A method for optimal charging station placement for ships

Combining a flow-refueling location model and an agent-based simulation

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TUDelft

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by

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to conclude the Master Engineering and Policy Analysis at the Delft University of Technology

Abstract

Extensive electrification of the inland shipping sector is necessary to achieve the EU goals to be climate neutral and increase inland shipping by 50% by 2050. This requires a thoughtful and large-scale roll-out of new charging stations layouts, for ships with relatively high and largely varying energy demands. Current approaches for optimal charging station placement, mostly neglect temporal demand fluctuations and cannot cope with varying charging demands. Therefore, we aimed to develop a method that combined a capacitated flow-capturing approach and an agent-based simulation. Moreover, the resulting method was applied to the Dutch inland waterway freight transport sector in a case study. Results indicated that a large-scale transition to battery-electric propulsion is technically possible, but is likely economically unfeasible. The case study can be used to support decision-making towards renewable shipping. In addition, the newly designed may also be used to site energy hubs. Forthcoming, methods to come to efficient charging station layouts will be needed to stimulate the uptake of electrified transportation and avoid lock-ins to inefficient investments.

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Preface

With this thesis, I conclude my master's programme in Engineering & Policy Analysis at the faculty of Technology, Engineering & Policy Analysis of the TU Delft. At the same time, my time as a student has also come to an end.

First off, I want to thank Dr. ir. P.W. Heijnen for the day-to-day supervision during my thesis. I am certain that thanks to her great commitment and critical eye, I was able to take my thesis to a much higher level. Besides, I also want to thank my second supervisor Prof. dr. M.E. Warnier for his feedback and approachability throughout my thesis. Also, I want to thank the people of Witteveen+Bos for their guidance and good company at the office. Not just my supervisors J. van Dongen, P. Hoogvorst and R. Eggermont, but all of the inspirational people at Witteveen+Bos. Being able to do my thesis at Witteveen+Bos was a real pleasure. In the office, I always had someone to spar with, which was enormously helpful. Finally, I also want to thank my family, friends and roommates, who encouraged me throughout my thesis.

F.P.S. (Fabian) Driessen
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Management summary

This research set off to design a new method to determine the optimal locations and capacities of charging stations for ships from a network perspective. Moreover, the goal was to apply this method to the Dutch inland freight shipping sector in a case study. To the author's best knowledge, optimal charging stations for ships had not been assessed from a network perspective before for ships in scientific literature. In contrast, optimal charging station placement along road networks for vehicles has been extensively studied in the past. Situating charging stations for vehicles with a limited range is fundamentally different compared to locating conventional refuelling stations, as a limited range and a significant recharging time have to be considered. Two key system characteristics which set apart battery-electric shipping from the more frequently studied battery-electric road transportation were identified: a relatively high absolute energy demand and highly varying energy demands between various types of ships.

Based on these characteristics, three factors which could be included in a model were found to be of increased importance:

1. Expected waiting times
2. Appropriate charging station sizing
3. The effects on the electricity grid

As such, the goal was to establish a method to guide decision-making regarding the optimal locations of charging stations for ships, which included these factors. To this end, two modelling methods were selected, which were found to complement each other well. The capacitated flow-refuelling model by Upchurch et al. (2009) and an agent-based simulation model (Epstein, 1999). These models were not earlier combined to the author's best knowledge. The capacitated flow-refueling model is a flow-capturing model, that can be applied to distribute a certain number of charging stations over a predetermined set of potential charging-station locations, based on trip-based origin-destination data. An agent-based model, on the other hand, is a simulation model which can be used to simulate the performance of a charging station layout.

Nevertheless, the capacitated flow-refueling model was designed to locate alternative refuelling stations for vehicles with a limited range. Not for battery-electric ships with highly varying energy demands. Hence, a modified version of the capacitated flow-refueling location model was established. This version of the flow-refueling model had several new features, to increase the suitability and determine optimal locations of charging stations for ships. Most importantly, it allowed for optimising the locations of charging stations considering the varying energy demands of various ships at the same time. An iterative method to guide decision-making regarding the optimal locations of charging stations was proposed and applied to the Dutch inland waterway shipping network. The first step of this method entailed applying the modified version of the capacitated flow-refueling model considering various potential ship ranges and roll-out strategies. This resulted in the optimal charging station layouts for these scenarios. Hereafter, the agent-based simulation was then applied to simulate these charging station layouts.

Before the method was applied to the case study, an actor analysis was established. Three aggregated actors were identified:

- Government agencies and other investors
- Shipping companies
- Port operators, land owners and grid operators

First off, government agencies and other investors can be seen as decision-makers regarding the actual realisation of charging stations. While maximum utilisation of charging stations leads to both the

highest profits and the highest possible CO_2 reductions, they have the same interests and goals. As such, the method for decision-making regarding the optimal locations and capacities of charging stations along waterways is established for mainly these actors. Besides, shipping companies are the ones who decided whether they want to switch to battery-electric propulsion systems. Finally, port operators, landowners and grid operators are actors which are crucial for enabling the realisation of any charging stations for ships. Of course, these actors can also benefit from battery-electric shipping. Based on the actor analysis, the average charging station utilisation and the average waiting time of ships were identified as the main model metrics to assess any charging station layout. Following this, the proposed method was applied to the case study.

Results indicated that neglecting temporal demand fluctuations may lead to infeasible designs and high waiting times. Moreover, a clear trade-off between the charging station utilisation and resulting waiting times was found. An increased utilisation always led to higher waiting times. Locating fewer, more powerful charging stations was found to lead to the best results in all studied experiments. Remarkably, considering a higher ship range and incorporating more potential charging station locations in the optimisation model, enabled more efficient charging station placement. In conclusion, it was successfully demonstrated that an agent-based simulation model can be used to simulate and complement a capacitated flow-refueling location model.

Forthcoming, the established method may be extended to study the optimal locations for energy hubs, by including multiple systems, such as shared mobility solutions, taxis, and busses. As for the case study, the range of a ship was identified as the most important uncertainty of the method. The range namely highly influences the possibilities for electrification of the Dutch inland freight shipping sector. Moreover, a large-scale transition of the Dutch inland shipping sector to battery-electric propulsion was found to be attainable, looking solely at the charging technologies and the expected developments. However, it is likely not economically feasible, because of the high number of required additional charging stops.

Contents

Nomenclature

Abbreviation	Definition
ABM	agent-based model
ABMS	agent-based modelling and simulation
AIS	automatic identification system
CEMT	Conférence européenne des ministres des Transports
CFRLM	capacitated flow-refueling location model
EDA	exploratory data analysis
EU	European Union
EV	electric vehicle
FRLM	flow-refueling location model
KPI	key performance indicator
OD	origin-destination
RWS	Rijkswaterstaat

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1. Introduction

Recently, the EU sharpened its CO_2 reduction goal and now aims to reduce emissions by 55% by 2035. By 2050, the EU even wants to be completely climate neutral (European Commission, 2021). Currently, the transportation sector is responsible for a fifth of the greenhouse gas emissions, and the urge to switch to renewable fuels intensifies (EEA, 2022). The application of renewable fuels, such as electricity, hydrogen or bio-diesel, often results in a limited range. This is because of the lower energy density of the concerned energy carriers (Varga et al., 2019). A vehicle may have to refuel multiple times, depending on where the refuelling stations are situated along the route (Kuby & Lim, 2005). This is illustrated in figure 1.1 for the round-trip between an origin (O) and destination (D). A vehicle can always reach the destination considering the range of 700 kilometres. However, in the first situation, a vehicle will run out of fuel travelling from B to A on its way back. If a refuelling station is located at the station at B, round-trips are feasible if vehicles refuel there twice. Also, the round-trip may be feasible with a refuelling station at A and an additional charging station. Though again, it matters where this additional refuelling station is located.

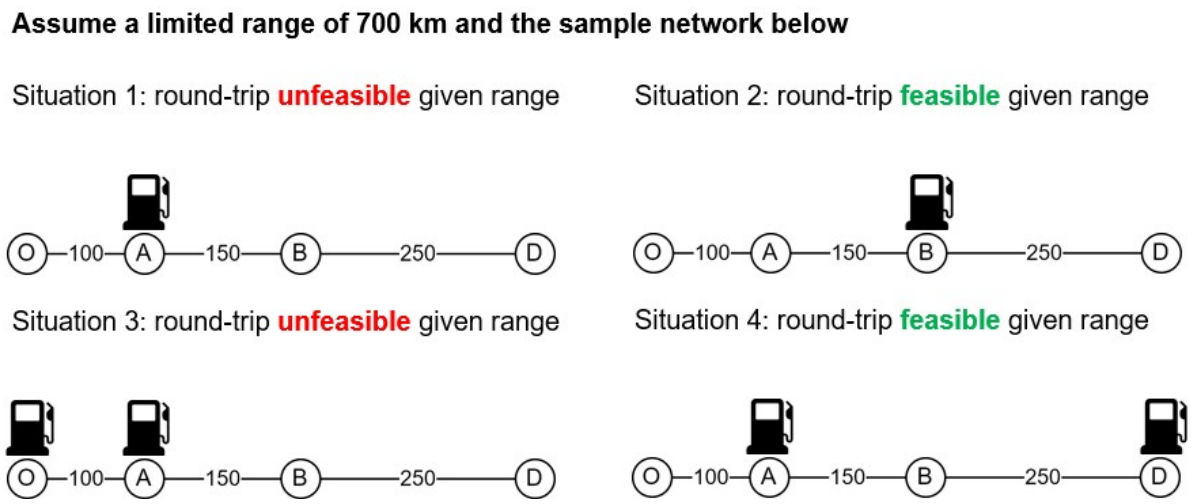

Figure 1.1: One or more refuelling stations may be needed to facilitate round-trips on the sample network considering a limited range. As illustrated, this heavily depends on their location.

In conclusion, the feasibility of a round-trip considering a limited range depends on the selected locations to site refuelling stations. Moreover, the needed number of refuelling stations may also depend on the selected locations. By contrast, methods designed to locate refuelling stations for 0conventional vehicles always assumed that a vehicle had to refuel at most once during a trip. Hence, situating refuelling stations for any means of transportation with a limited range is fundamentally different, compared to situating conventional refuelling stations. Battery-electric systems are currently seen as the most feasible technology to realise zero emission transport in the short- and middle-term (Stančin et al., 2020). Meanwhile, the required charging structure infrastructure which is needed to enable a large-scale transition is still in its infancy at most places and sometimes needs to be designed entirely from scratch. Therefore, methods are needed to determine the optimal locations of charging stations in a coordinated manner from a network perspective.

1.1. Complexity

Besides battery-electric systems, hydrogen-electric systems are expected to play an important role in the energy transition. Nevertheless, hydrogen is also needed for many other applications, so its availability for transport over short distances is likely to be limited. Especially as battery-electric systems offer a good alternative in this case (Stančin et al., 2020). Moreover, hydrogen's power-to-gas-to-power energy conversion efficiency is still only 15-40%, and wide-scale hydrogen production is yet to be realised (Egeland-Eriksen et al., 2021). Thus, using electricity to charge batteries is much more attractive from a sustainability perspective, and battery-electric systems will likely stay relevant within current prospects. Notably, previous research regarding the location problem for charging stations, almost solely considered road transport, particularly light-weight private electric vehicles (EVs). However, also in the energy-intensive inland shipping sector, battery-electric systems are seen as the most suitable technology to realise zero-emission transport in the short- and medium-term (Trahey et al., 2020; van der Geest & Menist, 2019; Varga et al., 2019).

1.2. Inland shipping

Inland shipping is considered a relatively clean form of transport because the emissions to transport a ton of freight over one kilometre are much lower than road transport (see figure 1.2. That is why the European Union (EU) aims to increase the shares of inland waterway and short-sea transport by 25% in 2030 and by 50% in 2050. However, at the same time electrification of the energy-intensive shipping industry is inevitable to achieve the sharpened European CO2 reduction goal to be climate neutral by 2050 (European Commission, 2021; Kumar et al., 2019). As of now, multiple battery-electric ferries and inland vessels are already in service (Karimi et al., 2020; NOS, 2021). Forthcoming, charging infrastructures will be needed along various inland shipping networks. Most of these will have to be designed largely from scratch. Hence, this study aimed to develop a method to determine the optimal charging station along waterways for ships.

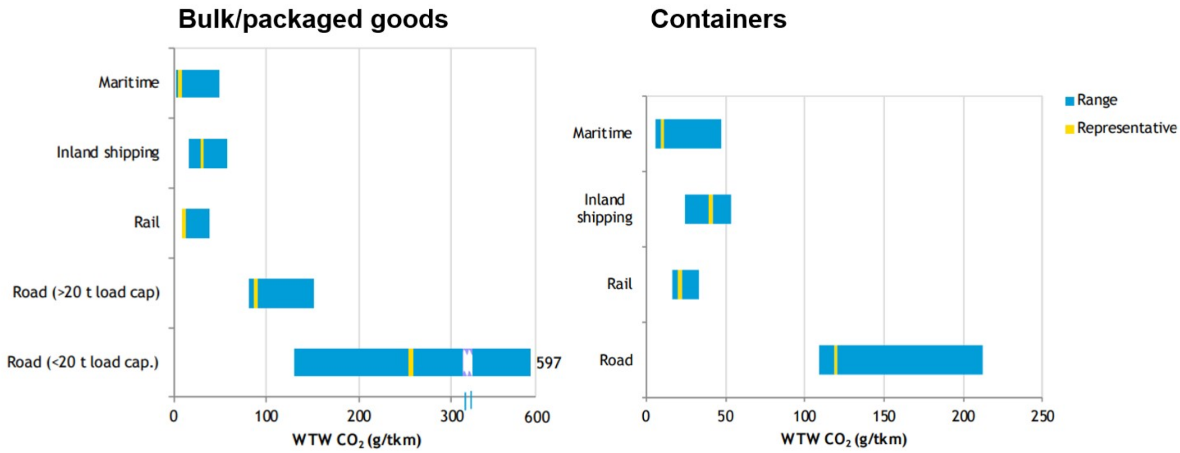

Figure 1.2: WTW (well-to-wheel for road and rail transport and well-to-wake for shipping) CO_2 transport emissions of bulk/packaged goods (left) and containers (right) to transport a ton over a distance of a kilometre adapted from Anne Klein et al. (2021). The WTW value includes all emissions which arise from fuel combusting during vehicle use, and all emissions which occur during the extraction, refinery, and transport of fuels or during electric power transmission and generation (Anne Klein et al., 2021).

Furthermore, the Dutch inland waterway freight transport network was selected as a case study to apply the method. The Dutch inland waterway freight transport network is the largest in Europe and transported 42.7 % of all Dutch freight in 2019 (Eurostat, 2021). The Dutch inland shipping sector is characterised by a large number of independent contractors which own one ship and some shipping companies which exploit several ships. As such, 4,100 companies were operating in the sector by the end of 2020, with around 4,500 ships (CBS, n.d.). Hence, it is unlikely that shipowners themselves will invest in costly battery swapping or charging stations. Thus, there is a clear chicken and egg problem here: shipowners will not switch to a battery-electric system if there are no charging stations, and no commercial parties will invest if there are no operational battery-electric ships. To cut through this, a Dutch national growth fund recently invested 50 million to electrify 45 ships and build 14 docking stations and 75 battery containers. Finally, the goal is to realise 150 battery-electric ships in 2030 and 400 battery-electric ships in 2050 (Klimaat, 2022).

1.3. Scope

Forthcoming, additional similar investments will likely be needed to achieve large-scale electrification in the Dutch inland freight shipping sector. Therefore, this research focused on developing a method to guide decision-making regarding the optimal siting and sizing of charging stations along an inland water transport network. To this end, existing approaches to optimally site charging stations on a transport network were assessed in a literature review. Notably, this problem is related to two separate physical networks, the electricity grid and the waterway network. This research aimed to determine the optimal locations of charging stations along the waterway network, explicit inclusion of the electricity grid was not within the scope of this research. Also, the construction costs at individual sites were not incorporated, a charging station at each location was assumed to incur the same costs.

1.4. Applications for decision-making

Remarkably, both private and public parties pursue the same goal when it comes to investments in charging infrastructure: maximum utilisation of the installed facilities. Doing so namely ensures both the maximum achievable CO2 reduction and the maximum achievable profit. Thus, the proposed method to support the decision-making regarding the optimal placement of charging stations along transport networks may be useful to guide both public and private decision-making. In particular, the proposed method may be used to guide capital-intensive long-term strategic investment decisions, and ensure the optimal use of funds. Even though the method was specifically designed to place charging stations along waterways, the method may also be applied to other transport networks or other types of alternative fuel stations. To do so, the relevant case-specific assumptions will need to be incorporated into the model.

1.5. Outline

First, core concepts and state-of-the-art literature are discussed in a literature review in chapter 2. Based on this literature review, a literature gap and research questions are formulated. Hereafter, the case study is introduced in detail and a conceptualisation is established based on the case study in 3. Then an iterative method is developed in chapter 4, after the two selected modelling methods are introduced. Finally, the results are presented in chapter 6, and the main implications of the results are discussed in chapter 7.

2. Literature review

The goal of this research was to develop a method to aid decision-making to optimally locate charging stations along a waterway network for battery-electric inland shipping in a coordinated manner. This chapter aims to provide an overview of the core concepts and state-of-the-art literature regarding the optimal placement of charging stations. Afterwards, a literature gap and research questions are presented. The literature review was conducted using the table search method, a detailed description of this process can be found in Appendix F.

2.1. Optimal charging station placement along waterways

Optimal and coordinated charging station placement along waterway networks to support battery-electric inland shipping has rarely been assessed in scientific publications. Piña Rodriguez (2021) earlier looked at the optimal places for battery swapping locations considering five different ships, sailing on 4 different routes in the Netherlands in her master thesis. Furthermore, Man Jiang et al. (n.d.) assessed corridor scale planning of bunker infrastructure for zero-emission energy sources in inland waterway transport in a still-to-be-published paper, as part of an ongoing PhD project. Also, various exploratory reports regarding the possibilities for battery-electric shipping in the Netherlands have been published (Abma et al., 2019; Poiesz et al., 2020; Rotteveel & de Boer, 2019; van der Geest & Menist, 2019). These reports mainly focused on the technical and financial feasibility and did not investigate optimal locations for battery charging stations for multiple routes. Besides, no specific scientific peer-reviewed research was conducted regarding optimal charging station placement to support inland shipping to the author's best knowledge.

In contrast, optimal charging station placement along road networks for vehicles has been extensively studied in the past. Situating charging stations for vehicles with a limited range is fundamentally different compared to locating conventional refuelling stations, as a limited range and a significant recharging time have to be considered (Kuby & Lim, 2005). Because of this limited range, a vehicle may have to charge multiple times, depending on where the charging stations are situated along the route. Lam et al. (2014) proved that the location problem for charging stations in a city is non-deterministic polynomial-time (NP) hard, meaning it is computationally impossible to find an exact solution within a reasonable amount of time. Hence, solutions must be approximated using heuristic methods, so-called location methods. Various location methods have been designed for road networks, which may also be feasible to apply to an inland waterway network. Therefore, literature regarding battery-electric shipping was reviewed to determine how battery-electric shipping on waterway networks differs from battery-electric road transport on road networks. Following, the main characteristics which should be incorporated in a model to determine the optimal locations for charging stations along waterways were determined.

2.2. Battery-electric shipping

To determine the main differences and similarities between battery-electric shipping and road transport, various reports which assessed the feasibility of battery-electric shipping were reviewed. Table 2.1 shows that in 2019, the volumetric energy density of batteries used in ships was more than 100 times lower than that of diesel, which they mostly replaced. Hence, just as with battery-electric vehicles, the limited range of a ship seems to be the most important factor which should be considered to optimally place charging stations. Also, studies regarding the possibilities for electrification of inland shipping in The Netherlands identified a clear trade-off between the battery size and the number of required stops on a route. Moreover, a larger battery also entails more investment costs, and comes at the cost of transport capacity, room for the engine, or accommodation (Abma et al., 2019; Rotteveel & de Boer, 2019).

In general, the charging station location problem for ships is highly comparable to the charging station location problem for vehicles. Drawing from the literature, the main difference is the relatively high energy demand per travelled kilometre of ships (Abma et al., 2019; Poiesz et al., 2020; Rotteveel & de Boer, 2019; van der Geest & Menist, 2019). This results in relatively high required battery capacities and charging times. In addition, the energy demand of different kinds of ships is also much more diverse, which cannot be neglected when locating charging stations. Finally, environmental variables such as river discharge may have a large influence which depends on the direction of travel. In conclusion, existing methods designed to optimally locate charging stations for vehicles may have to be adapted, but can likely also be applied to locate charging stations along an inland shipping network.

	MJ/L	MJ/kg
Batteries	0.4	0.3
Compressed hydrogen	3.8	9.0
Synthetic methanol	14.0	17.0
Organically bound hydrogen	5.5	5.2
Diesel	31.0	31.0

Table 2.1: Energy density of Batteries, other alternative fuels and Diesel compared (Rotteveel & de Boer, 2019).

2.3. Scope

As the placement of charging stations along water networks for vessels was found to be comparable to the placement of charging stations along road networks for vehicles, literature from the latter category has also been included in this review. Besides, the main difference appeared to be the high energy demand between shipping and road transport. Of particular interest for this literature review were publications that assessed suitable station size, power grid or expected waiting times. Many older publications focused on the optimal locations of alternative refuelling stations for limited-range vehicles in general. Only relatively recently, when the driving range of electric vehicles increased significantly, research also focused on the location problem for charging stations in particular. Although more factors such as the power grid and significant charging times play a role in the charging station location problem, a vehicle's limited driving range remains the most important factor in determining optimal charging station locations. Many charging station location methods thus build on older alternative fuel station location models. Therefore, the more general literature on the location problem for vehicles with limited range was also included in this literature review.

Furthermore, most research regarding optimal charging infrastructure planning considers either only the transport network or only the electricity distribution network (Deb et al., 2018). In the latter case, the optimal situation of charging stations in the distribution network is the main focus, considering voltage or thermal limits Shareef et al. (2016). While this was not within the scope of this study, these studies were not reviewed. On the other hand, methods which only consider the transport network was the main focus of this research. A small fraction of the research focused on planning methods to optimally locate charging stations considering both networks. Explicit incorporation of both the transport network and the distribution network involves incorporating the interaction of these two separate networks, this was also not within the scope of this research (Unterluggauer et al., 2022; Xiang et al., 2016). However, these methods were also considered for this literature review, as they may be of added value.

2.4. Optimal charging station placement along networks

Location models that mainly focus on the placement of charging stations on the transport network, can be subdivided into three categories: node-based, path-based and tour-based approaches (Deb et al., 2018; Metais et al., 2022). First off, the difference between these various approaches is explained based on the required input data. Secondly, a modelling framework which may be used to analyse research is introduced and an overview of the reviewed literature is presented. Then, the most adopted location methods for each of the three approaches are discussed in detail. Finally, the different approaches are compared with each other.

2.4.1. Input data

All three modelling approaches require a network with predefined potential charging station locations, which may be equal to all of the nodes in the network. In addition, node-based approaches only require the demand at certain nodes, which may be derived based on demographic data and (expected) EV adoption rates (Y.-W. Wang & Lin, 2013). Node-based approaches model the charging station location problem as a simple facility location problem, the goal is to spread facilities over nodes, to optimally meet the demand at nodes (Deb et al., 2018). On the other hand, path-based approaches require historic trip data between origins and destinations on the network (Hodgson, 1990). The goal is then to place charging stations in such a manner, to make as much of the historic flow feasible with battery-electric drive while considering the other included constraints (Hodgson, 1990; Kuby & Lim, 2005). Flow is usually defined as the number of charged EVs or the number of travelled kilometres (Deb et al., 2018; Metais et al., 2022). Finally, tour-based approaches (also named activity-based approaches) require the full consecutive historic trip data of each vehicle on the transport network during a certain period and aim to optimize for the daily routines of vehicles.

2.4.2. Modelling framework

Deb et al. (2018) established the framework in figure 2.1 for charging infrastructure planning models which only explicitly consider the transport network. All of the literature regarding location methods which were included in this literature review was analysed using this framework, the results are presented in table 2.2. First off, each research considered a specific transport network, based on the use case. Previous research mostly focused on road networks in combination with private EVs, but electric buses, taxi fleets and even autonomous fleets have also been assessed. Secondly, an objective function should be chosen based on the considered road network. The objective is usually to minimize costs or to maximize the number of served EVs. In addition, other approaches aimed to minimize waiting times, maximise the charger's utilisation, or minimise failed trips.

Finally, various aspects can be considered during the optimisation of all approaches. Three of these aspects were found to be the most relevant considering the identified high energy demands of the shipping sector: appropriate station sizing, the influence on the electricity grid and the expected waiting times. Whether these aspects were assessed in a publication, was also included in table 2.2. Remarkably, quite some of the research did not consider appropriate station sizing, and thus neglected the maximum capacity of the charging station. Some of these methods were designed for alternative fuel stations in general instead, but also methods which specifically considered charging stations did not always incorporate station sizing. Furthermore, the electricity grid was rarely considered. If it was included, it was in most cases incorporated as a constraint. Only in a single case, a grid-related model parameter was included. Whenever waiting time was included in a publication, it was usually only reflected upon, and not directly considered during the optimisation. In conclusion, none of the identified publications considered all three aspects during the optimisation.

2.4.3. Location methods to find optimal solutions

An overview of the main identified generally applicable location methods for each of the approaches is visualised in figure 2.2. First off, the main node-based approaches to determine optimal locations for charging stations are the set covering location model (SCLM) by Church and Revelle (1974), the maximum covering location model (MCLM) by Toregas et al. (1971) and the p-median model by Hakimi (1964). The MCLM aims to maximize the number of locations covered for a given number of stations. On other hand, the SLCM aims to minimize the number of facilities to cover all the demand. Lastly, the p-median model aims to minimize the distance between demand and stations for a given number of stations. S. Y. He et al. (2016) used all three location models to estimate charging demand based on socio-demographic data in Beijing and found that the p-median model outperformed the other two models, and gave more stable solutions.

On the other hand, path-based approaches to locate charging stations are based on the flow-capturing location model (FCLM) by Hodgson (1990) or the similar flow-intercepting location model by Berman et al. (1992). The FCLM assumes that service demand along networks is correlated with traffic flows, the goal of this method is to serve as many flows as possible with p facilities. The FCLM assumes that each flow only has to be served once, while vehicles with a limited range, may have to charge

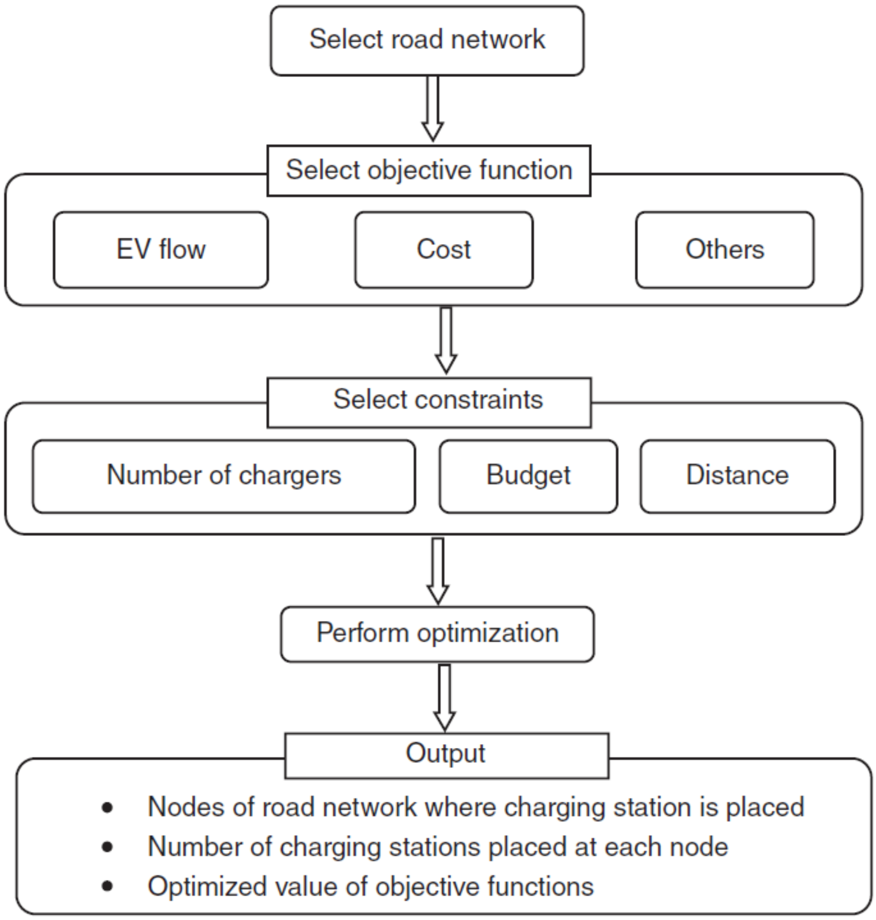

Figure 2.1: Framework for charging infrastructure planning model considering only the transport network (Deb et al., 2018)

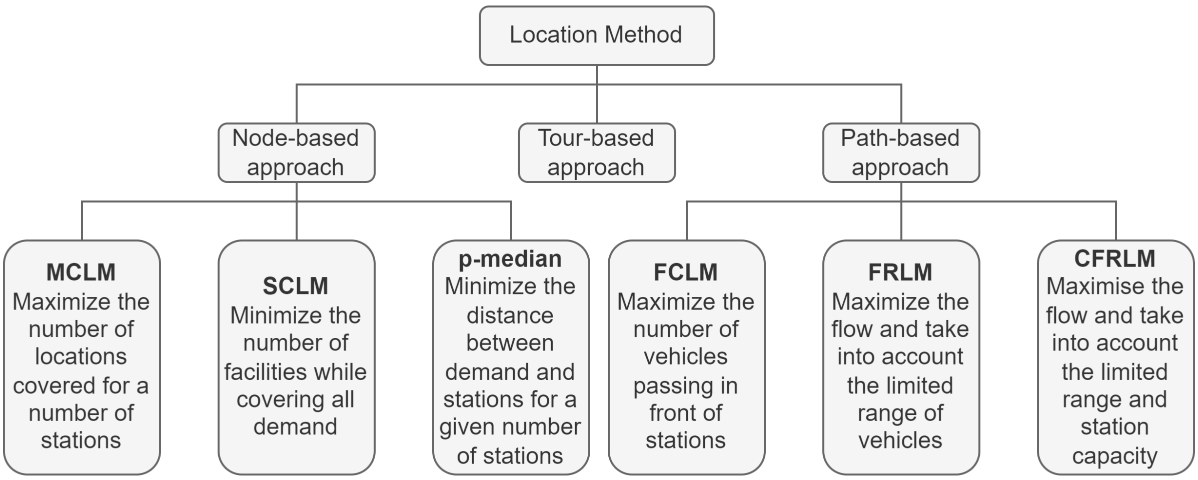

Figure 2.2: Various general location methods by approach adapted from Metais et al. (2022)

multiple times to complete a trip. Therefore, Kuby and Lim (2005) introduced an adapted version of the FCML for vehicles with a limited range, which they named the flow-refueling location model (FRLM). They formulated the FRLM using a two-stage approach: in the first stage all possible combinations of locations capable of facilitating a round trip on each route are determined, and then p facilities are located to maximize the flow refuelled given the feasible combinations created in the first stage.

Publication	Approach	Use case	Objective	Station sizing	Electricity grid	Waiting time
Y.-W. Wang and Lin (2013)	Node-based (various)	Private EVs	Maximise number of charged EVs	Yes	No	No
Sadeghi-Barzani et al. (2014)	Node-based	Private EVs	Minimize infrastructure to meet demand	Yes	Yes (parameter)	No
S. Y. He et al. (2016)	Node-based	Private EVs	Maximise number of charged EVs	Yes	Yes (constraint)	No
Upchurch and Kuby (2010)	Node- and path-based	private AFVs	Maximise feasible trips	No	No	No
Kuby and Lim (2005)	Path-based (FRLM)	Private AVFs	Maximize number of charged Evs	No	No	No
Kuby and Lim (2007)	Path-based (FRLM)	Private AVFs	Maximise number of charged EVs	No	No	No
Upchurch et al. (2009)	Path-based (CFRLM)	Private AVFs	Maximise number of charged EVs	Yes	No	No
H. Zhang et al. (2018)	Path-based (CFRLM)	Private AVFs	Maximise number of charged EVs	Yes	Yes (constraint)	No
A. Zhang et al. (2017)	Path-based (CFRLM)	Private EVs	Maximise number of charged EVs	Yes	No	Yes
Y. He et al. (2019)	Path-based (FRLM)	Private EVs	Maximise number of charged EVs	No	No	No
Chung and Kwon (2015)	Path-based (FRLM)	Private EVs	Maximise number of charged EVs	No	No	No
X. Wang et al. (2017)	Tour-based	Electric busses	Minimise costs of infrastructure for given demand	No	No	No
(Xylia et al., 2017)	Tour-based	Electric busses	Minimise costs and energy consumption	No	No	No
Cai et al. (2014)	Tour-based	PHEV taxi fleet	Maximize the charger's utilization	Yes	No	No
Tu et al. (2016)	Tour-based	EV taxi fleet	Minimise waiting time at station	No	No	Yes
Asamer et al. (2016)	Tour-based	EV taxi fleet	Maximise feasible trips	No	No	Yes
Shahraki et al. (2015)	Tour-based	PHEV taxi fleet	Maximise distance travelled	No	No	No

Table 2.2: Overview of all of the included research regarding location methods and the adopted approach and focus.

Following, various extensions of the original FRLM have been developed. Kuby and Lim (2007) extended the model by introducing methods to add candidate sites along arcs. Hereafter, Upchurch et al. (2009) came up with a capacitated flow-refueling location model (CFRLM), which limits the average number of vehicles served by a station in a given period. Later, Kim and Kuby (2012) adapted the original model to assess likely path deviations to refuel, considering a maximum allowable deviation and a penalty function. The difference between the FCLM, the FRLM and the CFRLM is illustrated using a sample network with three O-D pairs in figure 2.3. The FCLM, only places one station, as it only aims to intercept all of the flows. The FRLM, also places a second charging station, to make sure all of the O-D pairs can be completed using a battery electric drive. Lastly, the CFRLM places two stations at the intersection of all flows, while the combined demand of all O-D pairs exceeds the capacity of a single station.

2.4.4. Comparison of the different approaches

In conclusion, node-based approaches are the least advanced methods. Their main advantage is that they have the lowest data requirements. If demographic data is used for node-based approaches, their application may lead to good results. However, node-based approaches do not allow assessing issues that emerge from traffic flows, such as mutual competition of charging points (Hodgson, 1990; Kuby & Lim, 2005; Upchurch & Kuby, 2010). Especially if trip data is used to generate the required input data for node-based approaches, this may lead to skewed results. Certain flows may only be feasible for battery-electric drive with multiple intermediate stops, and some charging stations may compete with

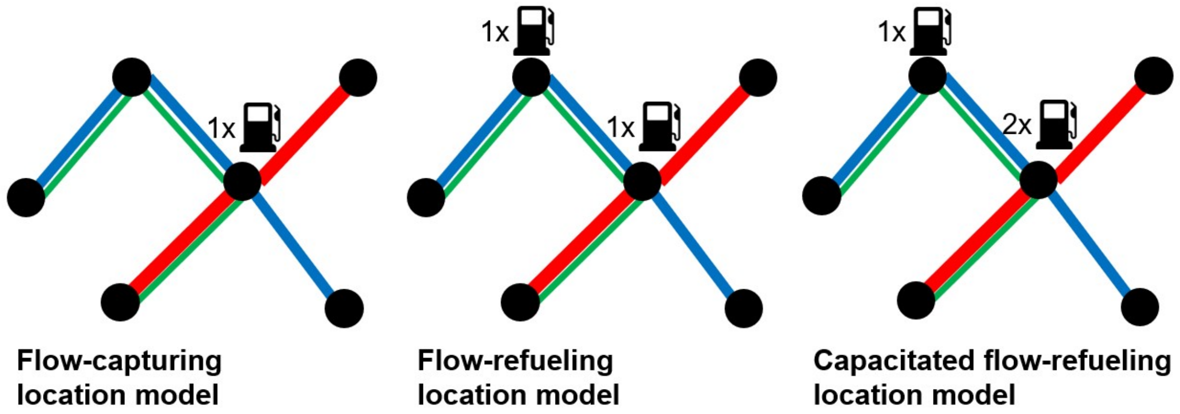

Figure 2.3: The functioning of the three path-based approaches compared, given a vehicle can travel at most 2 links before running out of fuel.

each other. To this end, flow-based approaches have been developed, which require more detailed data. Upchurch and Kuby (2010) found that flow-based approaches are more stable if the number of required charging stations increases. Therefore, most recent studies that apply a node-based approach, also explicitly include the effects of flows if this data is available. These path-based approaches are particularly well-suited to site charging stations along highways, based on anonymous low-resolution data.

Nevertheless, path-based approaches do not perform well in urban environments, as vehicles can be expected to make multiple consecutive trips, and may take a variety of routes. Lastly, tour-based methods are even more advanced than path-based methods and require the most detailed data. While tours instead of trips are observed, this approach allows us to determine the initial battery level at the start and the end of each trip. Moreover, a tour-based approach enables to only include the trips of vehicles or ships of which all trips would be feasible with battery-electric drive. Hence, tour-based methods require fewer assumptions and theoretically provide the best results in most environments. Only when highway systems are considered, less detailed path-based methods provide better results. However, the high data requirements may raise privacy issues, so they are mainly applied to commercial vehicles such as taxis and buses (Cai et al., 2014; Tu et al., 2016). All of the discussed aspects are visualized in table 2.3, which was adapted from the literature review of modelling options to plan for charging infrastructure by Metais et al. (2022).

Criteria	Method		
	Node-based	Path-based	Tour-based
Urban territory	+	–	++
Highways	-	++	+
Representation of charging needs	-/+	+	++
User behavior	-	-/+	++
Data requirements	Very low	Low	Very high

Table 2.3: Comparison of the location methods on key points

2.5. Agent-based modelling

In addition to the previously discussed location methods, agent-based models have been used to evaluate and compare the real-world performance of charging station placement policies and location model outcomes Chen et al. (2016), Sheppard et al. (2016), Sweda and Klabjan (2011), and Wolbertus et al. (2021). In an agent-based model (ABM), all entities are interacting in parallel, and all possible interactions are observed (Epstein, 1999). As such, ABMs may be used to observe waiting times and charging station utilisation rates, if they are used to simulate the real-world performance of a certain charging station layout. To this end, an ABM requires at least a charging station layout and the expected battery-electric flow on the network. Each trip may be seen as an individual trip, after which the vehicle is removed from the network.

Notably, this may require assumptions regarding the initial battery level of a vehicle. Alternatively, a limited set of vehicles which conduct subsequent trips may be considered. Besides, agent-based models may also be employed to find optimal charging station locations. For example, Pagani et al. (2019) utilized an ABM to evaluate 2500 scenarios of the transition to electric mobility in a mid-sized city. They used a sub-model to optimize the placement of EV public charging infrastructure that aimed to maximise the load factor of public chargers. Chargers were initially installed on all considered locations and were removed if the load factor was less than 1h/day, and replaced with fast chargers if the demand exceeded more than 20 vehicles/day. In conclusion, ABMs have proven to be well suited to assess charging station layouts and have also been used to iteratively improve them.

2.6. Temporal demand fluctuations

By design, flow-based approaches usually make estimations based on averages and do not consider likely fluctuations during certain periods in time. Shahraki et al. (2015) for example, acknowledged that their tour-based approach to locating charging infrastructures for taxis did not consider situations in which demand could not be met because all charging stations were occupied. In a similar vein, H. Zhang et al. (2018) indicated that their modelling approach to site fast-charging stations for plug-in electric vehicles only used peak demands and did not consider dynamic flows. Additionally, Y. He et al. (2019) pointed out that their research regarding optimal charging station locations for long-distance trips in the US did not assess charging station time of use or include station capacity restrictions regarding the number of vehicles that could charge at the same time.

On the other hand, Bae and Kwasinski (2012) was one of the first to assess spatial and temporal charging demand for a rapid charging station located near a highway exit. To this end, they combined a flow-based model with M/M/s queuing theory. However, they did not actually determine optimal charging station locations in the end. Later on, Tu et al. (2016) also investigated spatial and temporal demand coverage for a taxi network. They extracted taxi travel demand from a GPS dataset and used this as an input for a spatial-temporal demand coverage location model, which they solved with the help of a genetic algorithm. But, they did not consider the simultaneous presence of different types of charging stations and vehicles with different ranges. Finally, González et al. (2014) investigated cumulative charging demands during the day using an activity-based approach for EVs in Flanders. Nevertheless, they only specified the charging demand at certain places, they did not assess the optimal charging station locations.

2.7. Research gap

The inland shipping sector is characterized by high absolute energy demands and strongly varying energy demands. Therefore, the capacity of charging stations, the effects on the electricity grid, and temporal demand fluctuations are of special importance. However, in most of the reviewed literature these factors are often not assessed. Besides, the optimal placement of charging stations for the inland shipping sector has not been assessed before to the author's best knowledge. The flow-refueling location model has been found to outperform node-based methods to place refuelling stations for vehicles with a limited range. Moreover, flow-refueling approaches have been found to be the best for highway systems. A waterway network is the most comparable to such a system. Hence, capacitated flow-refueling location model may be well-suited to apply to a waterway network. Nonetheless, the ability of a found charging station layout to cope with fluctuating demands cannot be considered with a flow-refueling location model. On the other hand, an ABM approach has proven to be useful to assess the real-world performance of charging station layouts.

2.8. Research goal

Therefore, this research will aim to develop a method to support decision-making toward the placement of charging stations along inland shipping networks, that combines an capacitated flow-refueling location model with an agent-based model. ABMs have only been combined with node-based approaches in the past to the author's best knowledge, and not with superior flow-based approaches. Based on the agent-based simulation, the input parameters of the first stage optimization can be adjusted iteratively, to optimize real-world performance. Moreover, the agent-based simulation may be used to make trade-offs between the number of stations to place, the coverage, the expected waiting times, and utilisation rates. The method to support decision-making toward the placement of charging stations will be optimized for and applied to the Dutch inland freight shipping network.

2.9. Research questions

The following main research question was established: *"How may a flow-refueling model be iteratively combined with an agent-based simulation to optimally site charging stations along an inland waterway transport network?"*
Besides, the following sub-questions were derived:

1. Which characteristics of inland shipping should be considered to optimally site charging stations along waterways?
2. Which constraints should be considered to optimally site charging stations along the waterways?
3. How may the flow-refueling model be applied to the case study considering the input data, characteristics, and constraints?
4. Which assessment criteria should be considered to evaluate the charging station layouts to electrify inland freight shipping?
5. How may the flow-based model constraints be adjusted based on the output of the agent-based simulation?
6. Which policy recommendations for decision-makers that aim to reduce greenhouse gas emissions may be formulated based on the results of the iterative method?

3. Case study

The goal of this research was to establish a method to site charging stations, which iteratively combines a capacitated flow-refueling location model (CFRLM) with an agent-based simulation (ABM). Hereafter, the method was applied to the Dutch inland waterway freight transport network in a case study. In this chapter, the current inland waterway freight transport system is introduced. Also, currently prevalent and expected installed battery capacities, corresponding battery-electric ranges, and charging speeds are discussed. Then, a conceptualisation of the location problem for the Dutch waterway freight transport network is presented.

3.1. The waterway network

The Dutch waterway network consists of several rivers and canals as visualized in figure 3.1, which are all connected and cover most parts of the country. The main transport axis spans from the ports of Rotterdam and Amsterdam towards Germany and Belgium. Furthermore, other ongoing waterways lead to the North and the South of the country. In addition, other main waterways and national waterways connect many other industrial areas to the waterway network. The dimensions of the waterways differ, so not all of the ships can navigate over each waterway. To ensure the interoperability of large navigable waterways within West Europe, normative ship sizes were determined during the Conférence Européenne des Ministres des Transports (CEMT) in 1954. These so-called CEMT-classes were last revised in 1992, and are currently used to categorize ships and waterways. The CEMT-classification of a waterway refers to the largest normative ship that can navigate over a waterway. Hence ships with a different CEMT-classification may have to take different routes travelling from the same origin to the same destination on the waterway network ("Resolution No. 92/2 on new classification of inland waterways", 1992; Rijkwaterstaat, 2020).

3.2. Current shipping

The waterway network is sailed by motor vessels, barges and push convoys of various CEMT-classes. All ships have vastly varying dimensions, transport capacities, and engines. As seen in table 3.1, the ships of the three largest categories make up 48% of the total ships and transport 78% of the total weight. Three broad categories of freight are distinguished dry bulk goods, wet bulk goods and containers. In 2021, the total transported weight consisted of mainly dry bulk goods (%52.0), followed by wet bulk goods (%33.6) and containers (%14.4). Almost all operating ships are Diesel-powered, except for some ships that use LNG and some battery-electric ships. The Diesel is supplied by bunker stations and bunker ships, which are strategically located along busy waterways, mostly near harbours. Usually, a ship can sail for weeks on a full tank and can be refuelled within an hour. This sometimes happens while a ship is at berth, but frequently also by a bunker ship sailing along. Thus, refuelling is currently not an activity which takes a significant amount of time given the day-to-day schedule of an inland freight ship.

3.2.1. Battery-electric shipping

In contrast, battery-electric ships require refuelling much more often, as the volumetric energy density of batteries is still at least 100 times lower (see table 2.1). As such, a battery-electric ship may have to make additional intermediate battery-swapping stops to complete a trip. Moreover, recharging a battery-electric ship takes a significant amount of time, because of the high energy demand. Therefore, battery-electric shipping is fundamentally different, as charging will be a significant activity. Also, the current positions of bunker stations for conventional ships, we not found to be relevant for a potential charging station layout.

Battery-electric shipping in the Netherlands

ZES is currently the only company which has provides energy to inland ships in the Netherlands. The company operates battery swapping stations for battery-electric ships in the Netherlands. They solely

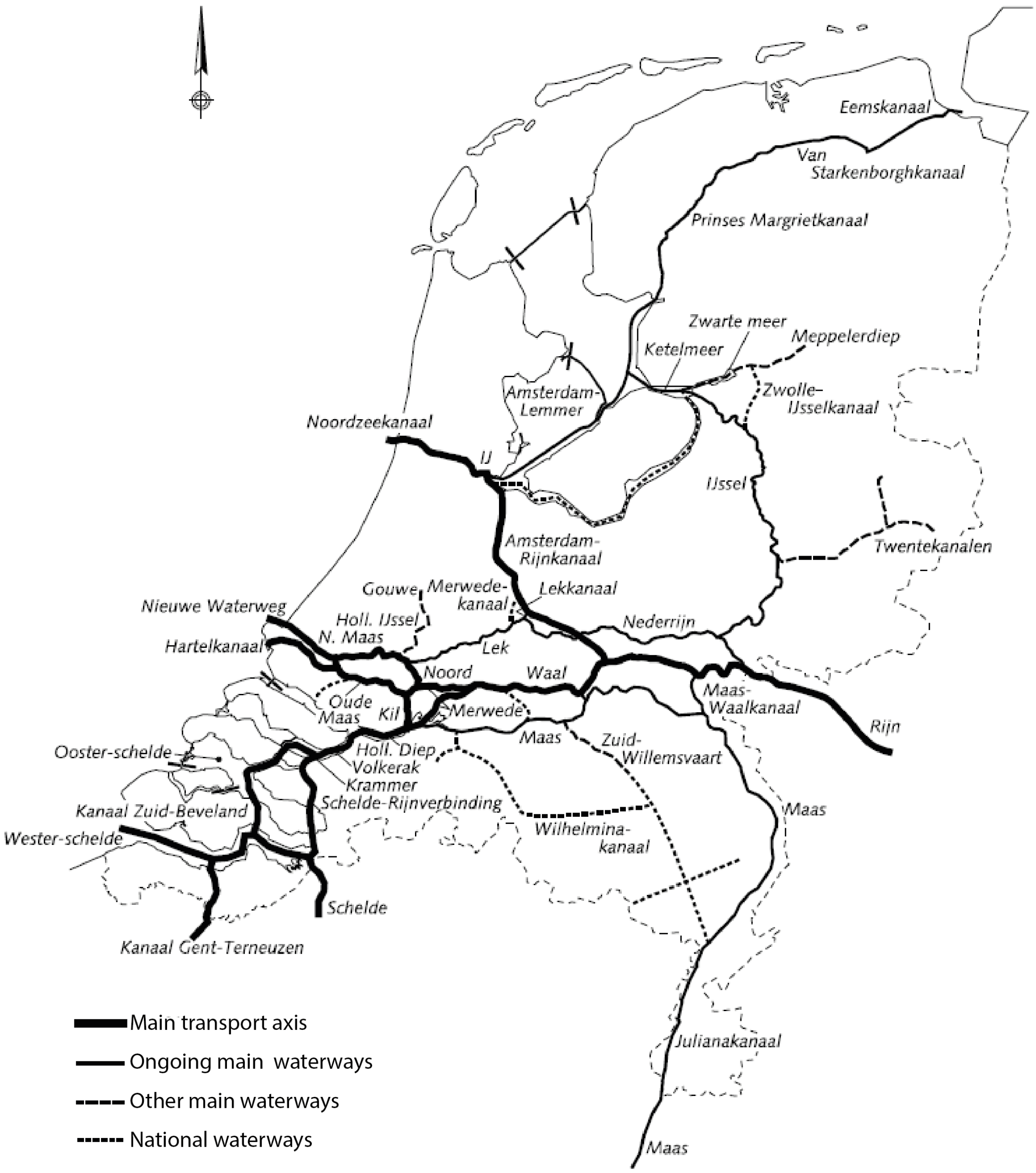

Figure 3.1: The Dutch inland waterway network, adapted from Rijkwaterstaat (2020)

serve container ships with exchangeable batteries, the batteries are exchanged and then charged afterwards. The batteries with a gross capacity of 2 MWh are located in containers, and are exchanged for full ones during the regular loading and unloading process(Poiesz et al., 2020; van der Geest & Menist, 2019; ZES, 2022). A ship may carry multiple containers, which have a guaranteed usable battery capacity of 1.2 MWh during their lifetime (Abma et al., 2019). Logically, a ship can only carry a limited number of battery containers, because they come at the cost of freight. When off the ship, two containers can be charged in parallel using a 2 MW docking station in 2 hours (van der Geest & Menist, 2019). Loading and unloading a container ship takes a significant amount of time. This depends on the terminal and the ship but generally takes 4-6 hours for a container ship(Poiesz et al., 2020). Hence, charging batteries during loading and unloading, may technically also be an option.

	Motor vessels		Barges		Push convoys	
	Total ships	Loading capacity [kton]	Total ships	Loading capacity [kton]	Total ships	Loading capacity [kton]
CEMT 0	395	60				
CEMT I	101	37	87	4	4	2
CEMT II	442	238	77	11		
CEMT III	921	855	105	47		
CEMT IV	667	1,023	111	119	24	40
CEMT V	857	2,378	386	815	86	442
CEMT VI	183	859	12	175	15	149
Total	3566	5,449	778	1,171	129	632

Table 3.1: All active ships and their loading capacity by ship kind and type in 2018 (van der Geest & Menist, 2019).

Foreign battery-electric shipping and expected developments

To get an overview of the technological possibilities, battery-electric shipping abroad was also assessed. Kumar et al. (2019) established a list of recent plug-in marine vessels, which consisted of various hybrid-electric and all-electric ferries and passenger ships. The battery capacity of the ships built after 2015 ranged between 1MWh till 5MWh. These ships were charged with capacities between 1 MW and 10.5 MW. In 2020, Corvus Energy installed a 10 MWh battery in the AIDA Perla, at the time this was the largest battery to be ever installed in a ship (“AIDA Perla”, 2020). Armand et al. (2020) estimated that the capacity of economically viable lithium-ion battery packs with a relatively high energy density would increase from 90-180 Wh/kg in 2020, to 190-230 Wh/kg in 2030, and >250 Wh/kg in 2050. Besides, they predicted that the typical fast charging time (20-80%) will decrease from 15-30 min in 2020, to 10-15 minutes in 2030 in under 10 minutes in 2050. In conclusion, an increase of approximately 33% at the top of the range in capacity can be expected and charging speeds may increase by 33-100%.

3.2.2. Possibilities to switch to battery-electric propulsion

Remarkably, commercial freight ships in the Netherlands usually operate for up to 60 years but have to replace their engine every 15-20 years Poiesz et al. (2020). Nowadays, ship owners may also choose battery- or hybrid-electric systems, instead of a new conventional Diesel system. Opting for a hybrid- or battery-electric system may provide several significant advantages over conventional diesel propulsion, such as reduced fuel consumption, superior dynamics and lower vibrations (Cupelli et al., 2015; Geertsma et al., 2017). Of course, a battery-electric system is only an option if charging stations or battery-swapping stations are available, or if enough funds to realise these are available. Moreover, a battery-electric system will result in a highly limited range. Technically, any ship is feasible for electrification if the batteries can provide the maximum power needed for manoeuvrability. However, many additional stops and charging stations may be needed to complete trips, which may make battery-electric propulsion unfeasible.

Whether a ship is feasible for electrification without changing its usual travel pattern, depends upon its sailing profile (van der Geest & Menist, 2019). The sailing profile indicates how heavily the main engine is loaded during a given period. Considering the limited range, a ship is more feasible for a battery-electric system if it sails relatively short distances, between a limited set of harbours. Currently, battery-electric systems have not been installed in dry- and wet-bulk ships, because exchanging the battery would be harder. Furthermore, electrification of these ships is arguably harder because of their more varying travel patterns (Poiesz et al., 2020; van der Geest & Menist, 2019). Nevertheless, these ships make up the majority of the ships, and will also have to switch to renewable fuels to achieve EU emission reduction goals. Especially as battery-electric shipping is considered the fastest way to realise zero emission shipping, it is important to also consider these ships for electrification to achieve the EU emission reduction goals Sustainable and Smart Mobility Strategy – putting European transport on track for the future, 2020. Therefore, this study considered charging instead of battery swapping and considered all inland ships for electrification.

3.3. Actor analysis

Three aggregated actors which should be considered to achieve large-scale adoption of battery-electric systems in the Dutch inland-shipping sector were identified (Abma et al., 2019; Poiesz et al., 2020; Rotteveel & de Boer, 2019; van der Geest & Menist, 2019):

- Government agencies and other investors
- Shipping companies
- Port operators, land owners and grid operators

Notably, this is not a fully comprehensive list of all of the involved actors. However, these three aggregated actors are the main actors which are expected to be involved in the roll-out of potential charging stations for battery-electric shipping and may benefit from the proposed method to support decision-making. In the following sections, their objectives and corresponding main questions are presented. Following, the extent to which this research aims to add to their decision-making is discussed.

3.3.1. Government agencies and other investors

First off, government agencies and other investors can be seen as decision-makers regarding the actual realisation of charging stations. As such, the method for decision-making regarding the optimal locations and capacities of charging stations along waterways is established for mainly these actors. All of these actors benefit from the highest possible charging station utilisation. This namely results in the highest possible charging station utilisation rates and CO_2 emission reduction. Their main question is what the optimal number of charging stations is and where these should be placed. Placing additional charging stations, may make additional ships feasible for electrification and reduce waiting times. Also if additional charging stations no longer increase the covered area, they may be needed to reduce waiting times. Remarkably, in this case, additional charging stations will always reduce the average utilisation rate.

Therefore, investors in charging station facilities may face a trade-off between utilisation rates and expected waiting times, when making decisions regarding the number of charging stations to be built for a given area and demand. Though in the end, they do not make any direct decisions regarding the actual electrification of ships. The actual decision for a certain form of propulsion is periodically made by shipping companies. The extent to which inland vessels switch to battery electric vessels is ultimately the most important factor influencing the profitability of charging station investments. Therefore, the considerations of inland shipping companies have also been considered, although not the main focus of this study.

3.3.2. Shipping companies

The Dutch inland shipping sector is characterised by a large number of independent contractors which own one ship and some shipping companies which exploit several ships. The main goal of these ship owners is profitable shipping, which can be translated into sub-goals as visualised in figure 3.2. All of the goals in figure 3.2 play a role when ship owners have to decide on a new propulsion system. Whenever battery-electric propulsion is considered, there is one main trade-off. On the one hand, a larger battery will decrease the number of forced stops and increase the serviceable area, given a set of available charging stations. On the other hand, a larger battery will also reduce the freight capacity and increase investment costs.

However, the available space for batteries is likely depending on the size of the ship and the required engine power. Therefore, this research assumed that range of all ships is always the same. The optimal battery capacity is not within the scope of this research. On the contrary, this research aims to develop a method to advise decision-makers regarding the optimal placement of charging stations. To do so, the previously described trade-offs may be incorporated as model parameters or constraints. For instance, a certain trip may only be deemed feasible for electrification if the ship has to make at most a certain number of refuelling stops given the assumed range. Also, the optimal location for various ship ranges may be explored.

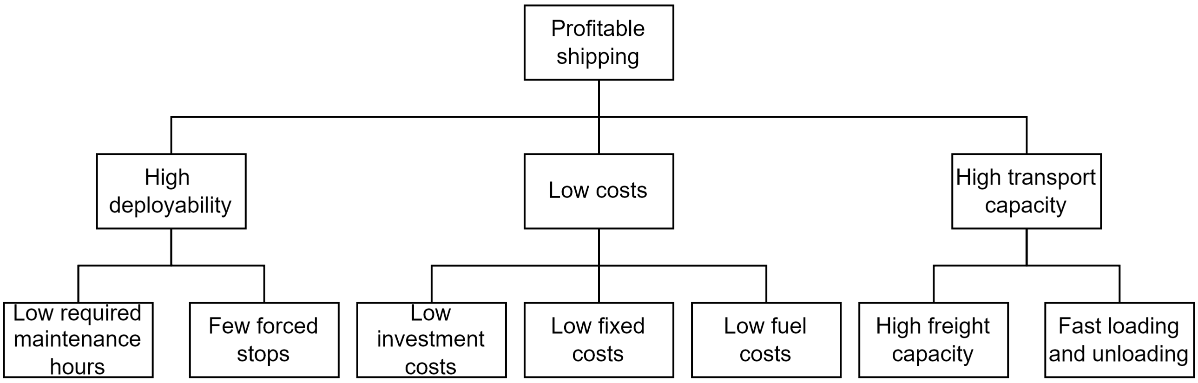

Figure 3.2: Goal and sub-goals of a shipowner

3.3.3. Port operators, land owners and grid operators

Finally, port operators, landowners and grid operators are actors which are crucial for enabling the realisation of any charging stations for ships. Of course, these actors can also benefit from battery-electric shipping. The main goal of port and grid operators is to facilitate the energy transition and remain a key player. Furthermore, landowners may see opportunities to valorise their strategically located land. Therefore, all of these actors can benefit from insights regarding the expected demand in their areas. Forthcoming, port operators and landowners may lobby to bring profitable business to their region. Besides, grid operators may use these insights to anticipate on the required grid capacity. Just as shipping companies, landowners, port, and grid operators are not the main focus of this research. However, the findings may still be relevant for them and point out opportunities.

3.4. Conceptualisation

Based on the established overview of the Dutch inland-shipping system and the actor analysis, a conceptualisation was established. First, logical potential charging station locations are discussed. Then, the assumptions which were made regarding the potential charging station locations, battery capacity and range of ships are presented. Finally, the most important design choices for decision-makers regarding the placement of charging stations are outlined.

3.4.1. Potential charging station locations

Currently, most of the ships sailing the Dutch waterway network are Diesel-powered. The range of Diesel-powered ships is usually enough to sail for over a month and conventional refuelling is currently not a significant activity. For battery electric ships, this would be fundamentally different as they have a very limited range. So limited that they have to recharge after almost every trip. Moreover, recharging a battery takes a significant amount of time. Hence, current conventional refuelling is significantly different compared to recharging. It, therefore, makes no sense to look at the current position of conventional refuelling stations to determine the position of recharging stations. Ships generally only idle for a significant time during loading and unloading. Hence, it was chosen to include all points of origin and destination as possible charging locations.

Furthermore, additional charging locations may be needed along the ongoing waterways for intermediate charging stops. However, it is not logical to assume that ships will make an unlimited number of stops if necessary. If more than a certain number of additional stops are required, ship owners will likely never opt for a battery-electric propulsion system. Therefore, a maximum of four refuelling stops was considered, including the origin and the destination. As such, a trip was only assumed to be feasible for battery-electric propulsion if it could be completed using at most four potential charging station locations on the shortest path.

3.4.2. Battery capacity and range

Logically, a larger ship can carry more batteries, because the room for batteries is likely relative to the size of the ship. Also, a large ship has a larger engine, which will consume more power and thus require more batteries to achieve the same range as a small ship. Therefore, it was assumed that all of the ships have the same range, given their travel speed and average engine power, the battery size was then calculated using the formula 3.1 below. As ships have an incentive to always transport as much load as possible, the loaded speed was used to calculate the energy consumption. In formula 3.1, the range of a ship (r) in kilometres is divided by the speed (v_a) in kilometres/hour, which gives the time that a ship should be able to sail in hours. Multiplying this with average engine output P_a in kW, thus gives the assumed battery capacity in c in kWh.

$$B_a = \frac{rP_a}{v_a} \quad \forall a \in A \tag{3.1}$$

where:
A = set of all considered ship types
a = ship type, $a \in A$
B_a = average battery capacity [kWh] of a ship of type a, $a \in A$
P_a = average power output [kW] of a ship of type a, $a \in A$
v_a = average speed [km/h] of a ship of type a, $a \in A$
r = range [km] of a ship

3.4.3. Main design choices for decision-makers

Up until now, only container ships have been considered for battery-electric propulsion. However, battery-electric shipping is seen as the best option to realise zero-emission shipping in the middle long term (Sustainable and Smart Mobility Strategy – putting European transport on track for the future, 2020; van der Geest & Menist, 2019). Therefore, this research considered all ships for battery-electric propulsion. The aim was to develop a method to enable network-wide electrification. The number of required charging stations likely depends on the capacity of a charging station and the range of a ship. Given that the Netherlands' climate and energy minister is already forced to make choices on how to allocate scarce grid capacity and the relatively high powers at which existing ships are charged, the grid likely limits the number of charging stations which may be placed at a single location (Algemene Rekenkamer, 2022). Furthermore, limitations regarding the available space or other site-specific variables are likely at play. As such, the following aspects were identified as the main design choices:

- The total number of stations to realise
- The maximum number of charging stations to place at a location
- The capacity of a charging station

Choices regarding the realisation of charging stations will influence each other in practice. Because of network constraints, a higher charging capacity may lead to a lower maximum number of charging stations at a location. Likewise, a higher charging capacity may require fewer individual stations to serve all ships. Furthermore, the expected range of a ship also influences the number of required charging stations to cover a certain area. A ship with a lower range will require more intermediate stops to complete an average trip, and will thus require more charging stations. Therefore, the range of battery-electric ships was identified as the main uncertainty.

3.5. Conclusion

The Dutch waterway network is sailed by multiple types of ships with largely varying energy demands. Most of these are Diesel-powered ships, though battery-electric ships are becoming more prevalent. For Diesel-powered ships, refuelling is currently not a significant activity, in contrast to battery-electric ships. Ship owners have to replace their propulsion system every 15-20 years. If they nowadays opt for a battery electric system, they may have to make additional charging stops depending on their range and sailing profile. More charging stations along waterways have to be realised to foster the uptake of battery-electric ships. This involves multiple parties, among which are government agencies and investors. In the first place, this research aimed to design a method to guide decision-making regarding the optimal locations and capacities for these charging stations. In addition, the outcomes may also provide relevant insights for port operators, land owners and grid operators. In this chapter, an overview of the current Dutch inland-shipping system was presented and a conceptualisation of the problem was established. Following, the methods will be developed based on this conceptualisation in the next chapter.

4. Methods

In this chapter, the two modelling methods which were selected in chapter 2 are discussed, flow-refueling location modelling and agent-based modelling and simulation. First, these methods and the established models are presented. Then, the last section elaborates on the proposed combination of the two established models.

4.1. Flow-refueling location modelling

All flow-refueling location modelling approaches stem from the flow-refueling location model (FRLM) by Kuby and Lim (2005). This is a path-based static optimisation model. It was designed to distribute a fixed number of refuelling facilities over pre-determined potential refuelling locations on a road network, for vehicles with a limited range. Considering a limited vehicle range means that multiple refuelling stations may be needed to complete a single trip, depending on the location of these refuelling stations. A flow-refuelling modelling approach requires at least the number of vehicles that travelled on a network in a specific period, on origin-destination (O-D) pairs. To determine this value, all vehicles are assumed to use the shortest path to travel between all of the O-D pairs. All trips in both directions between the two points of the O-D pair are summed, to determine a value for each O-D pair. In addition, most flow-refuelling approaches assume that each trip is a round-trip.

Then, the objective of any flow-refueling location model is to make as much historic traffic flow on a network feasible considering the limited range. Remarkably, it is thus assumed that vehicles with a limited range will not change their travel patterns and can only refuel at the selected refuelling locations. To achieve the objective of maximal flow-capturing, flow-refuelling location models aim to optimally distribute a pre-defined number of refuelling stations over predefined potential refuelling station nodes. A trip is deemed to be feasible if a round trip via the shortest path can be completed, considering the range of a vehicle and the selected refuelling locations. In addition, various other constraints related to the electricity grid or the availability of space may be considered during the optimisation Deb et al. (2018) and Metais et al. (2022). Previously, the flow has been defined as the number of trips or the distance travelled by vehicles with a limited range in most cases (see table 2.2). The main input parameter of a flow-refueling location model is the maximum number of refuelling stations to place in total. Besides, the approach requires at least a network with some potential refuelling station locations and a set of origin-destination (O-D) pairs with corresponding flow values.

4.1.1. The capacitated flow-refueling location model

To establish a location model to situate charging stations along waterway networks, an extended version of the original FRLM was selected as a basis, the capacitated flow-refueling location model (CFRLM) by Upchurch et al. (2009). Whereas the original FRLM assumes that the capacity of a refuelling station is infinite, the CFRLM allows optimising considering a limited average capacity of a refuelling station during a certain period. Multiple refuelling stations may be placed at each potential refuelling location. Just like the original FRLM, the CFRLM was designed to locate refuelling stations for vehicles with a limited range in general, and all vehicles were expected to have the same energy demand whenever they refuelled. As such, the maximum capacity of a refuelling station was defined as the maximum number of vehicles that could be served during a given period because of a limited total on-site bunking or production capacity. The CFRLM consists of two stages as illustrated in figure 4.1, the first stage involves the pre-generation of all feasible combinations for each O-D pair. Subsequently, the actual optimisation is performed during the second stage.

The first stage: pre-generation of feasible combinations

The first stage pre-generation of the feasible refuelling station combinations for all of the considered O-D pairs can be computed using the algorithm by (Kuby & Lim, 2005). The functioning of this algorithm is illustrated for a simple sample network in figure 4.2 and requires the observed O-D pairs, the

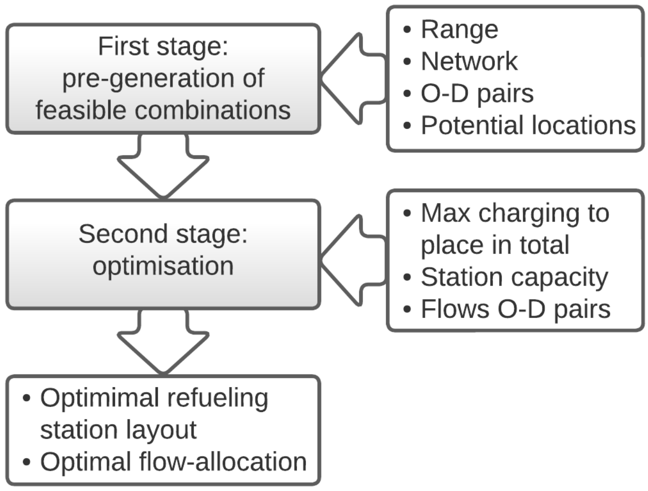

Figure 4.1: The two stages of the CFRLM by Upchurch et al. (2009)

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set of potential refuelling locations, and the network. The sample network consists of an origin (O) and a destination (D), which are 500 km apart. Besides, there are two additional nodes, A (100 km from O) and B (250 km from O). Let us consider all of these four nodes as potential refuelling station locations and a limited vehicle range (r) of 700km. The first step is to determine the shortest path for each O-D pair. In this case, the shortest path is O, A, B, D. Secondly, all possible combinations of refuelling stations on the shortest paths have to be computed. For the sample network, this results in the 15 combinations consisting of 1-4 potential refuelling locations presented in figure 4.2.

Following, their feasibility is evaluated in the third step, using the algorithm presented on the right side of figure 4.2. This algorithm is used to simulate a round-trip using each of the refuelling station combinations. The maximum range of a vehicle is defined as r and the current range at any time during the trip is defined as r_c. If a refuelling station is present at the origin, the tank is assumed to be full upon departure (r_c = r). Otherwise, the tank is assumed to be only half full ($r_c = \frac{1}{2}r$). This is done, as this guarantees that a round trip is feasible. After all, if the vehicle has previously made a round trip and refuelled at the last refuelling station before the point of departure, the tank must be at least half-full to reach that same filling station again.

Then, a round-trip on the shortest path for the observed O-D pair is simulated, one sub-trip at a time. The range is reduced after every sub-trip and if at some point the range becomes negative, the O-D pair is unfeasible. If there is a charging station present at a sub-destination and the range was still positive upon arrival, a vehicle is assumed to fully refuel (r_c = r). If the destination is reached and there is a refuelling station present there, a trip is also considered to be feasible, while the range will always be sufficient to reach the previous refuelling station. If there is no refuelling station present, the route is only feasible if the vehicle can double back to the origin.

Finally, all super sets are removed from the set of feasible combinations and the data is properly structured for optimisation. If the range would have been sufficient to complete a round trip, the set of feasible combinations would be equal to each of the potential refuelling stations on the shortest path. However, considering a range of 700km, B is the only single charging station location that can support round trips on its own. All combinations which contain B and another node, are thus super sets. Notably, no feasible combinations would have been found at all, if the range would have been smaller than 250km. A range of 250km, would require a refuelling station at 'D', 'B', and 'O' or at 'D', 'B' and 'A'. In conclusion, the range heavily influences the number of required charging stations to support a route and the number of unique feasible combinations which can support a route.

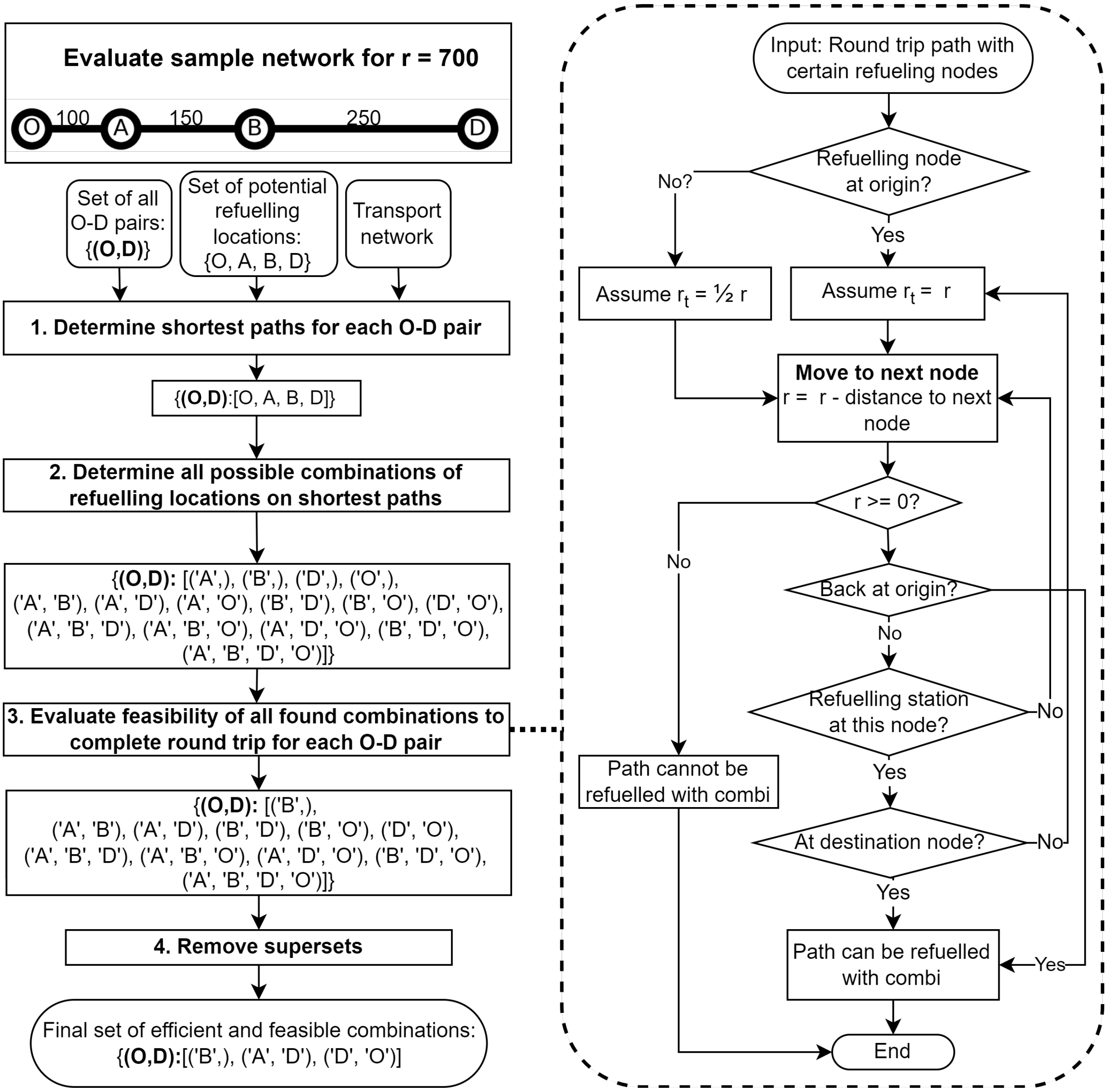

Figure 4.2: The full algorithm by Kuby and Lim (2005) to determine all feasible refuelling station combinations for each Origin-Destination (O-D) pair (left) and route evaluation which is performed for each route and combination (right)

The second stage: optimisation

Subsequently, the actual optimization is executed during the second stage using the generated feasible combinations of the first stage, the network, the O-D pairs and the corresponding flow values, and the total number of refuelling modules that should be placed. In addition, compared to the original FRLM, the CFRLM also considers a limited capacity of a single refuelling station during the optimization. The optimization returns the optimal number of refuelling stations that should be placed at each location and the share of each flow that should be captured by each combination of charging stations in the optimal situation. As the model considers a limited capacity for each station, some flows may be split over unique sets of refuelling stations. Moreover, only part of a flow may be captured in total, meaning only part of the vehicles could be served in the found optimal situation given the potential refuelling station locations and the constraints.

Upchurch et al. (2009) proposed two objective functions, which defined the flow as either the total number of trips or as the total number of travelled kilometres on the network. The second objective was selected for this study, as the main purpose of electrifying shipping is to reduce greenhouse gas emissions, which are likely directly related to the number of travelled kilometers. Let us consider a round trip flow of 1 between O and D on the sample network in figure 4.2 and a refuelling station capacity of 1. During a round trip, O and D are visited once, and the other stations are visited twice. Therefore, two refuelling stations at B are needed to support all of the flow in this situation. Alternatively, two single stations may be placed at O and D to support all of the flow. No more than 2 stations are needed to support all of the flow, thus placing more stations is not efficient. Moreover, placing just 1 station in total would mean that only half of the flow can be refuelled. Logically, this station should then be placed at B.

Mathematical formulation

The objective function of the CFRLM is presented in formula 4.1 and aims to maximise the number of travelled kilometres on the network:

$$Max\ Z = \sum_{q \in Q} f_q s_q \sum_{h \in H | b_{qh}=1} y_{qh} \tag{4.1}$$

Subject to:

$$\sum_{q \in Q} f_q e_q \sum_{h \in H | b_{qh}=1} g_{qhk} y_{qh} \leq c x_k \quad \forall k \in K \tag{4.2}$$

$$\sum_{k \in K} x_k = p \tag{4.3}$$

$$\sum_{h \in H | b_{qh}=1} y_{qh} \leq 1, \quad \forall q \in Q \tag{4.4}$$

$$y_{qh} \geq 0, \quad \forall q \in Q, h \in H \tag{4.5}$$

$$x_k \in \mathbb{N}, \quad \forall k \in K \tag{4.6}$$

where:

Decision variables

y_{qh} = portion [-] of $f_q,\ q \in Q$, being refuelled by facility combination $h,\ h \in H$
x_k = number of modules [#] located at site $k,\ k \in K$

Model parameters

r = range [km] of a vehicle
p = total number of refuelling modules [#] to be located
c = maximum average flow [# vehicles] which can be refuelled by a single charging station in the same time period as f_q

Other model variables

Q = set of all O-D pairs $q,\ q \in Q$ q = O-D pair, $q \in Q$ K = set of all potential facility locations $k,\ k \in K$
k = potential facility location, $k \in K$
H = set of all potential facility combinations of $k,\ k \in K$
h = combination of facilities, $h \in H$
f_q = average total flow volume [kWh] on the shortest path for O–D pair $q,\ q \in Q$ (in the same time period as c)
s_q = absolute shortest round trip path length [km] for O-D pair $q,\ q \in Q$
b_{qh} = coefficient equal to 1 if facility combination $h,\ h \in H$ can refuel OD pair $q,\ q \in Q$ and 0 otherwise
e_q = average fraction round trips [#] (if more than 1) which can be completed on O-D pair q before refuelling is required (see formula 4.7)
g_{qhk} = average number of times [#] a vehicle on path q stops and refuels at facility k in combination h

The coefficient g_{qhk} is equal to:

- 0 if facility k is not in combination h that can refuel path q;

- 1 if facility k is in combination h and at the origin or the destination;
- 2 if facility k is in combination h but not at the origin or destination, meaning the vehicle must stop at the station to refuel in both directions.

$$e_q = \frac{1}{max(1, int(\frac{1}{s_q}))}, \quad \forall q \in Q \tag{4.7}$$

4.1.2. A model to place charging stations for ships along waterways

The original CFRLM by Upchurch et al. (2009) which was designed to site alternative fuel stations for vehicles, was adapted to establish a model to place charging stations along waterway networks for battery-electric ships. The first-stage pre-generation in which the feasible combinations of charging stations for each O-D pair are determined was not changed. Based on the literature review in chapter 2 and the case study analysis in chapter 3 four changes were made to the second stage of the original CFRLM:

1. The flow (f_q^*) on each O-D pair which is maximised by the model, was redefined as the average total energy demand in kWh to travel over the shortest path (see formula 4.8). Remarkably, this also ensured the maximal reduction of CO2 emissions considering various types of ships.
2. Accordingly, the capacity constraint (4.10) was also adjusted to be related to the total energy which can be supplied by a single charging station of a certain capacity during the considered period. Demand assigned to a specific combination of charging stations was assumed to be equally spread over all stations in the combination.
3. Also, an additional constraint (4.14) was introduced to cap the number of charging stations which may be placed at every potential charging station location. This was done to prevent unrealistic outcomes, as the maximum number of charging stations that can be placed at a certain location is in reality likely also constrained by either the electricity grid or the available space.
4. Finally, the assumption that ships only conducted round trips on one specific O-D pair was dropped, as it was not found to be realistic and it was no longer necessary. The original CFRLM assumed this, to estimate the refuelling demand based on the number of round trips that could be conducted on a full tank. However, redefining the flow as the total energy demand on an O-D pair allows us to estimate the energy demand of charging stations in more detail. This led to an adaptation in the capacity constraint (4.10).

Flow calculation

In addition to the changes to the second stage, a new method was developed to determine the redefined flow values f_q^* for the energy demand on paths based on historic trip-based O-D data of ships. Using previously derived formula 3.1 and considering the number of ships of each type that travel on a path (n_{qa}), formula 4.8 could be derived for the average total energy demand on a path (f_q^*), which is logically independent of the range of a ship. The energy demand for one trip of an agent of type a simplifies to the fraction in formula 4.8, hence the total energy demand of all of the agents of a certain type a travelling on a path is calculated by multiplying this fraction with n_{qa}. Finally, the average total flow on a path (f_q), was calculated by summing up all of the total energy demands for each agent type a. Whereas the shortest path for an O-D pair q may be agent specific, s_{qa} is defined as the round trip distance associated with the shortest path for agent type a travelling O-D pair q. y_{qh} was defined as the portion of f_q being refuelled by facility combination h. b_{qh} is an coefficient equal to 1 if facility combination h can refuel OD pair q and 0 otherwise.

$$f_{q^*} = \sum_{a \in A} \frac{P_a \cdot s_{qa}}{v_a} \cdot n_{qa}, \quad \forall q \in Q \tag{4.8}$$

where:
Q = set of all O-D pairs
q = O-D pair, $q \in Q$
f_q^* = average total flow [kWh/day] on O-D pair q, $q \in Q$
A = set of all distinguished agent types

a = agent type, $a \in A$
n_{qa} = average number of trips [#/day] on path $q,\ q \in Q$, by agents of type $a,\ a \in A$
s_{qa} = absolute shortest path length [km] for an agent of type $a,\ a \in A$, and for O-D pair $q,\ q \in Q$
P_a = average power [kW] of an agent of type a, $a \in A$
v_a = average speed [km/h] of an agent of type a, $a \in A$, (travelling at average power $P_a,\ a \in A$)

Mathematical formulation
Compared to the original CFRLM, the objective function (4.9) and the capacity constraint (4.10) were modified. Furthermore, 4.14 was introduced as a new constraint to maximise the number of charging stations at each location. The objective function (4.9) of the established flow-refueling location model to place charging stations for ships along waterways, aims to maximise the energy which is used for battery-electric shipping:

$$Max\ Z = \sum_{q \in Q} f_q^* \sum_{h \in H | b_{qh}=1} y_{qh} \tag{4.9}$$

Subject to:

$$\sum_{q \in Q} f_q^* \sum_{h \in H | b_{qh}=1} \frac{1}{|h|} \cdot y_{qh} \leq c \cdot o \cdot x_k, \quad \forall k \in K \tag{4.10}$$

$$\sum_{k \in K} x_k = p \tag{4.11}$$

$$\sum_{h \in H | b_{qh}=1} y_{qh} \leq 1, \quad \forall q \in Q \tag{4.12}$$

$$y_{qh} \geq 0, \quad \forall q \in Q, h \in H \tag{4.13}$$

$$x_k \leq x_m, \quad \forall k \in K \tag{4.14}$$

$$x_k \in \mathbb{N}, \quad \forall k \in K \tag{4.15}$$

where:
Decision variables
y_{qh} = portion of $f_q,\ q \in Q$, being refueled by facility combination $h,\ h \in H$
x_k = number of modules located at site k

Model parameters
r = range [km] of an agent
m = maximum number of modules [#] that can be located at any single site
p = total number of charging modules [#] to be located
c = average charging capacity [kWh] of a single charging module
o = average operational time [hours] of a charging station (in the same time period as f_q)

Other model variables
Q = set of all O-D pairs $q,\ q \in Q$
q = all O-D pairs $q,\ q \in Q$
K = set of all potential facility locations
k = potential facility location, $k \in K$
H = set of all potential facility combinations of $k,\ k \in K$
h = combination of facilities, $h \in H$
f_{q^*} = average total flow volume [kWh] on the shortest path for O–D pair $q,\ q \in Q$ (in the same time period as c)
s_q = absolute shortest path length [km] for O-D pair $q,\ q \in Q$

b_{qh} = coefficient equal to 1 if facility combination $h,\ h \in H$ can refuel OD pair $q,\ q \in Q$ and 0 otherwise
Key metrics
Besides, some useful metrics were defined to assess the system. First off, formula 4.16, was derived to calculate the fraction of the total flow which is captured by the model.

$$u = \frac{\sum_{q \in Q} f_q^* \sum_{h \in H|b_{qh}=1} y_{qh}}{\sum_{q \in Q} f_q^*}, \quad \forall h \in H, \forall q \in Q \tag{4.16}$$

where:
u = fraction [-] captured of total

In addition, some key model metrics were derived based on the conceptualisation in chapter 3. First off, the main objective of decision-makers regarding a charging station layout is high expected utilisation. The average utilisation is maximised by the model. Utilisation was defined as the fraction of the time during which the station is used. To calculate the utilisation, formula 4.17 was derived based on formula 4.9 and formula 4.10.

$$E = \frac{\sum_{q \in Q} f_q^* \sum_{h \in H|b_{qh}=1} y_{qh}}{p \cdot c \cdot o}, \quad \forall h \in H, \forall q \in Q \tag{4.17}$$

where:
E = expected occupation [-]

Lastly, another model metric was derived based on the output of the first stage of the adapted CFRLM. The first stage returns all routes that can be served with a potential charging station layout. As such, the first stage can be used to estimate the fraction of the flow which may be captured if there are no capacity constraints. This may be of interest, to see whether adding more charging stations may be helpful. Based on the flows on these paths, the serviceable fraction was defined in formula 4.18.

$$\epsilon = \frac{\sum_{q \in Q} f_q^* \sum_{h \in H} b_{qh}}{\sum_{q \in Q}}, \quad \forall h \in H, \forall q \in Q \tag{4.18}$$

where:
ϵ = serviceable fraction [-]

4.1.3. Methods to determine additional potential charging station locations

Because of computational constraints, not all of the nodes in the network could be considered potential charging station locations. The origin and destination nodes were earlier identified as the most logical locations for site charging stations. Besides, intermediate charging station locations may be needed to make trips feasible with a limited range. Therefore, two heuristics were established to determine additional potential charging station locations on the network. The first heuristic aimed to determine additional charging station nodes on the longest arcs in the network. The second heuristic was designed to determine intersections in the network which are expected to add the most to the potential network coverage.

Heuristic 1: additional nodes on arcs
Earlier, Kuby and Lim (2007) investigated multiple heuristics to determine additional potential refuelling locations. They found that applying Added-Node Dispersion Problem (ANDP)-based approaches by Kuby et al. (2005) generally led to the best results. Based on the ANDP, they developed the MaxSumMin heuristic to split links by inserting a certain number of additional nodes. The MaxSumMin seeks to maximise the sum of the smallest subarcs while splitting up links by inserting nodes. Kuby et al. (2005) proved that if the longest subarc is an arc that was split p times before, to equally spread the $p+1$ nodes over the original link. By doing so, the sum of the longest subarcs is minimized. The functioning of this heuristic is illustrated in figure 4.3. This heuristic was applied to the Dutch waterway network to insert a fixed number of nodes. Alternatively, the heuristic may be applied until a certain minimum

maximum sub-arc length is achieved. While it was not deemed (economically) feasible, links crossing open water were not considered to insert additional potential charging station nodes.

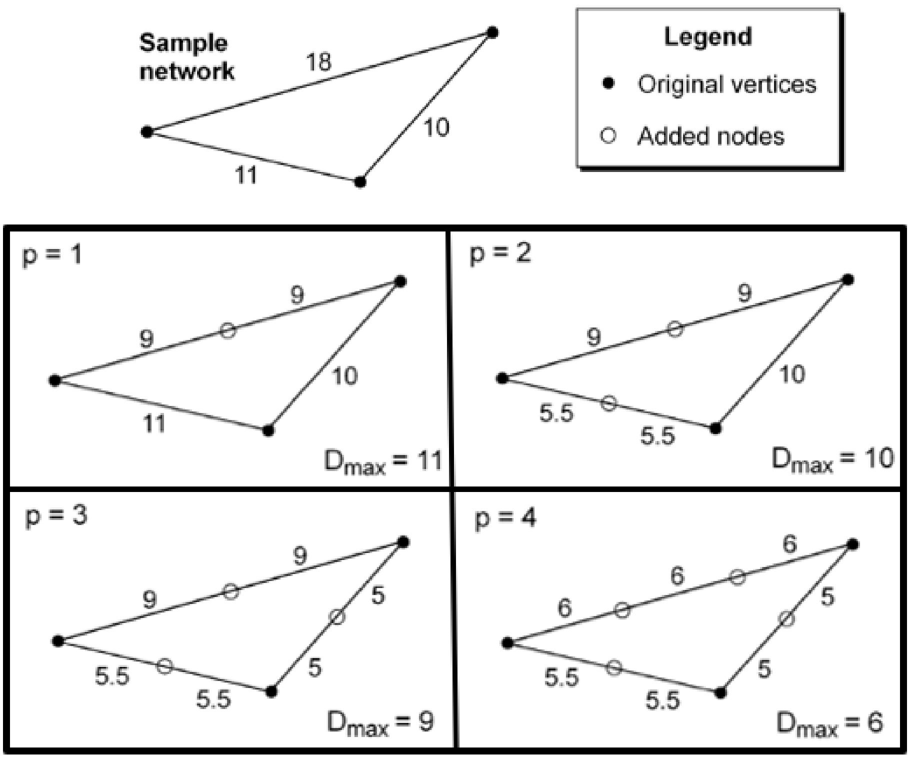

Figure 4.3: Functioning of the MinSumMax method adapted from Kuby and Lim (2007)

Heuristic 2: including intersections
The second heuristic was designed to select the intersections which were most likely to make additional routes feasible if a charging station was placed there. To this end, an iterative method was established. A substantial number of these nodes had a degree of 1, meaning that a charging station here could only support trips from and to this harbour. Each time the heuristic determined the intersection node which was the furthest away from all other potential charging station nodes with a degree larger than 1. Similarly as while applying the first heuristic, intersections situated in open water were excluded from the set of intersections to select potential charging station locations. The method kept including intersections until a certain number of intersections was added to the set of potential charging station locations. Each time an intersection was selected, the distance to the nearest charging station was redetermined for all of the intersections which were not incorporated yet, considering the previously selected nodes as potential charging station locations as well. The application of the heuristic to add two nodes to a sample network is visualized in figure 4.4.

4.1.4. The optimal number of charging stations

The adapted CFRLM aimed to maximise the share of the total flow that could be electrified with a given number of charging stations. If more charging stations than strictly necessary to capture all of the flow were placed, this did not lead to optimal results. Therefore, first, the maximal number of effective charging stations should be computed. This may be done by evaluating the CFRLM to locate an increasing number of charging stations. At some point, placing more charging stations barely has any effect. At that point, the optimal number of charging stations is found. It is assumed that this point is reached if, a charging station layout can support at least 99.9% of the captured flow.

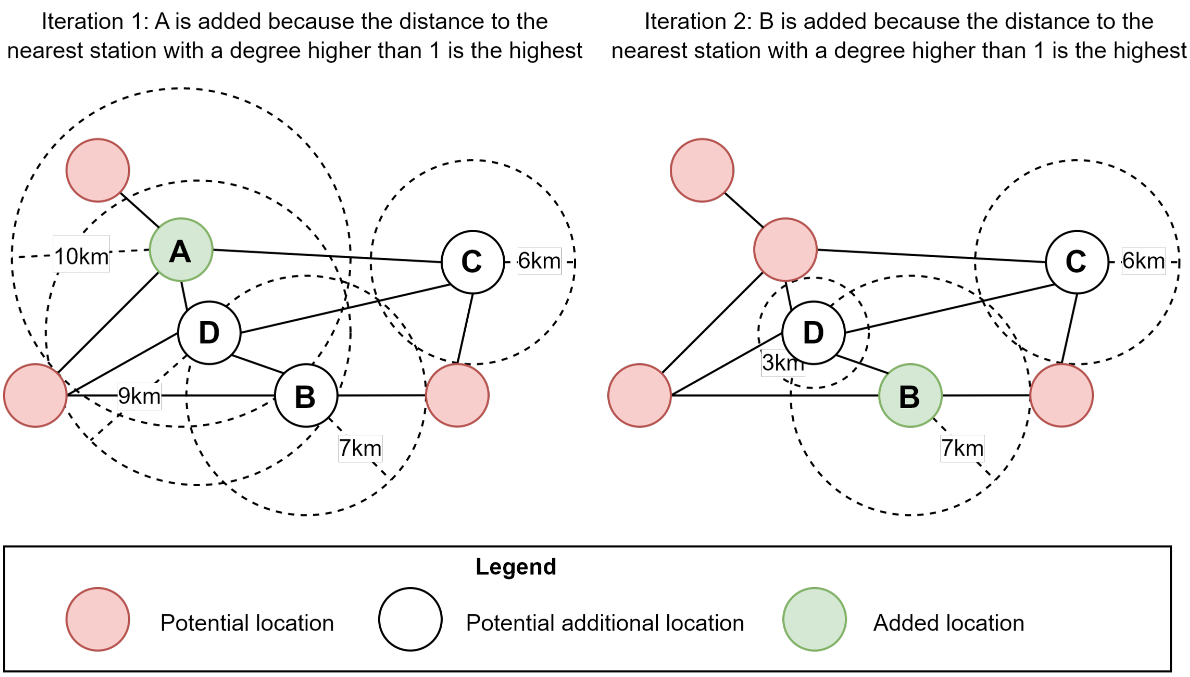

Figure 4.4: Application of the second heuristic to a sample network.

4.2. Agent-based simulation

In addition to the adapted CFRLM, an agent-based simulation model (ABM) was developed to simulate any charging station layout and assess its performance. In this simulation, ships were sailing using battery-electric propulsion on all of the O-D pairs which were feasible in each scenario according to the CFRLM, acting in parallel. During this simulation, the average and maximum utilisation rates and waiting lines of all charging stations were recorded. Moreover, the charging time, waiting time, and time in line were stored for each ship that completed its trip. The ABM was built using Python 3.10 and the MESA Python package (Masad & Kazil, 2015). The ABM was based on an agent-based transport simulation model by Yilin Huang, which is first presented. Then, the adaptations to the model are discussed and the established model ABM is presented.

4.2.1. The original transport simulation model

The ABM which was used as a basis was created by Yilin Huang of the TU Delft and was provided during the course of Advanced Simulation at the TU Delft. The model was established to observe the effects of floods on a road transport network in Bangladesh. The transport network was defined as a networkx graph and consisted of various nodes and links. Each of the nodes and links was of a certain agent class. The model was generated based on a CSV, that contained information regarding all of the included infrastructural objects. These were all agents, with specified dynamic behaviour, and a specified position in Decimal Degrees (DD). The following infrastructure-related classes were distinguished: Infra, Sink, Source, SinkSource, Link, Bridge, and Intersection. Besides, the network was driven by trucks, of the Truck agent class. Trucks were generated by objects of the Source class, depending on a set generation frequency. Then, trucks were assigned to a random node of the Source class in the network.

Subsequently, all of the trucks were assumed to drive via the shortest path to the sink node and travel at the same fixed speed. Agents driving from an origin to a destination were always headed for a (sub-)destination. Once they completed the path to their next destination, they moved to that object. Once arrived at the sink, they were removed from the model. During their journey, trucks may encounter objects of various classes. Agents of the Sink, Source and SinkSource class, only interacted with the trucks if they were either generated or removed. Link and Intersection class agents also did not interact with the agents either. Bridges, on the other hand, may result in delay times if they were broken. All of the bridges had a certain condition attribute. Based on this condition attribute, each bridge had a probability to break. If a bridge was broken, this resulted in delay times. Until this delay time passed, trucks that arrived at a bridge had to wait. After this waiting time has passed, they would start driving to their final destination again.

4.2.2. Model adaptations

The original ABM was adapted to simulate the functioning of a charging station layout for ships sailing between different harbours. Firstly, the original Truck class was used as a basis for a Vessel class. The Vessel class was given multiple new attributes, among which a type. This determined the individual travel speed and the battery size of an agent. Likewise, the SinkSource class was used as a basis for a Harbour class. The old Bridge class was used to establish a ChargingStation class. This class was used to represent intermediate charging stations at selected additional intersections or inserted nodes. The class was adjusted to assign a waiting time to agents if they were assigned to charge at that charging station.

In addition, a new separate class HarbourChargingStation was established for harbours which had a charging station. The HarbourChargingStation class had the attributes and functions of both the Harbour and the ChargingStation classes. Just as in the original model, the links and intersections did not interact with the ships. The sinks and sources were no longer used, as each harbour had to be able to generate and remove ships. Furthermore, the model was adapted to incorporate all of the outputs of CFRLM. As such, the generation of agents was no longer based on a general generation frequency but depended on the empirical data for a specific O-D pair and time of the day. These adaptations will be discussed in the next section in detail.

4.2.3. An agent-based model to evaluate charging station layouts

In this section, first, the input data of the agent-based model is discussed. Then, the generation charging and removal of ships are discussed. Lastly, the data collection is discussed.

Input data

The ABM required the following inputs:

1. The optimal number of charging stations at each potential charging station location.
2. The corresponding optimal flow allocation (which fraction of the flow on each O-D pair should use which charging station combination).
3. The waterway network, including all additional charging station nodes considered during the CFRLM.
4. The flow-based origin-destination data for all feasible routes with the charging station layout.
5. The range of a ship and the charging capacity of a single charging module is considered during the optimisation.
6. Average sailing speed and the corresponding power output of each ship type.

Generation, charging and removal of ships

The ABM was used to simulate and collect data for a period of 7 days considering a time step of 1 minute, data was collected after a warm-up period of 1 day. For each of the 9 scenarios, 100 iterations of the ABM simulation were run, which resulted in an expected range for all of the output values. Ships were randomly generated for all of the feasible O-D pairs, based on the trip-based origin-destination (O-D) data, with a 50% chance to start at either of the two harbours, headed for the other harbour. For each time step, the chance that a ship departed for each O-D pair, was depending on the total number of ships that had departed on that route during that year at that specific hour of the day. This was enforced by drawing a random number between 0 and 1 for each O-D pair at each time step, if this random number was higher than the total number of ships that had departed at this time of the day on this route divided by the number of minutes in a year, a ship assumed to depart on that O-D pair.

Subsequently, this ship was only generated in the model if a random number which was drawn, was higher or equal to the fraction of the total flow on this O-D pair which could be captured according to the CFRLM, otherwise, this trip was not considered to be feasible using the charging station layout.

Upon generation each ship was assigned to a certain charging station combination, if there were more options, a station was drawn. In this case, the probability to draw each feasible charging station combination was equal to the fraction of the ships that were assigned to each facility based on the CFRLM. Likewise, the ship type was determined, if 20% of the ships at the considered route had departed at this hour of the day in the dataset were of type A, there was a 20% chance the generated ship would be a type A ship. Finally, once the type of a ship was determined, the average travel speed and the average engine power were assigned based on the ship type. In line with the CFRLM, ships were assumed to depart fully charged if the harbour of origin had a charging station and otherwise half full.

Once on their way, ships were assumed to only charge at the charging stations of the charging station combination they were assigned to until they were full. Depending on the number of charging stations, a certain number of ships could be charged in parallel at a charging station location, which could either be a harbour with a charging station or an additional charging station node. If all stations were occupied when a ship arrived at a charging station location, this ship joined the queue, ships were assumed to be served according to the ”first in first out” principle. When ships arrived at their destination, they were first fully charged if they were assigned to use the charging station at the destination, before they were ultimately removed from the model. This was in line with the CFRLM and the generation of agents in the ABM, as it was assumed that each ship was fully charged whenever it departed from a harbour with a charging station.

Data gathering

When ships were removed from the model after the warm-up period because they arrived at their destination, their unique id, battery size, the hour of generation, the assigned combination, route, and time at which they departed were recorded. Moreover, their total travel time, waiting time, and charging time were also logged. This dataset was kept as a model variable which could be stored after the run, this was found to be an effective alternative for storing the information of all of the vessels each time step, which was much more computationally intensive. Furthermore, all of the charging stations and harbour charging stations kept track of their operational time, the cumulative number of waiting for ships during all time steps, and the maximum length of the queue. Based on these outputs, the average and maximum occupation of each charging station could be determined at the agent level for all the charging stations after the last time step.

4.3. Model verification and validation

To check whether the random generation of ships indeed worked as expected, the distribution of ships in the simulation was compared with the input data which was used to generate the ships. The distribution of ships with the data set is plotted on the left in figure 4.5 below. On the right, the average number of ships which were generated during a simulation period of a week for 100 runs with a unique seed is plotted. As the distribution is similar, it was concluded that the generation of ships had functioned correctly. Furthermore, the locations of the model which were the busiest visually checked and compared with the total flow on the network, and the travel times of the ships were compared with the expected values based on the length of the path. Following the assumptions, each ship had to charge at least once on each trip. Finally, individual ships were tracked during the simulation, to see whether they charged correctly and it was checked whether the most frequented routes in the empirical data were also the most frequented routes in the simulation.

4.4. Iterative combination of the CFRLM and the ABM

The ABM can be used to make a trade-off between charging station utilisation rates and waiting times as visualized in figure 4.6. Notably, this method requires predetermined thresholds for the minimum acceptable utilisation rates and the maximum acceptable waiting times. What waiting time is acceptable may be different in different systems, but the acceptable waiting time is likely depending on the total duration of the trip, as human drives will have to stop now and then to rest too. Considering that the ABM results in an expected range for both variables, the average, the maximum or a certain percentile may be chosen.

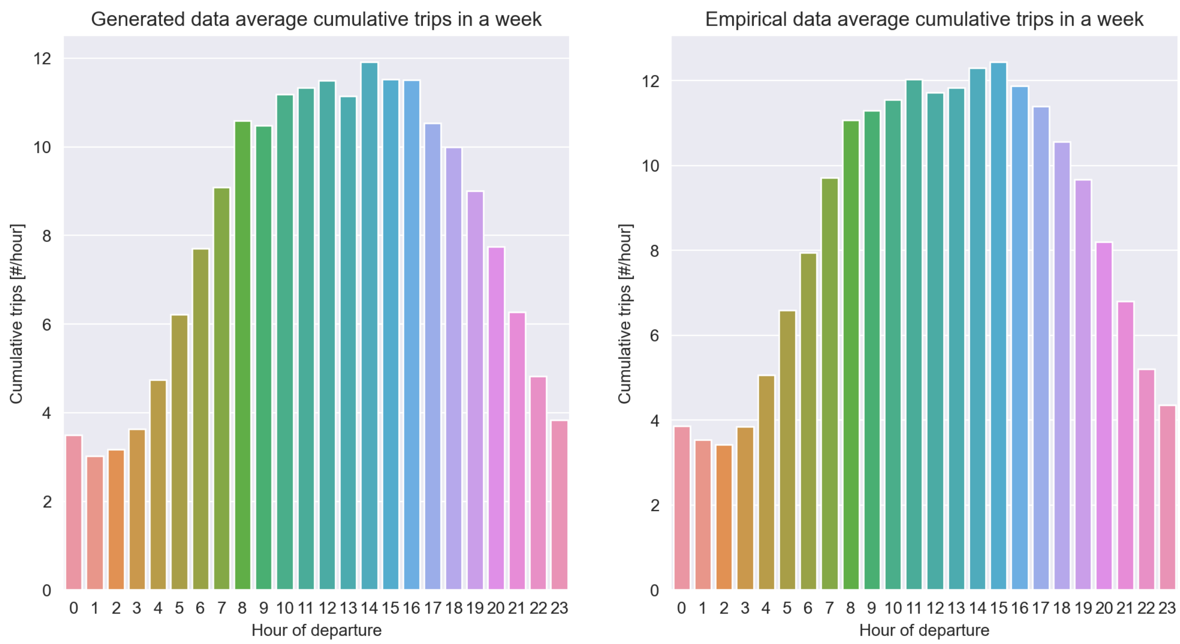

Figure 4.5: Comparison cumulative data average week hour of departure generated data (left) and empirical data (right)

Besides, the maximum number of stops to consider a route feasible also has to be determined, too many stops are likely unacceptable in most systems for economical reasons. If the ABM indicates that a certain charging station layout results in too low utilisation rates, the only way to increase utilisation rates is to place fewer stations or to include more charging station locations. A single additional charging station node may be able to serve multiple flows if this additional node is located at a section where the paths of two O-D flows overlap, but which first did not contain any charging station nodes.

Moreover, an additional charging station location may make additional O-D pairs feasible with the same amount of charging stations, because they can be positioned more efficiently. Nevertheless, only a limited set of additional potential charging stations can likely be realised from a practical perspective, and executing the CFRLM while considering many additional nodes also quickly becomes unfeasible. If including additional potential charging station locations is (no longer) an option, the total number of charging stations can only be reduced to increase utilisation rates of an optimal charging station layout, because the model already maximised for the captured flow.

Hereafter, the waiting times may then be evaluated using the ABM. If only certain stretches are unacceptably busy, additional constraints may be considered to demand at least 1 additional charging station on that route, if the goal is to make as much traffic feasible with electric drive with a given number of charging stations. Then, rerunning the optimisation with this additional constraint will either result in the model dropping another O-D pair and adding charging stations on that route, or in the fact that the model prioritizes additional routes. If the goal is to make all of the traffic feasible with the electric drive or a fixed percentage, the only option to reduce the waiting times is to place more charging stations in total, if there are still locations available on the network to place charging stations.

Whenever there are no places left to place charging stations on an unacceptably busy route, additional charging stations on this specific route may be considered as well. Finally, peak hour averages may be used in the optimisation of the CFRLM instead of daily averages, if a found charging station layout results in unacceptable waiting times in general. Alternatively, a lower capacity may be considered by the CFRLM, if the waiting times, in general, are too long. In conclusion, the ABM may be used to evaluate any optimal charging station on predetermined limits regarding the maximum waiting time and minimum charging station utilisation.

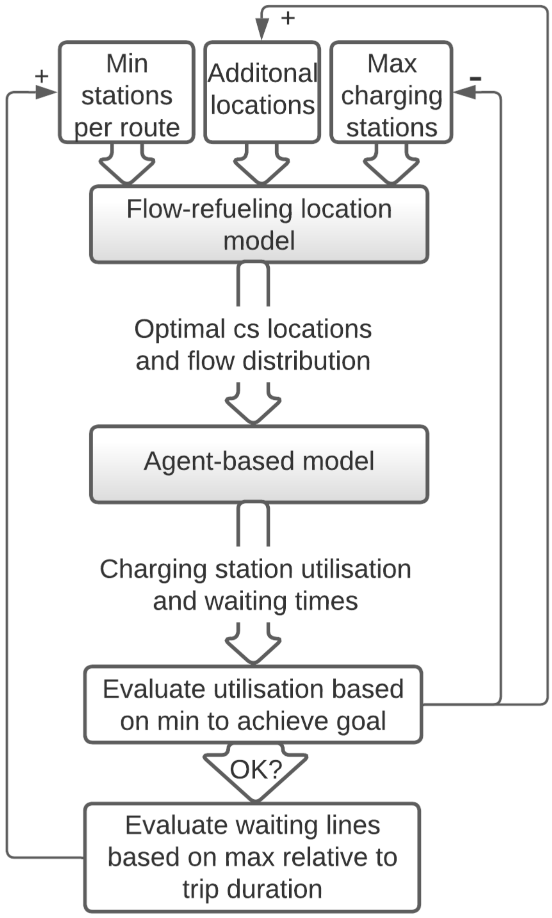

Figure 4.6: Iterative combination of the CFRLM and the ABM

5. Data preparation

To apply the adapted capacitated flow-refueling location model (CFRLM) to the Dutch inland shipping network, extensive data preparation was required. The main steps of this process are presented in this chapter, and all additional data preparation steps and corresponding assumptions can be found in appendix C. First, the required input data and parameters are discussed. Then, the selected data sets are introduced. Hereafter, the experimental setup is presented. Finally, the data sub-setting, aligning, and reformatting which was required is discussed.

5.1. Input data

The ABM required the same input data as the adapted CFRLM and the outputs of the adapted CFLRM. Given the model in section 4.1.2, the adapted CFRLM required the following inputs:

- The Dutch waterway network with predetermined potential charging station nodes.
- Aligned trip-based origin-destination (O-D) data, suitable to compute the total flow on a path using the established method in section 4.1.2.
- The range of a ship
- The number of charging stations to place in total.
- The capacity of a charging station.
- The maximum number of charging stations that may be placed at every location.

5.1.1. The Dutch waterway network

First off, the digital twin of the Dutch fairway system by Jong et al. (2022) was selected to represent the network. This is a digital twin of the Dutch Waterway network, which also contained information regarding the largest ship that can travel over each link in the network. This information was needed to compute the shortest path for each ship type and O-D pair. Remarkably, the network did not contain detailed information regarding the positions of harbours. This meant that any trip-based O-D data could only be linked to nodes on the network based on coordinates. Nevertheless, this network was chosen as it was found to be the most complete network which was available.

5.1.2. Trip-based O-D data

Secondly, trip-based O-D data was needed. The position of inland ships is live-tracked using the Automatic Identification System (AIS), a system that is meant to enhance the safety of navigation. The purpose of AIS is to enable good communication between skippers and between skippers and traffic stations. To this end, an AIS transponder is obliged for all ships longer than 20 metres sailing the Dutch waterway network (Waterstaat, n.d.). Potentially, historic AIS data would have been well-suited for this study. Especially if each trip was linked to an individual ship of which the average sailing speed and power consumption were known. However, historic AIS-data is not publicly available for privacy reasons and can only be requested for research purposes for a limited area and period. This study aimed to adopt a network perspective, and incorporate the data for a full year. Therefore, a request for extraction of this sensitive information was not considered worthwhile.

Instead, a trip-based anonymous O-D dataset for 2021 was extracted from Rijkswaterstaat (2022). Although less detailed than a full AIS information dataset, this data set included all of the necessary information to compute flow values using the established method in section 4.1.2. The dataset namely included the origin, the destination and the CEMT and RWS-type of the ship of trips in 2021. After the origin and destinations were linked to nodes on the network, the CEMT-class could be used to determine the shortest path for each ship. The RWS-ship type is a more detailed variant of the CEMT-class introduced in section 3.1. The average engine power and the average loaded speed were known for all of the 31 unique RWS-ship types (van Koningsveld & Baart, 2022). As such, all of the required data to determine the flow values for the O-D pairs using the method in section 4.1.2 were known.

5.1.3. Experimental setup

As earlier noted in chapter 3, all model input parameters likely depend upon each other. Moreover, the capacity which can be realized at each location is likely constrained. Hence, based on the prevalent supported charging capacities, ranges, and expected developments which were detailed in chapter 3, an experimental setup was established. Currently, operational battery electric ships in The Netherlands have ranges varying between 60-120 kilometres (van der Geest & Menist, 2019). In chapter 3, an expected increase of %33 was found in the literature. Based on this expectation and current ranges, three plausible range scenarios were developed. A low-range scenario in which the range was 70 km, a medium-range scenario in which the range was 110 km and a high-range scenario in which the range was 150 km.

Furthermore, it was assumed that the maximum capacity which can be realized at a single location is 10MW. Looking at the previously achieved charging capacities, a single module that delivers this capacity could be built. Alternatively, multiple facilities that deliver a lower capacity could be realized in parallel. Three alternative policies were established. In policy 1, a single charging module of 10MW was considered to place at each location. In policy 2, at most 3 charging stations of 3.33 MW were placed at a single location. The last policy entails building at most 5 stations of 2 MW at a location. Together with the three range scenarios, these three policies resulted in the 9 experiments detailed in 5.1. For each of these scenarios, the heuristics could be applied or not. As such, 18 experiments were evaluated in chapter 6.

Experiment	Range of a ship	Max stations per location	Module capacity
1	70 km	1	10 MW
2	70 km	3	3.3 MW
3	70 km	5	2 MW
4	110 km	1	10 MW
5	110 km	3	3.3 MW
6	110 km	5	2 MW
7	150 km	1	10 MW
8	150 km	3	3.3 MW
9	150 km	5	2 MW

Table 5.1: The experimental setup in which three range values and three policies are combined.

5.1.4. Data sub-setting

The full trip-based origin-destination dataset contained information regarding over 385,000 trips. These were not solely inland trips but also trips from and to The Netherlands and foreign trips. Only inland trips fell within the scope of this research, hence all other trips were dropped from the data set. Moreover, some additional data sub-setting steps were necessary, which can be found in appendix C. Finally, trips between over 10000 O-D pairs and 600 Dutch harbours were left. Not all of these harbours could be incorporated into the models, because of computational limitations. Therefore, it was chosen to only incorporate the 200 O-D pairs with the highest expected flow values. Doing so, resulted in including 52.0% of all trips, 65% of the expected flow on the network and 100 unique harbours. An overview of all steps can be found in figure 5.1.

5.2. Aligning the network and the trip data

The next step was aligning the network with the trip-based O-D data. This entailed assigning all 100 unique harbours to nodes in the network, based on their coordinates. First off, retrieving the coordinates of 100 harbours was not straightforward, because of incomplete data. This process is explained in section C.3 of appendix C. It was assumed that the path in and out of a harbour could be neglected and that ships passed by a harbour if they passed by the exit. This was done because this made it easier to consider harbours for intermediate recharging stops. Hence, the objective was to select the nearest node at an ongoing waterway (green), for each harbour (red) as illustrated in figure 5.2 for two harbour docks of Lobith. Based on some network attributes, the best nodes at ongoing waterways

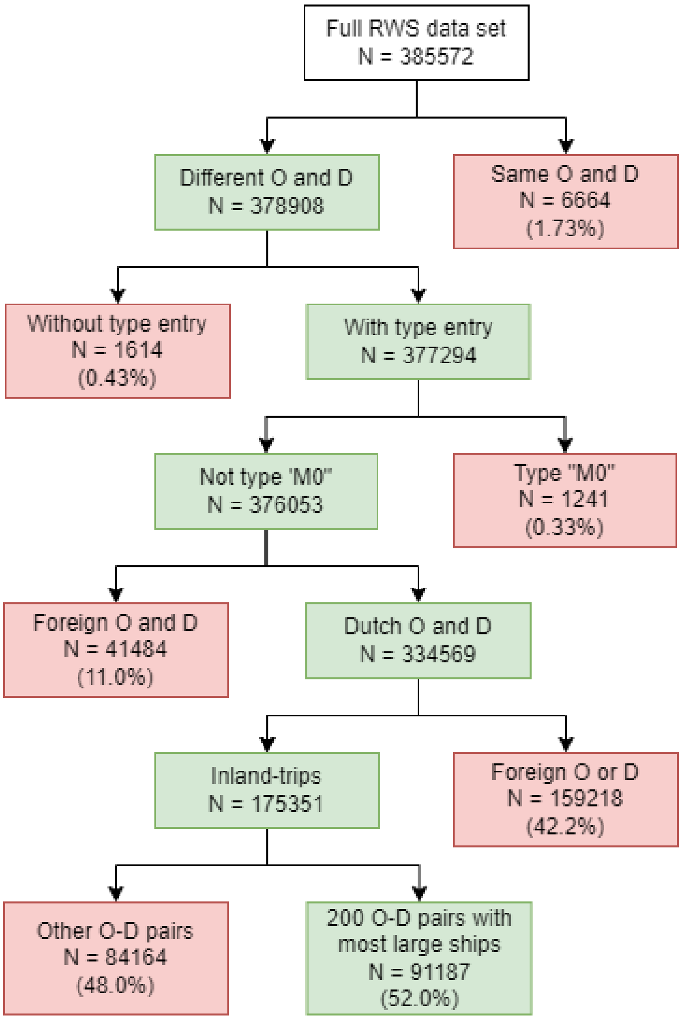

Figure 5.1: Data selection process

were selected for all harbours. This resulted in 97 unique harbour nodes, for the 100 harbours. In most cases, a node was found within a few kilometres of the determined coordinates for a harbour.

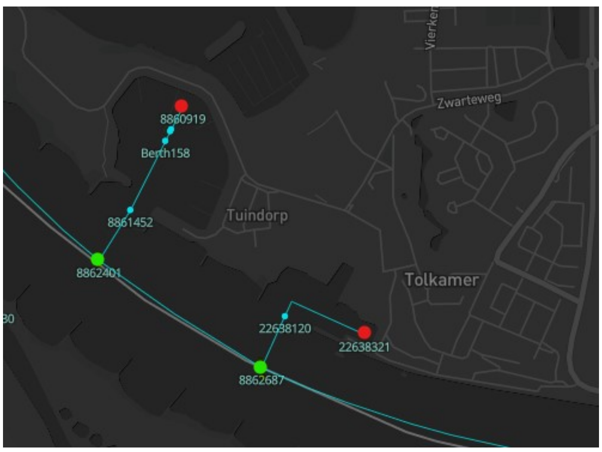

Figure 5.2: Nodes on ongoing routes (green) which would be selected for harbour nodes (red) using the designed method.

5.3. Network simplification

Lastly, the network was simplified for increased computational efficiency and to make the network suitable to apply the designed heuristics. First off, the K-means algorithm by MacQueen (1967) was applied to reduce the number of harbour nodes, as quite some harbour nodes appeared to be right next to each other. In this manner, the total number of harbour nodes was reduced to 82. Following the shortest paths for all of the ship types which had sailed the selected O-D pairs were determined. Following, only the subgraph with the nodes that were in the determined routes was kept. Also, all intermediate nodes with a degree of 2 were removed from the network. This resulted in the network which is visualized in figure 5.3. In this figure, the five found routes for various ship types are visualized.

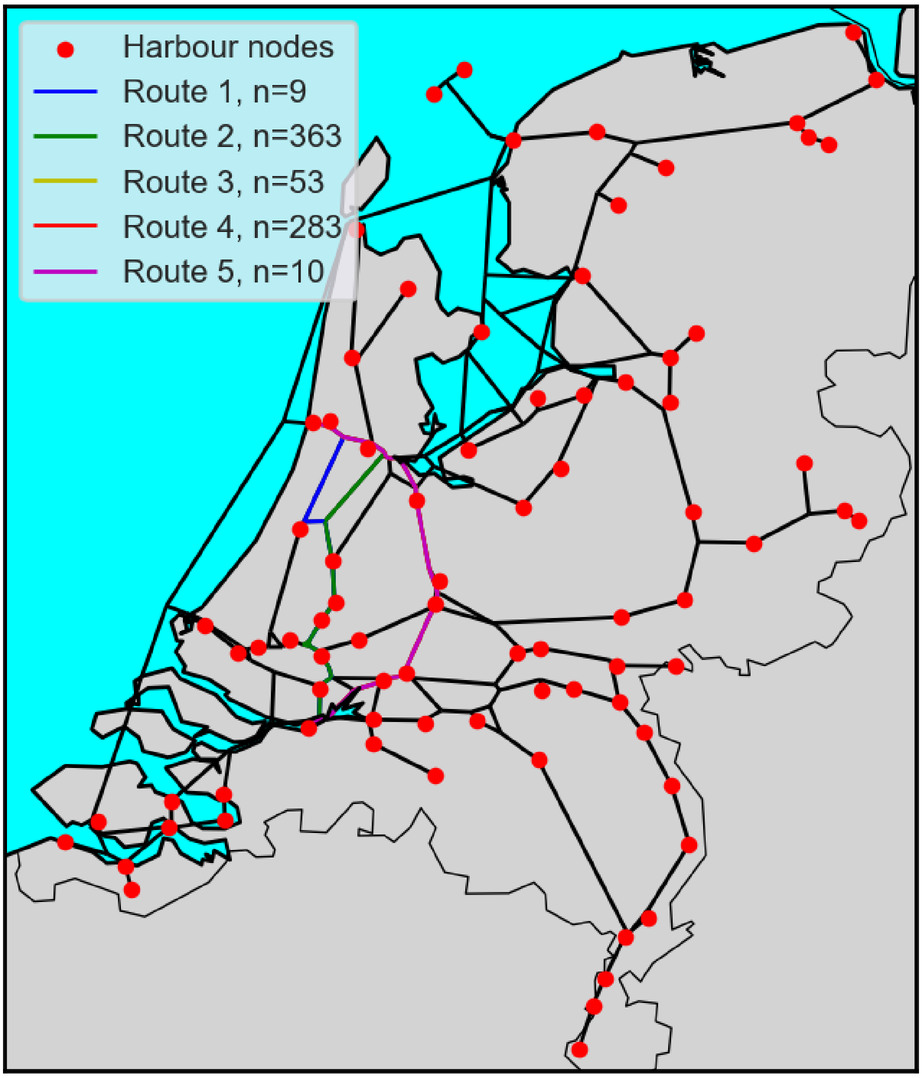

Figure 5.3: Different routes on the cleaned network from IJmuiden to Moerdijk and the corresponding number of ships (n) which were assumed to take these routes in 2021.

6. Results

The goal of this research was to iteratively combine the newly designed adapted capacitated flow-refueling location model (CFRLM) with an agent-based simulation model. To do so, an experimental setup was established in the previous chapter (see table 5.1). In this chapter, all of the experiments were assessed, with and without considering any additional potential charging station locations. In this manner, 18 experiments were evaluated. Consecutively, the results of the CFRLM and the ABM will be presented. A detailed description of how the results were generated can be found in appendix D, just additional figures.

6.1. The capacitated flow capturing location model

The adapted CFRLM aimed to maximise the share of the total flow that could be electrified with a given number of charging stations. Based on this objective, three main metrics were determined for the CFRLM in chapter 4. In this chapter, the model outcomes will be analysed according to these model metrics. First, the effects of the designed heuristics to determine additional potential charging station are assessed using the serviceable fraction and fraction of the total flow which can be captured. Then, the way in which the fraction of the total flow increases if more charging stations are placed for all 18 experiments is discussed. Hereafter, the expected utilisation of charging stations is assessed. Finally, the cumulative number of charging stations which were placed on the network in all of the experiments with and without considering additional nodes are presented using a density plot.

6.2. Heuristics for additional potential charging station locations

Two heuristics were established to determine optimal additional charging station locations. The optimal number of additional nodes added with each heuristic was determined empirically. First, both heuristics were applied to the case study network considering ship range of 70 kilometres, to an increasing number of charging stations. A maximum charging station capacity of 2MW and a maximum of 5 charging stations per location was considered. All possible ways to include the heuristics were tested. The results when considering an increasing number of charging stations to place in total is visualized in figure 6.1. It was clearly found that first applying the first and then applying the second heuristic yielded the best results. Henceforth, first applying the second heuristic and then applying the first heuristic was not considered.

In appendix section D, all heuristics were compared for various ranges as well. After it was found that both heuristics performed the best for all other ranges, the number of nodes to insert with both of them had to be determined. To this end, various experiments were performed. In these experiments, both heuristics were used to determine 5-30 additional charging station nodes. Then, the CFRLM was applied to locate 40 charging stations on the network considering various ranges, for each of these experiments. Besides the total fraction of the flow which could be captured in the optimal solutions, the number of used additional locations was also observed. A detailed overview of this analysis and the resulting plots can be found in appendix D. In summary, it was found that adding more than 25 additional nodes did not add value in most cases. Therefore it was decided to apply both heuristics to determine 25 additional locations in the scenario in which additional nodes were considered. The resulting network with 50 additional potential charging station locations generated by both heuristics is visualized in figure 6.2.

6.2.1. Captured fraction total flow

The resulting fraction of the total flow that could be captured without considering additional nodes with an increasing number of stations can be found in figure 6.3. Where the lines stop, 99.9% of the total flow which could be captured, given the range and the potential locations, is captured. As such, the points where the lines stop indicate the maximal number of effective charging stations in each of the

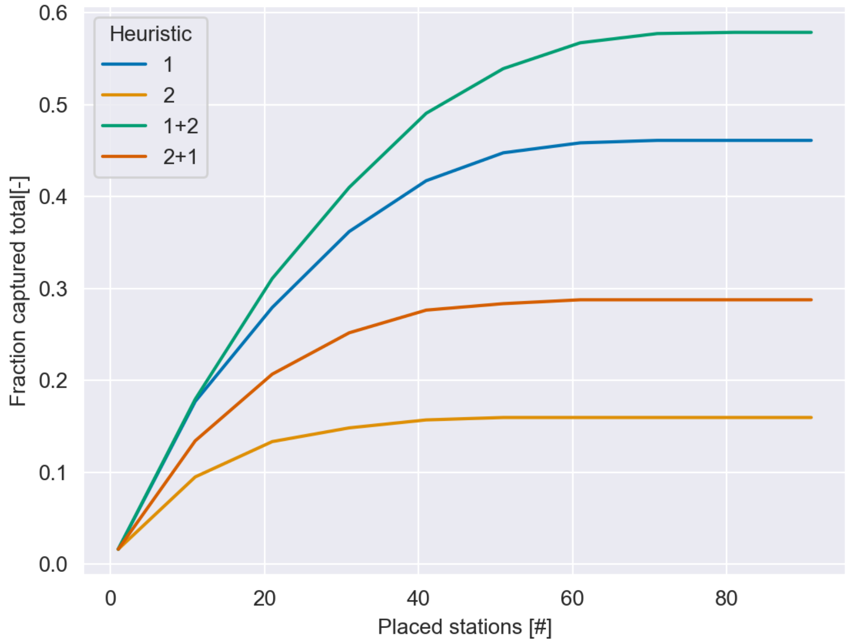

Figure 6.1: The results of all possible heuristics compared when an increasing number of stations is placed on the resulting network.

experiments. Without additional nodes, only about 10% of the flow could be served by the charging stations if a range of 70km was considered, in all three experiments. Hence, placing larger stations was never efficient in these scenarios, except if it would have reduced waiting times.

To the contrary, less, more powerful charging stations could satisfy significantly more flow in the medium and high range scenarios. Especially if few charging stations are placed in total. Even if just 1 charging station was placed in total in all experiments, the resulting total fraction of the total flow which could be captured diverged widely. When more charging stations were placed, these marginal effects of placing more stations reduced. The maximum fractions of the total flow which could be captured quadrupled to around 40% when a range of 110 kilometres was assumed. Finally, a range of 150 km resulted in a maximum captured fraction of the total flow of around 70%.

Remarkably, the maximum fraction which is captured is close to equal for each of experiments considering the same range. Although the number of charging stations which was required differed. The differences between the number of stations which are required to support all of the flow when different station sizes are considered, increased if the range increased. This was expected, while a longer range may allow to place charging stations more effectively. This also explained why the maximum number of charging stations which can be placed effectively increased relatively slow with the range, compared to the maximum fraction which is captured. This points to the fact that charging stations were likely a lot busier on average in high-range scenarios in reality. Lastly, it was apparent that the fraction of the total flow which was captured some times went up rather abrupt. This may be explained by the fact that placing an additional station may make new routes feasible with battery-electric drive. The extend to which the fraction which is captured increased, depended on the flow value of this route.

Furthermore, the resulting fraction of the total flow that could be captured considering additional nodes with an increasing number of charging stations, is visualized in figure 6.4. First off, it is apparent that much higher fractions can be captured in all experiments. When considering a range of 150km, 99% of all flow could be served. The captured fraction relatively increased the most when additional nodes are considered in the low range experiments. Remarkably an increasing range, allowed to capture more flow with fewer stations if additional nodes were considered. This was expected, as the additional potential charging locations may be on multiple of the shortest paths. Notably, the total number of

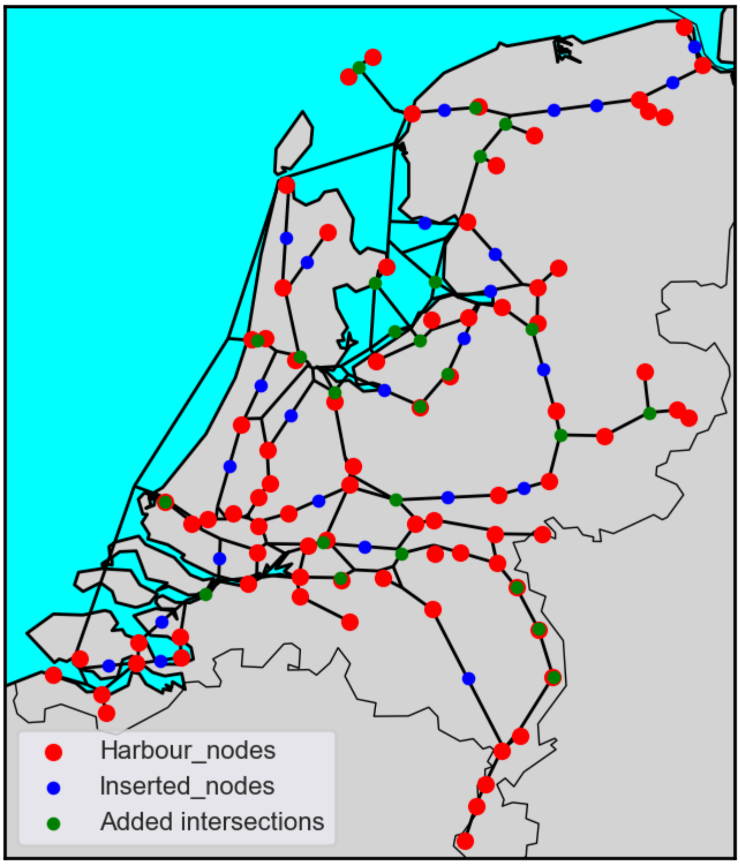

Figure 6.2: The final resulting network with 2 x 25 additional potential charging station locations. The blue points are added using heuristic 1 and the green points using heuristic 2. The red points are the harbours, which are always considered as potential charging station locations.

effective charging stations was higher for the low and medium range experiments if additional charging station locations were considered. The number of effective charging stations for all experiments can of course be seen in the graphs, but is also visualized using bar charts in D. However, looking at the high range 1x10MW experiment, the number of effective charging stations is lower if additional potential charging stations are considered.

6.2.2. Expected utilisation

Next, the expected average station utilisation was determined for all of the experiments with and without considering additional nodes. The expected utilisation rates increased if smaller stations were placed in all scenarios. As expected, the utilisation rates were much higher if additional nodes were considered, especially for the lower and medium range experiments. Furthermore, the overall utilisation increases with the range of a ship, as more routes become feasible. In general, utilisation rates ranged from just a few percent till almost 85% in absolute values. In appendix B, these utilisation rates were compared with the observed utilisation rates in the ABM as a means of validation of both methods.

6.2.3. Density plots

In addition to the previously presented metrics, density plots were made for all experiments. This was done to indicate which locations were frequently considering the optimal number of charging stations for each of the 18 experiments. Separate density plots were made for all experiments with and without additional nodes. All potential charging station nodes were scaled to the cumulative number of stations which were placed at that location. As such, the results provide insight into the expected demand at all potential charging station locations across all experiments. The resulting density plot when no additional nodes are considered is presented in figure 6.7. Looking at this density plot it is apparent that

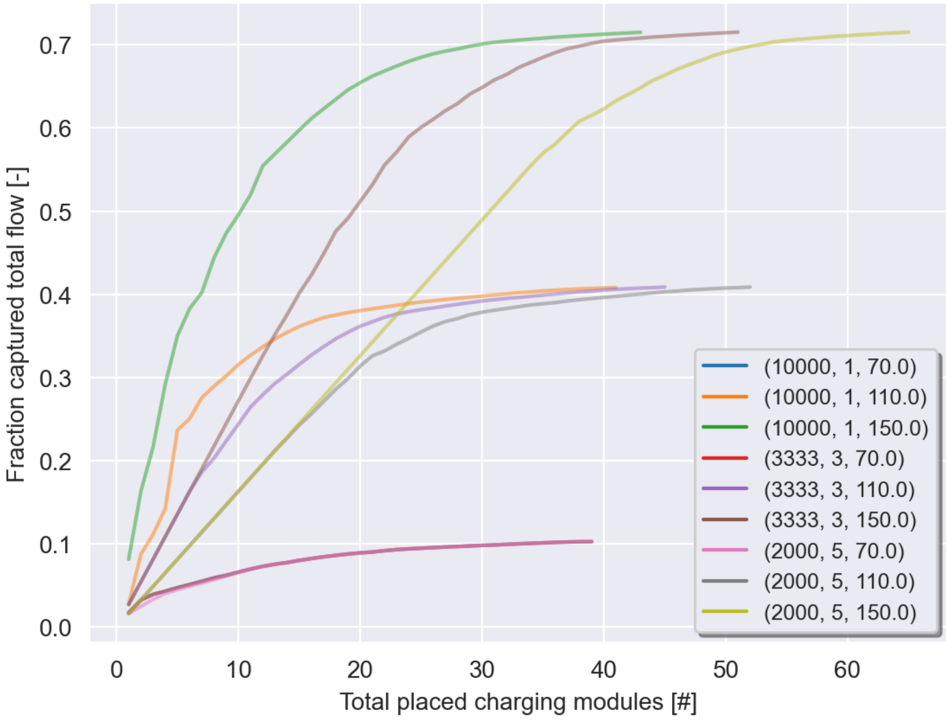

Figure 6.3: Fraction of the total flow captured by the charging station layout when additional nodes are not considered.

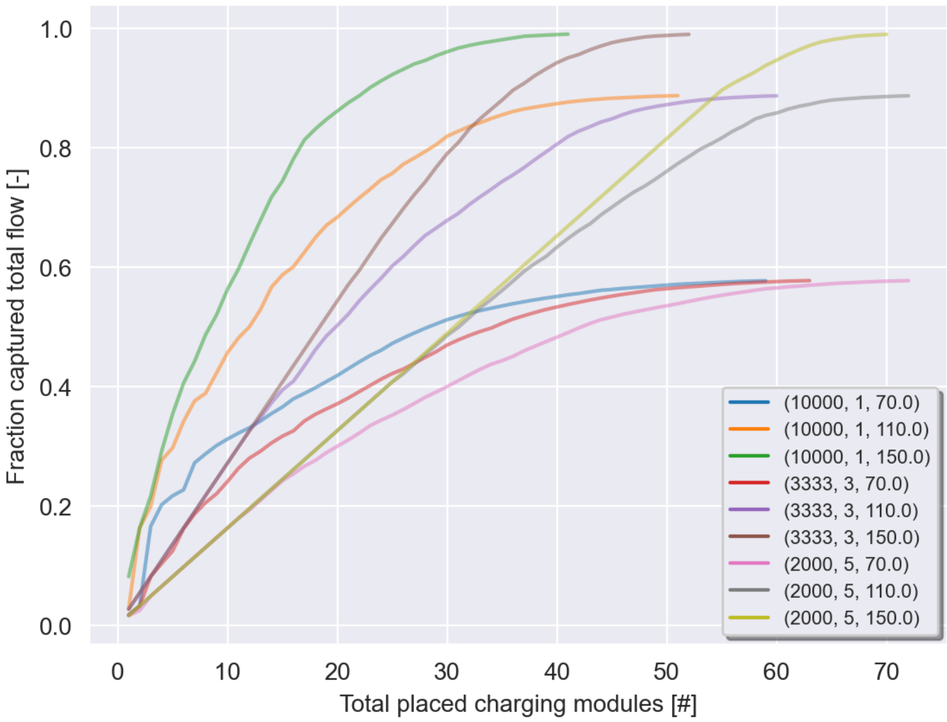

Figure 6.4: Fraction of the total flow captured by the charging station layout when additional nodes are considered.

the gravity point is centred around the route between Rotterdam and Amsterdam, as expected.

Furthermore, the density plot considering additional nodes is visualized in figure 6.8. It is clearly visible,

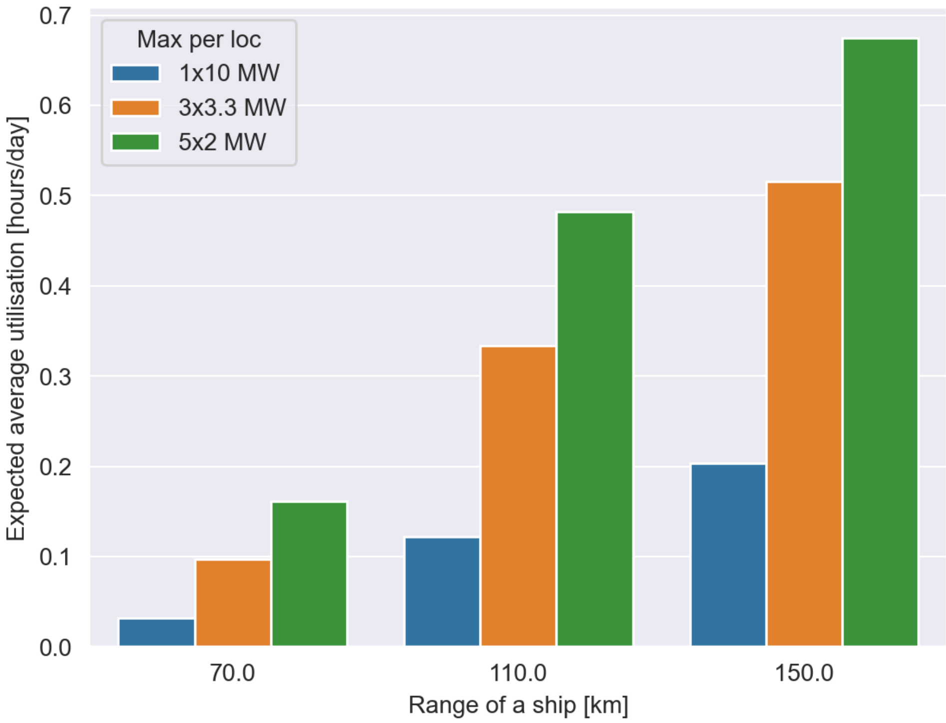

Figure 6.5: Expected utilisation when additional nodes are not considered.

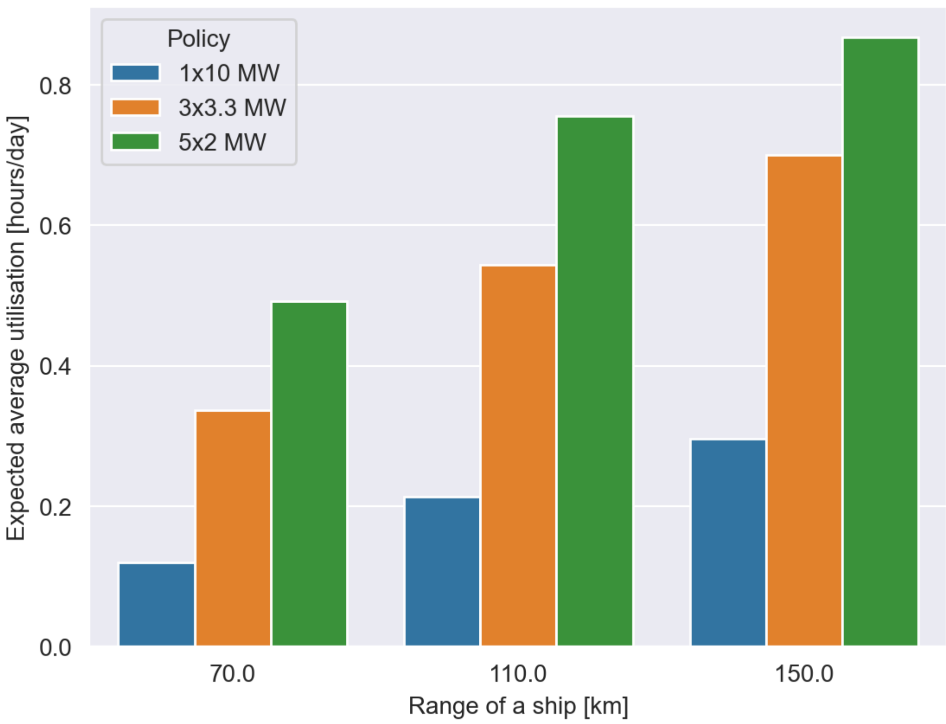

Figure 6.6: Expected utilisation when additional nodes are considered.

that there were more charging station placed in total, in the experiments in which additional nodes were considered. As a result of the increased demand, even more stations are placed in the West of the Netherlands. However, the total number of potential charging stations also increase. Hence, charging

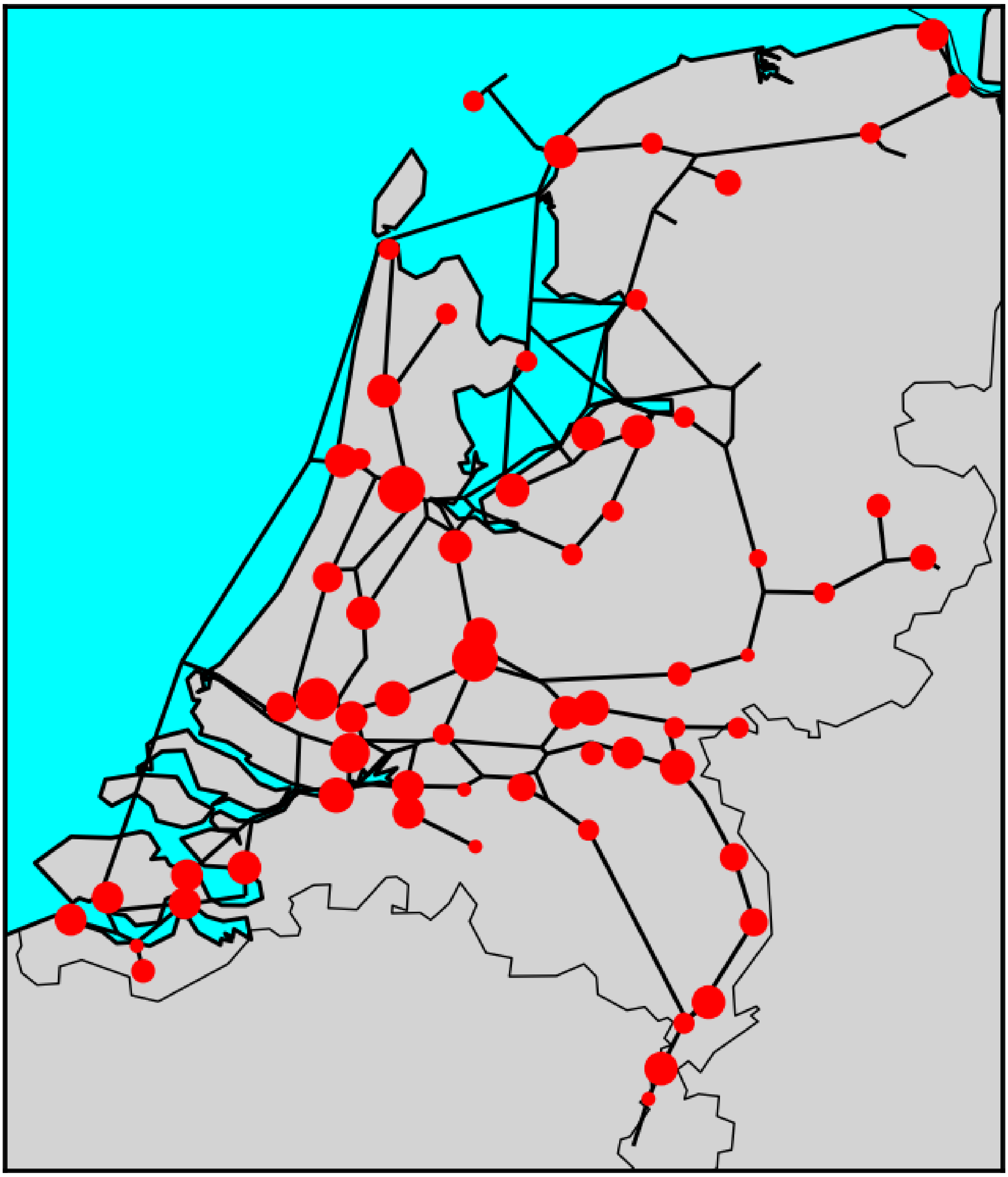

Figure 6.7: Density plot 9 scenarios without additional charging stations.

stations in some areas were more evenly divided. In general, the density of charging stations was much higher if additional charging station nodes were considered. In both figures, only at 5 places more than 1 station was placed on average. This meant that the influence of the experiment parameters was large. Finally, most additional stations were placed where there are relatively few potential charging station nodes present. This suggests that with the locations and input parameters identified, the flow on the busy path between Rotterdam and Amsterdam was already covered without additional potential charging station nodes. Hence, the contribution of additional charging stations was therefore mainly to enable more routes and not to increase the flow that can be supported on the busy paths.

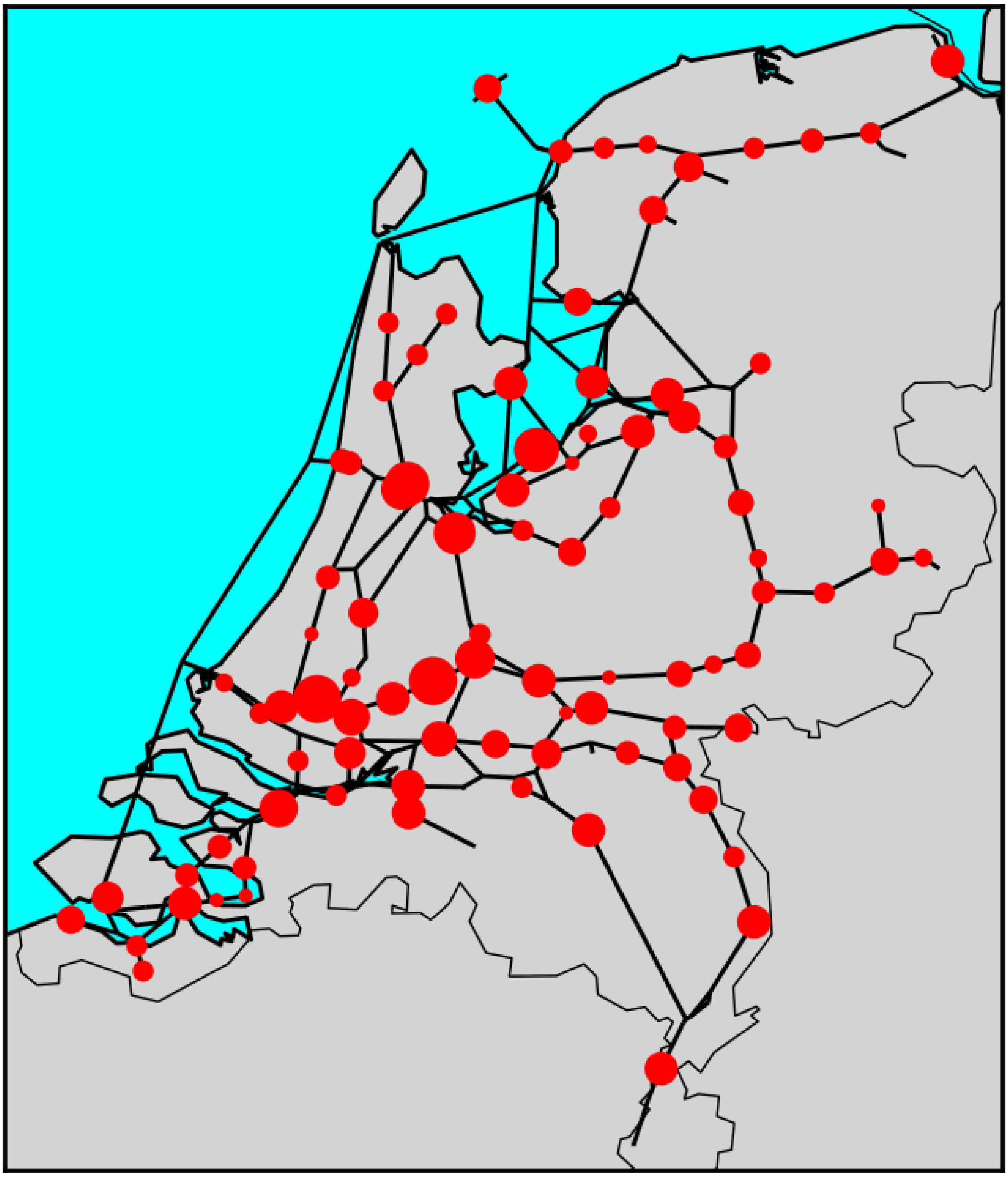

Figure 6.8: Density plot 9 scenarios with additional charging stations.

6.3. Results agent-based simulation

The ABM was used to simulate the performance of the optimal found charging station layouts for all of the 18 experiments. Information regarding the number of iterations for each experiment and the estimated convergence, can be found in appendix D. First, the average charging station utilisation and waiting time in each of the scenarios are presented. Following, an overview of the fraction of the time that ships spent sailing, waiting, and charging is presented for all experiments. Also, D.1 contains graphs of the absolute charging and sailing times.

6.3.1. Average station utilisation and waiting times

The found average waiting time and station utilisation rates for the experiments without additional charging station locations are plotted respectively figure 6.9 and figure 6.10. Remarkably, there is a clear trade-off between these two KPIs, as ideally high utilisation rates and low waiting times are preferred. Placing fewer, larger charging stations was found to be the most effective at reducing waiting times in for all considered ship ranges. However, this also led to much lower utilisation rates. As a result, with relatively fewer large stations, more traffic could be provided considering a small range. Relatively seen, the average utilisation increases much more than the waiting time for the 1x10MW scenario at higher ranges. Looking at the absolute values, the waiting times were ranged between 20-350 minutes and utilisation rates between 3-63% in the experiments without additional nodes. Arguably, the 3x3.3 policy performed slightly better than the 5x2.0MW policy. After all, the resulting difference in waiting time between these policies was a lot smaller that difference in usage hours

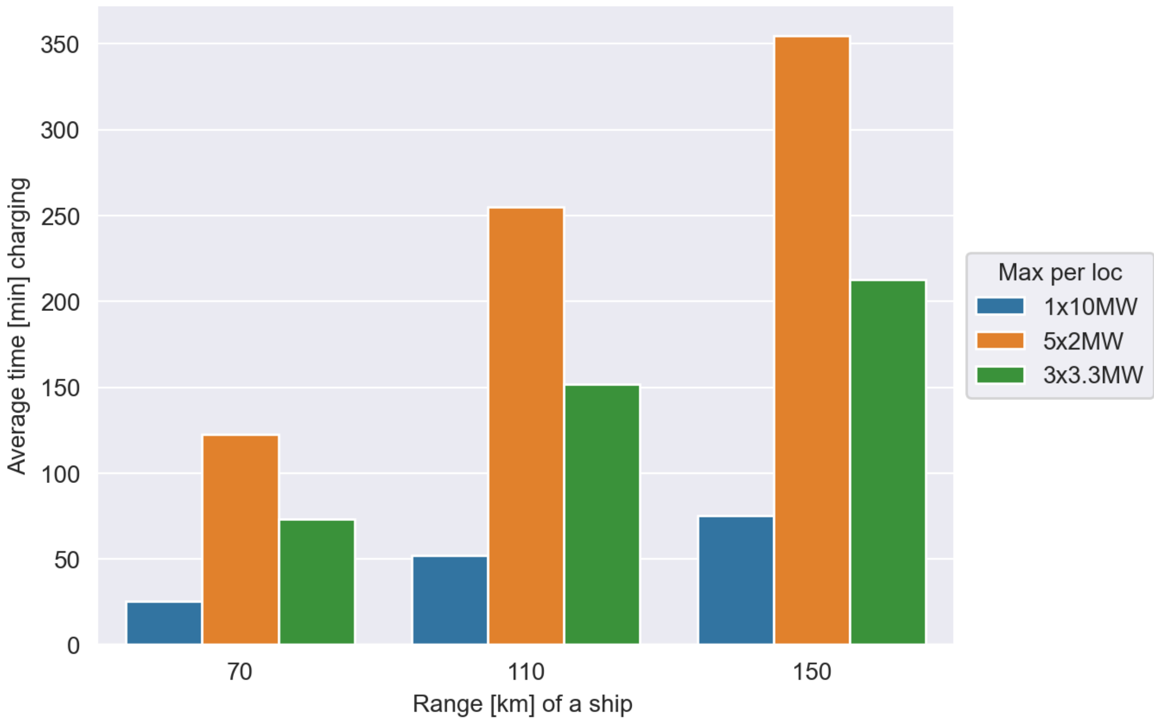

Figure 6.9: Average waiting time in minutes for each of the experiments without additional potential charging station locations.

Considering additional nodes, led to even higher waiting times and utilisation rates. As the optimal number of placed charging stations decreased with an increasing range, this was already expected. In general, larger charging stations performed worse than in the experiments without additional nodes. This was likely the case because larger charging stations could be placed more efficiently if additional nodes were considered. Absolute utilisation rates were much higher, and ranged between 12-80%. Moreover, the waiting times tripled in most scenarios and range between approximately 200-1200 minutes.

6.3.2. Relative waiting, charging and sailing time

Also, the relative waiting, charging and sailing times were assessed using the ABM. The results considering additional charging station locations are presented in figure 6.13. At low ranges the system performed relatively well. However, as the range increased, the waiting times went up. The relative charging times went up whenever less powerful charging stations were considered. However, as the range increased, the relative differences decreased. This was even more prevalent when additional potential charging stations were considered, as seen in figure 6.14. Remarkably, the fraction of the time that ships had to wait stayed relatively constant if the medium and high range scenario are compared.

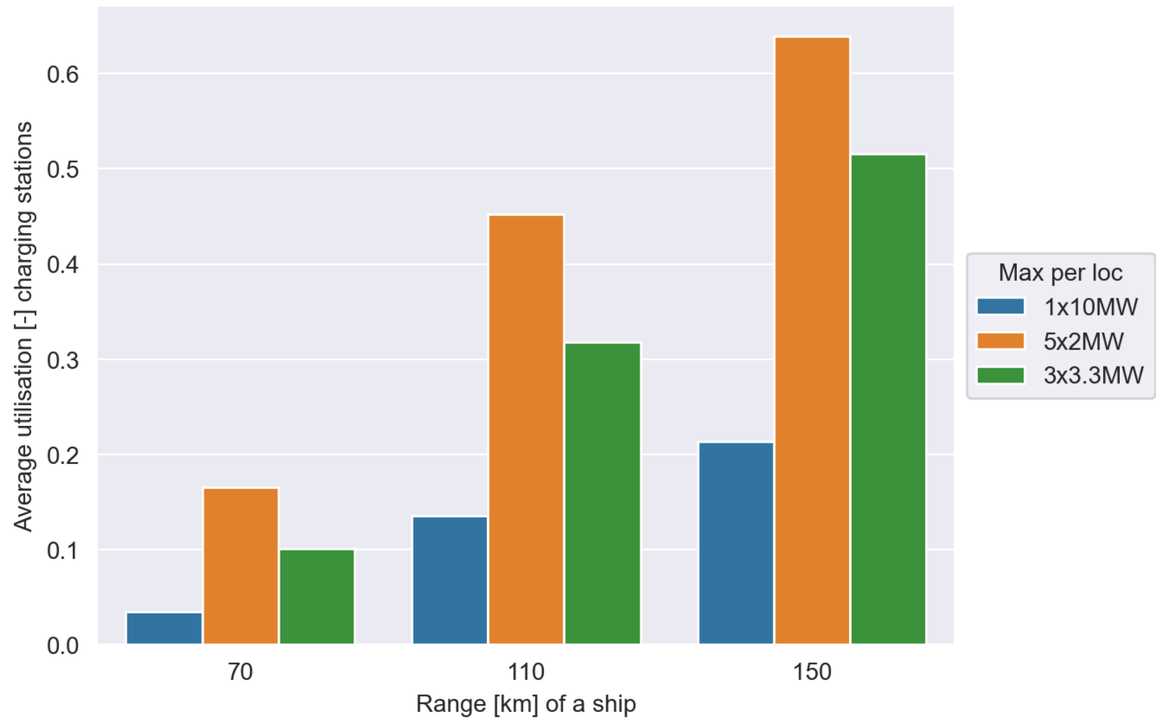

Figure 6.10: Average station utilisation for each of the experiments without additional potential charging station locations.

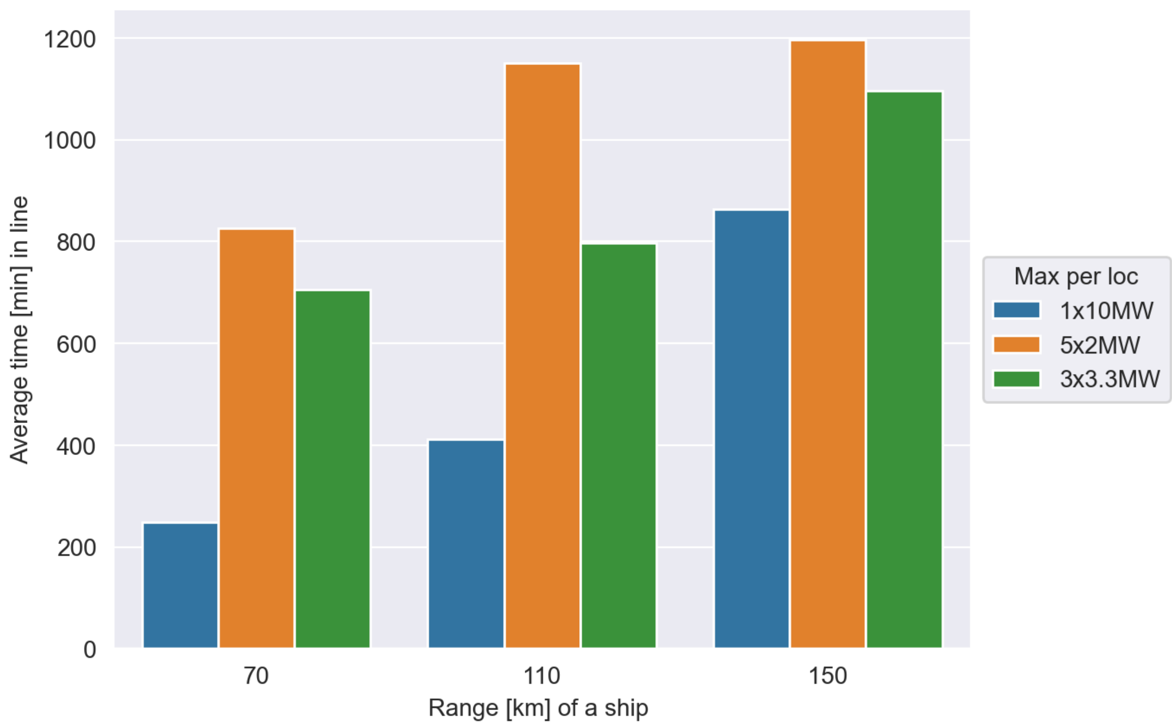

Figure 6.11: Average waiting time for each of the experiments with additional potential charging station locations.

6.4. Conclusion

In this chapter, first the optimal number of additional potential charging station locations was determined. then, the optimal charging station layout for 9 different experiments was determined. It was found that

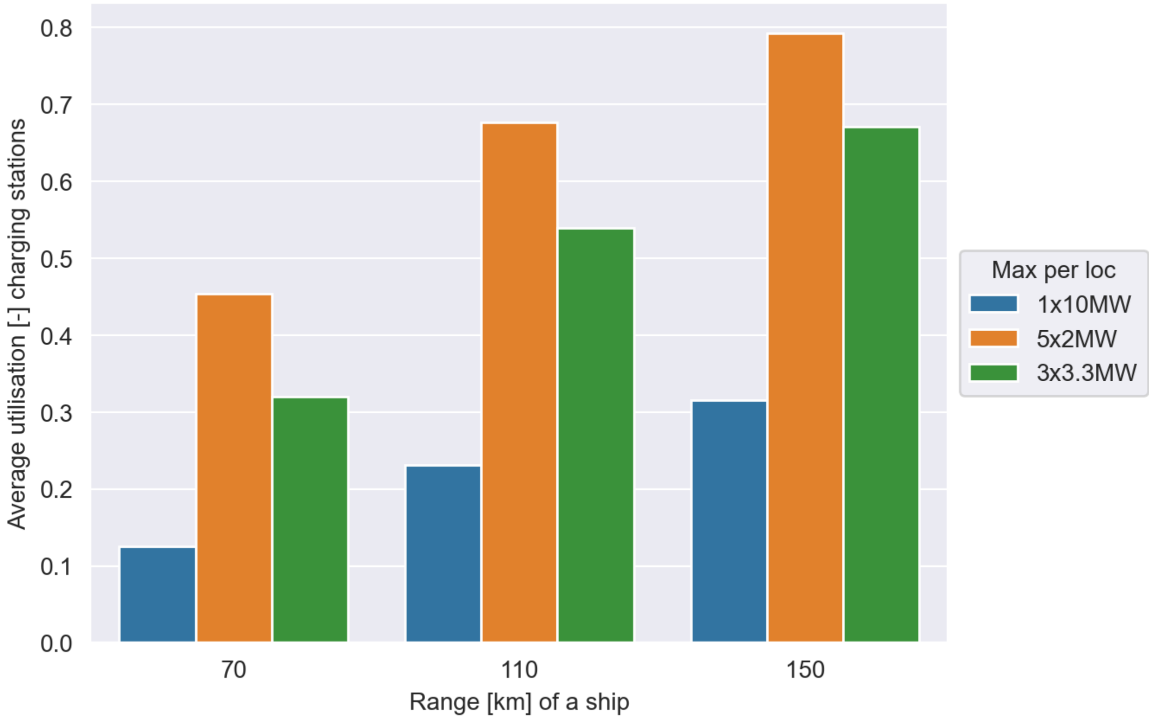

Figure 6.12: Average station utilisation for each of the experiments with additional potential charging station locations.

a higher range allowed to place charging stations more efficiently. Moreover, considering additional potential charging station locations was found to have a similar effect. If additional potential charging stations were considered, the optimal number of charging stations even decreased with the range. While more trips were feasible with higher ranges, this resulted in increased utilisation rates. Finally, it was found that there is a clear trade-off between utilisation rates and waiting times.

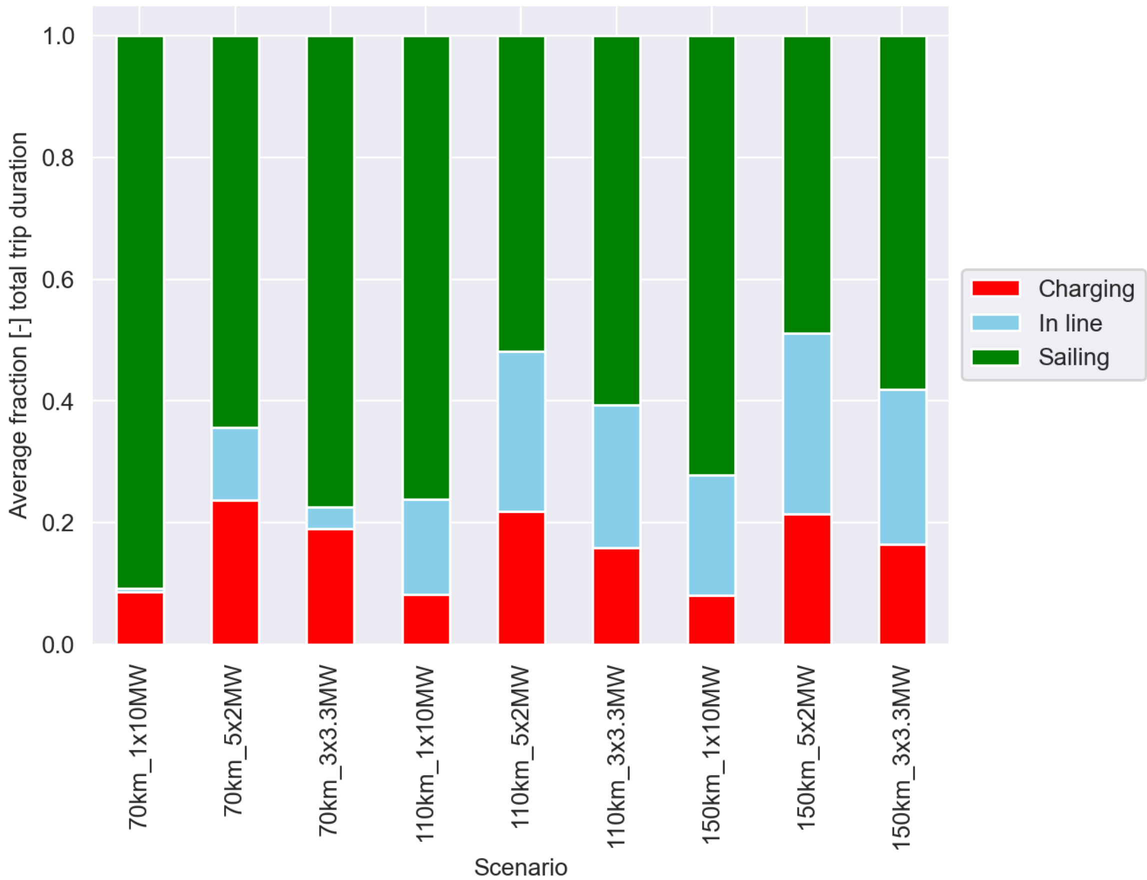

Figure 6.13: Fraction of the time that ships spent charging, inline and driving in each of the 9 experiments without additional nodes.

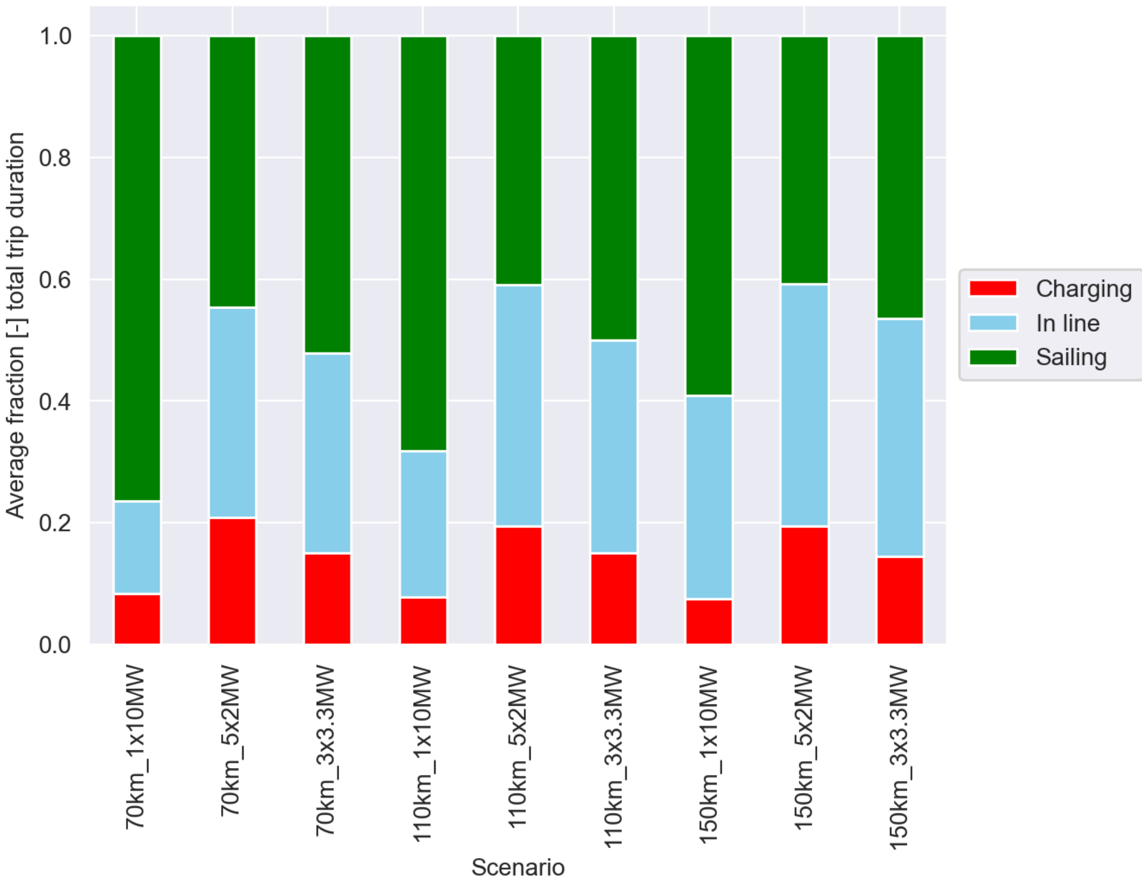

Figure 6.14: Fraction of the time that ships spent charging, inline and driving in each of the 9 experiments with additional nodes.

7. Discussion

This research aimed to develop a method to guide decision-making regarding the optimal placement of charging stations on a transport network. To this end, the goal was to combine a capacitated flow-refueling location model and an agent-based simulation. Moreover, the goal was to apply this method to the Dutch inland waterway freight transport network. In this chapter, first, the results of the case study were reflected upon and the underlying assumptions were discussed. Then, the more general developed method to site charging stations was evaluated, before the suggestions for future research were presented. A full overview of all assumptions which had to be made can be found in appendix A

7.1. Case study

The goal of this case study was to investigate the large-scale electrification opportunities from a network perspective. To this end, rather optimistic assumptions were made regarding the possibilities for electrification of ships. Each trip was assumed to be feasible with battery-electric propulsion, based on just the assumed battery-electric range and the placed charging stations. It was found that the range of a ship is of great importance for the possibilities for battery-electric shipping. Moreover, additional charging stops were found to be required in most cases. Various plausible charging station capacities and ship ranges were evaluated using the designed method. Considering just the observed harbours as potential charging station locations, only a limited number of ships was feasible for electrification. To the contrary, 99% of all observed trips on the Dutch waterway were found to be feasible for battery electric drive, additional potential charging station locations.

However, in reality, all trips are executed by a certain set of ships. Each of these ships is only feasible for electrification, if all of the trips of the ship are feasible with a given charging station layout. The approach which was adopted in this research neglected this. Even if the full observed network was feasible with battery-electric propulsion, a ship may be unfeasible for electrification. This could be the case, while it was not known whether the ship also sailed in on not observed waterways. Moreover, no detailed data regarding the ships was known. As such, the assumed average energy consumption and average speed of a ship were only rough estimates. In future research, this could be overcome if non-anonymous trip-data is used. Then, all trips of ships that only sailed in a certain area can be selected. Following, the adapted CFRLM can be used to locate charging stations to make all of these trips feasible.
Furthermore, the resulting waiting times were assessed for each of the found charging station layouts. A clear trade-off between charging station utilisation rates and resulting waiting times was identified. Higher utilisation rates, always led to longer waiting times However, the simulation assumed ships did not change their usual travel pattern. In reality, the roll-out of a charging station layout will likely come along with an extensive scheduling system. In any case, the ships still needed to charge for a significant amount of time. Depending on the chosen charger capacity and considered range, charging took 6-22% of the total trip time. Loading and unloading a ship takes a significant amount of time, and was identified as the main charging opportunity. However, in most cases ships also required intermediate refuelling stops. Moreover, a charging station can only be placed at a single dock. As such, much more charging stations will be needed if ships only charge during loading and unloading.

7.1.1. Model adaptations

The main feature of inland ships which was included in the modified CFRLM is their varying energy demands, and the ability to estimate the energy demand at a station. As the energy demand significantly varies between different vessels, the approach of the original CFRLM was not suitable. The original model assumed that each vehicle always had the same energy demand it it refuelled. The newly designed approach allowed the incorporation of different types of ships, by including a class-specific energy demand per travelled kilometre, and an average charging speed for all classes. Also, the maximum capacity of a station was redefined as the maximum supplied energy during a given period by a charging station. Following these assumptions, the model is more suitable to apply to battery-electric systems.

Notably, speeds and charging speeds were still assumed to be equal for all classes, and all classes were assumed to have the same energy demand travelling on any path in any direction. Also, the energy demand was assumed to be equally divided over all charging stations which were used by a ship to complete a certain path. This does not necessarily have to the case. Future research may assess the effects of varying energy demand of for example currents in detail, by considering a different energy demand for a path, based on the direction in which the path is followed. Now, it was implicitly assumed that the range of a ship was the minimum range in the worst possible conditions. This assumption allows the ship to travel at least the assumed range at all times. During this case study, the effects of environmental variables which affected the energy use were assumed to even each other out, meaning the net energy demand would stay the same.

7.1.2. Implications

Based on this study, it may be concluded that there are possibilities for large-scale ship electrification using battery-electric systems in the Netherlands. However, this will likely incur high costs. A relatively large ship range will have to be realised. In addition, high charging capacities are needed and additional stops will be required. This will lead to a decreased transport capacity. Furthermore, realising a lower number of more powerful charging stations was found to be the most effective to reduce waiting times. However, in reality various charging stations may be placed at the same time, this was not considered in this research. The current approach assumes multiple charging station at a single location can only be used for parallel charging. Optionally, various capacities may be included in the adapted CFRLM by assuming that multiple charging stations at a location can be used to charge a single ship. In each case, the clearly identified trade-off between charging station utilisation and average waiting times, stresses that temporal demand fluctuations exist and should be assessed.

In general, only a few large hubs with multiple parallel charging stations were placed by the CFRLM if small stations were considered. This points to the fact that any system will likely consist of some large hubs and multiple smaller stations. Remarkably, this could also be a more feasible result considering the electricity grid than siting less large charging stations too. Considering more additional locations did not lead to the intensification of the demand in certain areas, but rather to a better distribution of flows across the network. Large, single stations were found to perform the best at reducing waiting times, but led to low utilisation rates. Hence, it may be interesting to combine charging stations for ships with other e-mobility services in an energy hub. In this manner, utilisation of these stations may be increased while feasible waiting times are maintained at the same time.

7.2. Reflection upon the developed method

This research extended the capacitated flow-refueling model, to be more suited to locate charging stations for systems with with various energy demands. Furthermore, a charging station layout was successfully simulated using an agent-based model, considering various experiments. As anticipated upon, the CFRLM led to a somewhat sub-optimal situation, with some relativley busy charging stations which may be improved with additional model constraints. Nevertheless, this would require considering one scenario at a time and would also require specifying thresholds for acceptable waiting times and utilisation rates. The main goal of this research, was to develop and illustrate a method to guide decision-making regaring the optimal locations of charging stations for ships. Optimising for a certain expected ship range was not within the scope of this study.

Therefore, it was chosen to not apply the model in an iterative manner. This was not considered to add much value to this case study or to prove the effectiveness of the designed method. Especially, as the ability of the ABM to make trade-offs between average charging station utilisation rates and charging times was already successfully demonstrated. Moreover, a combination of smaller and larger charging stations appears to be the most effective. This was not considered in this research which only assessed placing one type of charging station at a time. In conclusion, it has been successfully demonstrated that an ABM may complement a CFRLM to guide decision-making toward the roll-out of a feasible charging station layout. Forthcoming, future research may apply a combination of these models considering the placement of multiple types of charging stations at the same time.

7.3. Future research

Based on the case study, full electrification of Dutch inland shipping seems to be technically achievable if the electricity grid would allow to site a set of relatively large charging stations. However, this is likely not the case. Moreover, compromises would be required. The transport capacity of ships will decrease and their deployability will decrease as well. This study only considered siting a single type of charging stations at a time, considering placing multiple charging stations at the same time was left for future research. Also, due to the network perspective adopted throughout this study, many details have been omitted. Future research regarding this case could focus on these aspects. For instance, the effects of currents, water levels, temperature and other environmental variables could be incorporated into scenarios or direction-specific energy consumption for paths. However, first research regarding the effects on the effects on the average energy demand on a smaller scale is likely needed, in which only some waterways are considered.

The model could also be applied in a different setting. However, especially transport systems with varying energy demands are interesting to assess. As such, a network with shared cars, shared scooters or taxis could be studied. For these networks, the required trip-based O-D data is more likely to be available. Furthermore, the newly designed method may be extended to consider placing multiple types of charging stations at the same time. Lastly, the method may be highly feasible to assess the positioning of energy hubs, when multiple systems are considered. As a single set of users is unlikely to be able to use all placed charging capacities at all times, this offers to explore opportunities to make charging sites more profitable and efficient at the same time.

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A. Assumptions

In this appendix, a list of all assumptions is presented, which had to be made to apply the models to the problem. First of the following assumptions regarding ships were for both models:

- Each inland trip was assumed to be feasible for electrification.
- All ships of a certain class were assumed to always travel at the same average speed based on their class.
- All ships of a certain class were assumed to always have the same average power consumption based on their class.
- Ships were assumed to have the same energy consumption travelling in any direction.
- Trips by ships were assumed to be unconnected, whereas, in reality, all trips are executed by a limited set of ships.
- The range of ships of all types was assumed to be the same. This was motivated by the idea that the battery capacity is relative to the installed power and ship size.
- Ships were assumed to be able to overtake each other at all times.
- Ships were assumed to be able to enter harbours and charging stations coming from all directions.
- A ship was assumed to be fully charged upon departure if there was a charging station present at the origin, and otherwise half-full.
- It was assumed that ships always took the absolute shortest path they could take given their size class.
- It was assumed that ships always travelled at their loaded speed, as they had the incentive to transport as much freight as possible at all times.
- It was assumed that ships always only refuelled at the assigned charging station combinations.
- Ships were assumed to always charge until they were full.
- In the ABM, ships were assumed to be served according to the ”first in first out” principle.
- In the ABM, ships were assumed to be fully charged at their destination before they were removed from the model.

Secondly, the following assumptions regarding charging stations were made:

- All placed charging stations in each experiment were assumed to have the same capacity.
- It was assumed that charging speeds were the same at all times and only depended upon the maximum average charging speed supported by the charging station.
- It was assumed that the maximum capacity that may be realized at a location was 10 MW because of constraints caused by the electricity grid, available space, or other external factors.
- The energy demand of a ship refuelling at multiple stations during a trip was assumed to be equally split over these charging stations.
- A likely fixed time to couple and decouple a ship from a charger was assumed to be neglectable.

Lastly, the adapted CFRLM entailed the following assumptions regarding the nature of flows:

- Each flow was assumed to be indefinitely divisible over sets of charging stations.
- Each flow was assumed to be a uniform flow.

B. Model verification and validation

To validate the adapted CFRLM, the flow on the network was observed. Then, the effects of an increasing range were observed.

B.1. Total flow on the network

The flow resulting from the conceptualisation was plotted in figure B.1 and compared with other data sources. It was concluded that the intensities were comparable with the intensities described in the literature (Rijkwaterstaat, 2020; van der Geest & Menist, 2019).

B.2. Siting a single station with an unlimited capacity considering an increasing range

As a means of model verification, a single station with an unlimited capacity was placed considering an increasing ship range. First, a range of 60 kilometres was considered in figure B.2. The station was then placed near Rotterdam, and only a single short route was could be supported. Then, the range was increased to 90 kilometres (see figure B.3). Now, multiple short routes could be supported. Increasing the range to 120 kilometres still did not enable trips on the busiest path of the network (see figure B.5). Finally, a range of 150 kilometres, allowed the model to capture the busiest route in the network between Rotterdam and Amsterdam (see figure B.5).

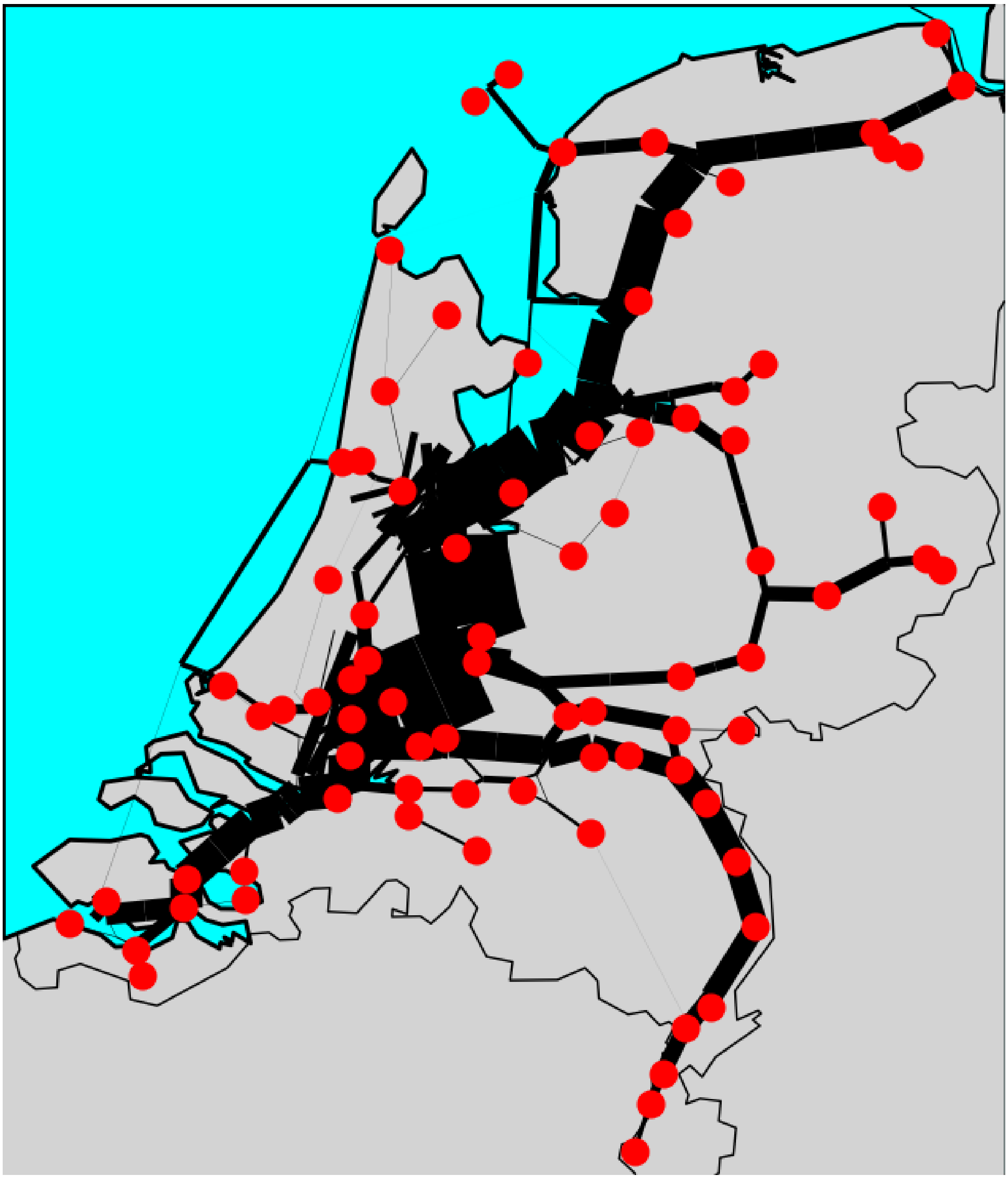


Figure B.1: Total flow on the network

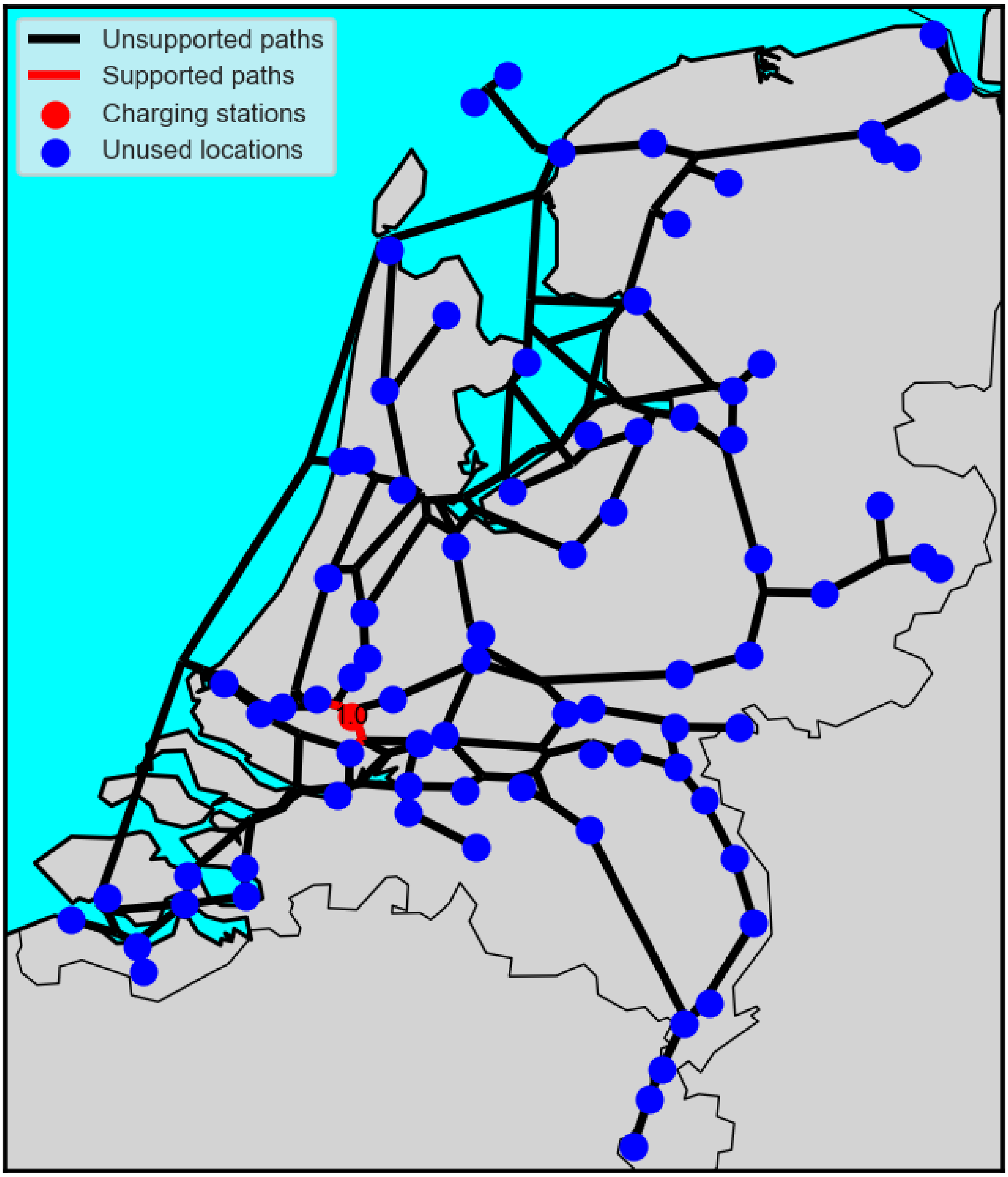


Figure B.2: Results single charging station with an unlimited capacity, considering a ship range of 60km

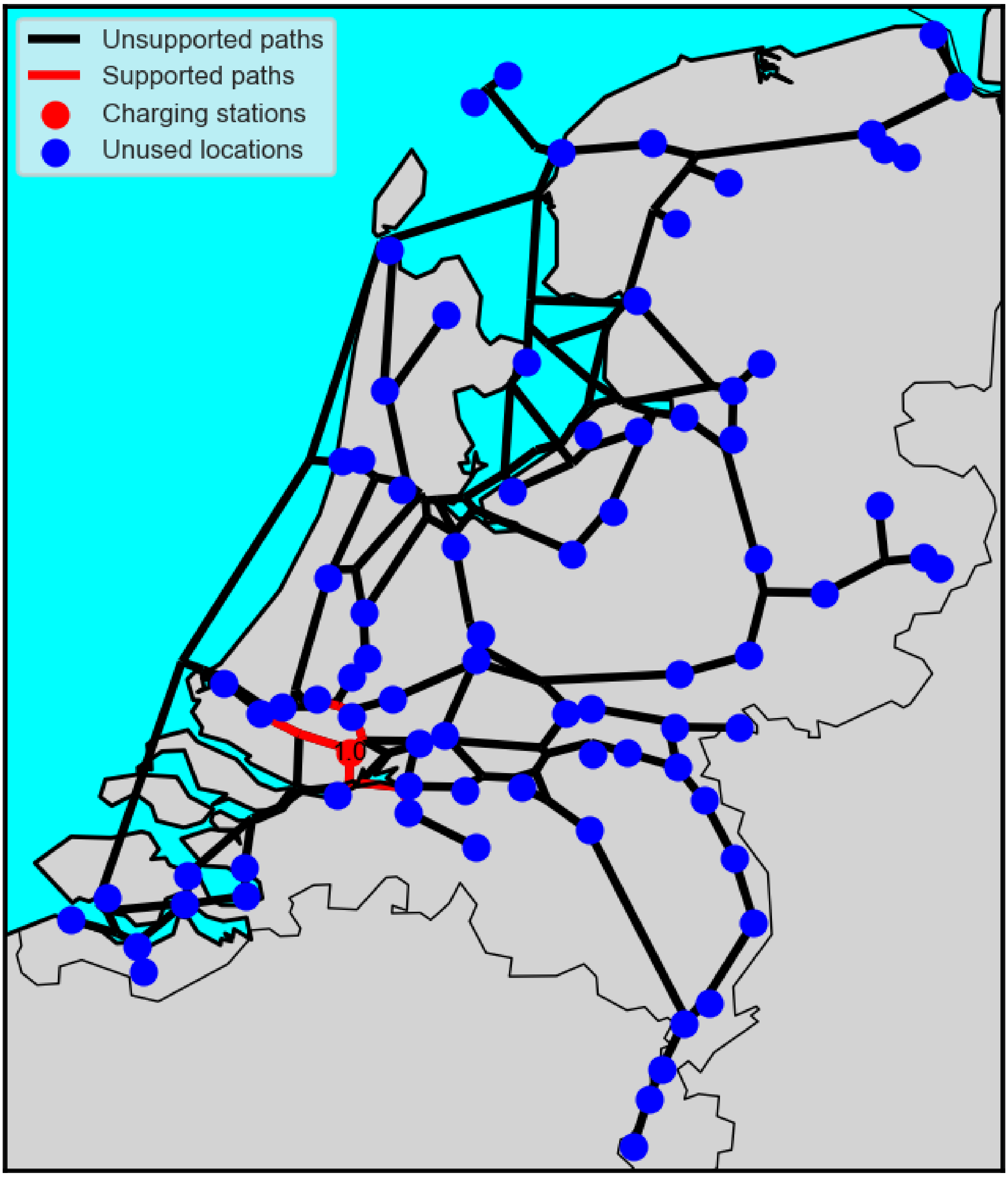


Figure B.3: Results single charging station with an unlimited capacity, considering a ship range of 90km

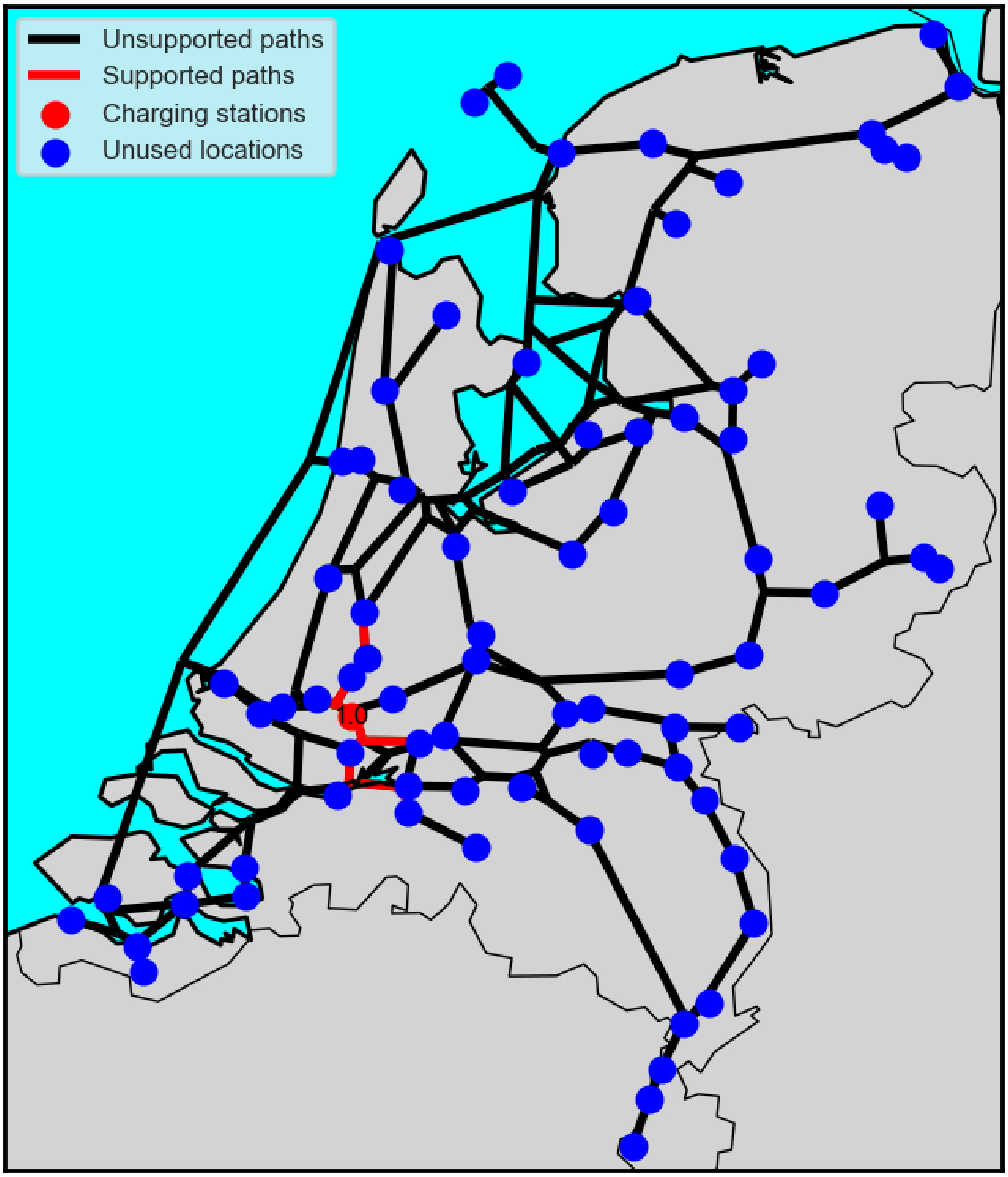


Figure B.4: Results single charging station with an unlimited capacity, considering a ship range of 120km

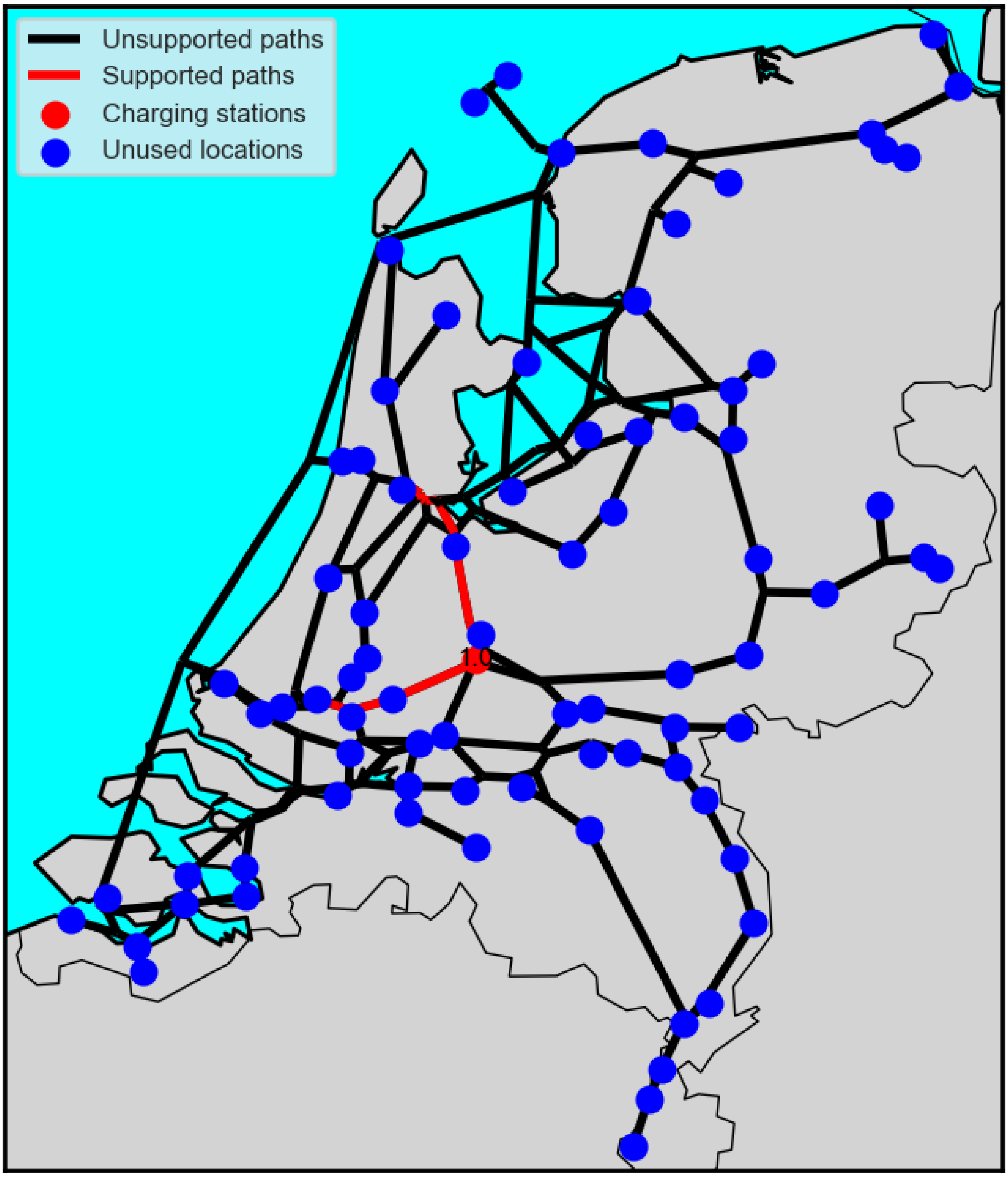


Figure B.5: Results single charging station with an unlimited capacity, considering a ship range of 150km

C. Data processing

In this appendix, all details regarding the data and the processing of the data can be found. First, the input data is discussed. Then, the data selection and reformatting are elaborated up on. Finally, it is discussed how the data is alligned and simplified.

C.1. Input data

The input data consisted of the Dutch waterway network by Jong et al. (2022) and trip-based origin-destination (O-D) data which was retrieved from Rijkswaterstaat (2022). Both data sources will be discussed in detail in this chapter.

C.1.1. Trip-based origin-destination (O-D) data

The full RWS dataset of 2021 contained information on 385,572 trips between origins and destinations in The Netherlands and neighbouring countries (Rijkswaterstaat, 2022). The data set included the United Nations Code for Trade and Transport Locations (UN/LOCODE) for the origin and destination, the date and hour of departure, data regarding the transport capacity and shipload, and the RWS ship classification code. The RWS ship classification code is based on the properties of a ship and the CEMT-classification system, which was established to ensure the interoperability of large navigable waterways within Continental Europe and Russia ("Resolution No. 92/2 on new classification of inland waterways", 1992; Rijkswaterstaat, 2022).

Exploratory data analysis

First, some exploratory data analysis (EDA) was conducted. An overview of all data characteristics can be found in figure C.1. The total number of trips in 2021 was quite constant throughout the year and is visualized in figure C.2. The same goes for the total amount of transported weight in 2021 (see figure C.3). Hence it was decided to use the full data set of 2021, as the total trips and the transported weight seemed to be relatively consistent throughout the year. Remarkably, the number of trips over time during the day was not constant, as seen in figure C.4.

	Week_no	Type_code_ship	Transport_capacity	v28_Beladingscode	Transported_weight	Transported_containers
count	385572.0	385572.0	385572.0	385572.0	278134.0	385572.0
mean	26.5	3.0	2445.8	4.8	1243360.3	14.5
std	15.0	5.3	2521.1	2.7	1583801.5	50.8
min	1.0	0.0	0.0	1.0	0.0	0.0
25%	14.0	1.0	1100.0	1.0	242000.0	0.0
50%	26.0	1.0	1820.0	7.0	996000.0	0.0
75%	40.0	2.0	3160.0	7.0	1700000.0	0.0
max	53.0	36.0	100000.0	7.0	99999000.0	1700.0

Figure C.1: Overview of the data characteristics

Figure C.2: Total amount of trips each month in 2021

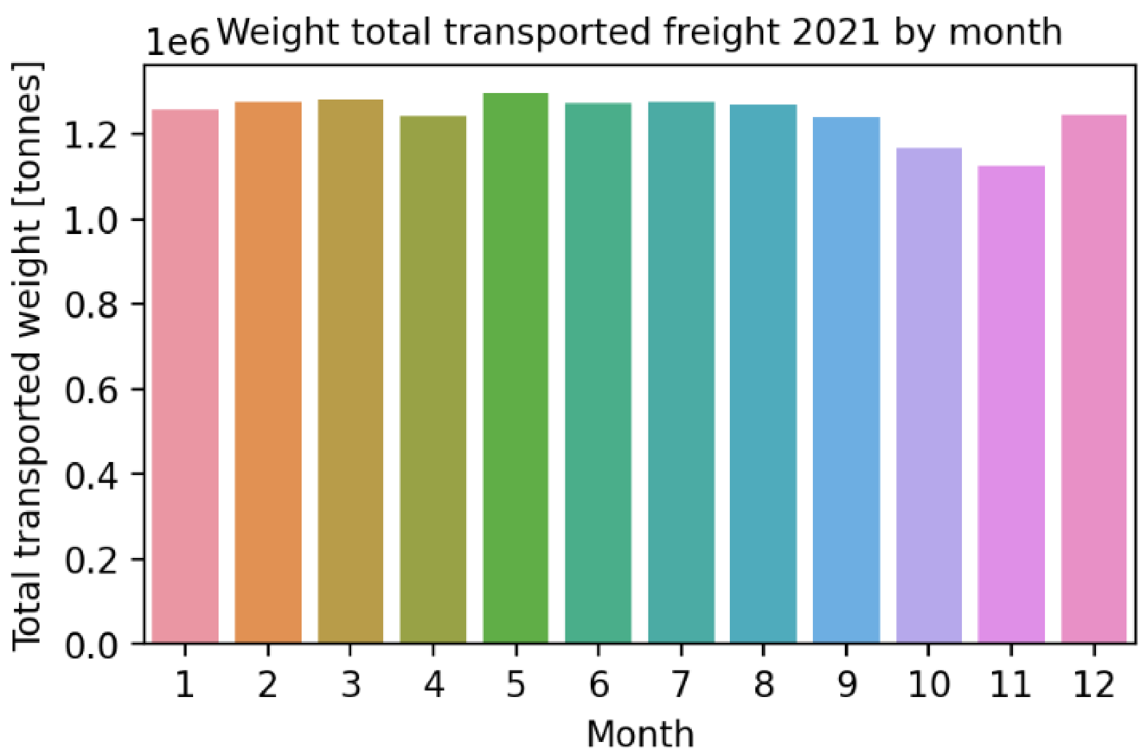


Figure C.3: Total amount of transported weight in each month in 2021

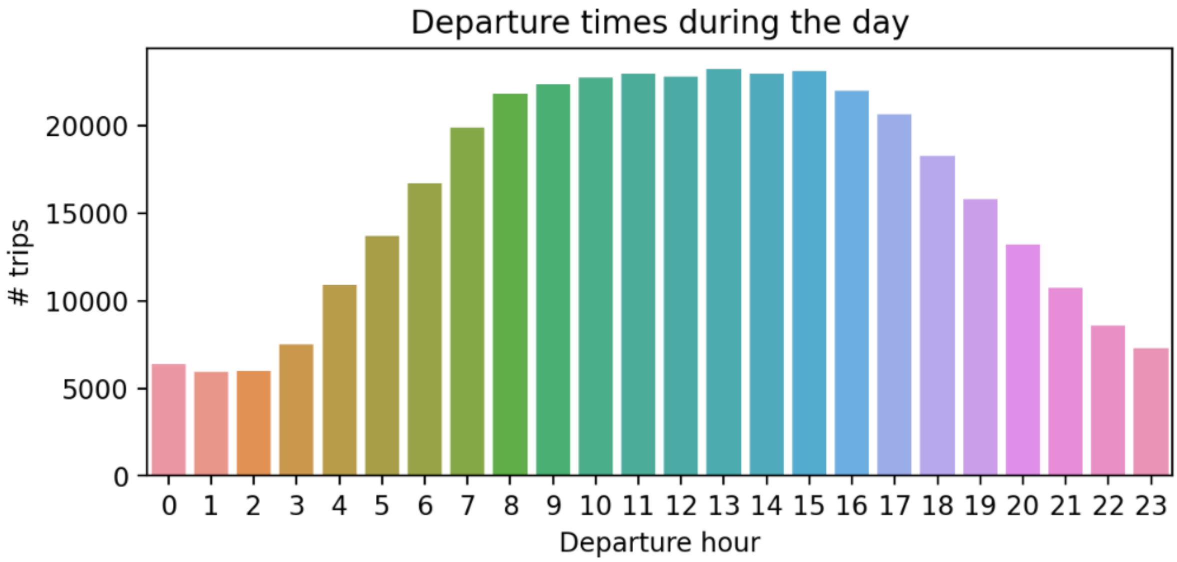


Figure C.4: Overview of the aggregated temporal distribution of departures

C.1.2. Dutch waterway network file

The Dutch waterway network file by Jong et al. (2022) was a detailed version of the network, which also contained information regarding the largest ship that can travel over each link in the network. Notably, the network contained 290 nodes which were labelled as a berth. However, the 290 berth nodes did not contain any further information, meaning they could only be linked to the O-D data based on their coordinates. Besides, the links also had some additional attributes regarding the dimensions of the waterway which were not used and a ”Name” attribute, which was used to couple the network with the O-D data, as it was found that all of the waterways going towards harbours had the same ”Name” label.

C.2. Data selection and reformatting

The data selection process consisted of multiple steps, which are visualised in figure 5.1 below. First, all of the trips with the same origin and destination were deleted (1.72 %), as these did not result in flows on the network. Secondly, a small fraction of the trips without an RWS type entry was identified (0.42%), these values were dropped from the data set since the energy consumption of these ships could not be estimated. This was also the case for ships of the M0 class (0.33%), a residual class for the smallest ships in which there is a great deal of variation. Characteristics such as average engine power and speed were not available for the M0 class, henceforth trips conducted by M0 ships were deleted. Hereafter, only inland trips were selected with an origin and destination within the Netherlands, because all other trips do not fall within the scope of this research. To this end, 41484 foreign trips and an additional 159218 inbound and outbound trips were deleted from the data set, resulting in 175351 trips for 10329 O-D pairs between 612 unique harbours in The Netherlands.

However, not all of the 10329 O-D pairs between the 612 unique harbours, could be incorporated into the model to maintain computational feasibility. Moreover, including all of the O-D pairs did not make sense, as many of them were only rarely sailed. Considering the objective to supply as much energy with a limited number of charging stations, ideally, the routes with the highest energy demands were selected. Nevertheless, calculating the energy demand of an OD pair given the assumptions required not just trip-based 0-D data, but also the distance on the shortest path for each O-D pair (see formula 4.8). To be able to determine the shortest paths for all of the O-D pairs, all O-D data had to be aligned with the network, which was also computationally unfeasible.

Alternatively, just the most frequented routes could have been selected, but this would have neglected the varying energy consumption of different types of ships. Possibly, this would have led to skewed results, because larger ships can be expected to undertake fewer individual trips and travel longer distances on average for economic reasons. Hence, it was decided to select the O-D pairs with the highest energy consumption per kilometre. To this end, the passing battery capacity in terms of equivalent M1 ships was determined for each path using the formula 3.1.

Following from formula 3.1, the battery capacity of any ship is relative to its average engine power (P_a), divided by the corresponding sailing speed (v_a). Additionally, the average engine power of an M1 ship was defined as P_{M1} and its corresponding sailing speed as v_{M1}. The relative battery capacity of any ship compared to the M1 ship was thus equal to P_a/v_a divided by P_{M1}/v_{M1}, which simplifies to the fraction in formula C.1. Formula C.1 determines the flow in terms of M1 ships for each path (α_q), by multiplying the total number of trips (n_{qa}) registered for each ship type (a) on each path (q) with the factor equal to the relative battery size of this type compared to the M1 class.

$$\alpha_q = \sum_{a \in A} \frac{P_a \cdot v_{M1}}{v_a \cdot P_{M1}} \cdot n_{qa} \quad \forall q \in Q \tag{C.1}$$

where:

Selection criterion
α_q = equivalent number of M1 trips [#] on path q, $q \in Q$

Other variables
A = set of all distinguished ship types
a = ship type, $a \in A$
P_a = average engine power [kWh] of a ship of type a, $a \in A$
v_a = average speed [km/h] of a ship of type a, $a \in A$
Q = set of all O–D pairs
q = O–D pair, $a \in A$
n_{qa} = number of ships [#] of type a, $a \in A$, travelling on path q, $q \in Q$
P_{M1} = average engine power [kWh] of a M1 ship
v_{M1} = average speed [km/h] of a M1 ship

The extent to which the percentage of included trips, M1 equivalent trips, and unique harbours increase when more O-D pairs are included is visualized in the figure C.5. Finally, the 200 O-D pairs with the highest M1 equivalent flow were selected for further analysis. As such, 91187 trips (52.0%) between 100 unique harbours (16.3%) were included. Even though only 1.9% of all of the O-D pairs were selected, 65.0% of all M1 equivalent ship flow was covered. Thereby, the least frequented O-D pair was Vlissingen - Vlaardingen with an equivalent of 1.49 M1 ship trips per day. The 200 selected routes, contained all of the OD pairs in the top 100 most frequented routes in terms of absolute trips, except for Nederweerdt-Born. In conclusion, a majority of the both total number of trips and the total flow in terms of M1 equivalent trips was included in the model.

C.3. Aligning the network and the trip data

After part of the data was selected to include in the model and the conceptualisation was established, the trip-based O-D data had to be aligned with the network. To do so, a node in the network had to be determined for all of the 100 unique harbours associated with the selected 200 0-D pairs. The UN/LOCODE for each of these harbours was known, and a location for part of the harbours could be found using the corresponding database (Nations, n.d.). The latitude and longitude were found to be missing for 60% of the harbours, however as the full name for each of the harbours was available, the missing values could be filled in using the Google Geocoding API (“Overview | Geocoding API”, 2022). This is a commercial API, but the usage for this project did not exceed the 200 euros/month free allowance each user received by far.

Hereafter, some positions had to be manually corrected, this was the case for Stein, Wageningen, Geertruidenberg, Terneuzen, Farsum and Delfzijl. Delfzijl was not correctly registered in the UN/LOCODE dataset, the latitude and longitude corresponding to a location in Germany. Furthermore, the harbour

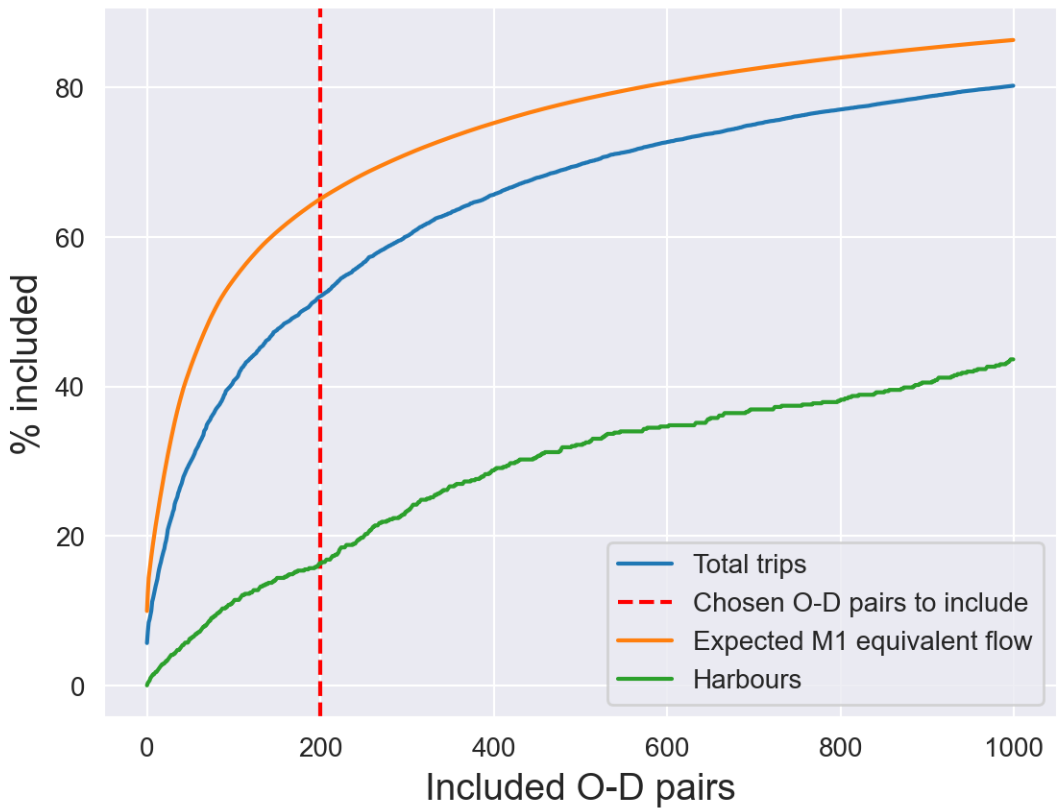


Figure C.5: Incorporated trips, flow, and harbours

of Stein could not be found using Google Maps, in most other cases an inland leisure harbour was selected, which was not located anywhere near the main route. Then, a harbour node had to be selected for each of the found harbour locations, because the nodes in the network were not labelled. To this end, a method was developed to identify the best node in the network to consider for each harbour. Beforehand, all of the links in the network that could only be used by leisure traffic were removed, because these were not of interest and should not be searched for harbour nodes. The network also contained some self-loops, and links from a location to the location itself, these links were also removed as they had no use in this research.

C.3.1. Determining harbour nodes

Next, a harbour node was determined based on the found location and the link attributes of the network. Whereas the nodes in the network had no additional attributes except for their latitude, longitude, unique ID and degree value that could be determined, the links of the network contained more information. All of the links that connected to or were part of harbours, were found to have the specific ”Name” label ”Vaarwegvak van 0 tot 0 - H”. In addition, each link had a ”GeoType” attribute, which was either section, lock, structure, bridge, or fareway (only used for links outside of the Netherlands), logically only sections should be considered as potential charging station locations. Furthermore, almost all of the harbours were not directly at ongoing routes, but one or a few nodes landed inwards. From a network perspective, a ship passes a harbour if it passes a harbour exit, which was defined as an intersection at an ongoing route which ends in a harbour.

Therefore, it was decided to select the harbour exits on ongoing routes as harbour nodes, as a result, the relatively short fairways between the main waterways and harbours were neglected. Points on ongoing routes were found to always have a solely numeric unique ID and links connected to harbours were found to have the harbour as their target. As such, harbour nodes were identified as the sources with a numeric name, of links with a ”GeoType” section, and with the label ”Vaarwegvak van 0 tot 0 -

H”, of which the source and target both laid within a given range of the originally found destination for the harbour.

Initially, all links with a source and a target with a latitude and longitude of 0.04 decimal degrees higher or lower (corresponding to approximately all points within a radius of 5.2 kilometres) were considered. If no harbour links were identified within this range, the range was first doubled and if necessary the requirement to have the ”Name” attribute was dropped, as this harbour was then likely not in the network. A harbour node was found within this range of 10 kilometres for all of the 100 incorporated harbours, which resulted in 97 unique harbour nodes. As visualized in figure C.6, most of the harbour nodes were just a few kilometres away from the point which was in the UN/LOCODE data set, or which was retrieved using the google maps API.

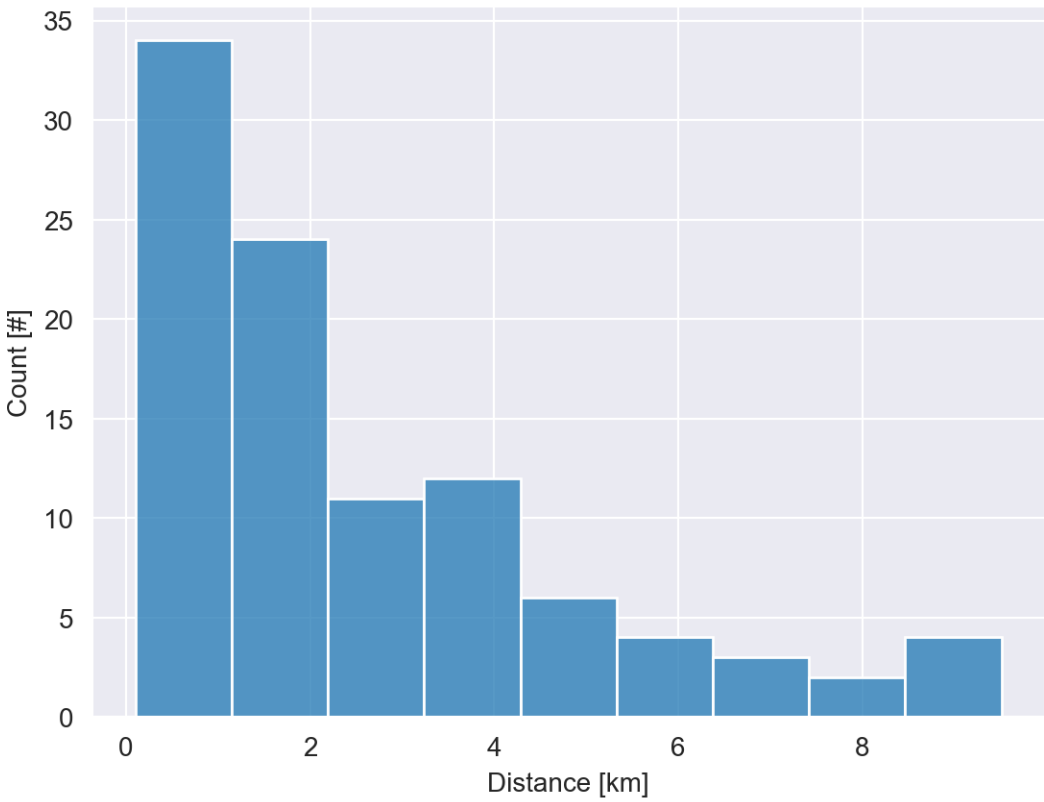


Figure C.6: Distance in kilometres between the selected network node and the initially found harbour location

Hereafter, the found positions of the harbours were visually checked, also harbours with the same harbour node were checked to make sure these were indeed harbours which were close to each other. Deest and Wageningen both had the same harbour node, but Deest lies along the Waal, whereas Wageningen is located along the Maas. However, the Maas and the Waal are not that far apart here, which explains this situation, the location of the harbour node for Wageningen was manually corrected. Nightevecht and Weesp and Wormer and Zaandam were found to be correctly assigned to a harbour node in between both harbours which were close together. Lobith and Spijk were both assigned to a different harbour node, of which one lay across the border in Germany, they were manually assigned to the same harbour node in between the found positions.

C.3.2. Application of K-means

Finally, the K-means algorithm by MacQueen (1967) was applied to reduce the number of harbour nodes, as quite some harbour nodes appeared to be right next to each other. The K-means algorithm was applied to create K clusters based on the latitude and longitude of the points and assigned each point to one of the clusters. The clusters are determined in such a way that the total distortion is minimised. The distortion was observed for 60 to 97 clusters using figure C.7, and the visual effect of clustering was also observed using figure C.8. Then, a cluster size of 81 was found to be optimal, as smaller clusters led to cluster centres in between different waterways.

Subsequently, each harbour was assigned to a new harbour node if there was more than 1 node in the cluster, this was done by selecting the nearest harbour node based on the cluster centre using the same method as was used to initially assign a harbour node based on a harbour location as previously explained. Even though this may only seem like a small reduction, the 16 dropped harbour nodes, significantly decreased the run time of the model. Moreover, only 2403 trips (2.6% of all trips) had to be removed from the data set as they no longer resulted in a flow on the network. Notably, these trips of just a few kilometres likely had a very small impact on the total flow anyway. However, the length of the trips could not be considered when the 200 O-D pairs were selected, because the nodes were not yet linked to the network at that time.

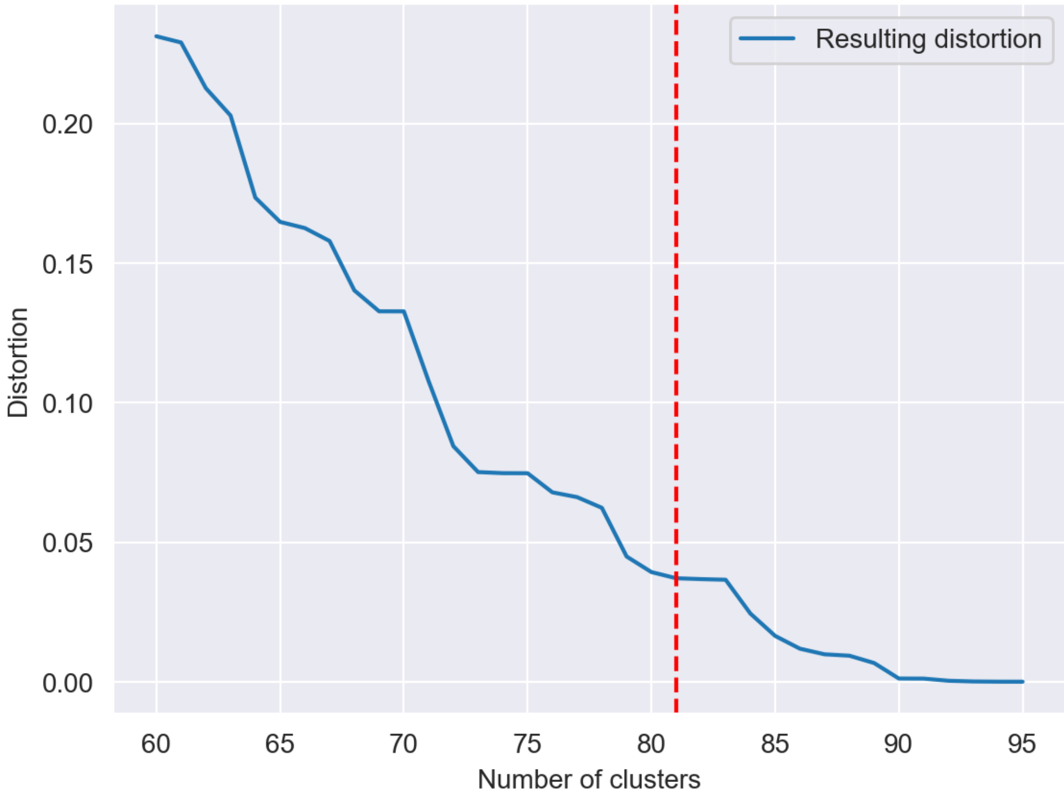


Figure C.7: Distance in kilometres between the selected network node and the initially found harbour location

C.4. Determining routes for different ship types

After the harbours of the trip-based O-D data were linked to nodes in the network, the routes were determined. Each ship was expected to take the shortest path that it could take based on its dimensions, to this end the ”Code” attribute of the links was used, which was the largest CEMT-class ship that could still take a route. To calculate the shortest path, the Dijkstra path was determined using the networkx package (Hagberg et al., 2008). Considering the CEMT-class for all of the RWS-classes was known, this was used to determine the shortest path a ship could take when travelling on a certain O-D pair. Since different ships travel via different routes, different types of ships may also pass different sets of charging stations.

Therefore the trip-based O-D data was split up whenever the path of the ships took a different route.

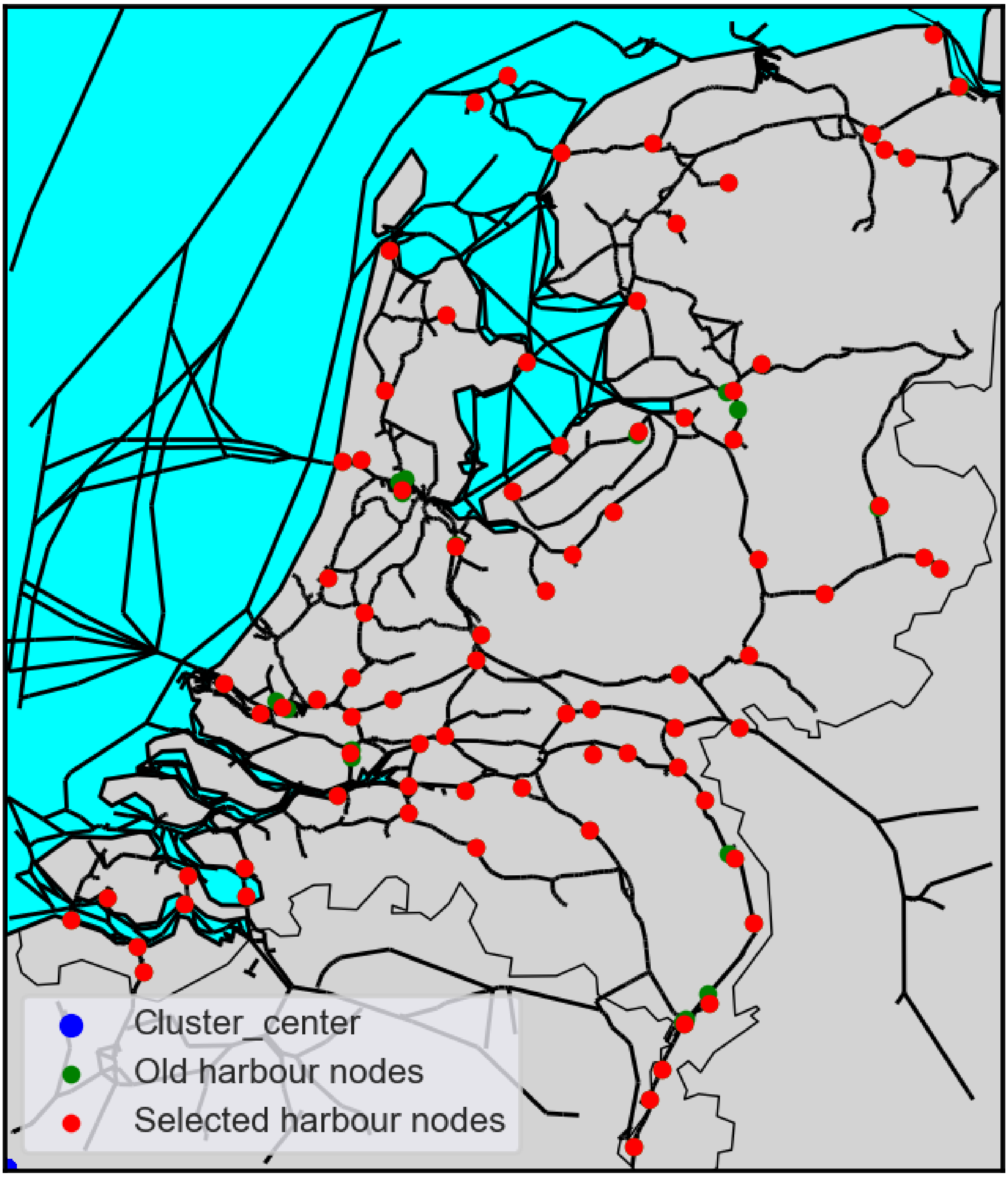
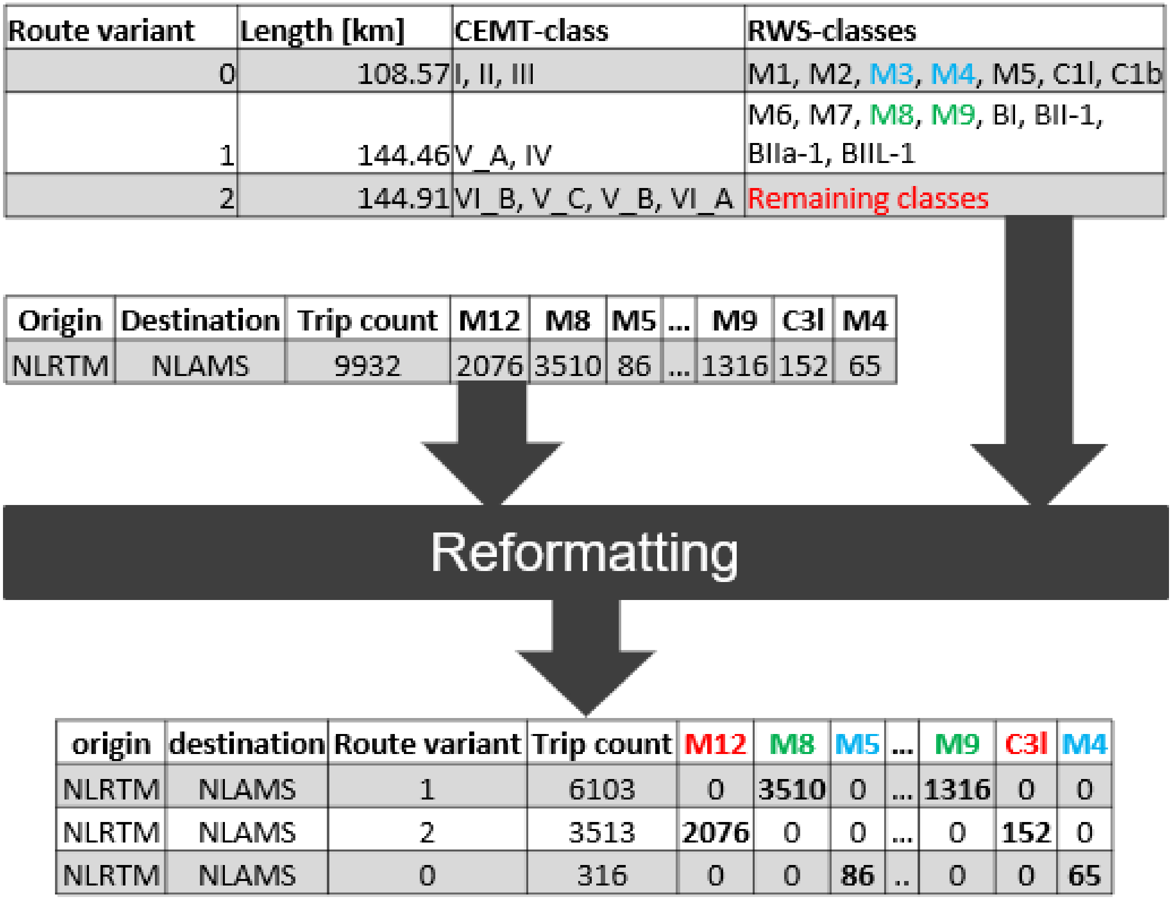


Figure C.8: Visualisation of the original harbour nodes, created clusters and new harbour nodes.

A data frame with a new row for each unique route for each O-D pair and an additional route column was created, and the total number of trips conducted by each ship type was copied into a row if a ship type took this route. If a certain ship type did not take a certain route, this meant that 0 ships of this type took this route. This data reformatting process is visualized in figure C.9 below for the O-D pair Rotterdam-Amsterdam, the most frequented O-D pair in the RWS-dataset. In conclusion, an O-D pair was redefined as a unique node sequence to sail between an origin and a destination, which was assumed to be used by a unique set of ships for which this was the shortest path that they could take given their dimensions.



Route variant	Length [km]	CEMT-class	RWS-classes
0	108.57	I, II, III	M1, M2, M3, M4, M5, C1l, C1b
1	144.46	V_A, IV	M6, M7, M8, M9, BI, BII-1, BIIa-1, BIIL-1
2	144.91	VI_B, V_C, V_B, VI_A	Remaining classes

Origin	Destination	Trip count	M12	M8	M5	...	M9	C3l	M4
NLRTM	NLAMS	9932	2076	3510	86	...	1316	152	65

origin	destination	Route variant	Trip count	M12	M8	M5	...	M9	C3l	M4
NLRTM	NLAMS	1	6103	0	**3510**	0	...	**1316**	0	0
NLRTM	NLAMS	2	3513	**2076**	0	0	...	0	**152**	0
NLRTM	NLAMS	0	316	0	0	**86**	..	0	0	**65**

Figure C.9: Reformatting the trip-based O-D data for Rotterdam-Amsterdam given the unique routes

C.5. Network simplification

Following, only the subgraph with the nodes that were in the determined routes was kept, to remove all of the redundant nodes from the network. Moreover, the network was further simplified to increase performance and enable application of the two proposed heuristics in subsection 4.1.3. The goal of the simplification process was to only keep the harbour nodes and the nodes with a degree higher than 2, as all of the other nodes were intermediate nodes which did not add anything to the model. Hence indirect links between the nodes that had to be kept were replaced with direct links, with a length equal to the summed lengths of the intermediate nodes. Afterwards, the routes also had to be updated removing all the removed intermediate nodes from each node sequence.

Finally, this resulted in the network visualised in figure 5.3, the five found variants of the route between IJmuiden and Moerdijk are visualized as well. The smallest ships could take route 1, increasingly larger ships had to take route variants with a higher route number. Routes 1, 2 and 3 differ, the difference between route 3 and routes 4 and 5 is not visible as they largely overlap. In conclusion, two vastly different routes were relevant looking at how often these routes were frequented in 2021. Moreover, a significantly longer route for the larger ships was found, neglecting different routes for different ships would thus have led to an underestimation of the energy demand, but also to an overestimation of the traffic that takes the shortest route and visits any charging station which may be located there.

D. Additional results

D.1. Applicaton of heuristics

The optimal number of additional nodes added with each heuristic was determined empirically. The main steps are presented in section 6.2. In the main text it was determined that first applying the first en then applying the second heuristic led to the best results. Hereafter, various variants of the heuristics were applied considering various ranges. The objective was to determine the optimal number of additional nodes which should be inserted. To this end, the serviceable fraction was observed. The serviceable fraction, was defined as the fraction of the flow which could be supported, if unlimited charging capacity could be installed at each and every location.

As such, the serviceable fraction was only influenced by the range of a ship and the positions of charging stations. The individual heuristics were used separately and combined, to insert 5-30 nodes. Then, the CFRLM was applied to determine the serviceable fraction, considering various ship ranges between 50 and 150 kilometres. This resulted in the overview presented in figure D.1. In the legend, the first number indicates the algorithm which was applied. The second number indicates the number of nodes which were inserted using each applied algorithm. It was concluded, that applying both heuristics outperformed the other options.

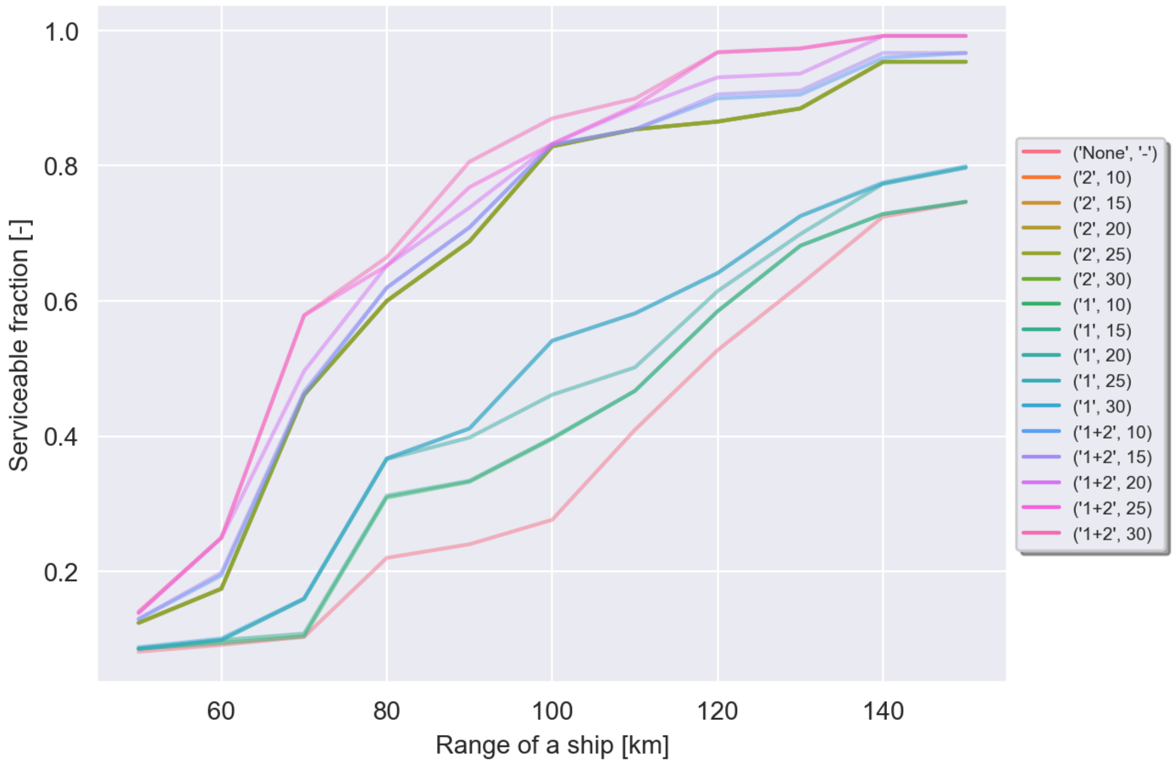


Figure D.1: Theoretically serviceable fraction for various ranges and (combinations of) heuristic variants.

In this section, the chosen number of nodes to insert with both heuristics is argued for. After it was found that both heuristics performed the best, the number of nodes to insert with both of them had to be determined. To this end, various experiments were performed. In these experiments, both heuristics were used to determine 5-30 additional charging station nodes. Then, the CFRLM was applied to locate 40 charging stations on the network considering various ranges, for each of these experiments. Furthermore, a charging station capacity of 2MW and a maximum number of 5 charging stations per location were considered.

The total fraction of the flow which could be captured is visualized in figure D.2. In addition, the number of used locations is visualized in figure D.3. Remarkably, adding more nodes, does not always lead to more used additional locations. In the beginning, a higher range leads to less additional nodes. However, if the range then increases, the number of additional nodes becomes more stable. Finally, the number of used additional nodes increases again if higher range values are considered. Including 25 additional nodes, was found to lead to almost the same results as including 30 additional nodes. Only for medium range values, the adding 30 nodes lead to a slightly higher captured fraction. On the other hand, including 30 nodes resulted in more used additional locations on average. Therefore, it was decided to apply both heuristics to add 25 nodes.

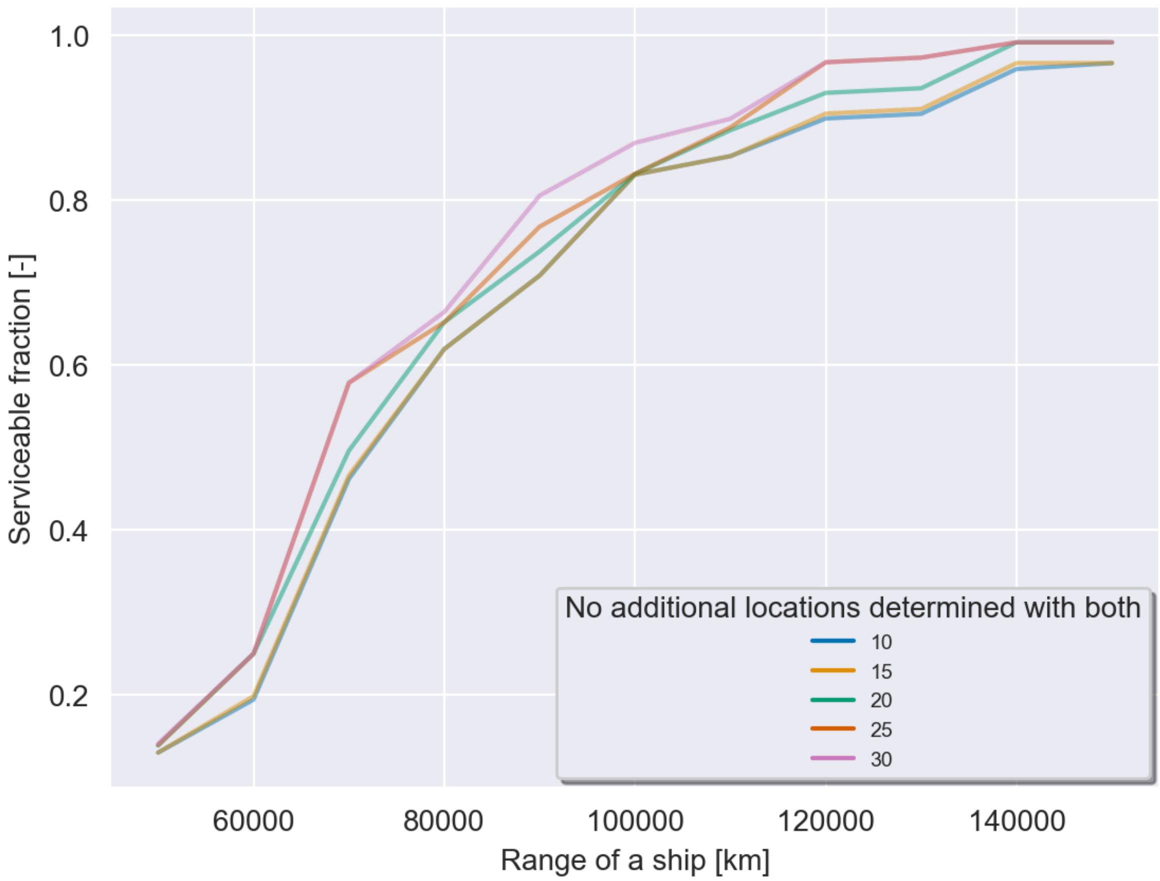


Figure D.2: The resulting total fraction captured if both heuristics were applied to insert a varying number of nodes (see legend) considering various ship ranges. All other parameters were kept constant.

D.2. The optimal number of charging stations

If more charging stations than strictly necessary to capture all of the flow were placed, this did not lead to optimal results. Hence, the optimal number of charging stations for each experiment had to be determined. Following from the conceptualisation, not all charging station combinations which could technically support a route were taken into account. Only charging station combinations consisting of at most 4 nodes were considered. First, the fraction of the total flow on the network which could be captured if 1-100 charging stations were placed was determined. In all cases, the maximum number of effective stations was lower than 100. Hence, after up to 100 charging stations were placed for each scenario the optimal number of charging stations was determined using the method described in

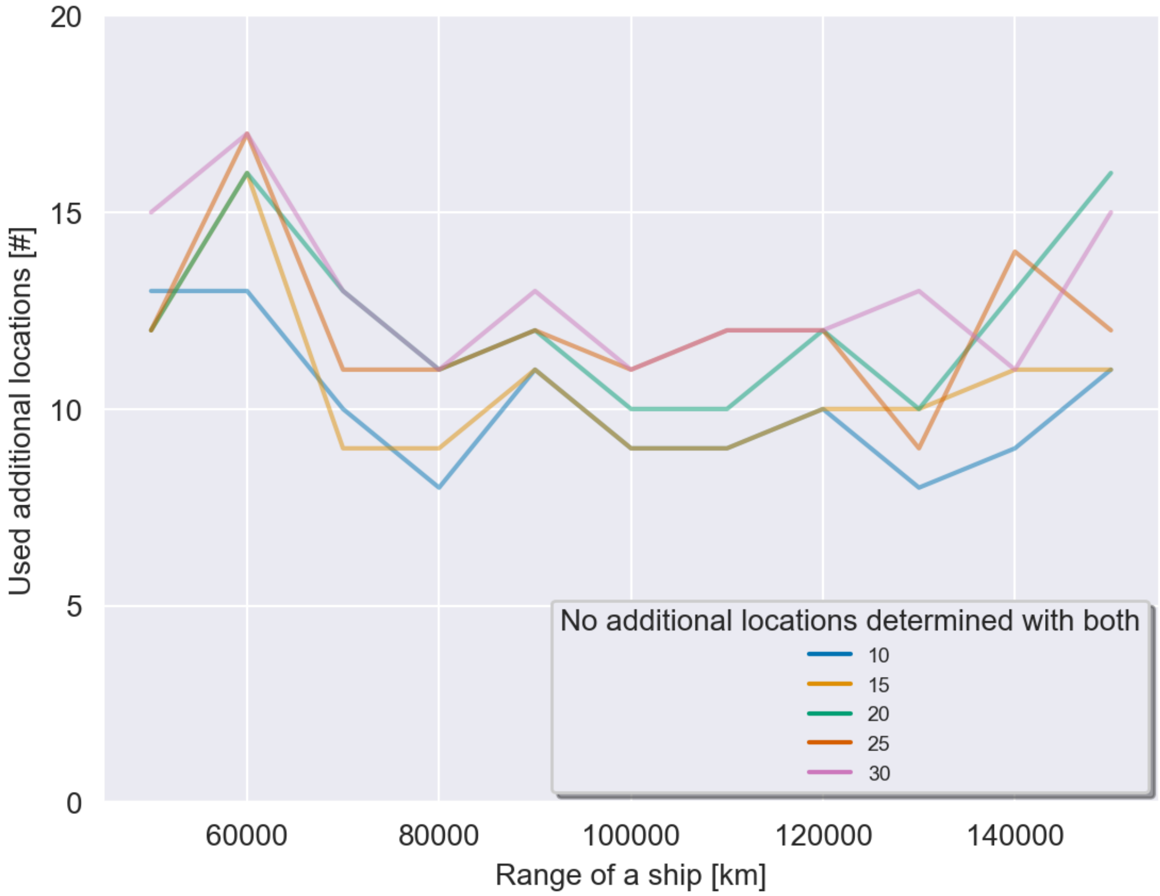


Figure D.3: Used additional locations if both heuristics were applied to insert a varying number of nodes (see legend) considering various ship ranges. All other parameters were kept constant.

subsection 4.1.4. As placing more stations was not useful, the with more than the optimal number of charging stations were removed from the data set. In this section, first the findings regarding the optimal application of the heuristics to identify additional potential charging station locations are presented. The resulting number of optimal charging stations in each of the experiments is visualized in figure D.4 and figure D.5.

D.3. Additional ABM results

In this section, the observed charging times and travel times of ships are presented. The travel times are presented in figure D.6 and figure D.7. As expected, the average travel time increases with the range of ships. Moreover, the absolute average charging time also slightly increases, because the energy consumption of ships of an average trip also increases. Finally, it may be noted that travel times are longer if additional nodes are considered. Additional nodes result in the fact that longer trips are feasible, thus this was expected. The travel times are presented in figure D.8 and figure D.9.

D.4. Computational details

To evaluate the models, a 2022 20-core Intel i7-12700H laptop was used, all experiments were run using all 20 cores. The CFRLM was evaluated in Python for all of the 9 scenarios, with and without additional nodes, using the PuLP package, the Gurobi solver and the EMA-workbench for parallel computing. Initially, the CBC solver was used instead of the Gurobi solver, but this solver resulted in unfeasible solving times. The ABM was evaluated using the MESA package, evaluating a single scenario took around 13 minutes on average. As such, the ABM was only evaluated for all of the scenarios considering the additional nodes, for the maximum number of feasible charging stations,

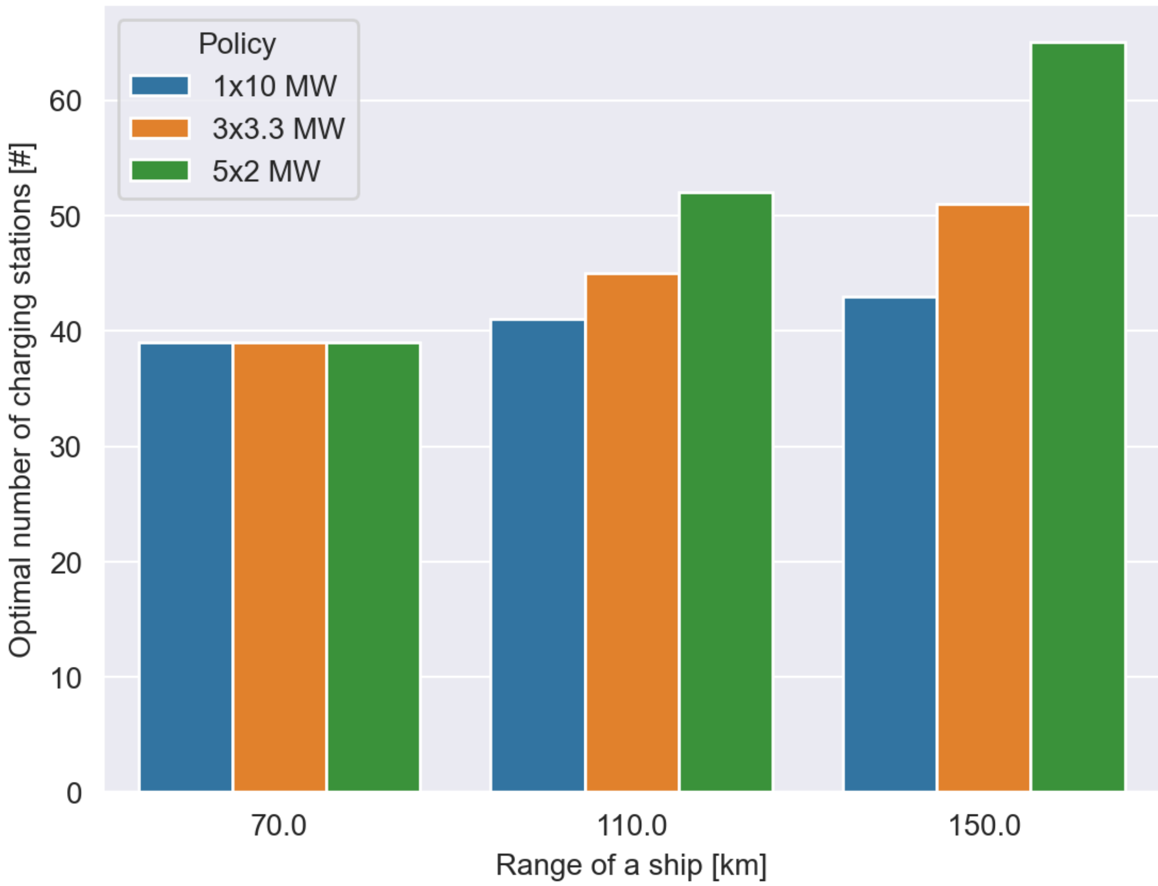


Figure D.4: Found optimal number of charging stations for the 9 experiments without considering additional nodes.

which was determined using the CFRLM.

D.4.1. Evaluation of the ABM

The convergence of the results of the ABM was assessed by evaluating the ABM for 20 and 100 scenarios for all experiments considering additional nodes. Following the relative difference between the average sailing, charging and waiting times of ships was assessed for all scenarios. The results are presented in the table below. It was concluded that convergence was likely achieved at 100 runs. Therefore, 100 runs were computed for all experiments. This thus resulted in 1800 ABM runs for all experiments.

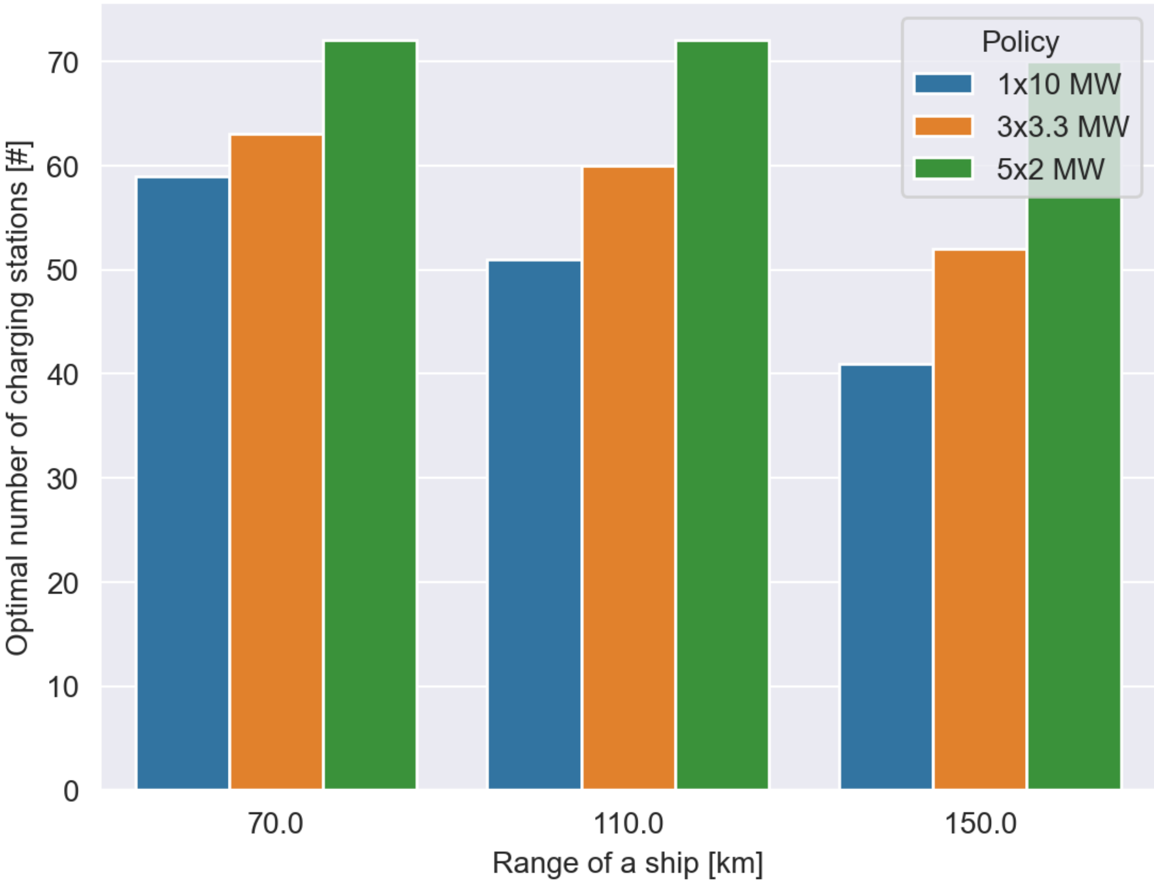


Figure D.5: Found optimal number of charging stations for the 9 experiments considering additional nodes.

Experiment	Difference 20 and 100 runs		
	Fraction charging	Fraction inline	Fraction sailing
70km_1x10MW	-0.0784%	0.7943%	-0.7159%
70km_5x2MW	-0.4451%	1.6512%	-1.2061%
70km_3x3.3MW	0.2847%	-0.6760%	0.3912%
110km_1x10MW	-0.1211%	2.0283%	-1.9073%
110km_5x2MW	0.3147%	-1.1052%	0.7905%
110km_3x3.3MW	-0.0905%	-0.2930%	0.3835%
150km_1x10MW	-0.0735%	0.5434%	-0.4699%
150km_5x2MW	0.4573%	-0.7183%	0.2610%
150km_3x3.3MW	0.3037%	-0.5423%	0.2385%

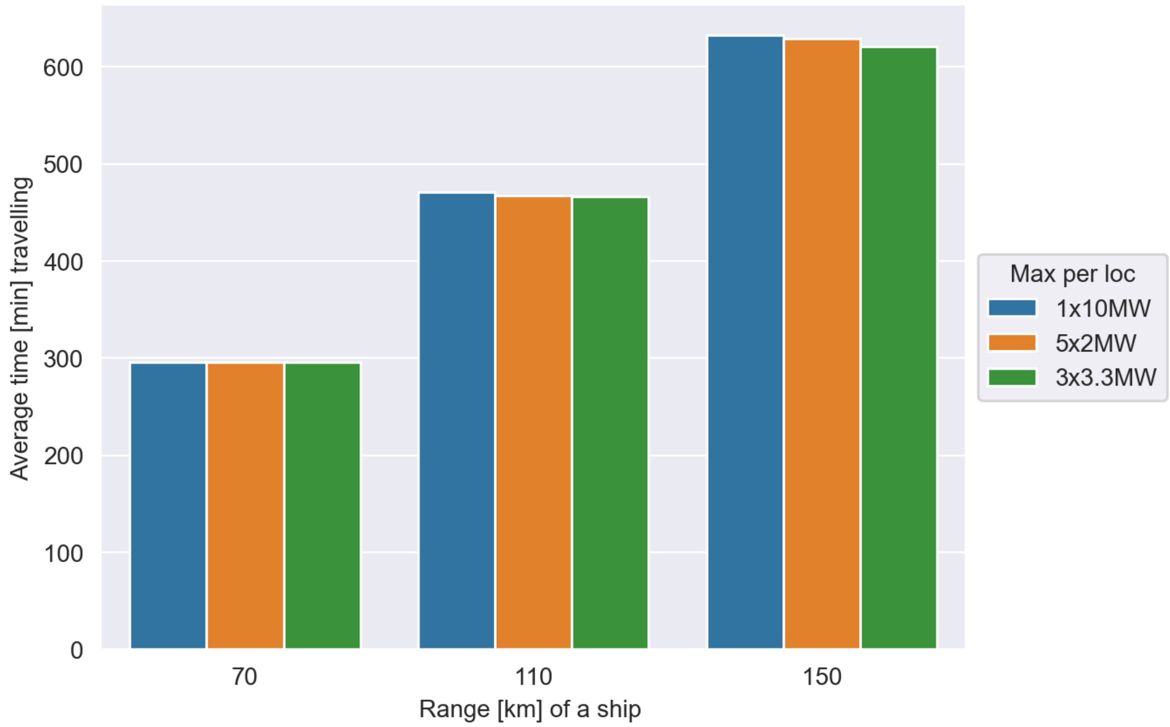


Figure D.6: Observed travel time experiments without additional nodes.

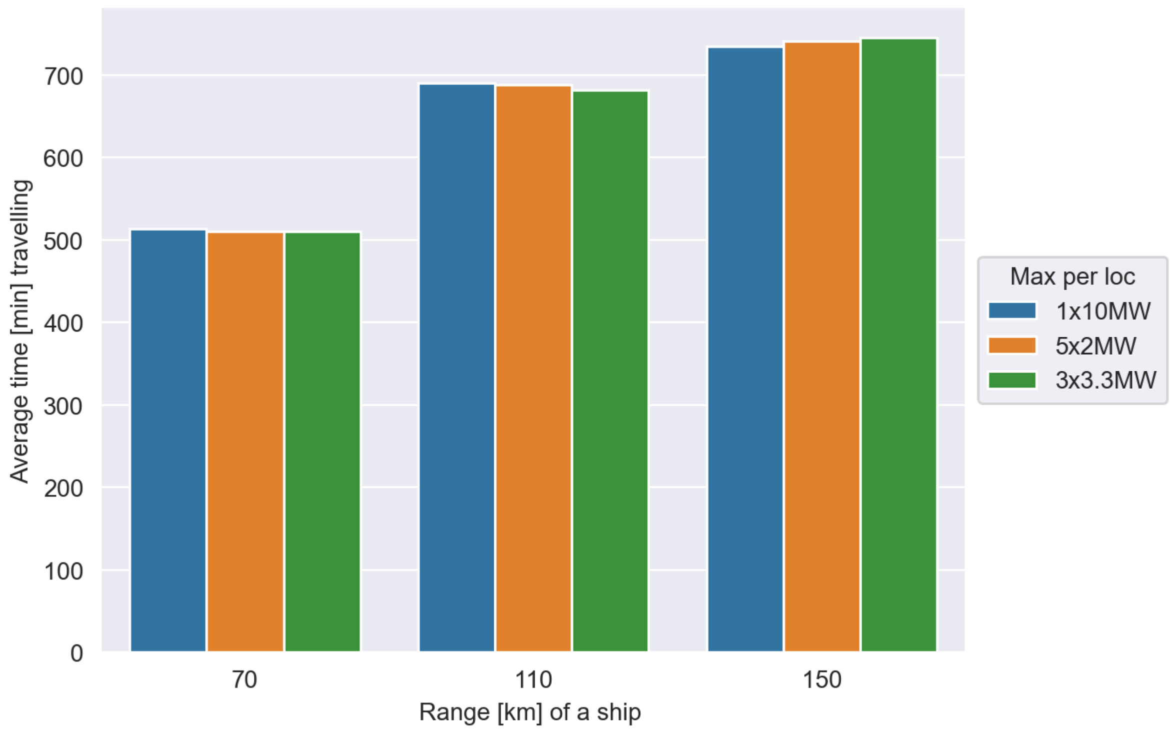


Figure D.7: Observed travel time experiments with additional nodes.

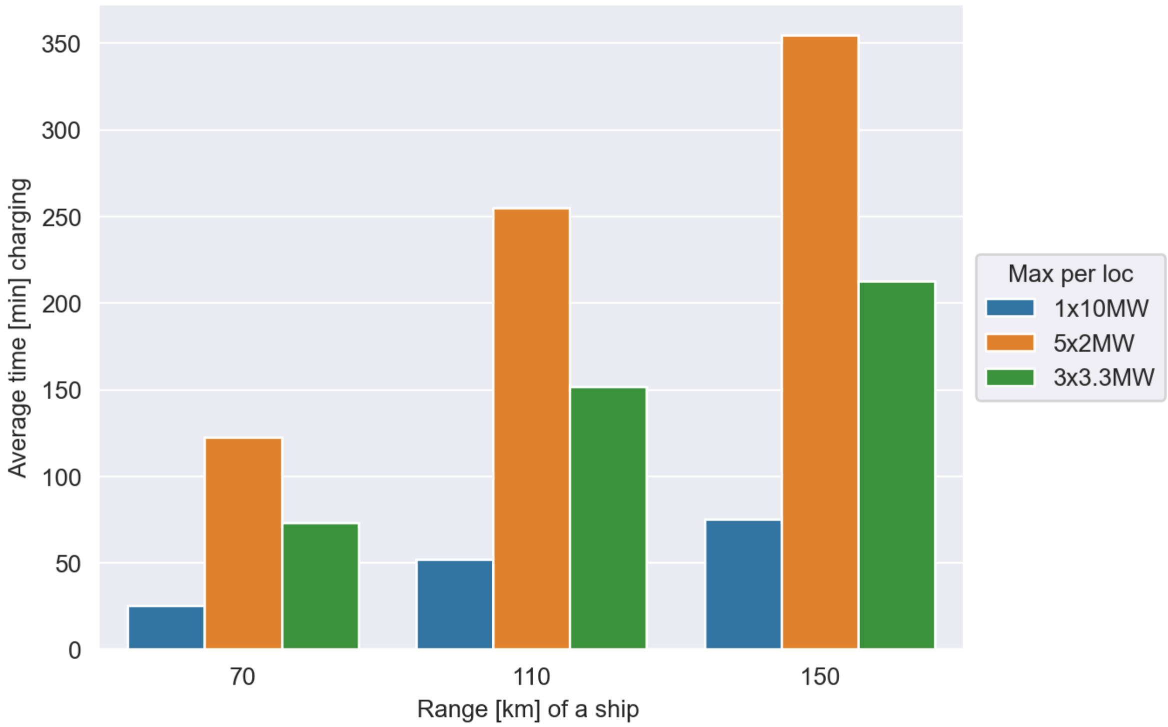


Figure D.8: Observed charging time experiments without additional nodes.

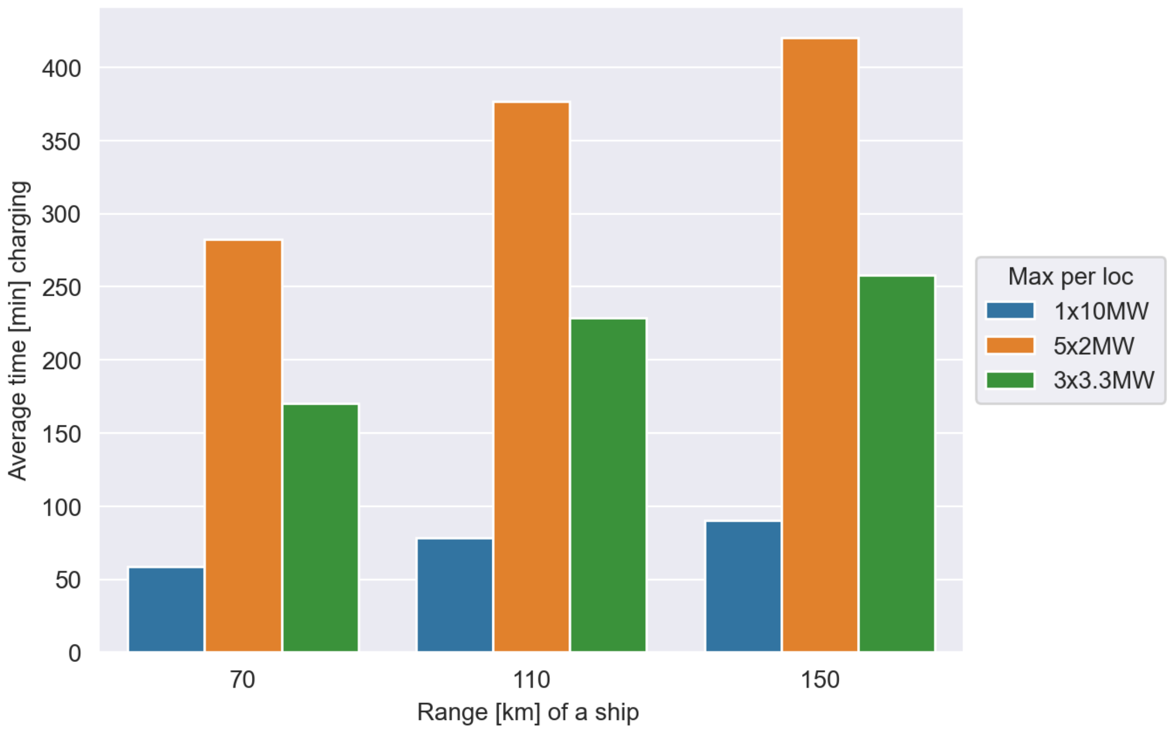


Figure D.9: Observed charging time experiments with additional nodes.

E. Python implementation

In this chapter the steps of the two stages of the established flow refueling location model are outlined. The first and second stage are presented subsequently.

E.1. first stage capacitated flow-refueling location model

Returns feasible charging station combinations for transport network G for routes in OD, considering travel range r, assuming that charging stations can be placed on any node of G.

E.1.1. Input variables

The input of the first stage optimisation consists of the following parameters:

- r : (float) range means of transport with full tank.
- G : (networkx.Graph) Must include all origins, destinations and any nodes where a refueling station may be placed.
- OD: (dict) This dict contains the travel data within network G, travel data from A-B and from B-A should be summed up and entered as either one of them. example input:

```
{(node_1, node_2, route_v1) : flow12_r1, (node_1, node_2, route_v2) :
flow12_r2, (node_1, node_3, route_v1) : flow13_v1}
```

- paths: (dict) Dictionary that contains all paths between the OD pairs that are in OD. example input:

```
{(node_1, node_2, route_v1) : [list of nodes consecutive],
(node_1, node_2, route_v2) :[list of nodes consecutive],
(node_1, node_3, route_v1) : [list of nodes consecutive]}
```

- path_lengths: (dict) Dictionary that contains all path lengths (in meters) between the OD pairs that are in OD, with the same keys as OD and paths dicts.
- df_h: (pd.DataFrame) This is a Dataframe as generated in revised_network_cleaning.ipynb, that contains the data of harbours and the corresponding harbour nodes in G.
- additional_nodes: (list) This is a list that should contain all additional harbour nodes to be considered, next to the origin and destination harbours.

E.1.2. Pseudo code

For each origin-destination pair:

1. Determine the shortest path and the nodes on the shortest path.
2. Determine all of the potential charging station locations on the shortest path.
3. Determine all possible combinations of these potential charging station locations using itertools.
4. Determine for each of these combinations whether it is a feasible combination for the assigned route.
5. Evaluate every combination by stimulating a trip using this combination:
    (a) Start at the origin
        i. Is this node is in the currently evaluated combination?

A. Yes? Assume the tank is full.
B. No? Assume the tank is half full.

(b) Try to travel to the next node of the related route and update the current range and position.

i. Is the remaining range positive?

A. Yes? This route may be feasible, continue to the next step
B. No? This route is not feasible with the given combination, continue with the next combination, if there are combinations left for the current O-D pair.

ii. If there is a fuel station at this node, refuel here and reset the range.
iii. Is the final destination reached?

A. Is there a charging station at the destination?
- Yes? This route is feasible.
- No? Double back to the origin by repeating step 4

6. Remove subsets, e.g. if the following feasible combinations are found for a route: [(b), (a, c), (a,b)], (a,b) is removed because it is a super set of (b).

Hereafter, the feasible combinations are stored in three data frames, which serve as an input for the second stage optimisation:

1. df_b with all of the b values, with a row for each route (q) and a column for each combination (h). b_{qh} is equal to:

   (a) 1 if route q can be refueled by combination h
   (b) 0 otherwise

2. df_g, with a row for each route and corresponding feasible combination (qh) and a column for each unique potential facility location. The coefficient is equal to:

   (a) 0 if facility k is not in combination h that can refuel path q;
   (b) 1 if facility k is in combination h and at the origin or the destination;
   (c) 2 if facility k is in combination h but not at the origin or destination, meaning the vehicle must stop at the station to refuel in both directions.

3. df_eq_fq, with a row for each route q, separate columns for the corresponding e_q and f_q values.

E.2. Second stage capacitated flow-refueling location model

This program optimally sites p charging stations with a max capacity p_c, based on three DataFrames that are generated by the first_stage_FRLM function. Moreover, r, v, b, o and c are used to calculate the maximal number base ships that can be served by a charging station per day.

E.2.1. Input variables

This optimisation requires the following inputs:

- r : (int) Range of a ship.
- v : (int) Travel speed resulting in the range.
- b : (int) Power of basis ship [M1].
- p : (int) Charging stations modules to locate on any node of G.
- p_c : (float) Maximum charging capacity of a charging station.
- max_per_loc: (int) Maximum number of charging modules that can be placed at a certain location.
- o: (float) operational hours of a charging station during same time period as c.
- df_g : (pandas.DataFrame) Output of first stage, explanation can be found there.
- df_b : (pandas.DataFrame) Output of first stage, explanation can be found there.
- df_eq_fq : (pandas.DataFrame) Output of first stage, explanation can be found there.

E.2.2. Pseudo code

[enumerate] To perform the optimisation, the pulp package was used. The following steps were taken to perform the optimisation:

1. The capacity of a charging station in base vessels/day is calculated using $\frac{o*P_c*v}{r*P_b}$
2. Declaration of the decision variables:
   (a) a flow_allocation variable is declared for each route (q) and corresponding feasible combination (h), based on the reset index of df_g.
      i. Each variable is declared as a continuous variable, as flows are assumed to be indefinitely split able.
      ii. The lowBound is set to 0 and the upBound to 1, as each charging station can serve 0-100% of a flow.
   (b) facilities_to_build, for each facility in the columns of df_g.
      i. Each variable is declared as a integer variable, as charging modules are assumed to be discrete units.
      ii. The lowBound is set to 0 and the upBound to max_per_loc, to make no negative number of stations is placed somewhere and to enforce the input parameter max per location.
3. Problem definition: the problem is defined as a linear problem and the objective is set to maximise.
4. Objective function: for all q and corresponding h values, the flow_allocation value is multiplied by the flow and the corresponding b value.
5. Definition of constraints:
   (a) Single station capacity constraint. For each facility the capacity constraint is implemented, regarding the maximum flow a station can serve.
   (b) Maximum total modules constraint. The total number of facilities is limited to input variable p.
   (c) Maximum O-D flow constraint. At most 100% of each flow may be served by all of the charging station combinations.
6. Optimisation of the problem using pulp solver.
7. Preparing outputs:
   (a) optimal_flows: (dict) Nested dictionary with the following layout if there are two feasible combinations and the flow should be distributed 30/70 over these combinations:

   ```
   optimal_flows[(origin, destination, route)]={combinations: [combi1, combi2],
   flows: [0.3, 0.7]}
   ```

   The flows are defined as the fractions served by the combinations in the list combinations.
   (b) optimal_facilities: (dict) A dictionary with a key for each potential location and the number of modules that were sited there as a value.
   (c) non_zero_flows: (dict) A subset of dictionary optimal_flows with only non-zero flows.
   (d) total_flow: (float) The model objective value, total supported flow with corresponding cs layout.
   (e) supported_routes: (int) Total number of routes supported by the optimal charging station lay-out.

F. The search table method

In this chapter the search table method is presented. The search table was iteratively filled with search terms to select core concepts and state-of-the-art literature. The columns are filled with the different aspects that were combined with an AND operator and the rows are filled with different synonyms that were combined with an OR operator in the search query. Scopus, Scholar, and Web of Science were used to select literature. Besides, connectedpapers.com was used to identify related work and contrasting opinions. As charging stations can be seen as a subclass of alternative fuel stations, ”alternative fuel” was also incorporated in the search query.

F.1. Search table

Search term 1	Search term 2	Search term 3	Search term 4
flow-capturing	charg*	optim*	deploy*
flow-intercepting	electri*	planning	placing
flow-based	renewable	decision	placement
flow-refuel*	alternative fuel	location problem	locat*
agent-based	alternative-fuel	allocation problem	siting
activity-based	battery	model*	sizing
travel data	”charging infrastructure”		
heuristic			

F.2. Search query

(“flow-capturing” OR “flow-intercepting” OR “flow-based” OR “flow-refuel*” OR “agent-based” OR “activity-based” OR “travel data” OR “heuristic”) AND (“charg*” OR “electri*” OR “renewable” OR “alternative fuel” OR “alternative-fuel” OR “battery” OR ”charging infrastructure”) AND (“optim*” OR “planning” OR “decision” OR “location problem” OR “allocation problem” OR “model*”) AND (“deploy*” OR “placing” OR “placement” OR “locat*” OR “siting” OR “sizing”)