.0585	0.06352	0.07298	0.07989	0.06965	0.06386	0.06329	0.06216	0.06191	0.06729	0.07069	0.07599	0.08165	0.08767	0.08458	0.0766	0.06971	0.0682	0.0638
15/02/2024	0.06167	0.06055	0.05941	0.05833	0.05963	0.06343	0.07014	0.0798	0.08206	0.07784	0.07351	0.06851	0.0648	0.06385	0.06684	0.07127	0.07411	0.08244	0.08454	0.07513	0.06956	0.06268	0.06266	0.05864
16/02/2024	0.05176	0.05108	0.04992	0.04881	0.05138	0.0522	0.0575	0.06888	0.0705	0.068	0.0612	0.0688	0.065	0.0612	0.06304	0.06496	0.07	0.07206	0.07973	0.08075	0.07453	0.07	0.07	0.0657
17/02/2024	0.0685	0.06264	0.068	0.0649	0.06489	0.07328	0.0606	0.0687	0.0753	0.08452	0.067	0.06083	0.05824	0.05525	0.0591	0.06707	0.0708	0.08501	0.10568	0.08951	0.08015	0.07416	0.07206	0.06911
18/02/2024	0.06213	0.05481	0.0514	0.05022	0.05	0.04847	0.04602	0.04897	0.04728	0.04303	0.04045	0.041	0.05	0.05017	0.0646	0.06693	0.06287	0.072	0.0841	0.07059	0.06471	0.05983	0.05733	0.05394
19/02/2024	0.044	0.04832	0.04646	0.04391	0.04492	0.05157	0.06863	0.07912	0.08387	0.07506	0.07088	0.06922	0.06247	0.05997	0.06418	0.0668	0.06986	0.07615	0.09989	0.08002	0.07192	0.06749	0.06627	0.05907
20/02/2024	0.05806	0.05432	0.05396	0.056	0.053	0.05481	0.07105	0.08607	0.08963	0.07877	0.06985	0.06092	0.05352	0.05151	0.05186	0.05589	0.06228	0.06898	0.07086	0.07076	0.06776	0.057	0.04844	0.04961
21/02/2024	0.04858	0.04691	0.04686	0.0448	0.04543	0.05006	0.06501	0.0797	0.08405	0.06965	0.0641	0.06039	0.05301	0.05121	0.05376	0.06471	0.0671	0.06831	0.06838	0.0616	0.05252	0.04631	0.04204	0.03557
22/02/2024	0.03087	0.02742	0.0275	0.02944	0.03551	0.04672	0.06426	0.075	0.08191	0.074	0.06944	0.06746	0.0669	0.06669	0.06349	0.0631	0.06093	0.06176	0.05995	0.0604	0.04792	0.04381	0.0349	0.0201
23/02/2024	0.00928	0.0015	0.00119	0.0001	0.0004	0.00113	0.03996	0.05796	0.0608	0.05354	0.0471	0.04204	0.03727	0.0329	0.038	0.04964	0.06321	0.0737	0.08644	0.08401	0.07297	0.06926	0.06798	0.0651
24/02/2024	0.06647	0.0639	0.0595	0.0552	0.05539	0.0571	0.06167	0.06611	0.0644	0.0576	0.04919	0.04581	0.04032	0.03222	0.0376	0.045	0.05596	0.07296	0.08195	0.07413	0.06517	0.05994	0.06402	0.06351
25/02/2024	0.05657	0.05544	0.05544	0.05495	0.05525	0.05507	0.0586	0.05992	0.075	0.0715	0.05668	0.05464	0.05	0.04603	0.04984	0.055	0.0689	0.08569	0.09388	0.079	0.06996	0.06582	0.06523	0.05838
26/02/2024	0.05783	0.05682	0.05567	0.0518	0.05324	0.05792	0.06844	0.07954	0.0816	0.07383	0.06665	0.06503	0.05842	0.05819	0.06129	0.06495	0.06992	0.077	0.08532	0.081	0.07221	0.06569	0.06521	0.06076
27/02/2024	0.05762	0.05755	0.05735	0.05687	0.05735	0.06275	0.07332	0.09287	0.09522	0.08081	0.06871	0.061	0.05549	0.05558	0.056	0.0599	0.0665	0.09395	0.11018	0.10517	0.08436	0.0725	0.0703	0.06497
28/02/2024	0.06036	0.0594	0.06134	0.06346	0.06374	0.06746	0.07408	0.09707	0.10449	0.08546	0.07399	0.06755	0.0631	0.0579	0.0585	0.06	0.07246	0.07	0.0898	0.07818	0.06555	0.06269	0.06408	0.0552
29/02/2024	0.05482	0.05302	0.04971	0.04662	0.04375	0.048	0.06137	0.07335	0.07385	0.07039	0.06565	0.06646	0.06	0.05777	0.06368	0.0652	0.07162	0.08	0.08626	0.08099	0.07277	0.06725	0.0649	0.0609
01/03/2024	0.06204	0.06142	0.05814	0.05783	0.0583	0.06249	0.07158	0.07936	0.08602	0.07804	0.06651	0.06453	0.04755	0.05	0.0632	0.07117	0.07828	0.0894	0.09373	0.08719	0.07749	0.07162	0.07006	0.06639
02/03/2024	0.05995	0.05603	0.05602	0.05548	0.05488	0.05599	0.05658	0.06067	0.06376	0.06575	0.06044	0.0538	0.05307	0.0549	0.05986	0.06608	0.073	0.08117	0.0936	0.0899	0.07698	0.06981	0.0699	0.0682
03/03/2024	0.0601	0.06921	0.06703	0.05791	0.05548	0.05888	0.06539	0.0698	0.07151	0.07249	0.06314	0.05	0.04751	0.04251	0.04684	0.05807	0.06028	0.07772	0.088	0.08696	0.0818	0.075	0.07218	0.07242
04/03/2024	0.06913	0.0679	0.06741	0.06622	0.06559	0.07083	0.08118	0.09667	0.10297	0.08502	0.07123	0.0632	0.0633	0.06104	0.0625	0.06986	0.0767	0.09347	0.10518	0.09913	0.08052	0.07139	0.06749	0.06393
05/03/2024	0.06196	0.06167	0.06133	0.05986	0.06056	0.06167	0.07153	0.07928	0.08302	0.077	0.07115	0.06972	0.06599	0.06581	0.0696	0.07062	0.0763	0.08186	0.10438	0.0966	0.07842	0.07307	0.066	0.07

Figure A.1: Heatmap energy prices per day per hour preview.

B
Interview protocol

All interviews where conducted via the protocol as shown in table B.1. This protocol allowed a structured interview for all different respondents but still has room for each individual to express their own opinion.

Table B.1: Interview protocol

Section	Purpose	Key elements
1. Start interview	Explanation of the aim of the interview	• Ask for permission to record • Set duration
2. Introduction	Get to know each other	• Function • Experience in inland shipping
3. Current situation	Understand the current way of working	• Ask for day-to-day tasks • Depending on job, ask more specific questions on how the current system works
4. Battery electric sailing	Explore potential of electric sailing	• Explain how battery electric sailing would work • Ask for their view on viability • Where do they see potential problems
5. Implementation of model output	Explore the potential of different pricing strategies	• Now take electric sailing for granted—what problems do you see with variable pricing? • Would any other strategy make the system easier?
6. Concluding	Final remarks	• Is there anything we did not discuss that you think could be of added value?

C

Research paper

Energy Price Setting in Optimal Routing, Scheduling and Battery Swapping for Electric Barges

M.N. Wijn

As electric barges are starting to appear in the Dutch inland waterway, questions arise on the pricing of the consumed energy. In this research, the impact of dynamic energy prices is investigated. Therefore, four different dynamic price settings have been determined based on historical data. A Mixed-integer linear programming model was formulated that modelled the optimal routing and scheduling of the e-barges. The different price settings were tested on this model in order to determine which setting would result in the greatest cost reduction in comparison with the current fixed price setting. It was found that a variable price setting, with a different price for each hour of the day, gave the best results. This setting was able to reduce the operational energy cost by about 15%. Other price settings came to a 12% cost reduction (flexible pricing) and around 10% cost reduction (on-/off- peak setting). However, interviews with stakeholders in the field exposed concerns about the variable setting and preferred the on-/off-peak price setting. Therefore, the study recommended to further investigate the impact of applying the on-/off-peak setting on the hinterland transportation chain on greater level.

Introduction

In order to reduce the emissions caused by cargo transport, as was agreed up on in the Paris Agreement (EURLEX, 2016), shifting a large part from freight transport by truck to transport by barge could be helpful. As transportation by barge is a cleaner way of transport in terms of emissions per tonne-kilometer, this shift can greatly improve the amount of greenhouse gases emitted by the transport sector (Port of Rotterdam, 2021). This way, the hinterland transportation can become greener and comply with the Paris Agreement.

The Alphenaar shows that the difference in emitted greenhouse gases can be even bigger than just the gain from shifting from truck to barge. The Alphenaar is the first fully electric operating barge with interchangeable batteries in The Netherlands (Port of Rotterdam, 2021). This ship carries containers within The Netherlands between Moerdijk and Alphen aan den Rijn. Two of the containers on board of the Alphenaar do not contain cargo, but are fully loaded with batteries. These batteries provide the power the ship needs. Once the batteries are empty, the container-batteries are unloaded from the vessel and replaced with loaded batteries, so the ship can continue its journey. With this battery technology, depending on the origin of the energy with which the batteries are reloaded, the barge can sail without emitting greenhouse gases at all.

This is, however, just one vessel on one trajectory and thus not making a large impact on the emission numbers of the transport sector. This research aims to contribute to an optimal roll-out plan for e-barges. To contribute to the roll-out plan, first a literature review is conducted to investigate all that is already known about the e-barges and their system. This literature review also reveals what is not researched before. Based on the revealed knowledge gap, a main research question is formed. The answer on this question should contribute to the roll-out plan by providing new knowledge. In the following sections, the literature review is described and the method used to answer the research question is discussed. Afterwards, the alternatives are generated and a model is constructed. The results of the model are shown in the following part and the practical viability of these results are discussed. The article is concluded with a discussion and conclusion section.

Literature review

Strategic level literature

Inland waterways in the Port of Rotterdam handle enormous freight volumes of about 500 million tonnes per year and about 110,000 barges visit the port each year (Kotowska et al., 2018), (Port of Rotterdam, 2025). This makes electrification of barges both a huge challenge as well as an opportunity. Early field tests such as the Alphenaar show that barges can run on large exchangeable battery containers, enabling zero-emission sailing (Port of Rotterdam, 2021), (Hir et al., 2024). These energy containers are comparable to general cargo containers and can be swapped out easily with common container cranes. Battery swapping is quite fast, in roughly 15 minutes a depleted battery can be exchange for a fully charged one. This charged battery allows a barge to continue sailing for another 4 to 5 hours before the next swap must be executed (Zero Emission Services, 2025). The containerised battery approach makes use of existing port infrastructure as cranes and docks and yields time savings and lower capital cost compared to fixed on-board batteries (Hir et al., 2024).

However, widespread usage of this system requires setting up a network of swapping stations. Initial studies on placement of these locations also highlight the high placement costs of these facilities (Hir et al., 2024). In essence, station planning must balance the number of swapping facilities and batteries against usage patterns (Blanc & Atasoy, 2024), (Rodríguez, 2021).

In summary, strategic studies confirm that Rotterdam's hinterland is well-connected by inland waterways and that battery swapping barges are technically feasible. Key system components such as swapping stations and shared battery pools have been conceptually validated (Rodríguez, 2021). Yet significant gaps remain; according to Li et al. (2025) there is little guidance on how many batteries or stations are needed economically. In particular, the long-term durability and lifecycle costs of high-capacity batteries have not been fully quantified. Addressing these gaps is critical before tactical and operational planning can be reliably built on this strategy level.

Tactical level literature

At the tactical level, studies have examined how to schedule and route e-barges on a daily to weekly basis and how to manage energy resources. Two pioneering studies illustrate these approaches. Adler and Mirchandani (2014) developed an online scheduling model that minimises total system delay by reserving batteries along barges' routes. This centralised strategy dynamically adjusts all routes to avoid congestion at swap stations, even though it may require some barges to take longer detours for the common good. In contrast, Verma (2018) focused on each vessel's cost minimisation via integer programming: comparing battery swaps to recharging, it was found that mix-and-match approaches, for example partial recharge plus swap, can lower operator costs. Verma also suggested incorporating dynamic electricity pricing so barges could schedule charging during low-price hours, but Verma's own model used a fixed price. Overall, these works agree that well-planned routing and scheduling, whether centrally or individually optimised, can significantly reduce delays and energy cost, thus making electric barges more attractive to operators.

Other tactical issues include energy demand management. The battery containers used are extremely large, comparable to 36 passenger car batteries, so their charging must be coordinated with the grid. Bi et al. (2015) note that charging many such batteries at once could strain the network, but if timed during off-peak or surplus generation periods, they could act as flexible storage capacity. Finally, monitoring and KPI tracking are vital in the tactical level. Important metrics include the number of swaps per vessel and vessel range per battery. More advanced tracking such as barge energy consumption profiles, is difficult to determine exactly because consumption varies widely with vessel size and load. Tactical literature recognises these measurement challenges, but state their importance for the correctness of the used models.

Overall, tactical research provides useful models for routing, scheduling, and basic energy considerations . But notable gaps persist: for example, no routing study has fully explored using partly charged batteries to reduce wait times, and no work has aligned barge charging schedules with fluctuating energy prices. Such gaps as the effects of partial charges and dynamic pricing need further research to refine tactical decision-making.

Operational level literature

The operational level concerns detailed optimisation models and algorithms for e-barge operations. A number of models have been proposed, differing in objectives but contributing to overall efficiency. Adler and Mirchandani (2014) was one of the first with such a model for e-barges; it optimises fleet-wide routes to minimise delays. Verma (2018) integer programming minimises total cost by jointly planning routes and battery-swaps versus grid charging. Blanc and Atasoy (2024) and Rodríguez (2021) extended this by treating network design: optimising the number of batteries and facility locations along with routing. Blanc et al. formulated a multi-objective model balancing investment cost and operational efficiency, while Rodríguez' model simultaneously sized both batteries and stations for a case-study network. These studies generally confirm that higher battery capacity and more swap sites improve service but at steep cost, suggesting a trade-off that still needs scalable solution methods.

Another line of work adds technical depth. Guo and Dai (2023) built a trip-planning optimisation that determines ideal ship speeds, swap points, and number of swaps. However, Guo's model assumes fixed energy prices. Guo and Dai, as well as numerous other studies, note that variable electricity prices over the day could further cut costs if integrated. Finally, Meherishi et al. (2025) addressed battery logistics: this study examined the repositioning of used batteries by truck or barge to balance the distribution of batteries of the facilities. The study found that active repositioning can significantly reduce the total batteries needed in the network. Meherishi also suggested future research on jointly optimising routing, swapping, and repositioning.

In conclusion, the operational literature offers robust mixed-integer programming and simulation models for e-barge routing, facility siting, and battery management. These models have proven that optimisation can cut delays and costs. However, several knowledge gaps remain. Dynamic electricity pricing has been omitted as no model yet fully integrates time varying prices into the decision. Computational scalability is also an open issue: many models struggle as fleet size or network size grows. And while several individual problems have been modelled, a optimisation that handles both routing and scheduling in combination with dynamic energy prices is still lacking, according to Meherishi et al. (2025). Addressing this gap, can be key to develop practical decision-support tools for electric barge operations. Therefore, the main research question used in this study is:

How can a routing and scheduling optimisation model for electric barges be developed to identify which price setting for battery containers minimises operational costs?

Method

To answer this research question, a mixed-integer linear programming model will be constructed.
Mixed-integer linear programming is chosen as it is very well capable of finding numerical optimal solutions. With this characteristic, the research question can potentially be answered. Moreover, MILP allows for including a time element, which is very likely to be needed. Finally, the restrictions of the system can also be included in the model, making the MILP a promising approach. On the downside, MILP requires precise input data, all required information must be known upfront in order to make the model work. As not many e-barges are sailing yet, collecting the needed information might be difficult. However, if no data is available dummy data could be used to overcome this problem. Once more e-barges start sailing, this dummy data can be replaced with real values. Besides the MILP method, also interviews are conducted. These interviews are used on one hand to verify the input data and on the other hand to test the practical viability of the proposed price setting.

Alternative generation

Historical energy price data is analysed to determine the average price for each hour of the day. The price of each hour, so from 00:00 to 01:00 and from 01:00 to 02:00 etc., corresponds with the average of all prices that were related with that hour in 2024. Analysing these prices show two distinctive time periods during the day during which the price of a kWh is significantly higher; from 07:00 until 10:00 in the morning and from 17:00 to 22:00 in the evening. In the hours around noon, the prices are lowest, even cheaper than at night. Presumably because of the presence of solar energy. The difference between electricity prices can be rather large. Compared to the most expensive hour (19:00 - 20:00) the cheapest hour (14:00 - 15:00) is almost twice as cheap. Although the difference of almost 4 Euro cents per kWh may not seem very relevant, it becomes significant when one considers a fully loaded battery container of 2600 kWh. On a full battery, it can thus save about 100 Euros. Expanding that further to a whole day, in which the barge might need to swap batteries every two hours, one can imagine the large cost differentiation.

With this knowledge, multiple price settings implemented by the intermediate player, the supplier of the battery containers, towards its customers (the skippers) can be considered. One could set the fluctuating price from the energy supplier from the grid through to the end-user, or charge an on- and off-peak hours price. Among the options are also a somewhat more flexible pricing than simply on- and off-peak or the current setting, a fixed price. In this research, different pricing scenarios will be tested to see if one price setting can be preferred over the others. The different strategies are shown in C.1

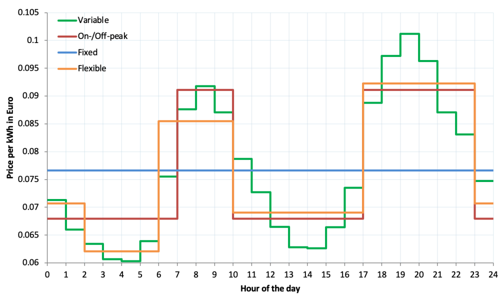

Figure C.1: Price per hour for all price settings

Mathematical model

An optimisation model as discussed in the method, is constructed to find the minimal cost for a fleet of vessels while respecting their operational constraints. These operational constraints can consist of factors such as delivery deadlines, time needed for swapping and the vessels maximum speed.

The model is built for the locations that are either already in use or identified as development focus locations for the near future. These locations are fully connected via inland waterways. The full connectivity ensures that between all combinations of locations one or more paths are available. Each path is exactly as long as the navigable route between the two locations. This avoids the use of too narrow and shallow waterways, so all routes can actually be sailed by the barges.

For scalability purposes, the model is developed in discrete time steps. The model consists of one hour time steps, from 00:00 to 01:00 until 23:00 to 24:00. This is because the price of electricity is expected to depend on the day-ahead price for each hour of the next day. A large time window for the operations in the model, is thus not very beneficial as the prices for hours further away than 24 hours are not know, and thus hard to optimise. Furthermore, this 24 hour window, leaves exactly enough room to include the requirements of the crews resting time.

Within the 24 hour window, the MILP model is searching for the lowest costs for the fleet of vessels in the model. This means that one vessel might be forced to make a little detour in order to minimise the cost for another vessel, but the optimisation ensures that the final solution is optimal for the fleet as a whole. Individual ships can optimise their operations within the same model, once that vessel is implemented as the only vessel of a fleet. The model determines the optimal solution by assigning each vessel to swapping locations, if swapping is needed. This is done in such a way that in the hour the swap takes place, energy prices are as low as possible within the operational constraints. Ensuring optimal arrival times at swapping location is done by determining a route from the origin to destination and assigning a speed over every arc for each vessel. Furthermore, the timing can be influenced by giving the vessels the possibility to wait at a swapping station before continuing their journey.

Below, some constraint that shape the model behaviour are discussed. The full mathematical model can be found in the appendix. Table C.1 shows the meaning of the different symbols used in the formulation.

Table C.1: Notation mathematical model

Sets and indices		
$\mathcal{L}$	Set of all legs	$\ell \in \mathcal{L}$
$R(\ell)$	Candidate routes for leg ℓ	$r \in R(\ell)$
$A^{\ell r}$	Arcs on route r of leg ℓ	$(i,j) \in A^{\ell r}$
H	Hourly time slots	$k \in H = \{0,\dots,H_{\max}-1\}$
S	Set of discrete speeds	$s \in S$
R_{all}	Swap-station nodes	$n \in R_{\text{all}}$
Parameters		
B_{cap}	Battery capacity per battery pack	[kWh]
p_k	Energy price at hour k	[Euro/kWh]
SF	Fee per swap	[Euro]
TC	Fraction lost on resale	[–]
d_{ij}	Distance of arc (i,j)	[km]
e_s	Energy per km at speed s	[kWh/km]
M_t	Big-M for time constraints	[h]
M_{soc}	Big-M for SoC / energy constraints	[kWh]
Decision variables		
$X^{\ell r}$	1 if route r chosen for leg ℓ	$\{0,1\}$
$z^{\ell r}_{ij,s}$	1 if arc (i,j) is traversed at speed s	$\{0,1\}$
$y^{\ell r}_{nk}$	1 if a swap occurs at node n at hour k	$\{0,1\}$
$\mathrm{pick}^{\ell r}_{nk}$	Packs picked up at node n at hour k	$[0, N_{\max}]$
$\mathrm{sell}^{\ell r}_{nk}$	Energy (kWh) sold back at node n, hour k	$[0, B_{\text{cap}} N_{\max}]$
$\mathrm{BA}^{\ell r}_{n}$	Packs on board upon arrival at node n	$[0, N_{\max}]$
$t^{\ell r}_{n}$	Arrival time at node n	$[0,\infty)$
$\mathrm{dep}^{\ell r}_{n}$	Departure time from node n	$[0,\infty)$
$E^{\ell r,\text{arr}}_{n}$	Energy on board upon arrival (kWh)	$[0, B_{\text{cap}} N_{\max}]$
$E^{\ell r,\text{dep}}_{n}$	Energy on board upon departure (kWh)	$[0, B_{\text{cap}} N_{\max}]$

Objective:

$$
\begin{aligned}
\min \sum_{\ell\in\mathcal{L}} \sum_{r\in R(\ell)} & B_{\text{cap}}\, p_{t^{\ell r}_{\text{orig}(\ell)}}\, \mathrm{BA}^{\ell r}_{\text{orig}(\ell)} \\
&+ \sum_{\ell\in\mathcal{L}} \sum_{r\in R(\ell)} \sum_{n\in R_{\text{all}}} \sum_{k\in H} B_{\text{cap}}\, p_k\, \mathrm{pick}^{\ell r}_{nk} \\
&+ \mathrm{SF}\Bigg(\sum_{\ell\in\mathcal{L}} \sum_{r\in R(\ell)} \mathrm{BA}^{\ell r}_{\text{orig}(\ell)} + \sum_{\ell\in\mathcal{L}} \sum_{r\in R(\ell)} \sum_{n\in R_{\text{all}}} \sum_{k\in H} y^{\ell r}_{nk} \Bigg) \\
&- \sum_{\ell\in\mathcal{L}} \sum_{r\in R(\ell)} \sum_{n\in R_{\text{all}}} \sum_{k\in H} (1-\mathrm{TC})\, p_k\, \mathrm{sell}^{\ell r}_{nk}
\end{aligned}
\tag{C.1}
$$

Subject to:

$$
E^{\ell r,\text{arr}}_{j} \le E^{\ell r,\text{dep}}_{i} - \sum_{s\in S} (\mathrm{d}_{ij} e_s)\, z^{\ell r}_{ij,s} + M_{\text{soc}}\Big(1 - \sum_{s} z^{\ell r}_{ij,s}\Big) \tag{C.2}
$$

$\forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ (i,j) \in A^{\ell r}$

$$\sum_{r \in R(\ell)} X^{\ell r} = 1 \tag{C.3}$$
$$\forall \ell \in \mathcal{L}$$

$$\sum_{s \in S} z^{\ell r}_{ij,s} = X^{\ell r} \tag{C.4}$$
$$\forall \ell \in \mathcal{L},\ r \in R(\ell),\ (i,j) \in A^{\ell r}$$

$$t^{\ell r}_j \geq \mathrm{dep}^{\ell r}_i + \sum_{s \in S} \frac{\mathrm{d}_{ij}}{s}\, z^{\ell r}_{ij,s} - M_t\,(1 - X^{\ell r}) \tag{C.5}$$
$$\forall \ell \in \mathcal{L},\ r \in R(\ell),\ (i,j) \in A^{\ell r}$$

$$y^{\ell r}_{nk} \leq X^{\ell r} \tag{C.6}$$
$$\forall \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\text{all}},\ k \in H$$

The formulas above for the heart of the mathematical model that is shown in full in Appendix B. The objective and constraints shown here give a great impression of the behaviour of the model.

The model starts with the objective function (C.1).The objective function intends to minimise the operational cost of the battery swapping system. The first two summations charge the energy initially on board at each leg's origin and any batteries picked up at stations at the prevailing hourly electricity prices (each multiplied by the battery capacity), while the SF term adds fixed swap fees for initial packs and for every executed swap. The final negative summation credits revenue from remaining energy that is sold back to the battery supplier by the skipper, reduced by the transaction TC, so the objective trades off purchasing energy, paying swap fees, and recovering value from sold back energy.

Constraint (C.3) ensures that for each leg a vessel must sail, exactly one route is chosen. This is important as there are multiple ways to get from A to B. The model must thus make sure the the optimal route is chosen. This optimal route is not necessarily the shortest, as it can happen that a detour is needed to pick up a battery container at a different location. Furthermore, on each arc that is part of the chosen route, exactly on speed must be selected for the vessel. This speed selection is the advised speed for the vessel to travel over an arc with. If a vessel needs to sail from A to B and then to C, a specific speed is selected for the arc from A to B and for B to C, which does not have to be the same as from A to B. Constraint (C.4) ensures that on each travelled arc, one speed is selected.

The general arrival time constraint (C.5) enforce that arrival at node j equals departure from i plus travel time (distance over speed). In a similar fashion, the remaining energy with which a vessel arrives is the energy it departed with from the previous node minus the energy that is consumed on the way, constraint (C.2) shows the mathematical formulation for this. Finally, the last constraint highlighted here makes sure that the model only lets vessels swap batteries if the vessel actually goes to that location. In other words, constraint (C.6) tells that the location where a battery swap is executed must actually be on the route of the vessel.

With the model now constructed, see also the appendix, the model is implemented in Python. This implementation allows the model to test the scenarios and return numerical output. This will be discussed in the next section.

Experimental plan & results

In order to determine the optimal price setting, not only is it important to investigate what would work best for the current circumstances, but an open view towards possible developments in the future is required. Therefore, besides a scenario that best describes the current situation of the system, also scenarios that hold future possibilities, are further looked into. The different scenarios that are tested are shown in Table C.2.

Table C.2: Different scenarios to test

Scenarios	**Vessels**	**# bat. / facility**	**# swapping facilities**	**Bat. cap. (kWh)**
Base	10	2	9	2600
Bat. cap. +15%	10	2	9	2990
3 bat. per facility	10	3	9	2600
Extra locations	10	2	13	2600
3 bat., extra locations	10	3	13	2600
Extra vessels	15	2	9	2600
Extra locations, extra vessels	15	2	13	2600

With help of the implementation of the mathematical formulation in Python, the different scenarios are tested for all four potential price settings. In Table C.3, the impact the different price settings have on the minimal energy cost is shown. In this table, the outcome of the fixed price setting is the baseline to which the other settings are compared to. The fixed price setting is used as base, as this is the currently used setting. The drop in percentages shows the potential cost reduction for the fleet of vessels.

Table C.3: Difference in percentage relative to fixed price setting (fixed = 1)

Scenarios	Variable	On-/Off-peak	Fixed	Flexible
Base	-15.74%	-11.22%	1	-13.44%
Bat. cap. +15%	-13.98%	-11.03%	1	-12.23%
3 bat. per facility	-16.25%	-11.76%	1	-13.68%
Extra locations	-14.78%	-10.35%	1	-12.30%
3 bat., extra locations	-15.22%	-10.95%	1	-12.82%
Extra vessels	-14.57%	-9.90%	1	-11.80%
Extra locations, extra vessels	-13.77%	-9.12%	1	-11.09%

From this table, it becomes clear that the variable price setting can ensure the largest cost reduction. Across the different scenarios, the variable setting can remove about 15%, the flexible alternative is capable of reducing the cost by around 13% and the on-/off-peak setting manages to reduce cost by around 10%. When comparing the numerical outputs of Table C.3 per scenario within the same pricing mechanism, the relative small impact of the different scenarios can be seen. For example, the gain in optimal outcome for a battery with 15% more capacity is only three-quarters of a percentage compared to the base scenario. The largest impact is in the scenario where the each facility has an extra battery available at the start and four additional locations are open. This results in a decrease of total costs of 2.4 to 3%, depending on the price setting.

While the different scenarios appear not to have a large impact on the solution, it is further investigated what the impact is of the current fleet optimisation model compared a model in which each vessel can sail its own optimal route. In the variance analysis where each vessel is independent of other vessels, the number of batteries available at swapping facilities is not limited any more. This way, vessels can determine their own optimal route without the interference of other vessels. When the results of the variance analysis, in Table C.4, are compared to those of the original experiments in table C.3, the similarities in outcomes become visible. The variance analysis results are almost identical, just marginally higher. This indicates, that also in a future scenario where sufficient battery containers for each vessel's demand are available, the variable price setting still ensure the greatest cost reduction.

Table C.4: Difference in percentage relative to fixed price setting (variance analysis)

Scenarios	Variable	On-/Off-peak	Fixed	Flexible
Base	-16.26%	-11.76%	1	-13.68%
Bat. cap. +15%	-14.67%	-11.15%	1	-12.59%
Extra locations	-15.22%	-10.95%	1	-12.82%
Extra vessels	-14.61%	-9.90%	1	-11.84%
Extra locations, extra vessels	-13.94%	-9.27%	1	-11.17%

Practical viability

Although the model showed favourable results for the variable price setting, the practical viability of the setting is discussed with those who are supposed to work with the system. These professionals in the field were interviewed to determine their opinions on the different settings. Industry stakeholders confirmed that potential energy cost reductions of the order of 10–15% are attractive, but they also highlighted important operational considerations for mainly the variable pricing scheme. In interviews, skippers who pay their own fuel costs enthusiastically welcomed more flexible price setting since these promise to lower their expenses, whereas contract skippers preferred a more stable pricing system as the variable pricing would leave little room for the skippers to determine their own rest hours. Freight planners similarly valued simplicity: they noted that imposing hourly prices would substantially increase scheduling complexity. Terminal operators emphasised the importance of evenly distributed vessel arrivals. They pointed out that very low night time prices as in the fully variable or flexible schemes could overload staff during off-peak hours.

In practical terms, the fully variable price setting, despite appearing to be most cost effective, faces implementation barriers. All groups agreed that it could shift work to inconvenient hours and constrain crew rest schedules. Skippers in particular would lose autonomy over timing their resting hours. While planners believed their software could handle hourly rates, they were concerned that sticking to this planning would cause problems. By contrast, an on-/off-peak tariff was viewed as far more manageable. Besides, it delivers most of the savings but only has two price levels, allowing flexible rest windows and removes any single cheapest hour at night. Overall, the implementability of each price setting mirrors its complexity. The existing fixed-rate approach is operationally simplest but offers the least cost benefit. Variable pricing can achieve the largest energy cost reductions in the model, but it would require significant adjustments in the planning and thus meets resistance in practice. The on-/off-peak tariff offers a middle ground; it does not push swaps towards times when terminals have minimal staff, and leaves most autonomy of the skippers over their resting hours. In summary, stakeholder feedback suggests that a on-/off-peak price setting is the most viable to implement, as it balances cost savings with practical scheduling and staffing constraints. Table C.5 summarises the acceptance of the different actors on the proposed price setting.

Table C.5: Perceptions of different professions on the price setting

Function	Variable	On-/Off-peak	Fixed	Flexible
Skippers	-	±	±	-
Planners	-	+	±	±
Terminal operators	-	±	±	-

Discussion and conclusion

The optimisation model consistently showed for all scenarios and both the standard model as well as the variance model that time dependent prices can yield substantial energy cost savings compared to a fixed price. Introducing a simple two-tier on/off-peak tariff already reduced costs by roughly 10%, while adding a third price level strategy brought savings up to approximately 12%, and fully variable pricing saved up to about 15%. That these numbers were more or less consistent across all tested scenarios, confirmed the robustness of the ranking. In every case tested, the variable setting achieved the lowest total cost, the fixed-rate setting the highest, and the on/off-peak and flexible settings were in between. Notably, the largest incremental gain occurred when moving from one flat price to a two-tier structure. An alternative analysis optimising each barge individually produced the same relative ordering of price settings, implying that the findings do not depend on the particular fleet optimisation.

However, these are just the model results, these results must be interpreted in context before they get there full value. The model demonstrates a clear trade-off: more fluctuating prices let barges shift swaps into low-price periods, but they also introduce complexity that can impede scheduling. The interviews underscored this balance. While planners and skippers sailing at own expense appreciate the ±10–15% potential savings from dynamic pricing, they also have practical concerns on planning complexity and the timing of crew resting hours. Accordingly, the study deems a simple on/off-peak setting to be the best compromise. It captures the bulk of the cost benefit while preserving scheduling simplicity and allowing crews some control over their own rest times.

These findings might have broader impact for hinterland transportation. They suggest that the battery container provider should consider time of buying price to encourage charging during off-peak periods. A properly designed price setting can help smooth electricity demand over the day and improve the business case for e-barges by lowering operating costs. At the same time, implementation must account for human factors and terminal capacities. For instance, a price setting that pushes too much activity into the odd working hours could strain crew and port resources. Overall, a well-structured on-/off-peak price setting could significantly reduce the energy costs of zero emission barge logistics while still respecting operational constraints. However, the impact further down the transportation line must be considered.

There are some limitations to this study that must be taken into account. The model optimises only the cost of energy; it does not account for other cost such as crew labour costs or loss of time costs. All travel times and swap processes were assumed deterministic, and batteries were treated as identical with fixed recharge times. In practice, variability in river currents, energy consumption and waiting times could negatively affect schedules. Batteries at different states of charge, on the other hand, could allow more flexibility than assumed. Furthermore, the interviews, while insightful, involved only a small sample of four skippers, three planners, and one terminal operator, all in the Dutch market; broader industry feedback might reveal additional perspectives. Consequently, the absolute savings reported should be considered with these limitations in mind.

Future work could address these limitations. An useful extension to the constructed model is to develop a multi-objective optimisation that includes labour and service costs alongside energy costs, or to incorporate stochastic elements such as uncertain travel times or energy consumption. Upscaling to a larger network of ports, terminals and swap stations, would test the scalability of the initial solution found in this research. Exploring battery repositioning and the consequences of dynamic pricing on the full logistics chain could reveal system wide impacts of varying energy prices for e-barges. Finally, empirical studies would validate how skippers and planners actually respond on variable prices, rather then only how they say the would respond. By tackling these areas, future research can further improve the understanding of the impact dynamic pricing can have on the e-barge system.

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Mathematical model

The mathematical model starts on the next page.

The mathematical model starts on the next page.

Table C.6: Notation for battery swapping model

Sets and Indices		
$\mathcal{L}$	Set of all legs	$\ell \in \mathcal{L}$
$R(\ell)$	Candidate routes for leg ℓ	$r \in R(\ell) = \{0, \ldots, K_\ell - 1\}$
$A^{\ell r}$	Arcs on route r of leg ℓ	$(i, j) \in A^{\ell r}$
$N^{\ell r}$	Nodes on route r of leg ℓ	$n \in N^{\ell r}$
D	Calendar-day indices	$d \in D = \{0, \ldots, D_{\max} - 1\}$
H	Hourly time slots	$k \in H = \{0, \ldots, H_{\max} - 1\}$
H_{start}	Feasible rest-block start times	$s \in H_{\text{start}} = \{0, \ldots, H_{\max} - L\}$
V	Set of all vessels	$v \in V$
S	Set of discrete speeds	$s \in S$
R_{all}	Swap-station nodes	$n \in R_{\text{all}} \subseteq V$
Parameters		
B_{cap}	Battery capacity per battery pack	[kWh]
$N_{\max}$	Max batteries per vessel	[–]
T_{swap}	Time needed per swap	[h]
L	Rest-block length (hours)	[h]
SF	Fee per swap	[€]
TC	Fraction lost on resale	[–]
C	Time needed to recharge a battery	[h]
d_{ij}	Distance of arc (i, j)	[km]
e_s	Energy per km at speed s	[kWh/km]
p_h	Price at hour h	[€/kWh]
I_n	Initial packs at station n	[–]
START^ℓ	Start time of leg ℓ	[h]
DEAD^ℓ	Deadline of leg ℓ	[h]
$orig(\ell)$	Starting location of leg ℓ	[-]
$M_t, M_{\text{soc}}, M_{\text{sell}}$	Big-M constants	[-],[-],[-]
Decision Variables		
$X^{\ell r}$	1 if route r chosen for leg ℓ	$\{0, 1\}$
$z^{\ell r}_{ij,s}$	1 if arc (i, j) on route (ℓ, r) at speed s	$\{0, 1\}$
$y^{\ell r}_{nk}$	1 if swap at node n time k	$\{0, 1\}$
$\text{pick}^{\ell r}_{nk}$	Packs picked up	$[0, N_{\max}]$
$\text{drop}^{\ell r}_{nk}$	Packs dropped	$[0, N_{\max}]$
$\text{sell}^{\ell r}_{nk}$	kWh sold back	$[0, B_{\text{cap}} N_{\max}]$
$\text{sbin}^{\ell r}_{nk}$	1 if selling activated	$\{0, 1\}$
$t^{\ell r}_n$	Arrival time at node n	$[0, \infty)$
$\text{dep}^{\ell r}_n$	Departure time at node n	$[0, \infty)$
$w^{\ell r}_{nd}$	Waiting hours at n on day d	$[0, \infty)$
$\text{BA}^{\ell r}_n$	Packs on board upon arrival	$[0, N_{\max}]$
$\text{BD}^{\ell r}_n$	Packs on board upon departure	$[0, N_{\max}]$
$E^{\ell r,\text{arr}}_n$	Energy upon arrival	$[0, B_{\text{cap}} N_{\max}]$
$E^{\ell r,\text{dep}}_n$	Energy upon departure	$[0, B_{\text{cap}} N_{\max}]$
$b^{\ell r}_{ns}$	1 if rest-block starts at s at n	$\{0, 1\}$
$v^v_{\text{rest},k}$	1 if vessel v rests in hour k	$\{0, 1\}$

Objective:

$$\min \sum_{\ell \in \mathcal{L}} \sum_{r \in R(\ell)} B_{\text{cap}}\, p_{t^{\ell r}_{\text{orig}(\ell)}}\, \text{BA}^{\ell r}_{\text{orig}(\ell)} + \sum_{\ell \in \mathcal{L}} \sum_{r \in R(\ell)} \sum_{n \in R_{\text{all}}} \sum_{k \in H} B_{\text{cap}}\, p_k\, \text{pick}^{\ell r}_{nk} \tag{C.7}$$

$$+\ \mathrm{SF}\left(\sum_{\ell\in\mathcal{L}}\sum_{r\in R(\ell)} \mathrm{BA}^{\ell r}_{\mathrm{orig}(\ell)} + \sum_{\ell\in\mathcal{L}}\sum_{r\in R(\ell)}\sum_{n\in R_{\mathrm{all}}}\sum_{k\in H} y^{\ell r}_{nk}\right)$$
$$-\sum_{\ell\in\mathcal{L}}\sum_{r\in R(\ell)}\sum_{n\in R_{\mathrm{all}}}\sum_{k\in H}(1-\mathrm{TC})\, p_k\, \mathrm{sell}^{\ell r}_{nk}$$

Subject to:

$\sum_{r\in R(\ell)} X^{\ell r}=1$	$\forall\,\ell\in\mathcal{L}$	(C.8)
$\sum_{s\in S} z^{\ell r}_{ij,s}=X^{\ell r}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ (i,j)\in A^{\ell r}$	(C.9)
$E^{\ell r,\mathrm{arr}}_{\mathrm{orig}(\ell)}=B_{\mathrm{cap}}\,\mathrm{BA}^{\ell r}_{\mathrm{orig}(\ell)}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell)$	(C.10)
$E^{\ell r,\mathrm{dep}}_{\mathrm{orig}(\ell)}=B_{\mathrm{cap}}\,\mathrm{BD}^{\ell r}_{\mathrm{orig}(\ell)}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell)$	(C.11)
$\mathrm{BA}^{\ell r}_i\ge X^{\ell r}$	$\forall\,\ell,r,\ (i,j)\in A^{\ell r}$	(C.12)
$y^{\ell r}_{nk}\le X^{\ell r}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(C.13)
$\mathrm{pick}^{\ell r}_{nk}+\mathrm{drop}^{\ell r}_{nk}\ge y^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(C.14)
$\mathrm{pick}^{\ell r}_{nk}\le N_{\max}\,y^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(C.15)
$\mathrm{drop}^{\ell r}_{nk}\le N_{\max}\,y^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(C.16)
$\mathrm{sell}^{\ell r}_{nk}\le B_{\mathrm{cap}}\,\mathrm{drop}^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(C.17)
$\mathrm{sell}^{\ell r}_{nk}\le (B_{\mathrm{cap}}-\epsilon)\,\mathrm{sbin}^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(C.18)
$y^{\ell r}_{nk}\ge \frac{1}{N_{\max}}\,\mathrm{pick}^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(C.19)
$y^{\ell r}_{nk}\ge \frac{1}{N_{\max}}\,\mathrm{drop}^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(C.20)
$t^{\ell r}_n\le k+M_t\,(1-y^{\ell r}_{nk})$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(C.21)
$t^{\ell r}_n\ge k-M_t\,(1-y^{\ell r}_{nk})$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(C.22)
$\mathrm{sbin}^{\ell r}_{nk}\le y^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(C.23)
$\mathrm{drop}^{\ell r}_{nk}\ge \mathrm{sbin}^{\ell r}_{nk}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(C.24)
$\mathrm{sell}^{\ell r}_{nk}\le E^{\ell r,\mathrm{arr}}_n$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(C.25)
$\mathrm{sell}^{\ell r}_{nk}\ge E^{\ell r,\mathrm{arr}}_n-M_{\mathrm{sell}}\,(1-\mathrm{sbin}^{\ell r}_{nk})$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}},\ k\in H$	(C.26)
$E^{\ell r,\mathrm{arr}}_n\le B_{\mathrm{cap}}\,\mathrm{BA}^{\ell r}_n$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}}$	(C.27)
$E^{\ell r,\mathrm{dep}}_n\le B_{\mathrm{cap}}\,\mathrm{BD}^{\ell r}_n$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in R_{\mathrm{all}}$	(C.28)
$t^{\ell r}_j\ge \mathrm{dep}^{\ell r}_i+\sum_{s\in S}\frac{\mathrm{d}_{ij}}{s}\,z^{\ell r}_{ij,s}-M_t\,(1-X^{\ell r})$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ (i,j)\in A^{\ell r}$	(C.29)
$t^{\ell r}_j\le \mathrm{dep}^{\ell r}_i+\sum_{s\in S}\frac{\mathrm{d}_{ij}}{s}\,z^{\ell r}_{ij,s}+M_t\,(1-X^{\ell r})$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ (i,j)\in A^{\ell r}$	(C.30)
$\mathrm{dep}^{\ell r}_n=t^{\ell r}_n+T_{\mathrm{swap}}\sum_{k\in H}y^{\ell r}_{nk}+\sum_{d\in D}w^{\ell r}_{nd}$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ n\in N^{\ell r}$	(C.31)
$\mathrm{BA}^{\ell r}_j=\mathrm{BD}^{\ell r}_i$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ (i,j)\in A^{\ell r}$	(C.32)
$E^{\ell r,\mathrm{arr}}_j\le E^{\ell r,\mathrm{dep}}_i-\sum_{s\in S}(\mathrm{d}_{ij}e_s)\,z^{\ell r}_{ij,s}+M_{\mathrm{soc}}(1-\sum_s z^{\ell r}_{ij,s})$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell)\ (i,j)\in A^{\ell r}$	(C.33)
$E^{\ell r,\mathrm{arr}}_j\ge E^{\ell r,\mathrm{dep}}_i-\sum_{s\in S}(\mathrm{d}_{ij}e_s)\,z^{\ell r}_{ij,s}-M_{\mathrm{soc}}(1-\sum_s z^{\ell r}_{ij,s})$	$\forall\,\ell\in\mathcal{L},\ r\in R(\ell),\ (i,j)\in A^{\ell r}$	(C.34)
$\sum_{k\in H}\mathrm{pick}^{\ell r}_{nk}\le I_n+\sum_{h\in H}^{h+C\le k}\sum_{\ell',r'}\mathrm{drop}^{\ell' r'}_{nh}-\sum_{h<k}\sum_{\ell',r'}\mathrm{pick}^{\ell' r'}_{nh}$	$\forall\,n\in R_{\mathrm{all}},\ k\in H$	(C.35)

$$t^{\ell r}_{\mathrm{orig}(\ell)} \geq \mathrm{START}^{\ell} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell) \tag{C.36}$$

$$t^{\ell r}_{\mathrm{dest}(\ell)} \leq \mathrm{DEAD}^{\ell} + M_t(1 - X^{\ell r}) \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell) \tag{C.37}$$

$$\mathrm{dep}^{\ell r}_{\mathrm{dest}(\ell)} \leq t^{\ell' r'}_{\mathrm{orig}(\ell')} \qquad \forall\, (\ell \in \mathcal{L},\ r \in R(\ell)), (\ell' \in \mathcal{L},\ r' \in R(\ell)) \tag{C.38}$$

$$\sum_{\ell \in \mathcal{L}(v)} \sum_{r \in R(\ell)} \sum_{n \in R_{\mathrm{all}}} \sum_{s=24\,d}^{24\,d+24-L} b^{\ell r}_{ns} = 1 \qquad \forall\, v \in V,\ d \in D \tag{C.39}$$

$$b^{\ell r}_{ns} \ \leq\ X^{\ell r} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\mathrm{all}},\ s \in H_{\mathrm{start}} \tag{C.40}$$

$$t^{\ell r}_{n} \ \leq\ s \ +\ M_t \left(1 - b^{\ell r}_{ns}\right) \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in N^{\ell r},\ s \in H_{\mathrm{start}} \tag{C.41}$$

$$\mathrm{dep}^{\ell r}_{n} \ \geq\ s + L\ -\ M_t \left(1 - b^{\ell r}_{ns}\right) \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in N^{\ell r},\ s \in H_{\mathrm{start}} \tag{C.42}$$

$$w^{\ell r}_{nd} \ \leq\ (24 - L) \left(1 - \sum_{s=24d}^{24d+24-L} b^{\ell r}_{ns}\right) \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\mathrm{all}},\ d \in D \tag{C.43}$$

$$\sum_{\ell \in \mathcal{L}(v)} \sum_{r \in R(\ell)} \sum_{n \in R_{\mathrm{all}}} w^{\ell r}_{nd} \ \geq\ 4 \qquad \forall\, v \in V,\ d \in D \tag{C.44}$$

$$w^{\ell r}_{nd} \leq X^{\ell r} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\mathrm{all}},\ k \in H \tag{C.45}$$

$$v^{v}_{\mathrm{rest},k} \ \geq \sum_{\ell \in \mathcal{L}} \sum_{r \in R(\ell)} \sum_{n \in R_{\mathrm{all}}} \sum_{s \in H_{\mathrm{start}}}^{s \leq k \leq s+L-1} b^{\ell r}_{ns} \qquad \forall\, v \in V,\ k \in H \tag{C.46}$$

$$v^{v}_{\mathrm{rest},k} \ \leq\ 1 \qquad \forall\, v \in V,\ k \in H \tag{C.47}$$

Non negativity and binary domain constraints:

$$X^{\ell r} \in \{0,1\} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell) \tag{C.48}$$

$$z^{\ell r}_{ij,s} \in \{0,1\} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ (i,j) \in A^{\ell r},\ s \in S \tag{C.49}$$

$$y^{\ell r}_{nk} \in \{0,1\} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\mathrm{all}},\ k \in H \tag{C.50}$$

$$\mathrm{sbin}^{\ell r}_{nk} \in \{0,1\} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\mathrm{all}},\ k \in H \tag{C.51}$$

$$\mathrm{pick}^{\ell r}_{nk},\quad \mathrm{drop}^{\ell r}_{nk},\quad \mathrm{sell}^{\ell r}_{nk} \geq 0 \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\mathrm{all}},\ k \in H \tag{C.52}$$

$$\mathrm{BA}^{\ell r}_{n},\quad \mathrm{BD}^{\ell r}_{n},\quad E^{\ell r,\mathrm{arr}}_{n},\quad E^{\ell r,\mathrm{dep}}_{n} \geq 0 \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\mathrm{all}} \tag{C.53}$$

$$t^{\ell r}_{n},\quad \mathrm{dep}^{\ell r}_{n} \geq 0 \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in N^{\ell r} \tag{C.54}$$

$$w^{\ell r}_{nd} \geq 0 \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\mathrm{all}},\ d \in D \tag{C.55}$$

$$v^{v}_{\mathrm{rest},k} \in \{0,1\} \qquad \forall\, v \in V,\ k \in H \tag{C.56}$$

$$b^{\ell r}_{ns} \in \{0,1\} \qquad \forall\, \ell \in \mathcal{L},\ r \in R(\ell),\ n \in R_{\mathrm{all}},\ s \in H_{\mathrm{start}} \tag{C.57}$$

Objective and constraints explanation

The model starts with the objective function (C.7).The objective function intends to minimise the operational cost of the battery swapping system. The first two summations charge the energy initially on board at each leg's origin and any batteries picked up at stations at the prevailing hourly electricity prices (each multiplied by the battery capacity), while the SF term adds fixed swap fees for initial packs and for every executed swap. The final negative summation credits revenue from remaining energy that is sold back to the battery provider by the skipper, reduced by the transaction TC, so the objective trades off purchasing energy, paying swap fees, and recovering value from sold back energy.

The constraints section begins by enforcing that exactly one route is selected per leg (C.8), and for each used route, exactly one speed is chosen for every arc (C.9). To ensure full battery deployment at each leg's origin, the arrival and departure energy at each start is tied to the number of packs multiplied by the battery capacity (C.10), (C.11), and any active arc must carry at least one battery pack (C.12).

Battery exchanges can only happen on legs that are chosen (C.13), and if a swap occurs then the sum of packs picked up and dropped off must be at least one (C.14). The pickup and drop quantities are limited by vessel capacity and linked to the swap decision via binary variables (C.15), (C.16), (C.19), (C.20).

Energy selling is enabled only when packs are dropped: the sold energy cannot exceed the dropped pack capacity (C.17), (C.18), and the sell-binary is tied to the swap event and drop action (C.23), (C.24). The amount of energy sold cannot exceed the energy on board upon arrival (C.25), and if selling is activated then all available arrival energy must be sold (C.26).

Temporal constraints ensure consistency: if a swap event occurs at hour k, the arrival time must match this hour (C.21), (C.22). The general travel-time constraints enforce that arrival at node j equals departure from i plus travel time (distance over speed) (C.29), (C.30), and each node's departure time equals its arrival time plus swap duration plus any waiting (C.31).

Flow constraints link battery packs and energy: packs on board carry over from arc start to arc end (C.32), and arrival energy equals departure energy minus consumption from travel (C.33), (C.34). Both arrival and departure energy are bounded by the pack capacity (C.27), (C.28).

Station inventory is balanced by ensuring that cumulative pickups at a node do not exceed the initial inventory plus all previously dropped packs that have recharged (C.35).

Scheduling constraints enforce that each leg departs no earlier than its start time (C.36) and arrives by its deadline (C.37); the next constraint guarantees that if one leg follows another, its departure occurs after the predecessor's arrival (C.38).

Mandatory waiting and rest are modelled via daily rest blocks of fixed length L: exactly one rest block per vessel per day (C.39). Rest blocks are tied to chosen legs (C.40) and enforced by requiring arrival and departure times to bracket the rest interval (C.41), (C.42). No waiting hours occur during a scheduled rest (C.43). Each vessel must accumulate at least four waiting hours per day (C.44), and waiting hours can only occur on active legs (C.45). The hourly rest indicator ensures consistent scheduling: if a rest block starts at hour s, the vessel is in rest for hours s through $s+L-1$ (C.46), and at most one rest indicator can be active at any time (C.47).

Finally, all decision variables are restricted to appropriate domains: selection and event variables are binary (C.48), (C.57), while pack, energy, time, and waiting variables are non-negative (constraints (C.52), (C.55).