Strategic location selection for water cab moorings

A case study in optimising urban water transport

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Master Thesis

Strategic location selection for water cab moorings

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Preface

In this thesis, I have done my best to provide a clear and comprehensive description of my research on a method for determining moorings. This topic came my way during the subject TIL Research Project (TIL4020-20) in February 2025. What started as a subject assignment grew into an interesting and challenging project. The combination of mobility and programming appealed to me so much that I decided to explore this topic further in my thesis.

The completion of this research marked the end of my student time. It was an intensive journey, but also one in which I learned a lot and enjoyed working. At the same time, I am also satisfied that this chapter has been completed and I can take the next step.

I would like to thank everyone who helped me during this process. In particular, I would like to thank my supervisors Shade Sharif Azadeh and Oded Cats for their involvement, critical eye and valuable feedback. Your insights and comments really helped me in improving my research. A special word of thanks is addressed to Patrick Stokkink. Our weekly meetings were of great value to me, not only because of the substantive feedback, but also because of the nice way of sparring. Moreover, you always responded very quickly to my e-mails, something I greatly appreciated, which always enabled me to move on quickly.

I would also like to thank my friends and family. You supported me not only during my thesis, but actually throughout my entire studies. Moreover, you made this period a lot more fun and sociable.

Finally, I hope this report is not only informative, but can also inspire others who are concerned with urban mobility and infrastructure. I kindly invite you to explore the content further.

Sasha Leemans
Delft, September 2025

Summary

Over the years, pressure on the urban mobility network has been increasing, resulting in longer journey times, higher pollutant emissions, rising costs and reduced accessibility. Policies designed to reduce car traffic, such as restricting parking spaces or reducing lanes, often prove insufficiently effective or bring unintended negative consequences. Therefore, there is a need for smart and alternative solutions that do not further burden the existing infrastructure. One such solution is the implementation of an on-demand water cab, which makes efficient use of existing waterways. This transport offers opportunities to alleviate the negative impacts mentioned, provided the moorings are strategically positioned. To determine such optimal positions, location optimisation models are essential.

Existing location models, such as the Facility Location Problem (FLP) and the Hub Location Problem (HLP), have mainly been developed for other transport modes, such as buses, shared mobility and electric vehicles. These models typically assume static allocation of users, assume no interaction between facilities and do not take into account the on-demand and multimodal nature of water cabs. The Flow Capturing Model (FCM) is a promising approach, as it selects locations that maximally capture passenger flows, without predetermining which traveller takes which route. However, so far this method has not been applied to water cabs in urban areas. This study therefore develops a modified approach, inspired by the FCM, which is tailored to the demand-driven nature of urban water cabs. The corresponding research question is as follows:

"What are the optimal locations for on-demand water cab moorings in cities with navigable waterways and how can these contribute to improved accessibility and mobility using an optimisation-based approach?"

The proposed method was applied to a case study in Rotterdam, with the aim of selecting mooring sites from a set of potential locations for an on-demand water cab that contributes to shorter journey times and improved accessibility. First, a comprehensive set of potential mooring sites was identified, distinguishing between moorings that serve as interchanges for public transport and moorings that function as starting and ending points in residential and work areas.

Based on data on population, employment, public transport and navigable waterways, a multimodal network was constructed. For each origin destination pair, travel time and travel costs were determined for both public transport and the water cab. Water cab travel time and costs were calculated via the optimal combination of two moorings. The weighted function of travel time and cost was minimised by selecting the optimal mode of transport for each pair, public transport or water cab. This approach prioritises high-demand connections, aiming to significantly improve accessibility on frequently used routes.

From the previously identified set of potential moorings, an optimal subset was selected using an Adaptive Large Neighbourhood Search (ALNS) heuristic. This heuristic combines several removal and insertion operators and applies Simulated Annealing to also accept inferior intermediate solutions to escape local optima. This ALNS heuristic has proven to be effective. It offers solutions of comparable quality and structure to an exact MILP model, but with significantly shorter computation times. Moreover, it performs better than an LNS without an adaptive weight mechanism. This makes the method suitable for complex and large scale optimisation problems.

The results for Rotterdam show that an efficient water cab network is feasible with a limited number of strategically chosen mooring locations. This increases network coverage, shorter travel times and ensures better distribution, bringing more residents within reach. Unnecessary moorings, such as locations close to each other that serve the same passenger flows, contribute little and increase maintenance costs. By removing these and adding new locations in areas that are difficult to reach, with high passenger pressure or in emerging neighbourhoods, the network can become more robust and the pressure on existing public transport lines can be relieved. The scenario analysis shows that the network is robust to passenger behaviour assumptions, with the most frequently used moorings located in or near the city centre or at public transport hubs.

Although the model provides valuable insights, it also has limitations. For instance, travel times were modelled in a simplified way and physical constraints such as high quays, shallow water or limited space at the quay were not considered when identifying possible moorings. Nevertheless, it was a useful method within the context and scope of this study. Future research could include the financial aspects of network expansion to better assess economic feasibility. It is also important to investigate user preferences and behaviour more extensively and to include other modes of transport to obtain a more complete picture of urban mobility.

For cities considering introducing a water cab network, these findings offer valuable insights. Investment decisions should primarily be guided by strategic value of mooring locations within the network, with priority given to poorly connected areas, locations with high transport demand and locations close to public transport. In addition, it is important to design the network to be flexible and scalable so that it can respond to future changes in passenger demand and urban developments. Furthermore, the use of water cabs can be encouraged through public campaigns, better integration into travel apps and pricing policies. This will increase the likelihood that water cabs will develop into a valuable, sustainable and popular part of the urban mobility network.

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1 Introduction

Major cities worldwide are facing increasing pressure on their mobility networks [1]. Traffic congestion leads to longer journey times, which not only causes frustration among road users but also has wider societal consequences. Economic damage occurs to transporters, but also to businesses that receive late delivery of products [2]. In addition, congestion has a negative impact on the liveability of cities by worsening air quality, increasing greenhouse gas emissions and making urban areas less accessible [3]–[5].

Rotterdam is no exception. As a densely populated port city with complex infrastructure, the city experiences the effects of traffic congestion on a daily basis [6], [7]. To alleviate these problems, several measures have been taken, such as reducing car traffic by reducing lanes and parking spaces [8]. However, these measures do not always have the desired effect. Reducing lanes often leads to more congestion elsewhere as road users take alternative routes. It also reduces accessibility to certain areas, as alternative routes are often not as efficient or suitable [9]. Reducing parking spaces also proves difficult, as motorists look for parking spaces elsewhere, which increase parking pressure in adjacent neighbourhoods [10]. As a result, traffic congestion and accessibility remain a persistent problem.

As traditional measures prove insufficient, it is important to look at alternatives that are both fast and efficient while not further burdening existing infrastructure. One possible but underused solution is to integrate urban waterways into the transport system. Many cities, including Rotterdam, have extensive water networks that are mainly used for freight transport and leisure activities, but not for efficient passenger transport [11]. Water cabs, which offer on-demand transport via water, could ease pressure on the road network by providing direct and flexible connections between different parts of the city [12]. This type of transport is particularly suitable for areas that are less accessible through traditional infrastructure and could contribute to a more efficient and sustainable mobility system.

The effectiveness of waterborne transport is largely dependent on the strategic placement of moorings. Poorly placed moorings can lead to inefficiencies, keeping travel time high and limiting accessibility and integration with other transport modes. Identifying optimal mooring locations is therefore crucial to maximise the benefits of water cabs in urban mobility.

This study aims to develop a methodology for determining optimal mooring locations for on-demand water cabs, using Rotterdam as a case study. This study creates a framework for identifying strategic locations that improve connectivity and reduce travel times. In doing so, this study contributes to the broader discussion on how cities can better use their waterways to improve urban transport.

1.1 Research Questions

The objective of this research is to develop a method for identifying optimal moorings for on-demand water cabs. This aims to improve accessibility and mobility in cities with navigable waterways. The core of the research is to apply an optimisation-based approach to strategically determine these locations. The main research question is therefore formulated as follows:

What are the optimal locations for on-demand water cab moorings in cities with navigable waterways and how can these contribute to improved accessibility and mobility using an optimisation-based approach?

To address this main question, several sub-questions have been formulated. Each sub-question focuses on a specific component of the problem, from the underlying factors influencing mooring location decisions to the development and application of an optimisation-based method. A case study of Rotterdam is used to explore these aspects in a real-world urban setting, where waterborne transport can play a key role in sustainable mobility. The sub-questions are as follows:

1. What factors influence the placement of water cab moorings, particularly in terms of accessibility and demand?

2. How can potential locations for water cab moorings be identified before applying an optimisation-based approach?

3. How can an optimisation-based approach be developed to determine optimal water cab mooring locations, considering key parameters, constraints and objective functions?

4. How can the developed optimisation approach be applied to real-world case studies, such as Rotterdam, to determine optimal water cab mooring locations and assess their potential to improve accessibility and mobility?

5. How can the results of the optimisation approach inform policy decisions regarding sustainable urban transportation and water cab moorings in Rotterdam?

1.2 Research Methodology

The research methodology consists of several interconnected steps, which are visualised in figure 1.1. The process starts with a literature review to understand the relevant factors influencing the placement of water cab moorings and to investigate existing approaches. Based on the relevant factors, a set of candidate locations is defined.

An optimisation approach, based on existing models, is then developed to select the most suitable mooring locations from the set of candidates based on travel time, costs and network connectivity. Finally, this approach is applied to a case study in Rotterdam, using various data sources, including geospatial data.

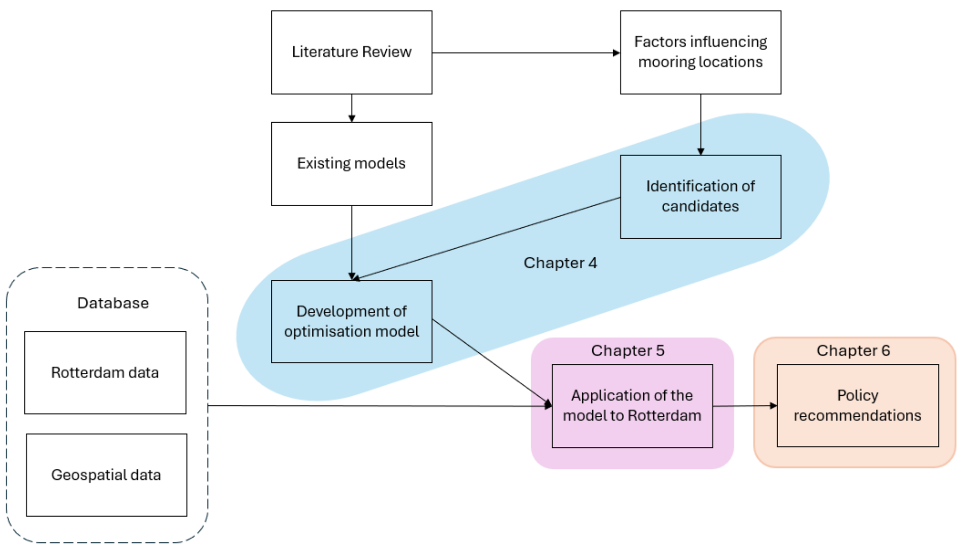

Figure 1.1: Conceptual model of research methodology

1.3 Report Structure

The report is structured as follows. Chapter 2 presents a literature review exploring the potential of waterborne transport in urban areas. In addition, this chapter discusses the factors influencing the location choice for moorings, as well as an analysis of existing optimisation models. Next, Chapter 3 described the problem, discussing the specifics of on-demand water cabs and the limitations of existing models. Following this, Chapter 4 describes the research methodology, explaining how to determine the optimal set of moorings, starting with identifying potential locations and then developing an appropriate optimisation model. Next, Chapter 5 focuses on the application of this method within the Rotterdam case study and discusses the results of the optimisation, including scenario analysis. Finally, Chapter 6 provides the main conclusions, limitations, policy recommendations and suggestions for future research.

2 Literature Review

This chapter reviews existing literature on waterborne transport. It covers the benefits and challenges of water transport, factors influencing the placement of moorings and insight drawn from other urban transport systems. In addition, relevant location models, such as the Facility Location Problem (FLP) and Hub Location Problem (HLP), are discussed.

2.1 Waterborne Urban Transport

Water transport refers to the movement of passengers through navigable waterways such as rivers and canals [13]. On-demand water transport offers flexible scheduling, allowing passengers to request vessels as needed. Although pick-up and drop-off locations are fixed, times are adjusted based on passenger demand, similar to taxi services such as Uber for road transport [11].

2.1.1 Advantages and potential

Waterborne transport offers several advantages in urban environments, making it a promising alternative or complement to road transport. A key advantage is the low investment costs. Waterways are often considered 'natural highways' as they require minimal infrastructure investment compared to land-based transport systems such as roads or railways. This cost-effectiveness is a strong incentive for cities and passengers to consider water transport as part of their mobility strategies [14], [15]. Moreover, this form of transport can carry a significant number of passengers, making it an efficient solution for mass transport in urban environments [16].

In addition, water-bound transport offers significant advantages in terms of travel time. Studies show that water cabs can contribute to shorter journey times by providing direct routes over water, bypassing congested roads and detours over bridges and tunnels [17], [18]. The shorter travel times not only improve user satisfaction, but also help relieve pressure on the road network. The shorter journey times and convenience of water cabs mean more people, including motorists, switch from cars to water transport. This leads to fewer vehicles on the road, potentially reducing traffic congestion [19], [20].

Furthermore, reducing traffic congestion also contributes significantly to the sustainability of the city. Less congestion means that cars idle less often with the engine on, resulting in lower pollutant emissions [15]. Moreover, well-fitted boats emit fewer pollutants per passenger than cars [19]. Electric powered boats further enhance this environmental effect by further reducing emissions while causing virtually no noise pollution [21]. In addition, water cabs are usually located at some distance from densely populated areas, which further reduces nuisance for local residents [15].

2.1.2 Operational challenges

Despite these benefits, water-bound transport also has several challenges. First, there are safety concerns. Factors such as passenger overloading, recruitment of unskilled crews and low standard maintenance of Inland Water Transport (IWT) channels contribute to safety risks [22]. In addition, water-based transport can be relatively expensive for passengers compared to land-based alternatives. Fares are often higher due to increased personnel costs and limited economies of scale [23].

Moreover, using water-based transport often requires additional transfers. Because water transport typically operates within a multimodal network, passengers often have to transfer between different modes of transport. Studies show that passengers prefer routes with fewer transfers, as each transfer increases the risk of delays and adds to the perceived inconvenience of the journey [24]–[26].

Finally, water transport is seasonal in nature, so transport is not available year-round [16], [27]. These challenges must be considered when planning and developing waterborne transport.

2.2 Factors influencing the success of waterborne transport

For successful implementation of water-bound mobility, several critical factors must be considered. One of the most essential is the strategic placement of moorings. These stops should be located to minimise inconvenience for passengers transferring to other modes of transport. Ideally, moorings are situated near major city areas and are well connected to public transport networks such as train stations, bus terminals and shared mobility hubs. This integration ensures that water transport becomes a seamless part of a multimodal transport system, thereby increasing its convenience and attractiveness for travellers [21], [28], [29].

In addition to location, comfort and accessibility are crucial to the success of water-bound mobility. Research indicates that passenger satisfaction is strongly influenced by the overall travel experience, both onboard and at the mooring. Onboard features such as adequate seating, shelter from weather conditions and a smooth, quiet ride enhance user experience [13]. On land, accessible and well-maintained moorings, combined with clear signage and barrier-free access, enable a diverse group of passengers, including those with reduced mobility, to use the service effortlessly [28], [30].

Another determining factor is service availability and response time. Unlike traditional transport services with fixed schedules, water cabs operate on-demand, meaning passengers request a ride when needed. To effectively compete with other transport options, response time must be fast and reliable, especially during peak hours. Long waiting times can discourage users from choosing water transport, as passengers expect a high level of convenience [30], [31].

2.2.1 Location planning insights from traditional transport systems

Valuable insights for the placement of moorings for water cabs can be gained from research on other urban transport facilities, such as charging stations for electric vehicles (EV), bus stops and shared mobility hubs. Although these transport facilities perform different functions, they share important location principles relevant to water-based transport.

For example, studies on electric vehicle charging stations recommend placing them in areas of high demand, such as commercial centres and transport hubs, to increase accessibility and minimise unnecessary detours [32]–[34]. Similarly, bus stops are most effective when positioned near key destinations or areas with high pedestrian traffic [35], [36]. Moreover, bus stops must be well integrated with other transport networks to ensure a smooth and efficient transition between different modes of transport [37], [38]. These principles also apply to water cab moorings, situating them near urban centres and multimodal nodes promotes both accessibility and use.

A crucial challenge in location planning is balancing accessibility and efficiency. Studies on bus stop placement emphasise that adding more stops along a route can increase the number of passengers due to improved accessibility. However, this can also extend total travel time, as vehicles must stop and accelerate more frequently [39]–[42]. Although water cabs do not operate on fixed routes, a similar trade-off exists. Adding more docking stations can enhance user accessibility by reducing the distance passengers must travel to board a water cab. However, too many docking stations may lead to operational inefficiencies, such as longer travel distance for empty trips between pick-up points and higher maintenance costs. Striking a balance between accessibility and efficiency is therefore crucial.

Another crucial consideration is understanding demand patterns. Unlike fixed-route transport modes such as buses, which generally experience predictable demand during peak hours, water cabs operate in a dynamic environment. Demand can vary significantly depending on factors such as weather conditions and tourism [20]. This resembles challenges found in EV charging systems, where fluctuating daily usage must be considered when planning locations [32], [33]. Furthermore, it is crucial to consider the integration of passenger flows between origins and destinations. Properly managing the flow of passengers across the network can reduce congestion, optimise waiting times and ensure seamless transitions between the various modes of transport, improving the overall efficiency of the water cab system [43], [44].

As discussed, the placement of water cab moorings depends on multiple interrelated factors. An overview of these factors is provided in table 2.1. The demand & usage factor refers to indicators of travel patterns and potential demand, such as observed routes, population density and the distribution of passenger flows. Travel time represents the total journey duration for the user, including access time, in-vehicle time and any transfer or charging time, where applicable. Accessibility refers to the extent to which a mooring is reachable from key points in the city, such as public transport hubs, economic centres and tourist attractions. Costs include, among other things, implementation expenses, operation costs and user-related costs such as ticket prices or charging fees.

Table 2.1: The selection of influential factors to be used in the methodology for determining the locations of water cab moorings.

Publications	**Mode**	**Demand & Usage**	**Travel time**	**Accessibility**	**Costs**
Chioni et al. (2020)	Bus	✓		✓	
Luo et al. (2022)	Public Transport			✓	✓
Iamtrakul and Wongbumru (2019)	Water transport		✓	✓	
Harshil and Nagababu (2024)	EV charging	✓		✓	✓
Verbakel et al. (2000)	Water transport		✓	✓	✓
Vu (2011)	Water transport			✓	
Blad et al. (2022)	Mobility hubs	✓	✓	✓	✓
Suleiman et al. (2023)	Public Transport			✓	✓
Van Berkel (2020)	Water transport		✓		
Cheemakurthy et al. (2017)	Water transport		✓	✓	
Carra et al. (2022)	EV charging			✓	✓
This paper	**Water transport**	✓	✓	✓	✓

2.3 Evaluating Location Models for Water Cab Moorings

To identify optimal mooring location for water cabs, several mathematical optimisation models from the transport planning literature can provide valuable insights. Two commonly used models are the Facility Location Problem (FLP) and the Hub Location Problem (HLP).

The FLP focuses on selecting the best locations for facilities from a predefined set of candidates, to minimise overall costs, taking into account constraints such as demand distribution and operational efficiency [45], [46]. This model has been successfully applied to urban infrastructure planning, such as the siting of electric vehicle charging stations. Important considerations include electric vehicle distribution, passenger flows, waiting times and travel distances [43], [44]. These principles are also relevant for water cab systems, by placing mooring locations in areas with high demand and good connections to other transport modes, accessibility can improve and waiting times can be reduced.

In contrast, the HLP focuses on optimising nodes within a network and takes into account the efficient consolidation of transport flows within a network [47], [48]. The aim is typically to minimise overall transport costs and improve connectivity between origin and destination points [49], [50]. It is widely used in public transport systems, such as bus or metro networks, to streamline interchanges between transport modes to reduce journey times [51], [52]. Similarly, water cab moorings can act as nodes in a multimodal network, facilitating connections between the water network and other modes of transport.

While both models offer important insights, they appear to have several structural limitations in the context of on-demand water cab services. First, both models assume a static and foreknown demand, whereas water cabs are inherently demand responsive [45], [53]. Secondly, FLP treats facilities separately, neglecting the interdependencies between locations [54], [55], yet in water cab networks, the effectiveness of a mooring may depend heavily on its position within the wider network [56].

In addition, both models assume a fixed allocation of users to facilities [55], [57], whereas passengers in a water cab system dynamically determine their route choice based on availability, interchanges and preferences. This implies a network behaviour that is understudied in classical models. Important aspects such as waiting times and vehicle availability, which are precisely crucial for the quality of an on-demand service, are also largely ignored in HLP models [58], [59].

These limitations suggest that while FLP and HLP provide valuable frameworks, they cannot fully capture the complexity of on-demand water cabs. The following section therefore presents a problem description and explores an alternative modelling approach better suited to capturing the dynamic, user-driven nature of on-demand water transport.

3 Problem Description

As discussed in the previous chapter, on-demand water cabs offer promising benefits for urban mobility, such as shorter journey times and lower environmental impact. However, its successful implementation depends heavily on the strategic placement of moorings. The location of moorings affects travel time, accessibility and efficiency of the system. Factors that make a location more attractive include proximity to major urban areas, integration with other modes of transport and passenger comfort.

Although classical location optimisation models, such as the Facility Location Problem (FLP) and Hub Location Problem (HLP), provide valuable insights, these models are not fully suitable for modelling on-demand water cab systems. These models typically assume fixed demand distribution and static user allocation, while in reality travellers base their choices on actual availability, waiting times and transfer options. In doing so, they do not take into account the dynamics of traveller behaviour, interactions between moorings and dependence on vehicles moving flexibly through the network, elements that are precisely what determine the effectiveness of a water cab system.

A more suitable model is the Flow Capturing Model (FCM). Unlike traditional models, FCM focuses not on demand at nodes, but on capturing travel flows between origin and destination pairs within a network [60]–[62]. A facility is considered effective when it is located on the route between such a pair and thus capable of capturing that flow. In the case of water cabs, the FCM can be used to identify mooring locations along common travel routes between origin and destination pairs. Instead of pre-assigning passengers to specific mooring locations, the model assumes that passengers choose the most suitable option in real time. This flexibility makes FCM well suited for dynamic systems where user behaviour is influenced by factors such as travel time and costs.

Several studies have applied the Flow Capturing Model to determine optimal locations for electric vehicle (EV) charging stations [62]–[64]. These applications aimed to maximise the amount of captured traffic flow, explicitly accounting for uncertainty in where charging demand would arise. Such studies illustrate the model's applicability within mobility systems characterised by uncertain or dispersed demand patterns. However, the FCM has not yet been adapted to the problem of water cab mooring placement in urban settings. This research addresses this gap by developing a tailored application of the FCM to determine optimal mooring locations in an on-demand water transport network. The aim is to select from a collection of candidate locations a subset that both reduces travel time and increases accessibility, enabling attractive and efficient services.

3.1 Formulation of the mathematical model

The approach consists of two parts. First, a broad set of potential mooring locations is identified. Then, the mathematical model selects the optimal subset of moorings that minimises the weighted sum of travel time and costs across all origin and destination pairs. This involves choosing a mode of transport for each pair, public transport (PT) or water cab (WT), where the total sum of travel time and costs is minimised. The travel time and cost of the water cab depend on the moorings chosen.

The number of moorings that can be realised is limited by budgetary and operational capacities. In addition, when selecting moorings, the busyness of connections is taken into account, with connections with higher passenger flows having a greater influence on the selection, so that reducing travel times on these routes benefits a larger number of passengers. In a network consisting of a set of nodes (N), each node is considered a potential mooring location. The demand in the network is represented by a set of origin-destination (OD) pairs (Q), where each pair has an associated unidirectional passenger flow (f_q). This leads to the following mathematical equation.

Table 3.1: Mathematical model

Sets and indices		
N	Set for the moorings	$i, j \in N$
Q	Set for the OD pairs	$q \in Q$
Parameters		
t_q^{PT}	time between origin and destination pair q with public transport	
t_{qij}^{WT}	time between origin and destination pair q with the water cab through mooring i and j	
f_q	flow between origin and destination pair q	
c_q^{PT}	cost of OD pair q with public transport	
c_{qij}^{WT}	cost of OD pair q by water cab via mooring i and j	
p	maximum number of moorings	
Variables		
y_{qij}	1, if origin destination pair q uses the water cab via moorings i and j, otherwise 0	
x_i	1, if mooring i is selected, otherwise 0	

The mathematical formulation then follows as:

$$\min \quad \sum_{q \in Q} \Big((t_q^{PT} + c_q^{PT}) \cdot (1 - \sum_{i,j \in N} y_{qij}) + \sum_{i,j \in N} (t_{qij}^{WT} + c_{qij}^{WT}) \cdot y_{qij} \Big) \cdot f_q \tag{1}$$

Subject to:

$$\sum_{i \in N} x_i \leq p \tag{2}$$

$$y_{qij} \leq x_i \qquad \forall q \in Q, i, j \in N \tag{3}$$

$$y_{qij} \leq x_j \qquad \forall q \in Q, i, j \in N \tag{4}$$

$$\sum_{i,j \in N} y_{qij} \leq 1 \qquad \forall q \in Q \tag{5}$$

$$y_{qij} \in \{0, 1\} \qquad \forall i, j \in N, q \in Q \tag{6}$$

$$x_i \in \{0, 1\} \qquad \forall i \in N \tag{7}$$

Constraint 2 ensures that no more moorings are selected than allowed. Constraints 3 and 4 ensure that the water cab can only use moorings that are actually selected. Constraint 5 states that for each origin and destination pair, a maximum of one combination of moorings (i, j) is selected for the water cabs route. As a result, the water cab cannot have multiple routes for the same pair, only the route with the lowest travel time and cost is selected. Finally, constraints 6 and 7 are linked to the decision variables, both of which are binary.

The travel time between an origin and a destination depends on which mooring locations are active and selected as access points. Although each origin-destination (OD) pair uses only two moorings (for embarkation and disembarkation), these are selected from a large set of n possible mooring locations. For each OD pair, two moorings must be chosen from this set, resulting in $O(n^2)$ possible combinations per OD pair. Since the network consists of m OD pairs, the total number of travel alternatives scales with $O(m \cdot n^2)$. This exponential growth of the solution space makes it computationally infeasible to solve the problem exactly. Therefore, a heuristic approach is applied, which is capable of finding a high-quality solution within an acceptable computational time.

4 Methodology

This chapter presents the methodology for identifying optimal mooring locations for water cabs within an urban multimodal network. The approach consists of two main steps, namely generating a set of potential mooring locations and selecting the most effective locations. The methodology is designed to be transferable to other contexts and cities, provided relevant spatial and demand data are available.

4.1 Identifying potential locations

Potential mooring locations are identified based on two functions, namely interchanges on public transport and the starting or ending point of a journey. Because these functions have different roles within the network, each is determined differently.

4.1.1 Transfer points

Figure 4.1 shows the schematic steps for identifying potential mooring locations based on proximity to public transport. Several studies show that a good connection to public transport contributes to the attractiveness and use of the water cab by providing passengers with a seamless connection between the water cab and other modes of transport [21], [37].

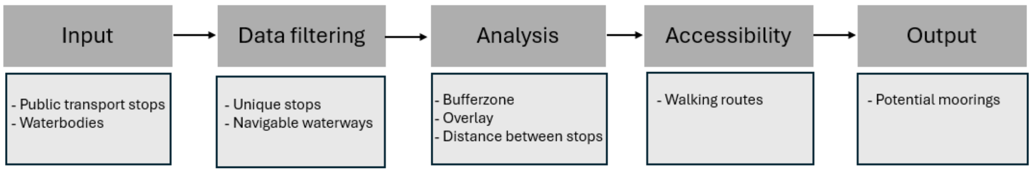

Figure 4.1: The steps for determining transfer points.

To map moorings to serve as interchanges, a spatial buffer is defined around existing public transport stops, based on an acceptable walking distance. This threshold is based on the distance travellers are typically willing to walk to transfer. The distance can be adjusted according to local conditions, such as infrastructure quality and height differences [65]. Within each buffer zone, potential moorings are generated along the edges of navigable waterways, ensuring both proximity to public transport and the physical feasibility of the mooring.

Finally, the potential moorings are further filtered based on pedestrian accessibility. Only moorings accessible by a continuous walkway from public transport stops will be retained. Routes interrupted by water without bridges or tunnels, for example, are excluded to ensure practical usability.

4.1.2 Living and working places

Figure 4.2 illustrates the steps in identifying potential moorings based on passenger flows and demand. In addition to interchanges, moorings should also serve areas of high potential demand [34], [35]. Demand is approached based on residential and employment. Areas with a high concentration of residents and workers are expected to be more likely to generate and attract trips [66], [67]. Placing moorings around these areas can increase the effectiveness of the water cab.

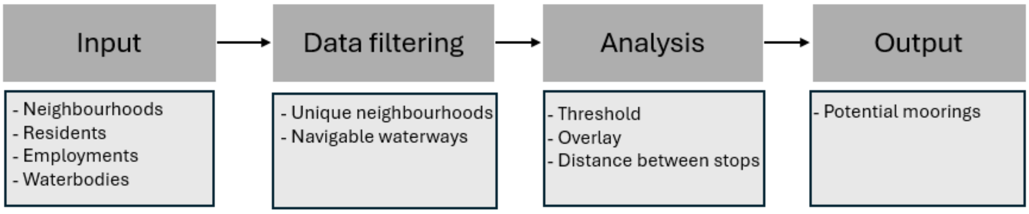

Figure 4.2: The steps for determining living and working places.

The study area is divided into smaller areas, such as neighbourhoods or districts, for which population and employment data are collected. For each area, the combined number of inhabitants and jobs is used as a measure of trip generation. Only areas that exceed a minimum demand threshold and are adjacent to navigable waterways are considered. Within these selected areas, potential moorings are evenly distributed along the quayside to ensure coverage and flexibility in subsequent selection.

4.2 Network construction

In this part of the methodology, a network is constructed representing the movement of commuters through urban areas. The network consists of nodes and arcs. Nodes represent the start and end points of journeys, while arcs represent possible travel routes between them. This structure allows estimating passenger flows within the network, which is essential to assess the impact of different moorings on journey times.

Construction begins by defining the nodes of the network. These are based on locations where people typically start or end their journeys, namely residential and commercial areas. Commuting patterns account for a significant proportion of total passenger flows [68].

The neighbourhoods previously identified are subdivided into smaller zones representing residential or work areas. This further segmentation captures travel movements in more detail. A higher degree of segmentation leads to more detail and accurate representation of travel patterns, however, the computational complexity goes up. So there is a trade-off between accuracy and computational feasibility. To ensure realistic zone placement, unbuilt areas, such as water bodies and parks, are excluded. After the zones are defined, the number of people living and working in each segment is determined. These values are then used to estimate potential movements between zones. The number of travellers from a residential zone n_o to a work zone n_d is calculated using the following formula:

$$r_{o,d} = n_o \cdot \frac{n_d}{\sum_{d \in D} n_d} \tag{8}$$

Where $r_{o,d}$ is the estimated number of travellers from residential zone to work zone. This approach assumes that the proportion of people in the residential zone is evenly distributed among all destinations, in proportion to the number of jobs per work zone.

After defining the residential and working zones, the network structure is defined by connecting each residential and working pair. Only connections are made between residential zones (origins) and work zones (destinations), as the model only focuses on commuting trips. Each connection between origin and destination represents a potential movement within the network. A travel time and cost are assigned to each connection based on public transport. For each OD pair, the expected travel time is calculated, resulting in a two-dimensional OD matrix. As an illustration, figure 4.4 shows a simplified representation of the network, showing origins, destinations and their connections.

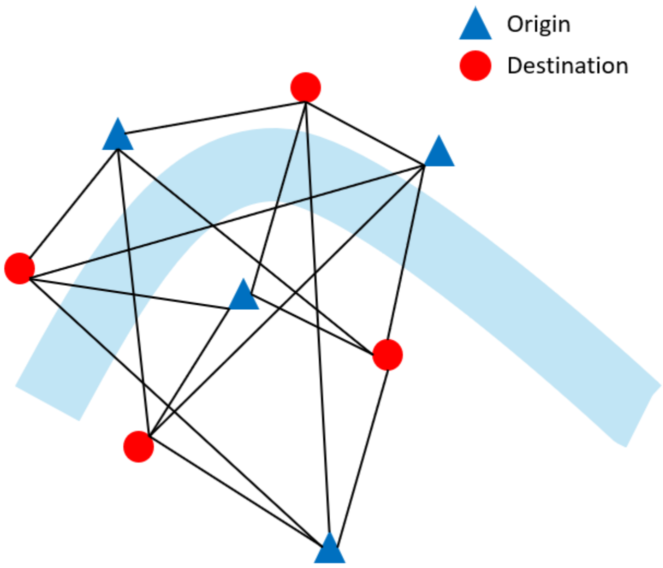

Figure 4.3: Schematic representation of direct origin–destination connections

In addition, a four-dimensional matrix is constructed to evaluate the impact of the introduction of water cab moorings. Unlike the 2D matrix, which contains only direct connections between origins and destinations, the 4D matrix captures routes through two intermediate moorings. For each OD pair, it determines the combination of two moorings that results in the shortest possible travel time. These two moorings are stored as the optimal route for each OD pair. Figure 4.4 shows an example of a network structure that belongs to a 4D matrix. For the sake of clarity, only the connections are drawn in this figure for one origin and one destination.

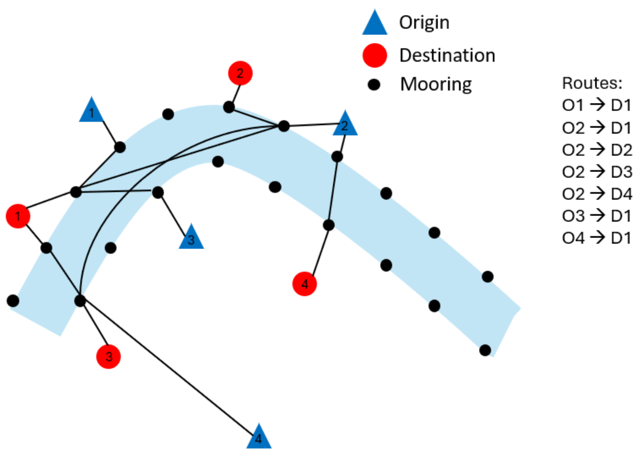

Figure 4.4: Schematic representation of connections via selected mooring points

To construct the 4D matrix, a shortest path problem is solved for each combination of origin (o) and destination (d). All possible combinations of two moorings (i, j) are evaluated, where the total travel time consists of three components:

$$T_{o,d} = T_{o,i}^{\mathrm{PT}} + T_{i,j}^{\mathrm{WT}} + T_{j,d}^{\mathrm{PT}} \tag{9}$$

Here, $T^{\mathrm{PT}}_{o,i}$ is the travel time from the origin to the mooring i by public transport, $T^{\mathrm{WT}}_{i,j}$ is the travel time between the moorings i and j and $T^{\mathrm{PT}}_{j,d}$ is the travel time from mooring j to the destination by public transport. The pair of moorings that provides the shortest total travel time is then stored for that OD pair. This reduces the 4D matrix to a new 2D matrix containing the minimum travel time through two moorings for each OD pair. This allows direct comparison with the original 2D matrix with direct travel times.

The literature shows that travellers base their transport choice not only on travel time, but also on other factors such as costs [69], [70]. Therefore, to make the choice in the model more realistic, fixed and variable costs have also been added to the model. Variable costs depend on the time between origin and destination pairs.

$$C_{o,d} = C_f + C_v \cdot T_{o,d} \tag{10}$$

In this, $C_{o,d}$ is the total cost of a connection from origin o to destination d, where C_f is the fixed cost and C_v is the variable cost. These costs are determined separately for each mode of transport, public transport and water cab.

4.3 Objective function

The aim of the model is to determine a selection of moorings that minimises the total weighted generalised travel cost across all origin destination (OD) pairs. For each origin destination pair, the model determines both the travel time and monetary cost of two transport modes, public transport and water transport. To ensure comparability between travel time and monetary cost, the value of travel time (VoT) is used to convert travel time into an equivalent monetary cost. Although time already plays a role in variable travel costs, the addition of VoT ensures that the subjective time burden for the traveller is explicitly recorded, in addition to the amount paid to the operator. This results in a generalised cost per trip, which is the sum of actual travel cost and time cost. For each transport mode $m \in (PT, WT)$, public transport and water cab, respectively, the generalised travel cost is calculated as follows:

$$GC^m_{o,d} = T^m_{o,d} \cdot VoT + C^m_{o,d} \tag{11}$$

Where:

$T^{\mathbf{m}}_{o,d}$ the travel time by mode m from origin o to destination d

- $T^{\mathrm{PT}}_{o,d}$ the travel time by public transport between origin o and destination d, taken from the 2D-matrix
- $T^{\mathrm{WT}}_{o,d}$ the shortest travel time by water cab via the optimal pair of moorings from the 4D-matrix

$C^{\mathbf{m}}_{o,d}$ the travel cost by mode m from origin o to destination d

VoT value of travel time, used to convert minutes to costs

The model selects for each OD pair the mode of transport with the lowest total generalised travel cost. This takes into account that connections with higher passenger demand are more important. The optimisation goal is therefore to minimise the weighted generalised travel cost by always selecting the best option, either water cab or public transport, for each OD pair, while prioritising OD pairs with higher expected demand.

$$\min \sum_{(o,d)\in OD} r_{o,d} \cdot \min\left(GC^{\mathrm{WT}}_{o,d}, GC^{\mathrm{PT}}_{o,d}\right) \tag{12}$$

Where:

$r_{o,d}$ the number of passengers travelling from origin o to destination d

Given the complexity of the problem and the size of the solution space an exact optimisation approach is computationally infeasible. Therefore, this study applied a heuristic solution method designed to efficiently explore the solution space. The following section describes the applied heuristic, Adaptive Large Neighbourhood Search (ALNS).

4.4 Adaptive Large Neighbourhood Search

ALNS is a metaheuristic designed to solve complex optimisation problems efficiently [71]. The algorithm iteratively improves an initial solution by repeatedly removing parts of it and rebuilding it in a different way [72]. Thanks to this approach, ALNS explores large parts of the solution space, improving its ability to avoid local optima [71]. ALNS builds on Shaw's Large Neighbourhood Search (LNS) heuristic, with the main improvement being an adaptive component that learns which removal and insertion operators are effective [73], [74]. This makes the algorithm flexible, robust and to some extent self-calibrating [72], [75].

The general structure of the algorithm is shown in Algorithm 1. Each step of this algorithm is discussed in detail in the following sections. The algorithm starts by generating an initial solution s, as described in Section 4.4.1 and additionally requires a parameter q, which indicates the number of moorings to be removed. In each iteration, a removal operator is first selected based on weights that reflect their previous performance. Next, moorings are removed from the current solution. Then, an insertion operator is selected to restore the solution by adding moorings to the solution. Both removal and insertion operators are explained in Sections 4.4.2 and 4.4.3, respectively. The selection of operators significantly affects the performance of the algorithm. The selection is done adaptively via a roulette wheel mechanism as described in Section 4.4.4. After recovering the solution, it is checked whether it is still feasible. If so, simulated annealing acceptance criterion is used to determine whether the new solution is accepted, as described in Section 4.4.5. Based on the quality of the solution, the weights of the operators used are updated so that successful strategies are chosen more often in future iterations.

Algorithm 1 Adaptive Large Neighbourhood Search

Function: ALNS ($s \in \text{solutions}, q \in \mathbb{N}$)
solution $s_{best} = s$
repeat
    $s' = s$
    Choose a destroy operator
    Remove q moorings from s'
    Choose a repair operator
    Reinsert moorings into s'
    If $f(s') < f(s_{best})$ **then**
        $s_{best} = s'$
    End if
    If $accept(s', s)$ **then**
        $s = s'$
    End if
    Operator adaptive weight adjustment
until stop-criterion met
return s_{best}

4.4.1 Initial solution

The initial solution is randomly generated. This involves randomly selecting a predetermined number of locations from the full set of moorings. This approach avoids bias in the initial set and ensures that the algorithm is not affected by a specific initial solution. However, the size of this initial set, or the number of selected moorings, has a significant impact on the final performance of the algorithm. Therefore, tuning this parameter is essential to achieve good results.

4.4.2 Removal operators

This section describes the removal heuristics applied within the ALNS algorithm. Three different removal operators are used: random removal, distance-based removal and least-used removal.

Random Removal
The random removal heuristic randomly selects a number (q) of moorings and removes them from the current solution. Although this technique seems inefficient at first glance, since well-functioning moorings can also be removed, it greatly contributes to the diversification of the solution space. Moreover, this heuristic is computationally lightweight and therefore significantly faster than more complex removal strategies [74], [76].

Distance-Based Removal
The distance-based removal heuristic is implemented to optimise the geographical distribution of moorings in the network by removing moorings that are close to each other. The aim is to reduce overlap or redundancy in the network, which can increase network efficiency. This heuristic is inspired by previous applications in literature [72], [77], but in this implementation, the relatedness measures between moorings is based solely on geographical distance. This heuristic can be described as follows:

Algorithm 2 Distance-Based Removal Heuristic

Function: DB Removal $(s \in \text{solutions}, q \in \mathbb{N}, p \in \mathbb{R}^+)$
$D = \emptyset$
$P =$ an array of all pairs $(a, b) \in s$ with $T(a, b) \leq T_{max}$
While $|D| < q$ **do**
    Sort P in ascending order of $T(a, b)$
    Choose a random number y from the interval $[0, 1)$
    $(a, b) = (a, b) \cup \{P[\lfloor y^p |P| \rfloor]\}$
    $D =$ randomly select a or b from (a, b)
End
Remove the moorings in D from s

The selection of a pair of moorings from list P is done via a biased technique. First, a random number y is drawn from the interval $[0, 1)$. This determines the index on the list P, where a higher value of p increases the probability of selecting a pair with a short distance between them. On the contrary, at a lower value of p, the selection is distributed more randomly throughout the list. Then, one of the two moorings is randomly selected from the selected pair and added to the deletion list D.

Least-Used Removal
The least-used removal heuristic is based on the worst removal strategy [72], [77]. This heuristic focuses on the removal of high-cost customers in the solution, in this study it is chosen to remove moorings that are relatively little used within OD routes. The assumption is that such moorings have limited added value and take up space that could be better utilised. Removing these will create space for potentially more effective moorings.

Algorithm 3 Least-Used Removal Heuristic

Function: LU Removal ($s \in \text{solutions}, q \in \mathbb{N}, p \in \mathbb{R}^+$)
While $q > 0$ **do**
    L = all moorings in s, sorted by descending usage(a,s)
    Choose a random number y from the interval $[0, 1)$
    $a = L[\lfloor y^p |L| \rfloor]$
    remove a from solution s
    $q = q - 1$
End

The term usage(a,s) refers to the frequency of use of a specific mooring a within the solution s, in other words, it is a measure of how often a mooring occurs in the solution. To calculate the frequency of use, for each solution it tracks how often the moorings are used, either via which moorings the shortest route from origin to destination takes place. This provides insight into the relevance of each mooring within the network, with less frequently used moorings being more likely to be removed in the least-used removal heuristic.

4.4.3 Insertion operators

This section discusses the insertion heuristics applied within the ALNS algorithm. Four different insertion operators are used: random insertion, best-candidate insertion, learning-based insertion and couple insertion.

Random Insertion
Random insertion is a simple but effective heuristic where randomly selected moorings from the set of unselected moorings are added to the current solution. The method introduces variation in the solution space. Random insertion creates noise, which helps to avoid identical or very similar solutions [78], [79].

Best-Candidate Insertion
The best-candidate insertion heuristic adds moorings to the current solution in a way that aims to minimise the increase in total travel time. From a set of possible moorings, a mooring that makes the solution the least worse in terms of travel time is selected each time. This approach is based on strategies in which entities are added with the minimum diversions or cost increase [72], [78], [80]. The process is repeated until the desired number of moorings is added, leading to a more efficient solution with the least additional travel time.

Algorithm 4 Best-Candidate Insertion Heuristic

Function: BC Insertion ($s \in$ solutions, $q \in \mathbb{N}$)
While $q > 0$ **do**
  L = set of moorings not in s
  Calculate travel time of s without a: T_s
  Best_insertion = null
  Best_improvement = $-\infty$
  For each mooring a in L **do**
    Calculate travel time of s with a: $T_{s\cup\{a\}}$
    Calculate improvement: $\Delta T_{a,s} = T_s - T_{s\cup a}$
    If $\Delta T_{a,s} >$ best_improvement **then**
      best_improvement = $\Delta T_{a,s}$
      best_insertion = a
    End if
  End for
  Add best_insertion to s
  $q = q - 1$
End while

This heuristic can be computationally intensive because for each possible mooring that is not yet in the solution, the travel time has to be calculated. This means that for each iteration, the algorithm has to calculate the travel time for all unselected moorings, which can lead to longer computation time, especially for large networks. To optimise computation time, techniques such as limiting the number of moorings to be considered (L) can be considered.

Learning-Based Insertion
The learning-based insertion heuristic is an adaptive method that uses historical information to guide mooring selection. Instead of randomly adding moorings, moorings that were more often part of high-quality solutions in the past, solutions with low generalised travel cost, are biased in selection. In this way, the algorithm learns which moorings are likely to contribute to efficient solutions. This idea is in line with existing literature in which insertion strategies are based on historical information to improve solution quality [81], [82].

Algorithm 5 Learning-Based Insertion Heuristic

Function: LB Insertion ($s \in$ solutions, $q \in \mathbb{N}, p \in \mathbb{R}^+$)
While $q > 0$ **do**
  L = set of moorings not in s
  Compute $P(a)$ for each a in L
  Select mooring a from L using weighted random choice based on p
  add a to solution s
  $q = q - 1$
End

The value $P(a)$ represents the estimated probability of adding mooring a to the solution, based on historical performance. This probability is determined from the frequency with which mooring a occurred in previous solutions with low generalised travel cost. To allow randomness in the selection process, a deterministic parameter is used. A higher value of p leads to a stronger preference for moorings with higher frequency, while a lower value allows more randomness. The probability is defined as follows:

$$P(a) = \frac{\mathrm{f}(a)}{\sum_{b \in L} \mathrm{f}(b)} \tag{13}$$

If a new solution is accepted, this solution is assumed to contribute to a more efficient network. In that case, the scores of the moorings included in the solution are increased by a constant value (β). The update can be represented as follows:

$$\mathrm{f}(a) = \mathrm{f}(a) + \beta \quad \text{for each } a \in s \tag{14}$$

Couple Insertion
The couple-based heuristic takes into account not only the individual performance of moorings, but also the interactions between pairs of moorings. This heuristic recognises that some moorings may perform poorly on their own, but perform well in combinations with other moorings. This interaction between moorings can significantly improve the overall performance of the solution.

Algorithm 6 Couple-Based Insertion Heuristic

Function: CB Insertion ($s \in$ solutions$, q \in \mathbb{N}, p \in \mathbb{R}^+$)
New = $\emptyset$
While $|New| < q$ **do**
    Couples = all possible couples (a, b) with their frequency
    Sort couples in descending order by frequency
    Choose a random number y from the interval $[0, 1)$
    $(a, b) = L[\lfloor y^p |Couples| \rfloor]$
    If a in s and b in s **then**
        continue
    Else if a in s and b not in s **then**
        Add b to s and to New
    Else if a not in s and b in s **then**
        Add a to s and to New
    Else
        add a and b to s and to New
    End if
End

4.4.4 Adaptive weight adjustment

Sections 4.4.2 and 4.4.1 define the removal and insertion operators, respectively. In each iteration of the ALNS algorithm, one removal and one insertion operator are applied. By alternating between the different remove and insert operators, a more robust algorithm is achieved. Operator selection is based on assigned weights and the roulette wheel selection principle. This means that operators with higher weights have a higher probability of being selected than operators with lower weights. If there are k operators with weight w_i, $i \in \{1, 2, .., k\}$, then operator j is selected with probability:

$$\frac{w_j}{\sum_{i=1}^{k} w_i} \tag{15}$$

The remove and insert operators are selected independently. Although it is possible to manually set the weights, this process quickly becomes complex with a large number of operators. Therefore, an adaptive weight adjustment method is used in this algorithm, where the weights (w_j) are automatically adjusted based on statistics from previous iterations [77], [83].

The basic idea is to keep a score for each operator indicating how successful it has been recently. A high score indicates a successful operator. The search is divided into segments, where a segment consists of a fixed number of iterations of the ALNS algorithm. At the beginning of each segment, the scores for all operators are set to zero. In this way, old performance is prevented from having too much influence on the selection of operators. During the segment, the scores are increased based on performance, as shown in Table 4.1.

Table 4.1: Score adjustment parameters [77].

Parameter	Description
σ_1	The last remove-insert operation resulted in a new global best solution.
σ_2	The last remove-insert operation resulted in a solution that is better than the current solution.
σ_3	The last remove-insert operation resulted in a solution that is worse than the current solution, but the solution was accepted.

An operator that generates a new global best solution receives the highest reward. A distinction is made between σ_2 and σ_3 because although improving the solution is preferred, operators that provide diversification in the search process are also valuable. Therefore, worse but accepted solutions are also rewarded, although to a lesser extent.

In each iteration, both a removal and an insertion operator is applied. The scores for both operators are updated with the same reward, as it is not possible to determine which of the two is responsible for the success of the generated solution. At the end of each segment, the new weights are calculated. In this first segment, all the weights are the same, but in the following segments, the weights are adjusted as follows:

$$w_{i,j+1} = w_{i,j} \cdot (1 - r) + r \cdot \frac{\pi_i}{\theta_i} \tag{16}$$

Where π_i is the score obtained by heuristic i in the previous segment, or the sum of the σ values assigned to heuristic i during that segment and θ_i is the number of times heuristic i was applied in the last segment. The parameter r is the response factor and determines how fast the operators change their weights. When r is zero, the original weights remain unchanged, when r is one, the new weights are entirely based on the performance in the current segment and reduce the influence of the previous weight [82].

4.4.5 Acceptance and stopping criteria

In each iteration of the ALNS algorithm, a new solution is accepted if it is better than the current solution, namely lower generalised travel cost. However, to avoid the algorithm from getting stuck in a local minimum, solutions that are worse than the current solution are occasionally accepted. The acceptance criteria of simulated annealing is used for this purpose. The probability of accepting a worse solution s' is based on the temperature and the difference in objective function values. The acceptance probability P is given by:

$$\mathrm{P} = e^{\frac{-(\mathrm{f(s') - f(s)})}{T}} \tag{17}$$

Where f(s) is the value of the current solution, f(s') is the value of the new solution and $T > 0$ is the temperature. The temperature starts at T_{start} and is reduced after each iteration according to a predefined cooling scheme, which determines how fast the algorithm converges:

$$\mathrm{T} = \mathrm{T} \cdot \mathrm{c} \tag{18}$$

Where c is the cooling rate, with $0 < c < 1$, which determines how fast the temperature decreases. A fast decrease leads to faster convergence, but increases the probability of getting stuck in a suboptimal solution. A slow decrease allows for more thorough exploration, but makes the algorithm slower. As the temperature decreases over the course of the algorithm, the probability of accepting worse solutions also decreases [84]. The starting temperature T_{start} is calculated from the initial solution value (z), using the following formula:

$$T_{start} = \frac{w \cdot z}{ln(2)} \tag{19}$$

Where w is a control parameter for the starting temperature. The assumption is that a solution that is $w\%$ worse than the current one is accepted with a 50% probability. This approach ensures that the temperature is realistically matched to the problem [77]. The algorithm stops after a predetermined number of iterations.

5 Results and Analysis

This chapter presents and analyses the main results of the study by applying the method described above to the municipality of Rotterdam. The aim is to investigate how the approach works in practice. First, the case study and the data used are described. Next, the performance of the ALNS heuristic is evaluated by comparing it with a MILP model and an LNS heuristic. Next, the optimal network configuration is presented and analysed, followed by a scenario analysis to investigate the robustness of the network.

5.1 Case study and data description

This section introduces the Rotterdam case study and describes the data used. It describes which locations were selected as potential mooring places for the water cab and how the network within the municipality was constructed. Figure 5.1 shows the scope of the area studied, with the defined area of the case study highlighted. The analysis focuses on the entire municipality of Rotterdam, as this provides a complete picture of how the method works at the urban level.

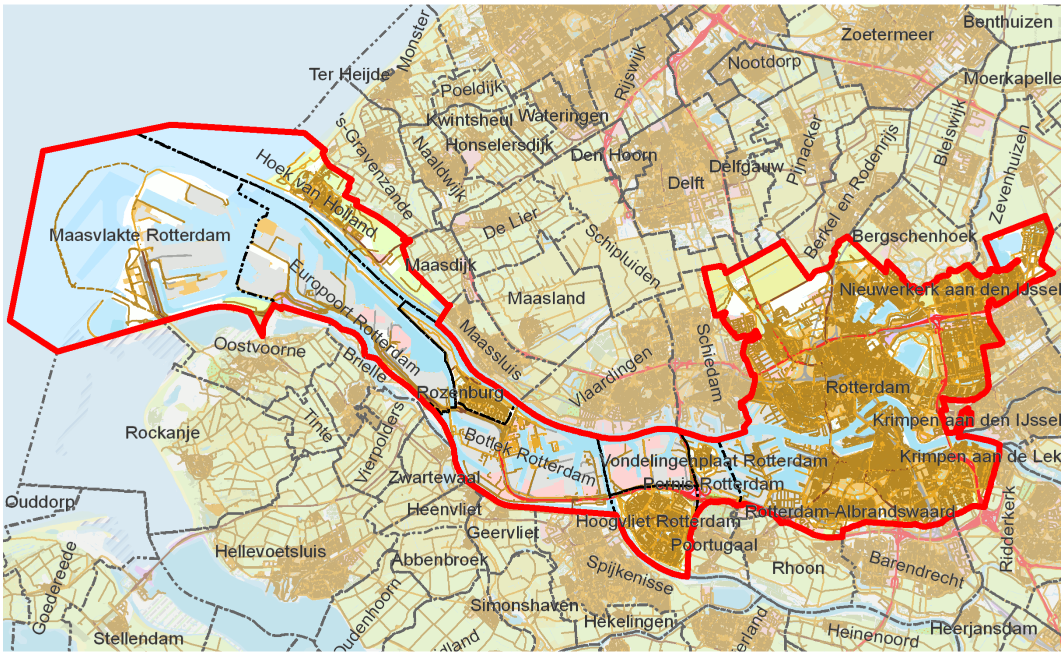

Figure 5.1: Geographical scope of the case study

5.1.1 Identification of potential mooring locations in Rotterdam

This section applies the methodology to identify potential mooring locations within the municipality of Rotterdam. The first analysis focuses on moorings close to public transport locations. The second approach looks at residential and business areas. By combining these two analyses, a picture of promising locations for moorings emerges.

Transfer points in Rotterdam

The aim of the analysis is to identify potential moorings based on the public transport network to ensure seamless transfers between different modes of transport. First, Rotterdam's public transport infrastructure was mapped. For this purpose, the Overpass API was used, a web-based database that retrieves data matching specific query criteria. Using this method, all bus, tram, metro and train stops were collected. Stops of the same name were merged, such as Beurs, which acts as a hub of transport with various modes of transport.

In total, 479 public transport stops were identified and used as reference points for determining potential mooring sites.

Next, a buffer zone of 400 metres was defined around each public transport stop. This walking distance is based on research showing that people's willingness to walk to a stop decreases significantly beyond 400 metres [85]. Within this distance, walking is generally perceived as comfortable under normal conditions [86]. To ensure a sufficient density of options within each buffer zone, potential moorings were placed at 100 metre intervals along the water's edge.

To ensure that the moorings are situated adjacent to the water, two datasets were combined: a shapefile containing all water bodies in the form of polygons and multipolygons and another shapefile with navigable waterways represented as linestrings. A shapefile is a digital file containing geographical information, such as the shape and location of rivers, roads or buildings. While the first dataset provides a better representation of the width of rivers and the location of quays, the second specifically indicates navigable routes. By overlaying these two datasets, moorings could be precisely positioned along accessible waterfronts. Following this approach, 712 potential moorings were identified.

However, not all of these sites are accessible, as some are interrupted by waterways without bridges or tunnels. After further analysis, a final set of 624 moorings remained, which are considered accessible for interchange between public transport and water cab. Figure 5.2 shows part of the identified mooring locations in Rotterdam. The blue icons represent public transport stops, with the circles indicating the accessible walking distance. The red markers indicate the identified potential moorings.

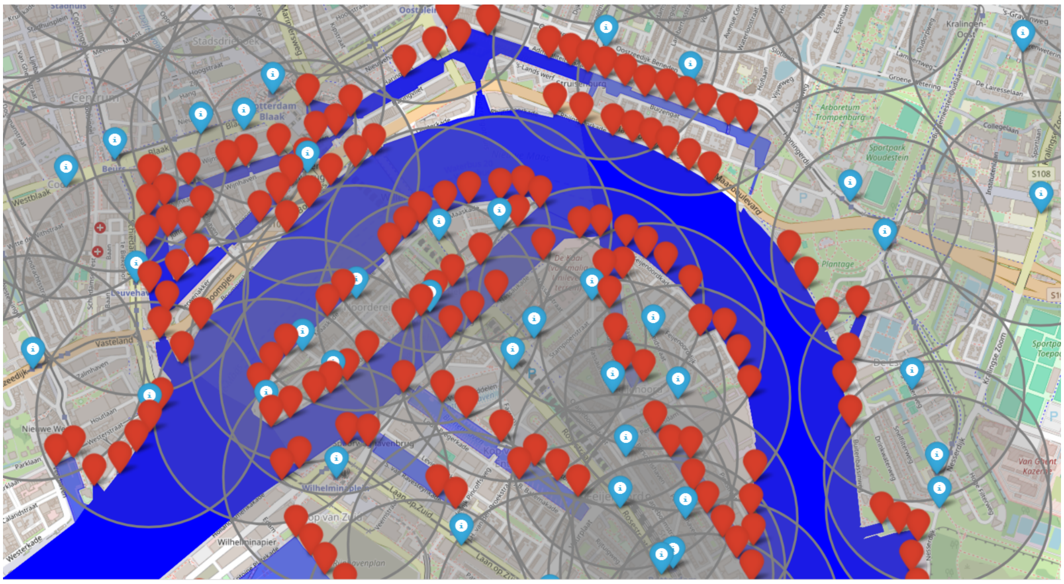

Figure 5.2: Identified mooring locations acting as intermodal transfer points

Living and working points in Rotterdam

The aim of this analysis is to identify potential moorings based on the origin and destination of trips within Rotterdam. By studying where most people live and work, it becomes possible to determine the most strategic location for water cab moorings. First, Rotterdam is divided into 92 neighbourhoods based on a shapefile. Since only waterfront neighbourhoods are suitable for mooring placement, the analysis was limited to these. This results in a selection of 61 neighbourhoods.

For each of these neighbourhoods, the total number of residents and employees was calculated to estimate the potential transport demand. The neighbourhoods Stadsdriehoek showed the highest concentration of both residents and employees, while Noordzeeweg had the lowest numbers. To optimise moorings, neighbourhoods are classified according to their potential transport demand. Multiple threshold values are chosen on the basis of percentiles. The top 5% of neighbourhoods, those with the highest expected demand, are allocated a mooring every 100 metres. Neighbourhoods in 5-25% range are allocated a mooring every 300 metres and those in the 25-75% range every 500 metres. Neighbourhoods below the 75th range are not assigned a mooring. In this way, the density of the moorings matches the expected transport demand, maximising the efficiency and use of the water cab.

In total, 46 neighbourhoods remain above the demand limit. Of these, four neighbourhoods received moorings every 100 metres along their entire waterfront, 12 neighbourhoods every 300 metres and 30 neighbourhoods every 500 metres. This resulted in a total of 903 mooring locations. Figure 5.3 below shows part of the identified moorings in Rotterdam. This concerns the neighbourhoods of Oud Charlois, Tarwewijk, Kop van Zuid, Nieuwe Westen, Dijkzigt and Stadsdriehoek. The black lines mark the boundaries of the neighbourhoods, while the red markers indicate the proposed moorings.

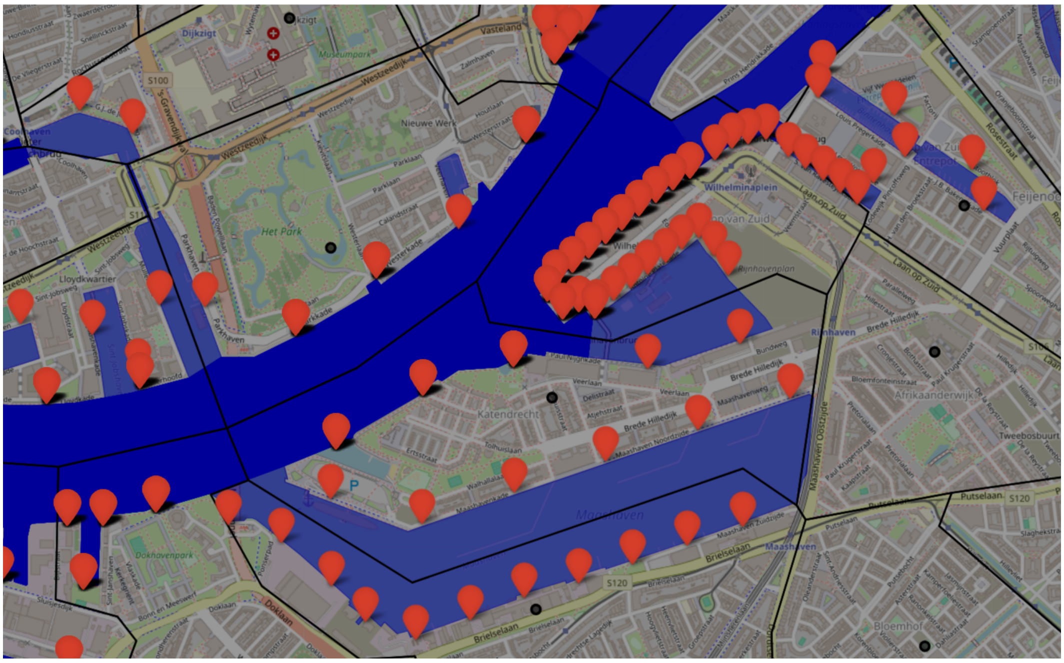

Figure 5.3: Identified mooring locations acting as origin and destination points

All possible mooring locations
To get a complete overview of all possible moorings in Rotterdam, both methods have been combined, moorings based on public transport and based on living and working. This means that both strategic interchanges and locations with high travel demand have been included. Figure 5.4 provides a complete picture of the potential locations where a water cab could moor. A total of 1,527 potential locations have been identified.

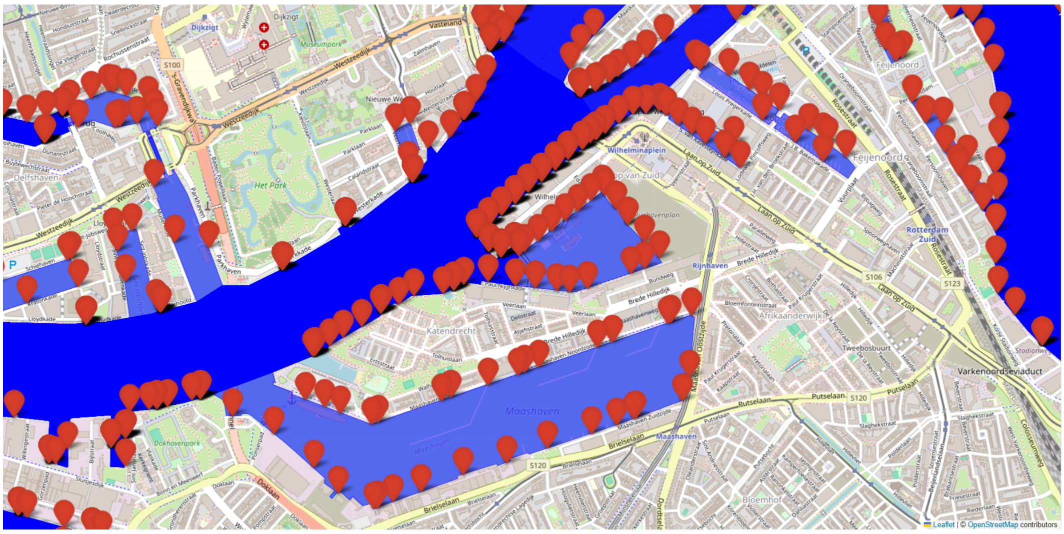

Figure 5.4: All potential water cab mooring locations in Rotterdam

5.1.2 Network of Rotterdam

This section describes the construction of the network for the municipality of Rotterdam. The network consists of nodes and connections between them. It first explains how the nodes were selected, followed by the construction of the connections and the corresponding travel time and costs.

Origin & destination of Rotterdam

The purpose of this analysis is to identify the start and end points of passenger flows, or the locations from which passengers start and end their journeys. Data show that trips to and from work represent one of the highest frequencies [68]. Given the high proportion of work-related trips in overall travel behaviour, residential and employment locations are used as a proxy for travel origins and destinations.

To identify these locations, Rotterdam's neighbourhoods were subdivided into smaller zones. The first step was to map the number of residential and work addresses within each neighbourhood. Based on this, a parameter was set for both residential and work zones. For residential was chosen to cluster 1500 addresses into one zone, while for work the threshold is slightly lower, namely 500 addresses per zone. This difference in threshold is based on the difference in distribution. Work addresses tend to be more concentrated in specific areas, such as office buildings. While residential addresses are more spread over a wider area. In total, this resulted in 441 zones, of which 268 are residential zones and 173 are work zones.

Next, each zone was assigned a share of the total population of the neighbourhood. The total number of residents and employees in a neighbourhood was evenly distributed among its respective residential and work zones. For example, the Nesselande neighbourhood has a total of 13.134 residents and 3.056 employed, resulting in 4 residential zones and 2 employment zones. By distributing residents and workers uniformly, each housing zone receives 3.284 residents and each work zone 1.528 employed. These numbers form the basis for calculating the number of travellers between residential and work zones. As explained in formula 8 of the method, the more travellers travelling on a link, the more important it is to reduce the travel time.

The location of each zone is randomly assigned within the boundaries of the corresponding neighbourhood. However, areas unlikely for habitation or work, such as forests, parks and water, are excluded. This exclusion is based on geospatial data obtained from OpenStreetMap. As a result, the zones are only places within built environment, increasing the realism of spatial placement. In addition, the zones are resized, smaller zones indicate a more segmented neighbourhood. The figure 5.5 below shows the start and end points of Rotterdam, with employment zones marked in red and residential zones in blue.

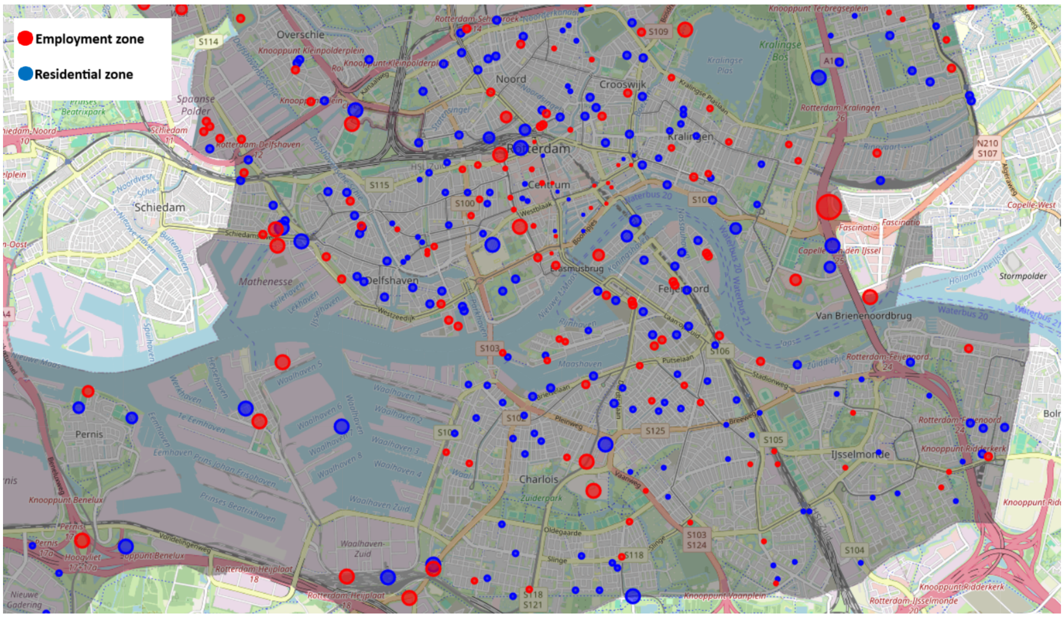

Figure 5.5: Overview of all identified origin and destination points in Rotterdam

Connections and travel times

To construct the network between residential and work zones, only connections from residential zones (origin) to work zones (destination) are included. A direct connection is defined between each origin destination pair, resulting in a total of 46,364 connections (268 origins · 173 destinations). For each connection, the travel time by public transport was determined. These travel times were collected in a 2D matrix, with each row corresponding to a residential zone and each column to a work zone. The value at position (o,d) in the matrix represents the expected travel time by public transport from origin o to destination d, expressed in minutes.

The public transport travel times were obtained via the Google Maps Directions API. For each route, the travel time was requested. The API takes into account realistic walking distance to and from stops, transfer times, timetables and transport modes (bus, tram, metro, train). This provides a realistic and detailed picture of the total travel time per connection.

In total, the travel time matrix comprises 46,364 connections, with a combined travel time of about 2,205,645 minutes, which amounts to an average of 48 minutes per connection. This matrix is an essential input for the optimisation in the next section, which seeks strategic locations for moorings that make the network as efficient as possible. To illustrate, Table 5.1 shows a cut-out of the travel time matrix, with the first five residential zones (rows) and work zones (columns).

Table 5.1: Section of the public transport travel time matrix in minutes.

	D1	**D2**	**D3**	**D4**	**D5**
O1	4.7	5.9	23.6	20.7	19.4
O2	24.4	28.5	27.1	9.4	10.0
O3	28.0	32.2	30.8	3.5	10.0
O4	25.6	29.8	28.4	4.5	5.3
O5	22.9	27.1	25.6	2.4	7.7

In addition to public transport journey times, travel times by water cab were also determined for each link, based on a selected set of potential mooring locations. For each OD pair, the optimal path was calculated via two moorings, as explained in the methodology. The optimal mooring pair is selected based on the shortest total travel time from origin to destination.

The total travel time by water cab consists of three components namely the travel time from the residential zone to the first mooring, the sailing time between the two moorings and the travel time from the second mooring to the work zone. The travel time between a zone and a mooring is calculated in two ways depending on the euclidean distance. If the distance is less than 1 kilometre, it is assumed to be walked at 5 km/h. If the distance is greater than 1 kilometre, the trip is assumed to be made by public transport with an average speed of 25 km/h and a waiting time of 5 minutes to approximate interchange time [87]. The sailing time between moorings is also based on the euclidean distance, assuming an average speed of 15 km/h [88].

Besides travel time, the cost is also calculated for each connection for both public transport and water cab based on formula 10 from the methodology. Table 5.2 shows the values used to calculate the costs of each connection.

Table 5.2: Cost parameters, used to compute generalised travel times [89], [90]

Parameter	**Value**	**Description**
C_f^{PT}	1.12 €	Fixed cost for public transport
C_f^{WT}	2.50 €	Fixed cost for water cab
C_v^{PT}	0.07 €/min	Variable cost for public transport
C_v^{WT}	0.15 €/min	Variable cost for water cab
VoT	0.16 €/min	Value of time

5.2 Application of ALNS to Rotterdam

The number of possible routes increases enormously with the number of moorings. For each origin-destination (OD) pair, there are at most $\frac{n(n-1)}{2}$ possible combinations of two moorings. With a total of $n = 1{,}527$ moorings, this means more than 1 million combinations per OD pair. Given that there are 46,364 OD pairs, this leads to a total search space of more than 54 billion possible routes that need to be evaluated. This size makes it impossible to solve the problem exactly within a reasonable computation time. Therefore, a heuristic approach was chosen. First, the selected input parameters are discussed, then the performance of the different operators is evaluated.

5.2.1 Parameter configuration

This section explains the main input parameters of the ALNS heuristic. Table 5.3 lists the parameters, their symbol, the values tested and the final selected value based on parameter study. The justifications for the choices made for each parameter are given below and the results are shown in Appendix A. The selection of the best values is primarily based on minimising total travel time, with additional consideration of solution stability (standard deviation) and computation time.

Table 5.3: An overview of the input parameters.

Parameter name	Symbol	Range	Selected values	Best value
Remove parameter	q	[0,1]	[0.2, 0.4, 0.6, 0.8]	0.4
Initial solution	s	≥ 1	[10, 20, 30, 40, 50]	30
Random parameter	p	≥ 1	[1, 5, 10, 20]	5
Cooling rate	c	(0,1)	[0.8, 0.85, 0.9, 0.95]	0.95
Reaction factor	r	(0,1)	[0.2, 0.4, 0.6, 0.8]	0.2
Score adjustment factor	σ_1	$\mathbb{R}^+$	[10, 20, 30, 40]	30
Score adjustment factor	σ_2	$\mathbb{R}^+$	[5, 10, 15, 20]	10
Score adjustment factor	σ_3	$\mathbb{R}^+$	[5, 10, 15, 20]	5

The number of moorings in the starting solution and the removal number per iteration were analysed together, as these parameters are related. Different combinations were tested in a grid search. The results show that high removal rates yield lower travel times on average, but this is associated with greater instability of the solution, visible in the higher standard deviations. Lower percentages provide more stable outcomes, but increase the probability of getting stuck in local optima [77]. The combination of 30 moorings in the start solution and a 40% removal rate provides a good balance between exploring the search space and maintaining structure. This is confirmed by a relatively low travel time and limited standard deviation.

In addition, the computation time analysis shows that larger starting solutions lead to significantly longer iteration times. For example, the combination $s = 50$, $q = 40\%$ takes almost three times as much computation time per iteration as $s = 30$, $q = 40\%$. Since the difference in travel time between the two combinations is limited, this makes large starting solutions inefficient. Finally, practical constraints also come into play. The goal of this study is not to implement the maximum number of mooring places, but to explore the most effective configuration within realistic limits. In densely populated urban areas such as Rotterdam, physical space, budgetary constraints and functional utility limit the number of mooring places that can be created. The choice of 30 moorings is therefore in line with both the computational analysis and practical feasibility.

Also, a parameter study was conducted on the randomisation parameter p, which determines the degree of randomness within the removal and insertion operators. The analysis shows that the average travel time varies little between different values of p. As no significant performance differences were found, $p = 5$ was chosen. This value represents a balance between complete randomness ($p = 1$) and highly targeted choices within little variation ($p = 20$). By allowing some degree of randomness, more variation in the solution space is explored, which contributes to the robustness of the algorithm.

Moreover, a parameter study was conducted with different values for the cooling rate. The results showed that the influence on average travel time is limited. As there are no obvious performance differences and a cooling rate of 0.95 is more often used in the literature [91], [92], it was chosen to keep this value. This ensures a relatively slow cooling rate, which continues to explore the solution space widely.

In the adaptive part, the reaction parameter determines how strongly new performance is taken into account in updating scores. To investigate the influence of this parameter on heuristic selection, different values were tested. The results showed that average travel times hardly differed between these values. However, it was found that higher values of r were associated with a larger standard deviation, indicating instability and overreaction to incidental successes. Therefore, a value of $r = 0.2$ was chosen, which ensures stable, gradual adjustments of scores based on consistent performance.

Finally, appropriate values for the score adjustment factors used to update operator scores within the ALNS were examined. This involved testing different combinations of three parameters corresponding to finding a new global best solution, finding an improvement over the previous solution and accepting a worse solution. The parameters were chosen in proportion to each other, with ratio based on values found in the literature [77], [82], [93]. The results showed minimal performance differences between the combinations. Based on these findings, the combination 30:10:5 was chosen.

5.2.2 Performance analysis of ALNS operators

In this section, the performance of the different operators within the ALNS algorithm is studied. Here, several aspects are considered including the CPU time required, the weights of the operators and the effectiveness of the combination of remove and insert operators.

CPU time indicates how much computation time an operator needs to generate or modify a solution. Figure 5.6 shows the average CPU time per application of each operator, measured in seconds, during a full execution of the heuristic. Since the same operator is called several times, the average per operator has been averaged over all these calls. The values are shown on a logarithmic scale, because of the large variation between operators, without this scale shorter computation times would not be easily visible.

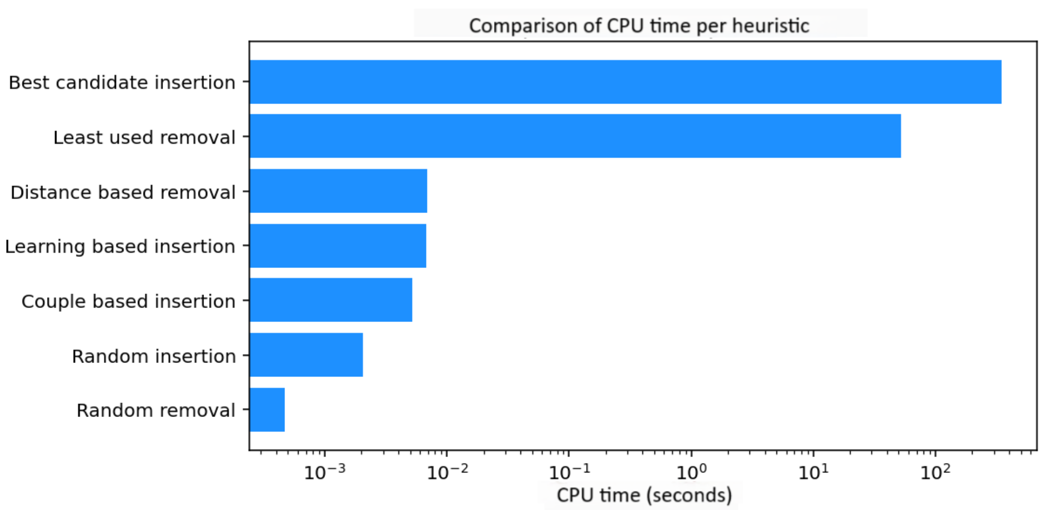

Figure 5.6: Average CPU time per operator

The figure shows that the best candidate insertion operator consumes by far the most computation time, averaging over 5 minutes per application. This operator evaluates the impact on total travel time for multiple possible moorings, leading to relatively high complexity. To reduce computation time, it was chosen not to perform this evaluation for all possible moorings, but only for a selection. Nevertheless, this operator remains computationally heavy. Among the removal operators, it is noticeable that the least used removal operator is relatively slow, with an average of 52 seconds per call. This makes it, after the best candidate insertion operator, the slowest overall. The other operators all have significantly shorter run times, ranging from less than hundredth of a second to even microseconds. As such, these operators are not a bottleneck within the algorithm.

Figures 5.7 and 5.8 show how the weights of the remove and insert operators evolve over time. The weights of these operators all decrease, due to the acceptance criteria for simulated annealing in the ALNS. In the initial phase, less good solutions are also accepted with a certain probability, rewarding operators more often with a score. Towards the end of the search, however, almost exclusively improvements are accepted. This makes it harder for operators to achieve high scores, resulting in lower weights.

Figure 5.7: Developing the weights of removal operators during iterations

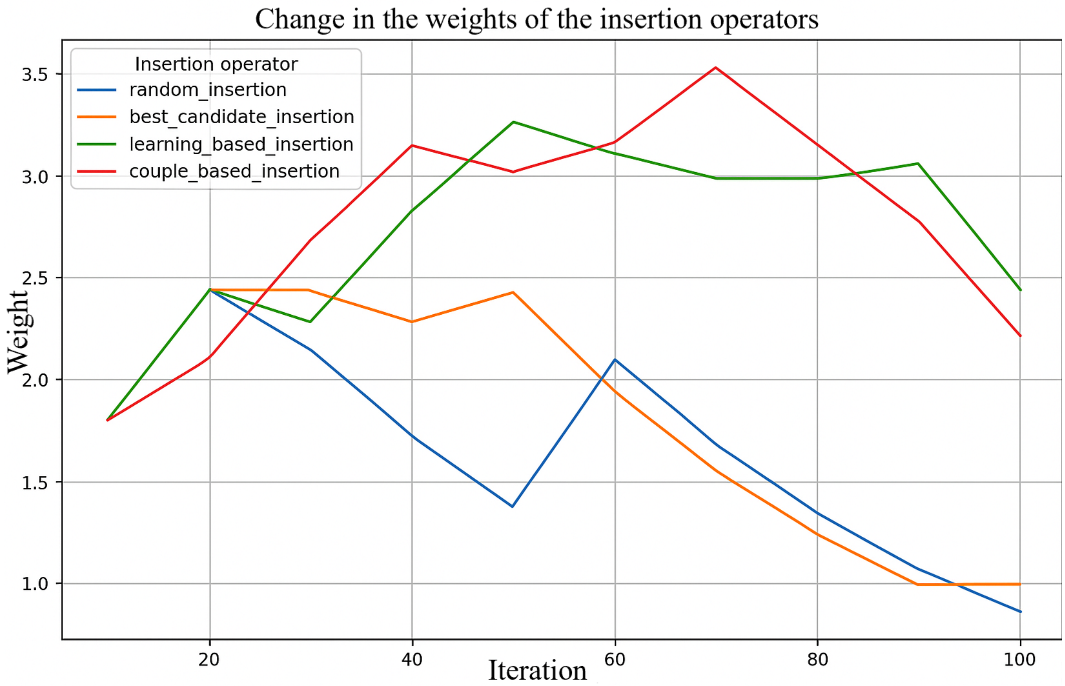

Figure 5.8: Developing the weights of insertion operators during iterations

Figure 5.7 illustrates that the random removal and the least-used removal perform almost equally well, while the distance-based operator performs worst. This is evident from the weights over time, a lower weight indicates that this operator contributes less often to high-quality solutions than the other operators. Figure 5.8 shows that the couple based and learning-based insertion operators perform significantly better than the other two, namely random and best-candidate. This suggests that the couple based and learning-based operators contributed more often to improving the objective function. As a result, the latter are selected less frequently.

The assignment of weights to operators also clearly translates to their actual contribution to successful solutions. Figure 5.9 shows a heatmap of combinations of operators for which solution improvement has been identified. This shows that operators with high weights in particular, such as couple based and learning-based, also appear most often in combinations that result in a reduction in journey time. On the other hand, it shows that operators with lower weights, such as distance-based and best-candidate, are not only selected less frequently, but also contribute less to successful iterations. This confirms that the ALNS is able to reward performance effectively.

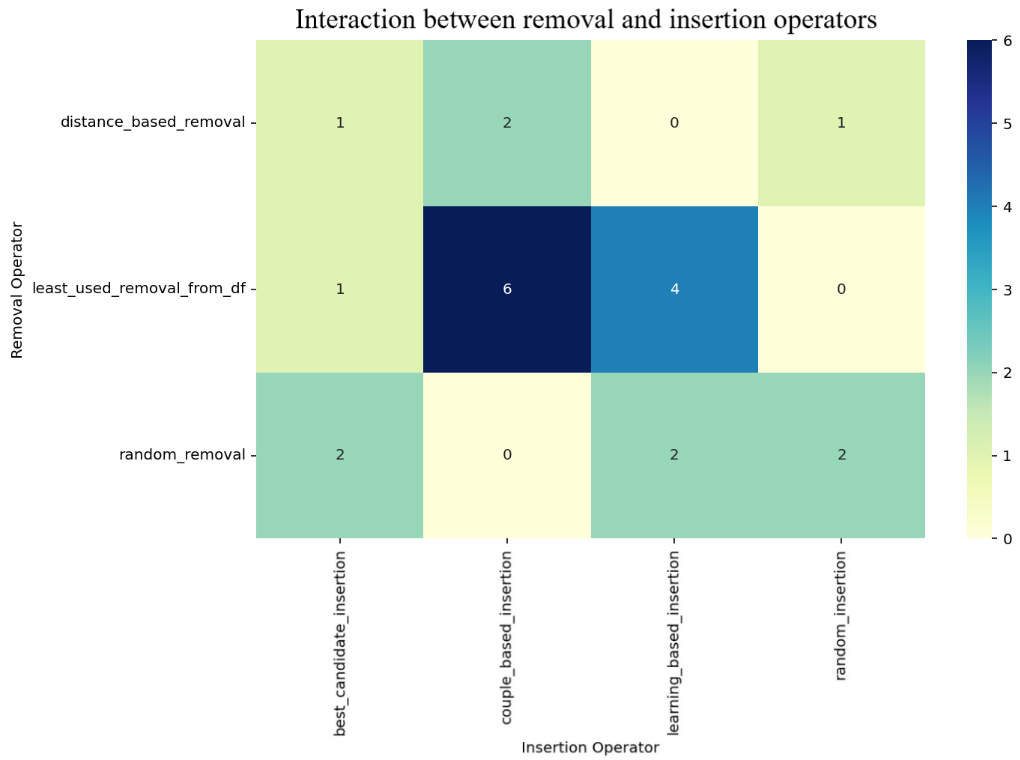

Figure 5.9: Successful combinations of removal and insertion operators

5.3 Comparison of solution approaches

This section evaluates the performance of the ALNS method. First, the optimality gap is determined by comparing the solutions of ALNS with those of a MILP model, an exact solution method. Next, the performance of ALNS is examined in relation to the LNS heuristic, which is similar but less complex. This provides insight into the effectiveness and efficiency of ALNS.

5.3.1 MILP versus ALNS

To assess the quality of the solution obtained by the ALNS method, the optimality gap was calculated. The optimality gap is a measure of how close a solution is to the optimal solution, expressed as a percentage. The optimality gap is calculated as follows:

$$\text{Optimality Gap} = \frac{ALNS - MILP}{MILP} \cdot 100\% \tag{20}$$

Since ALNS is a heuristic that does not guarantee that the global optimum is reached, a Mixed Integer Linear Programming (MILP) model was established to determine the actual optimum. The mathematical model of the MILP is shown in Chapter 3. Although MILP can find the optimal solution, for large instances it is often too slow or runs into computational limitations [94]. Therefore, it makes sense to compare the performance of ALNS and the MILP model with smaller representative instances.

To make this comparison, three instances were generated with an increasing number of OD pairs and moorings. In each case, the number of moorings to be selected was scaled along with it. The medium representative instance corresponds to about 5% of the complete dataset. Table 5.4 shows the values within the different instances. For each instance, both the optimal MILP value and the ALNS value were calculated, as well as the computation time of both methods.

Table 5.4: The characteristics of the three instances

Instance	Number of moorings	OD pairs	Selected moorings
1	31	$5 \cdot 3 = 15$	6
2	76	$13 \cdot 7 = 91$	15
3	107	$19 \cdot 12 = 228$	21

The results, shown in table 5.5, reveal that ALNS at the smallest instance is very close to the optimum, with a deviation of only 1.51%. At the medium and large instances, the optimality gap rises just above 8%. However, the deviation between instance 2 and 3 hardly increases, despite the increase in the number of OD pairs and moorings. This suggests that ALNS is able to provide relatively consistent results even for larger instances. In addition, the difference in computation time is visible. Here, it can be seen that ALNS is quite a bit faster than the MILP model in all instances. At the largest instance, the MILP model's time goes towards 100 seconds, while the ALNS turns out to be under 3 seconds. This shows that ALNS significantly improves the computation time compared to the MILP model.

Table 5.5: Results of MILP and ALNS on three instances

Instance	MILP obj.	ALNS obj.	MILP gap [%]	ALNS gap [%]	MILP time [s]	ALNS time [s]
1	6681.00	6781.70	0.00	1.51	0.16	0.074
2	24425.30	26430.62	0.00	8.21	7.03	0.79
3	98377.60	106544.90	0.00	8.30	98.90	2.29

According to the literature, a method with optimality gap between 1% to 5% is excellent [95]. Although the optimality gap of instance 2 and 3 are outside this range, it is still acceptable. In various literature on heuristics compared with MILP, deviations up to 10% are considered good enough [79], [96]. This makes the method within acceptable range and found in a short time, making ALNS suitable for larger problems where a method such as MILP is practically unfeasible.

In addition to comparing the objective value and runtime, the configuration of the solutions obtained with ALNS and MILP was also compared for instances 1 and 2. Figure 5.10 shows the selected moorings. Mooring locations selected exclusively by MILP are marked in red, mooring locations selected exclusively by ALNS are marked in blue and mooring locations that appear in the solutions of both methods are marked in purple. This visualisation shows that not only are the objective values close to each other, but also that the structure of the solutions is similar. ALNS tends to select moorings in similar areas as the optimal solution of MILP. In addition, the assignment of OD pairs to the moorings was analysed, which showed that both MILP and ALNS generate similar routes. Despite the small differences in the selected moorings, there are clear similarities in the routes and the use of the network.

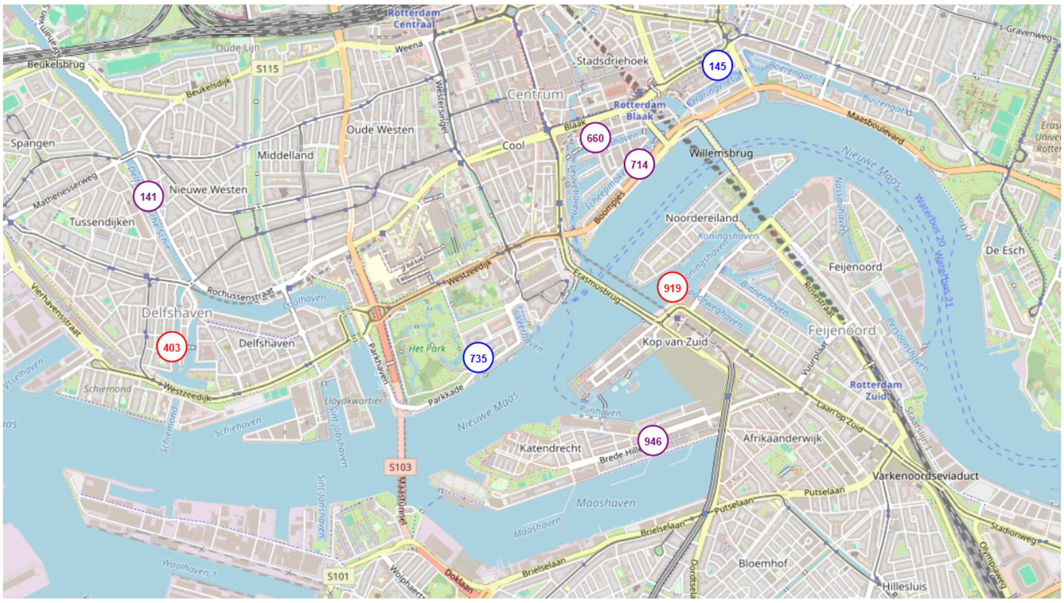

Figure 5.10: Selected mooring locations in MILP and ALNS solutions

The configuration of the selected mooring locations by MILP and ALNS also shows similarities in the second instance. For example, 9 of the 15 mooring locations are the same in both solutions, while the remaining mooring locations that differ are usually located in the same geographical areas. Due to the clustering and overlap of the mooring locations, the map for this instance is less clear and has therefore been included in Appendix B. A comparable pattern applies to the allocation of OD pairs to mooring locations. Similarities can also be seen here, but the configuration differs slightly more than in instance 1.

5.3.2 LNS versus ALNS

This research applied Adaptive Large Neighbourhood Search (ALNS), an extension of Large Neighbourhood Search (LNS). The main idea behind the LNS heuristic is to easily explore a large solution space by a removal method and a repair method. A removal method removes part of the current solution, while a repair method rebuilds the destroyed solution [75]. Both destruction and repair methods usually contain an element of stochasticity, so that different parts of the solution are destroyed and rebuilt each time the method is called.

The main difference between ALNS and LNS is that ALNS consists of multiple destroy and repair methods and selects these methods adaptively in each iteration. The probability of choosing each method is determined based on its historical performance during optimisation [97], [98]. In contrast, LNS works with a fixed combination of one or more operators. In general, the adaptive mechanism promotes performance. Although some studies show that the adaptive layer has an extremely limited impact on solution quality [97], [99].

Given these divergent findings, this study compares LNS and ALNS. Here, it is investigated whether ALNS actually provides better solutions than LNS, or whether the difference is limited. First, it evaluates how the different removal and insertion techniques perform within an LNS heuristic. The experiments were conducted on a subset of the data. The resulting solution has been compared with the optimal solution of the MILP model. Table 5.6 shows a summary of the results of this experiment.

Table 5.6: LNS operators compared to ALNS with dynamic weight adjustment

	Conf.	**Dist**	**Rand**	**Least**	**Rand**	**Coup**	**Learn**	**Best**	**Avg. gap (%)**	**Avg. time (s)**
LNS	1	•					•		2.3	0.46
	2		•				•		2.1	0.31
	3			•			•		1.8	0.51
	4			•	•				2.5	0.48
	5			•		•			1.4	0.50
	6			•				•	2.7	2.20
	7	•	•	•	•	•	•	•	2.2	0.54
ALNS	8	•	•	•	•	•	•	•	1.4	0.48

The first three configurations are aimed at investigating the influence of the removal operators on the solution quality. In all configurations, the same insertion operator is used, learning-based, in order to assign differences to only the removal operators. The results show that the least-used operator performs best, followed by the random removal operator and distance-based yields the worst performance. These findings are consistent with the results of the ALNS analysis in section 5.2 and confirm that the choice of removal operator does affect the solution quality, even if the differences are small. Thus, it could be useful and interesting to conduct experiments with other removal operators. The computation time shows that the random removal operator is the fastest, while the least-used operator takes more time due to the additional calculations required to identify the least used mooring.

The following three configurations show the performances of the insertion operators. Here, the least-used operator is used for the removal operator because it performed best in the previous configurations. In these experiments, it can be seen that the insertion operator couple-based has the best performance, with an average gap of 1.4%. The random and best-candidate insertion operators do perform a lot less, suggesting that more complex heuristics that learn over iterations achieve better results than simpler operators. This confirms the importance of the choice of insertion operators within the LNS heuristic. Moreover, it is noticeable that the calculation time of the best-candidate insertion operator is significantly higher. In addition to these configurations, an LNS was also tested in which the removal and insertion operators are randomly selected in each iteration with equal probability, without an adaptive weighting mechanism. On average, this configuration performs reasonably well, with the less performing operators being compensated by the better ones, leading to a stable result.

The last row of the table shows the performance of ALNS. This shows that it is comparable to the couple-based insertion operator, both having an optimality gap of 1.4%. While this suggests that ALNS does not offer a clear added value over LNS, it is noticeable that in all other cases ALNS performs better. Unlike LNS, which depends heavily on the specific choice of operators, ALNS is consistent in generating good solutions by adjusting the process based on performance. The results confirm that the adaptive layer of ALNS does not have an extreme impact on solution quality, but does contribute to a more flexible and robust method, especially in situations where there is no prior information about which operators perform best.

In addition, an analysis of the scalability and robustness of the heuristics was performed. For LNS, configuration 7 from table 5.6 is used, in which all removal and insertion operators are available and are selected with equal probability in each iteration. An experiment was conducted on three datasets with increasing sizes from 20% to 60% of the full dataset. Both LNS and ALNS were run five times each for each subset. The solution quality and computation time were recorded for each run. The results are shown in table 5.7 and provide insight into how both methods deal with increasing complexity.

Table 5.7: Comparison of LNS and ALNS on subsets of increasing size (the gap (%) column shows the relative difference in objective value between LNS and ALNS).

Instance	**Objective**		**Time (s)**		**Gap (%)**
	LNS	**ALNS**	**LNS**	**ALNS**	
20%	707358.00	705230.50	12.9	12.3	0.30%
40%	3670551.40	3599420.40	34.7	26.7	1.98%
60%	10209742.20	9797717.00	88.3	82.9	2.57%

The results show that the ALNS heuristic outperforms the LNS heuristic on both indicators. In addition, it is visible that ALNS becomes more attractive as the dataset gets larger, both the objective and the computation time are better. Interestingly, the computation time of LNS is higher than that of ALNS in all cases, despite using the same operators. One reason for this behaviour is that the best-candidate insertion operator takes more computation time than the other operators and is hardly selected in ALNS, as this operator performs less well. The LNS heuristic does not take this into account, so this operator is used more often.

5.4 Managerial insights

This section presents the main findings from the optimisation analysis. Based on the results, insights are provided into how the network of water cab moorings can be improved to increase accessibility and connectivity in Rotterdam. In addition, scenario analysis is used to examine the robustness of the network.

5.4.1 Results of the optimisation

In this section, the results of the implemented ALNS algorithm are discussed. The output consists of an optimal set of moorings for the water cab network in Rotterdam, aiming to minimise the total generalised travel cost for all travellers in the network. The results are compared with two reference situations, namely a situation without moorings and a situation that includes the current moorings in Rotterdam.

Figure 5.11 shows the optimal locations of moorings in Rotterdam. This shows the central part of Rotterdam, where most passenger flows converge. The full map including all locations is included in Appendix C. Each red numbered point represents a mooring, with the number corresponding to the ID in the dataset.

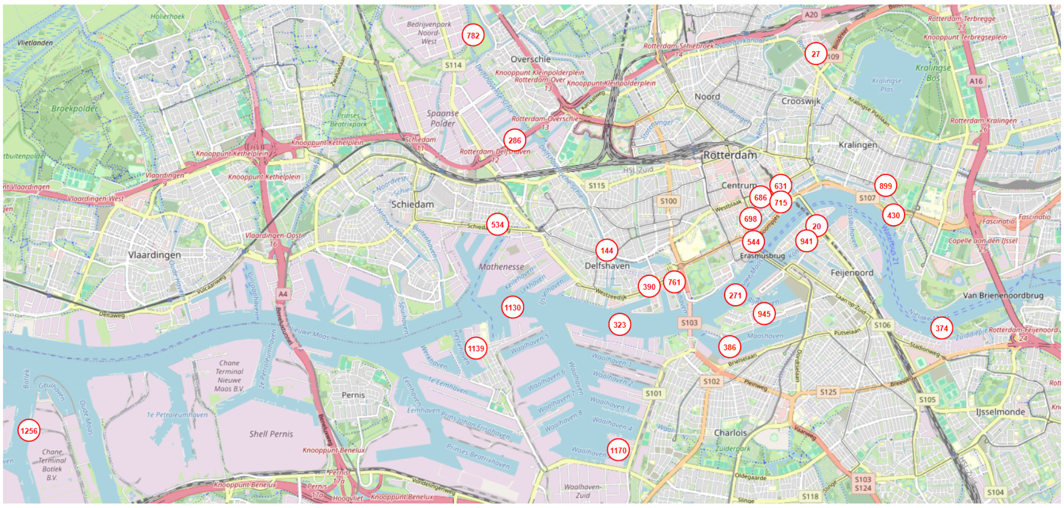

Figure 5.11: The locations of the moorings in Rotterdam using ALNS

The moorings are geographically well distributed throughout the urban area. There are more strategic moorings in the city centre, including at Leuvehaven (698), Beurs (686), Blaak (631) and near Boompjes (715). These locations are close to public transport stops, indicating a strong potential for multimodal transport. Moorings are also present in and around Delfshaven (144, 761, 390). These moorings serve the busiest departure points. In addition, moorings have also been introduced at port areas, such as Waalhaven (1170, 323, 1130) and Eemhaven (1139). These areas are characterised by relatively low public transport accessibility, which increases the added value of the water cab here.

Figure 5.12 shows the expected crowding for each mooring, expressed in the number of passengers using the mooring. These values are derived from the modelled passenger flows between origin-destination pairs and the corresponding routes. It shows that mooring 715 is the busiest within the network, with more than 45,000 passengers. This may be due to its central location and close proximity to public transport hubs, such as stops Leuvehaven, Blaak and Beurs. Other high traffic moorings are 941 and 20. Together with mooring 715, they connect passenger flows from north to south and allow avoidance of physical barriers such as bridges and tunnels. Moorings with lower user intensities such as 1170 (at the port) and 782 (at the business area), may be especially important for spatial coverage despite a relatively limited number of passengers.

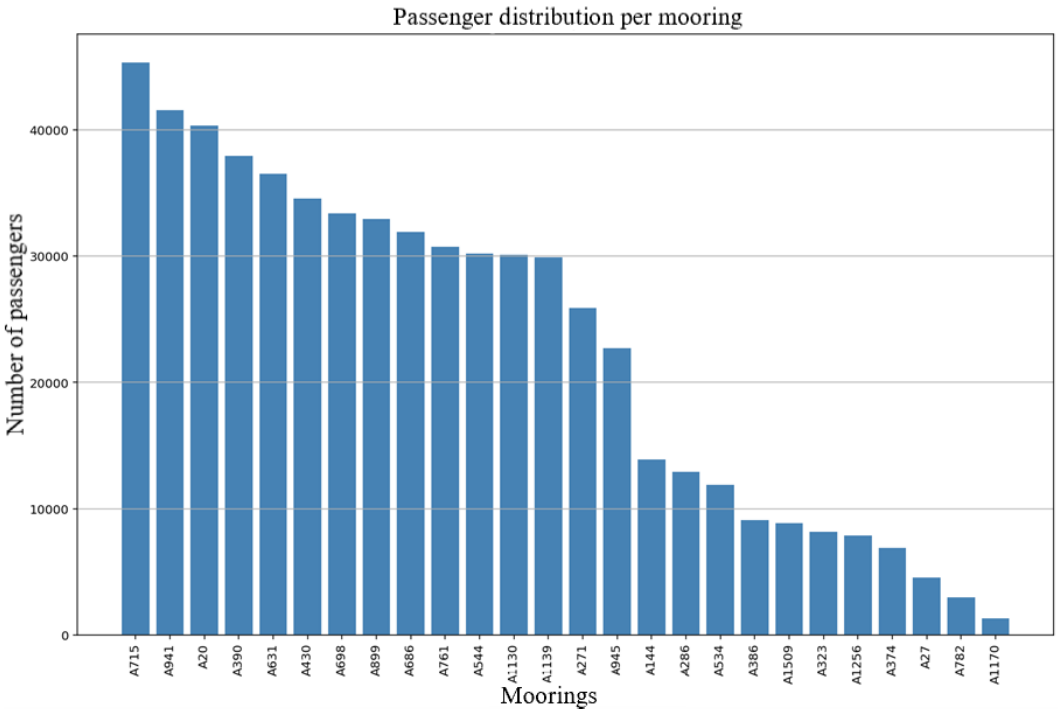

Figure 5.12: The number of passengers using the moorings

The average travel time per passenger in the network comes to 38.5 minutes with the optimal moorings. Figure 5.13 shows how this value gradually decreases during the iteration process of the ALNS algorithm. From iteration 146 onwards, the travel times stabilises, indicating that further improvement in the solution was not found. This suggests that the algorithm has reached a stable and probably near optimal solution.

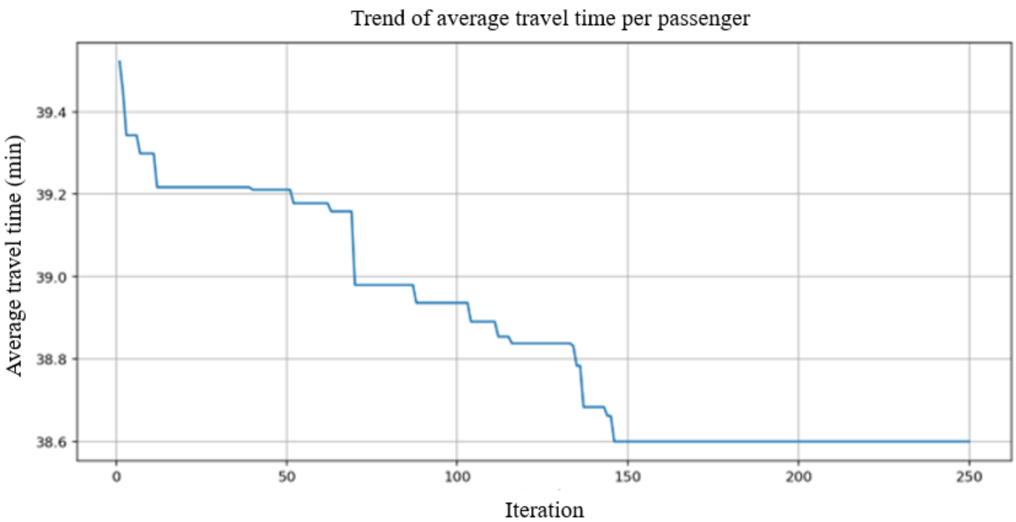

Figure 5.13: The average travel time per passenger per iteration

Comparison of results

To assess the quality of the proposed moorings, a comparison was made between Rotterdam without moorings and Rotterdam with the current moorings for the water cab.

In the first situation, where there are no moorings for the water cab, all trips are made using existing public transport. In this scenario, the average travel time per passenger is 46.5 minutes. The introduction of a water cab network with the proposed moorings reduces this travel time to 38.5 minutes, representing a reduction of about 17%. This improvement indicates significant contributions of the water cab to accessibility, connectivity and overall travel time within Rotterdam. The modal split also changes. In the proposed network, the water cab is the preferred mode of transport for 25.3% of travel connections between residential and work zones.

The second comparison compares the proposed network with the existing network, which consists of 47 moorings. This existing network results in an average travel time of 38.9 minutes per traveller. Although the difference with the proposed network seems limited, only 0.4 minutes, the result is remarkable. The ALNS solution achieves a slightly better journey time with only 26 moorings, almost half as many. This suggests a more efficient network structure, with possibly lower investment and maintenance costs. The choice of transport mode is based on the minimum generalised costs per OD pair, as specified in the objective function. The proportion of travel connections for which the water cab is the optimal mode is slightly higher in the proposed network, 25.3% compared to 24.7% in the current solution.

Table 5.8: Comparison of three network scenarios in Rotterdam

Scenario	**Number of moorings**	**Travel time per passenger**	**Share of water cab**
No moorings	0	46.5	0.0%
Current solution	47	38.9	24.7%
Proposed solution	26	38.5	25.3%

A key difference between the two networks is the spatial distribution of moorings. Figure 5.14 shows the position of the current network. It shows that most moorings are concentrated along 'de Nieuwe Maas', especially in and around the centre of Rotterdam. As a result, centrally located districts are especially well served, while other areas such as Botlek, Tussendijken en Nieuwe Westen are relatively less represented. In contrast, in the proposed network, moorings are more evenly distributed across the entire municipality of Rotterdam. This distribution increases the coverage of the network and ensures that more residents live within reach of a mooring, which stimulates the use of the water cab.

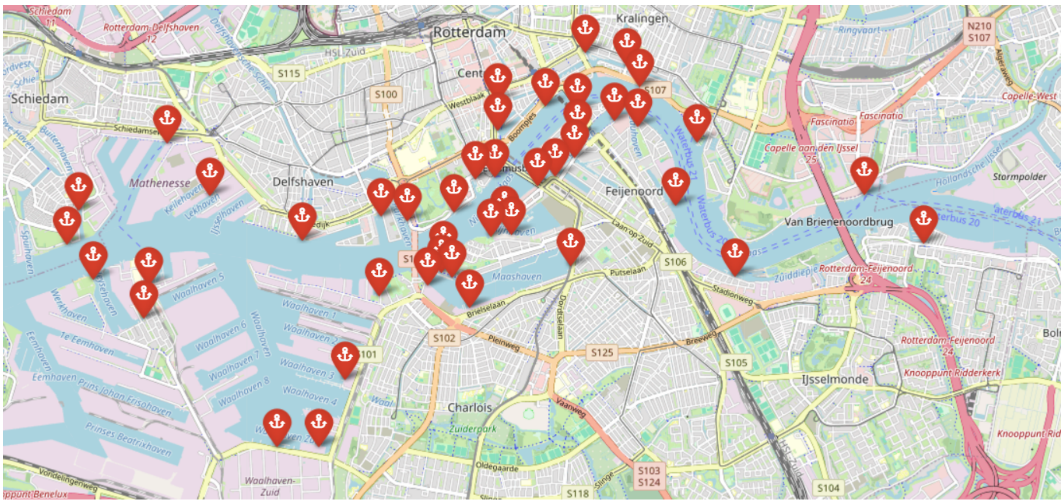

Figure 5.14: The locations of the current moorings in Rotterdam

The findings from the optimisation show that strategically placing water cab moorings can improve accessibility, travel time and connectivity in Rotterdam. The model identifies locations with the greatest added value, with investments primarily focused on areas that are currently poorly accessible by public transport, such as along the Delfshavense Schie and in the Botlek. Locations with high passenger pressure or new developments also deserve priority. This will enable water cabs to relieve pressure on busy public transport and strengthen the accessibility of emerging neighbourhoods.

At the same time, the model shows that an efficient network can be achieved with fewer mooring locations than are currently in use. Some existing moorings, for example in Waalhaven, are located close to each other and serve similar passenger flows, which leads to low utilisation. Removing these redundant mooring locations can reduce maintenance costs. By strategically adding moorings in underserved areas and removing less used locations, the efficiency and robustness of the network will improve.

In summary, the results show that despite the smaller number of moorings, the proposed network is more efficiently designed. This suggests the importance of strategic location selection over maximising the number of moorings. The optimisation model appears to be able to achieve higher performance with fewer moorings.

5.4.2 Scenario analysis

To examine the sensitivity of the network to changes in passenger behaviour, a scenario analysis was performed. In the current model, passenger flows between residential and work zones are determined solely on the basis of the number of jobs in each work zone. This approach assumes that each person in a residential zone is equally likely to work at each destination, weighted by the number of jobs in each zone. Studies have shown that most people prefer to live close to their jobs [100], [101]. Therefore, a new scenario is run that considers both the number of jobs and the distance to each destination. The adjusted formula for the estimated number of travellers from a residential zone to a work zone ($r_{o,d}$) is as follows:

$$r_{o,d} = n_o \cdot \frac{n_d \cdot \frac{1}{t_{o,d}}}{\sum_{d \in D} n_d \cdot \frac{1}{t_{o,d}}} \tag{21}$$

This assumes that people are more likely to choose nearby work locations than distant ones, taking into account the relative employment in each work zone. This adjusted distribution changes the degree of crowding at certain connections between zones. To analyse this effect on the network, several indicators were calculated such as average travel time per traveller, share opting for the water cab and the use of the moorings. The results of the adjusted scenario compared with those of the references are shown in table 5.9.

Table 5.9: Comparison between reference and distance-sensitive scenario

Indicator	**Reference**	**Scenario**	**Difference (%)**
Average travel time per passenger (min)	38.5	32.4	15.8
Share of water cab (%)	25.3	25.3	0.0
Weighted travel time by water cab per passenger (min)	30.8	28.2	8.4
Weighted travel time by PT per passenger (min)	41.2	33.1	19.7

The results show that the adjusted passenger distribution leads to a reduction in average travel time. This suggests that a distribution of travellers that takes travel time into account leads to more efficient movements within the city. In addition, it can be seen that the proportion of connections for which the water cab is selected remains the same, while the number of passengers using the water cab decreases. In this scenario, there is an 8.9% decrease in the number of passengers using the water cab. This means that the water cab is still used on the same connections, but that fewer people are using these connections.

Figures 5.15 and 5.16 show the distribution of travel time per mode of transport for both the reference and scenario case. In the scenario, the share of passengers using the water cab is lower than in the reference case across the entire travel time range, while the share for public transport is higher. This pattern is in line with the 8.9% decrease in the number of water cab passengers and the increase in the use of public transport. In the scenario, the tail of the travel time distribution, longer travel times, is also less prominent, indicating that fewer very long journeys are being made. This corresponds to the decrease in weighted travel time, as shown in table 5.9.

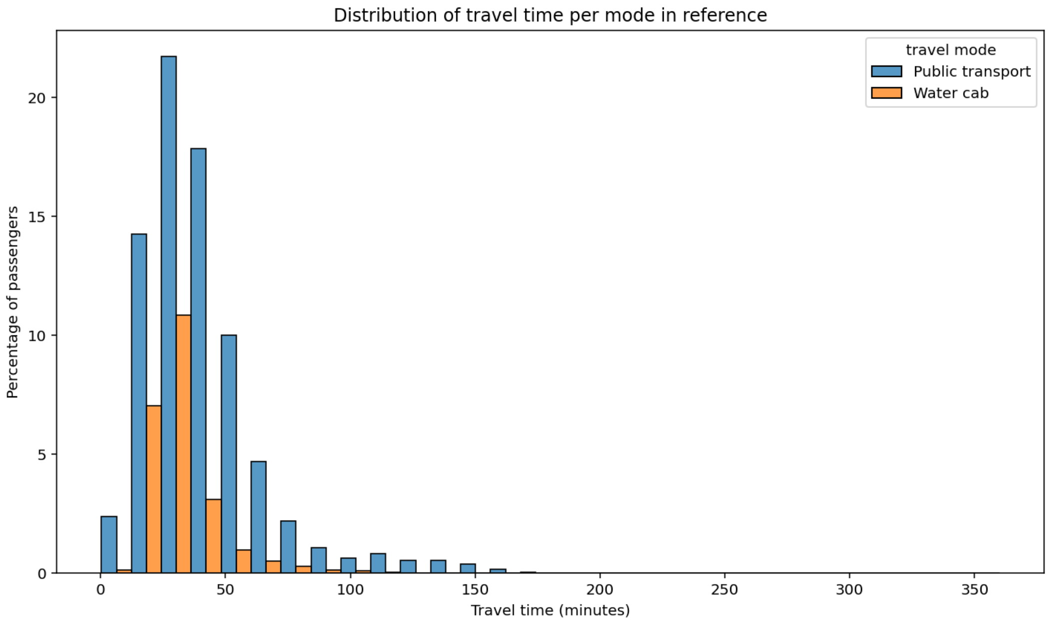

Figure 5.15: Distribution of travel time per mode in reference

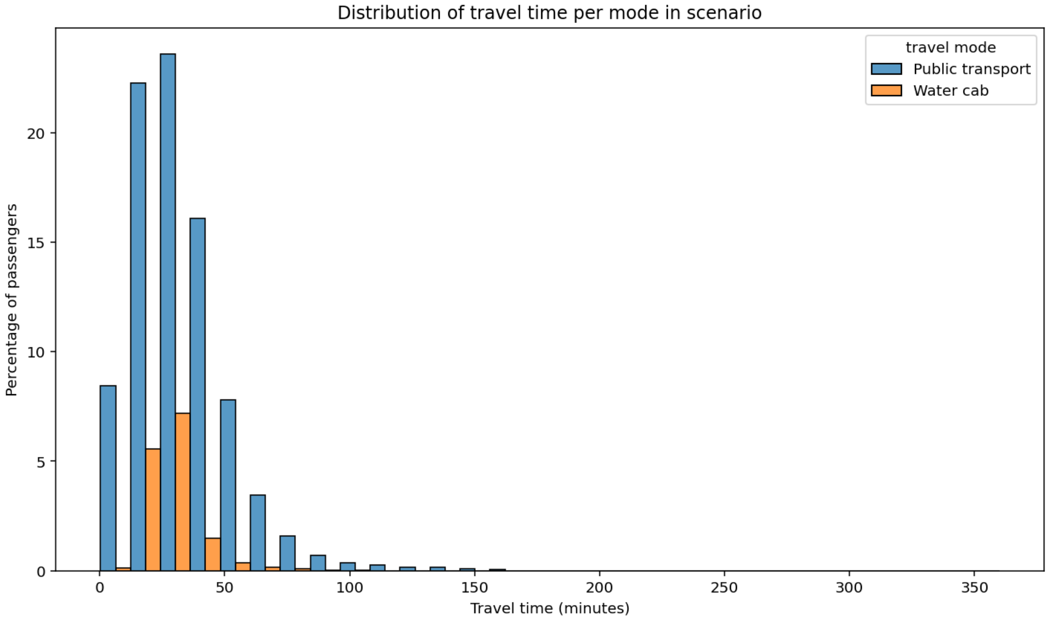

Figure 5.16: Distribution of travel time per mode in scenario

Although the total use of all moorings in the scenario has decreased due to the declining number of water cab passengers, there is a shift in where use is relatively increasing or decreasing. Figure 5.17 shows this change, with green mooring places indicating a relatively higher user intensity in the scenario and red ones indicating a decrease. It is notable that the mooring places in and directly around the centre almost all show a relative increase, while those on the outskirts show a relative decrease. This separation reflects the change in passenger flows resulting from the adjusted commuting patterns.

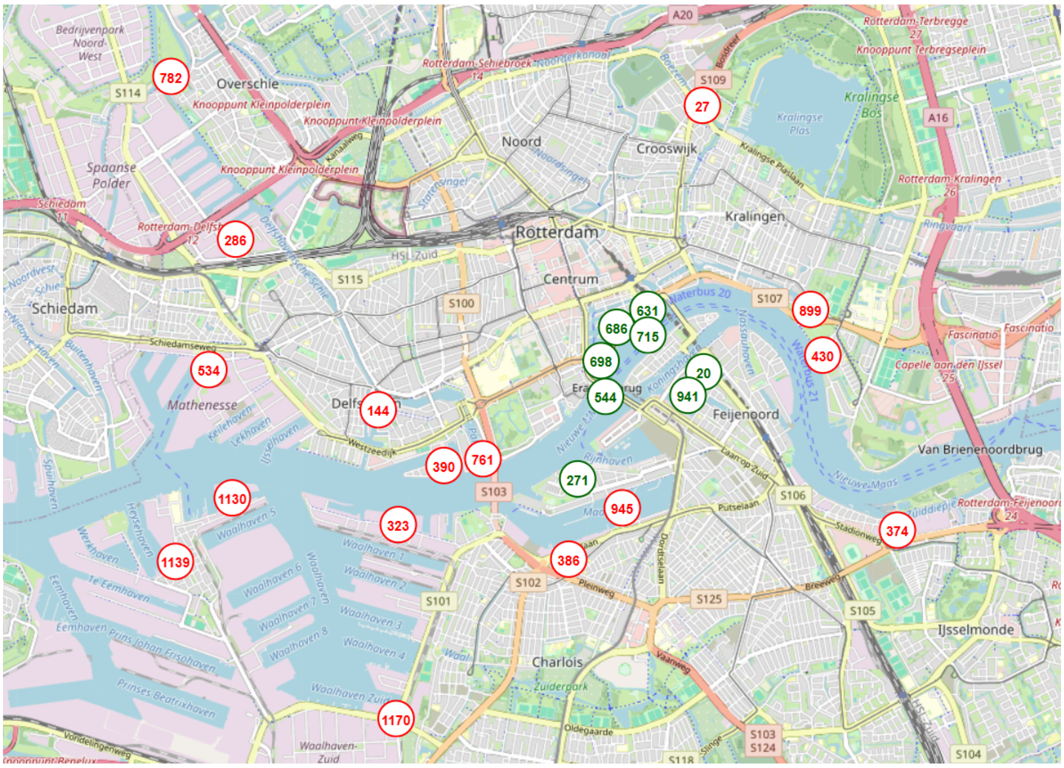

Figure 5.17: Change in relative use of moorings between reference and scenario

In the scenario, more people choose to work closer to home, leading to a higher concentration of commuter traffic within the city centre and its immediate surroundings. This area is characterised by a high density of both residential and workplaces. In addition, connections to the city centre are generally good and fast, making the city centre particularly attractive as a place to work. This reinforces the use of the associated mooring places. Furthermore, the mooring places in the city centre generally offer better integration with other forms of public transport, such as the metro, tram and bus. These multimodal connections make it easier for passengers to combine the water cab with other modes of transport, allowing the water cab to function as an efficient and attractive link in the network. Mooring places outside the city centre are often located in less densely populated areas. With the new distribution, the number of passengers travelling from other parts of the city to the outskirts will decrease, causing these mooring places to lose usage. These moorings are more dependent on passengers in their immediate neighbourhood, but these passengers are less likely to choose the water cab.

The analysis shows that the network is reasonably robust. The connections on which the water cab is used remain the same. At the same time, it appears that changes in passenger behaviour influence the use of the moorings within the network. This emphasises the importance of carefully modelling passenger choices and monitoring changes in spatial dynamics in order to adequately tailor the water cab service.

6 Conclusion & Discussion

This study has developed an optimisation method to identify the network of on-demand moorings for water cabs, with the aim of providing a more effective and attractive alternative within the existing mobility system to counteract increasing urban congestion and the associated negative effects, such as longer travel times, economic damage and reduced accessibility. This final chapter presents a conclusion on this topic and discusses the research results and the implications of the study. The chapter concludes with recommendations for future research.

6.1 Conclusion

The literature shows that factors such as travel time, comfort, accessibility, costs and, in particular, the location of moorings are critical to the success of a water cab network. Strategically placed moorings should be well connected to other modes of transport, such as public transport. Furthermore, they should be aligned with actual demand and passenger flows. Existing models for location optimisation, such as Facility Location Problem (FLP) and Hub Location Problem (HLP), do not fit well with the characteristics of on-demand water cab. The Flow Capturing Model (FCM) offers a more suitable framework by taking into account dynamic user allocation and interaction between moorings, but has not yet been applied to this type of transport.

This research therefore developed a new optimisation method, based on the FCM and adapted to the dynamic and demand driven nature of water cabs. First, potential moorings were selected based on demand patterns (living and working) and proximity to public transport. Because the number of possible locations was large, the Adaptive Large Neighbourhood Search (ALNS) was applied to select an optimal set. The model minimises the total weighted generalised travel costs for all origin destination pairs by selecting the mode of transport, public transport or water cab, with the lowest combined travel time and costs for each OD pair, giving priority to connections with high passenger flows.

The application to a case study in Rotterdam shows that an efficient network is possible with a limited number of moorings, provided they are strategically distributed. This leads to higher network coverage and shorter average travel times. The most frequently used moorings are located in or near the city centre or in the immediate surroundings of public transport hubs. Furthermore, the network remains robust under different scenarios for passenger behaviour. The ALNS heuristic provides high quality solutions within significantly shorter computation times compared to an LNS heuristic without adaptive weights and a MILP model.

In summary, this research indicates that an on-demand water cab network can be effectively designed using an ALNS method. The approach is applicable in urban contexts and offers practical tools for both transport companies and policymakers to identify strategic mooring locations that increase accessibility, reduce travel time and support sustainable urban mobility.

6.2 Discussion

This section first discusses the limitations, followed by the implications and recommendation of the study. Finally, recommendations for further research are also made.

6.2.1 Limitations

The study also has some limitations. The first limitation concerns the accuracy of the data used. Exact travel times between the different moorings were not available. Therefore, these travel times were estimated based on distances and assumptions about time. In addition, travel times from departure point to mooring and from mooring to destination for all possible trips could not be fully retrieved via the Google Maps API due to limitations on the number of requests. As a large part of these requests had already been used to calculate times between the starting and ending points, these travel times were also estimated based on distances and assumptions. These inaccuracies may affect the quality of the results, as the actual travel time per route may be shorter or longer than assumed in the model.

Moreover, the model does not take into account physical constraints such as high quays, shallow water or limited space at the quay when identifying possible moorings. As a result, some moorings considered suitable in the model may not be usable in reality. Prior manual checking of these potential moorings was omitted due to the lack of available data and the large number of possible moorings. The results can be seen as an insight into promising locations, which require further practical validation.

Another simplification concerns the distribution of passengers using the water cab. In the model, more people are expected to use the water cab than in practice. This may be due to disregarding preferences and actual travel purposes. Although the total number of passengers is probably overestimated, it is plausible that the relative distribution of passengers flows between zones does give a good indication of actual patterns. This leaves the model valuable for identifying promising mooring locations and optimising the network, even if the absolute numbers should be interpreted with caution.

Finally, there are also limitations to the method used. In this study, Adaptive Large Neighbourhood Search (ALNS) was applied because of its flexibility and relatively short computation time. However, recent literature shows that standard ALNS methods can be prone to instability and slow convergence [102], [103]. Nevertheless, the implementation in this study shows that ALNS is able to find a solution within reasonable time with an optimisation gap of about 8%. This suggests that, despite its limitations, ALNS was a useful method within the context and scope of this study.

6.2.2 Policy implications and recommendations

The results of this study offer valuable insights for cities that want to develop or optimise a water cab network, even if they do not yet have an existing water cab service. The analysis reveals a number of principles that can help to increase the accessibility, efficiency and use of on-demand water cabs.

Firstly, it appears that an efficient network can often be achieved with a relatively limited number of moorings, provided that these are chosen strategically. Mooring places that are close to public transport hubs or in areas with high passenger flow offer the greatest added value. It is therefore advisable for cities to critically evaluate existing mooring places and reconsider redundant or inefficient locations. In addition, it is crucial to set up the network in a flexible and scalable manner so that changes in urban developments, passenger patterns or technological innovations can be responded quickly.

Exploiting the full potential of the water cabs also requires targeted promotion of their use. Many travellers see the water cab primarily as a means of leisure transport, as they may not be aware of the range of services and advantages offered by water cabs. Public campaigns, signage and better integration in travel apps can encourage their use for commuting.

Affordability also plays an important role. The water cab is currently quite a bit more expensive than public transport, which is a barrier to their use. Making prices more competitive with public transport, integrating the water cab into existing systems such as the public transport chip card or introducing a combined ticket could increase the number of passengers.

Furthermore, the construction and operation of new mooring locations require close cooperation between the municipality and other public parties. Suitable locations may be found on public land, such as parks, recreational areas and redevelopment sites. In that case, the implementation of the proposed locations require coordination between these parties. Finally, water cabs can contribute to sustainable urban mobility, provided that clean technologies are used. Investments in electric or hybrid vessels are therefore recommended to make the network future proof.

By applying these insights, cities with a water network can better exploit the potential of on-demand water cabs and successfully integrate this form of transport into their urban mobility system.

6.2.3 Recommendations future research

For future research, it is valuable to include the financial dimension of network design. In this study, the investment and operational costs of the moorings and vessels were not taken into account, as well as the revenues generated per passenger. By including the costs and benefits in the model, a cost-benefit analysis can be performed to determine under which circumstances the expansion and restructuring of the water cab network is financially viable. This can also examine how many moorings and vessels are optimal from an economic perspective. More vessels and moorings increase the coverage and attractiveness of the network, but also involve higher costs. Such a model can help cities make investment decisions and substantiate applications for possible subsidies or collaborations.

In addition, more attention to user behaviour and preferences in future research would be valuable. In this study, travel time and costs were considered the most important factors in choosing between public transport and water cab. However, in practice, mobility choices are influenced by a wider range of factors, such as preferences, flexibility and reliability. Expanding the model to include these aspects could help to better predict the actual choices made by travellers and thus provide a more realistic estimate of network usage. Moreover, it may be interesting to include other modes of transport, such as cars, in the analysis. This will provide a more complete picture of multimodal competition and complementarity between modes of transport, which is crucial for designing effective and attractive urban mobility policies. This can support cities in developing transport networks that better meet the needs of their residents.

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Appendix A – Parameter study

This appendix includes several figures used to support the values for the parameters. The main text explains why specific values were chosen.

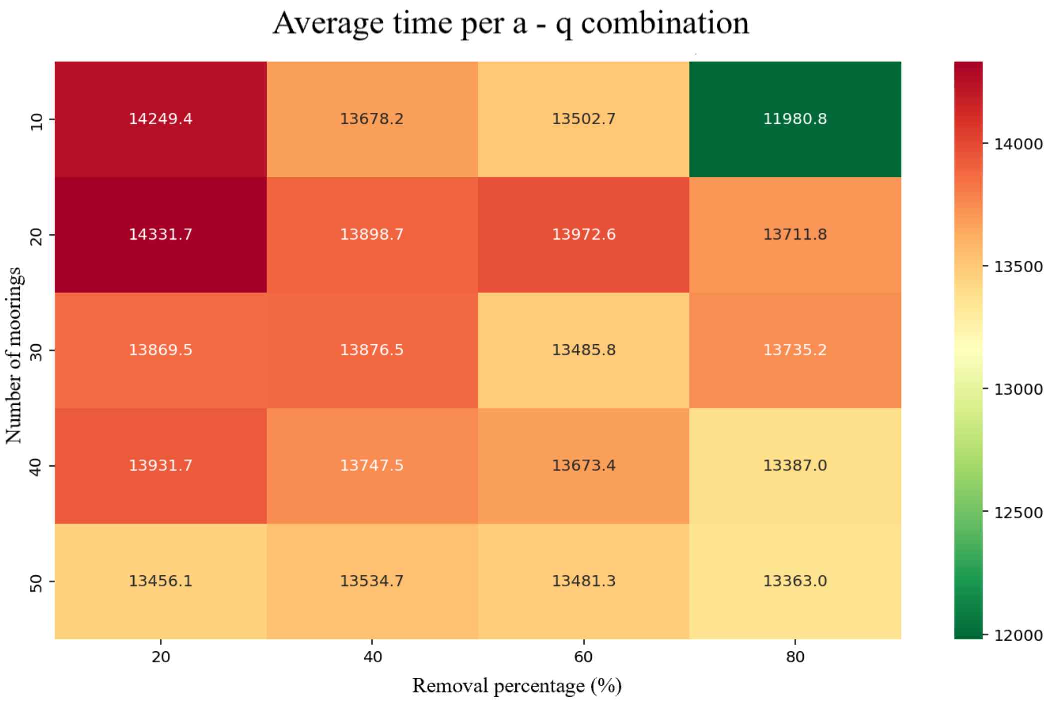

Figure A.1: Average travel time by combination of number of moorings and removal rate.

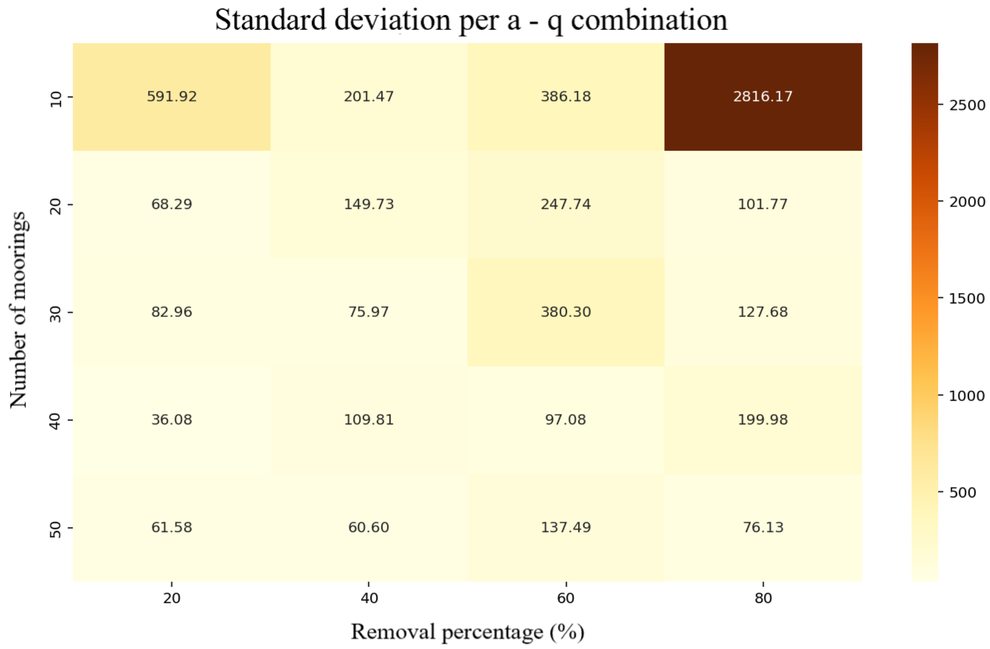

Figure A.2: Standard deviation of travel time by combination of number of moorings and removal rate.

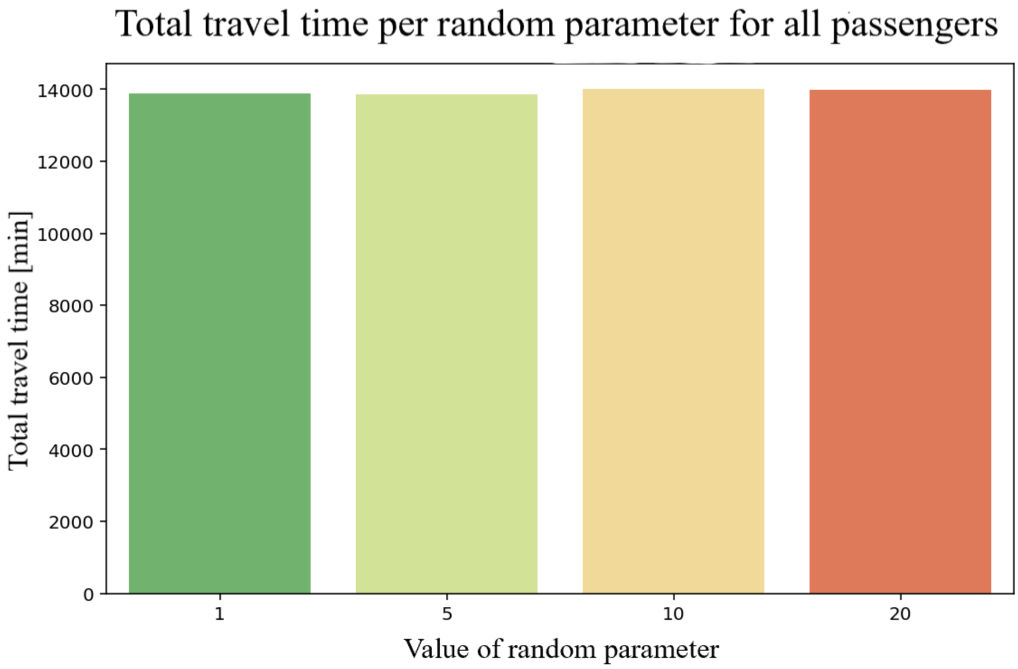

Figure A.3: Average travel time for different randomisation parameter values

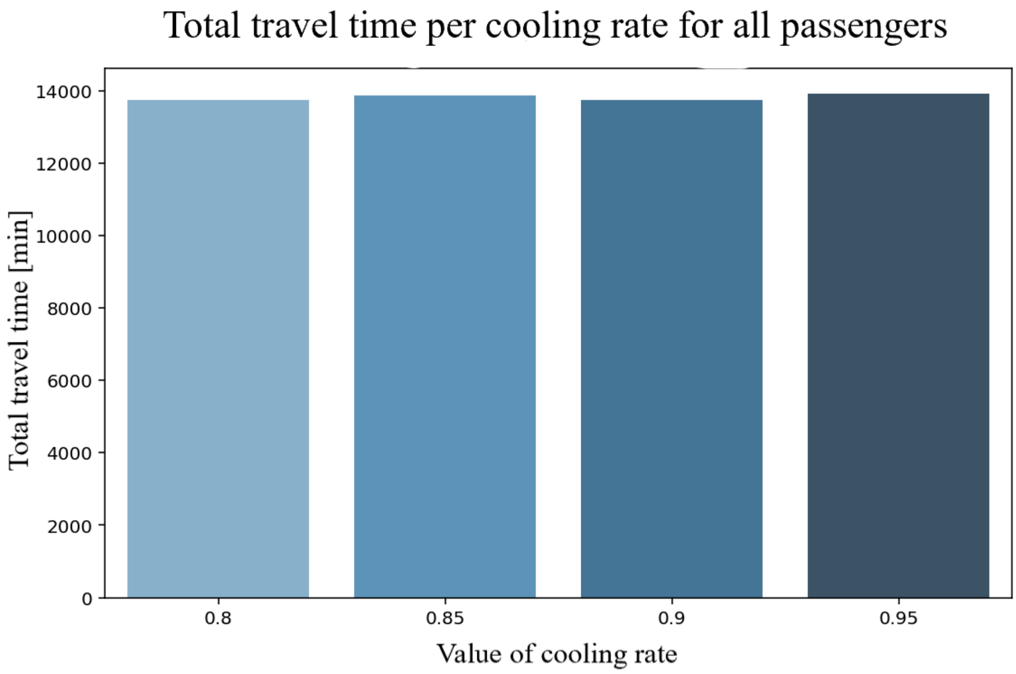

Figure A.4: Average travel time for different cooling rate values

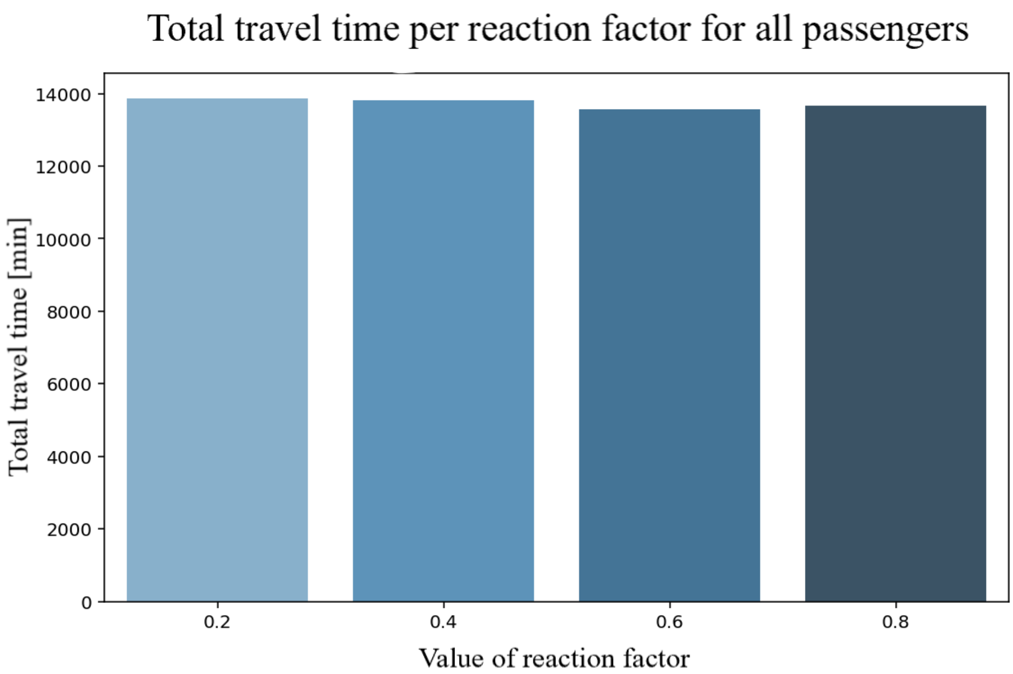

Figure A.5: Average travel time for different reaction factor values

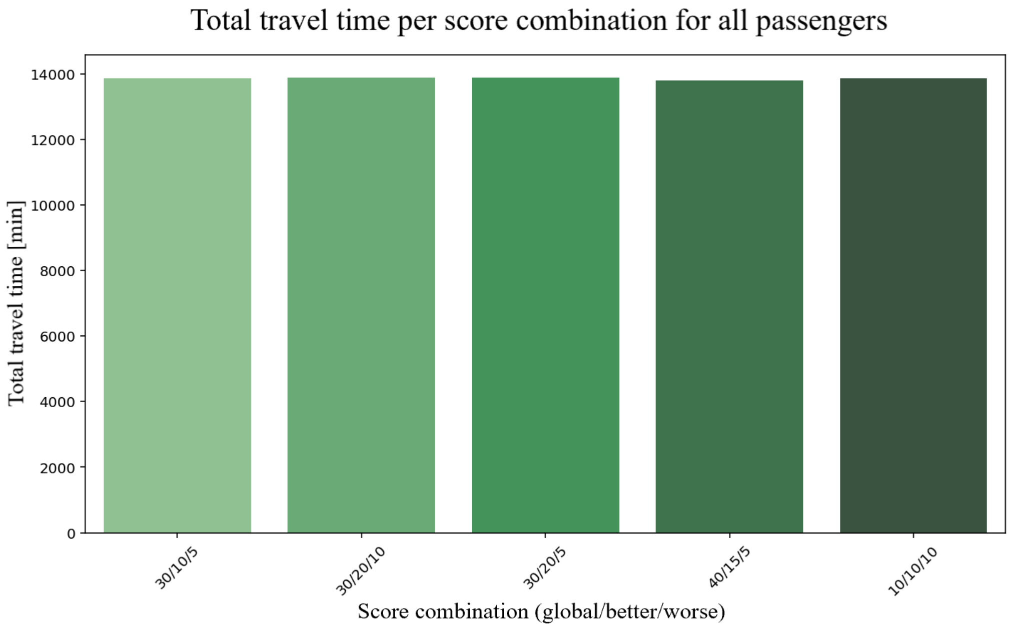

Figure A.6: Average travel time for different combinations of score adjustment parameters

Appendix B – Comparison of MILP and ALNS

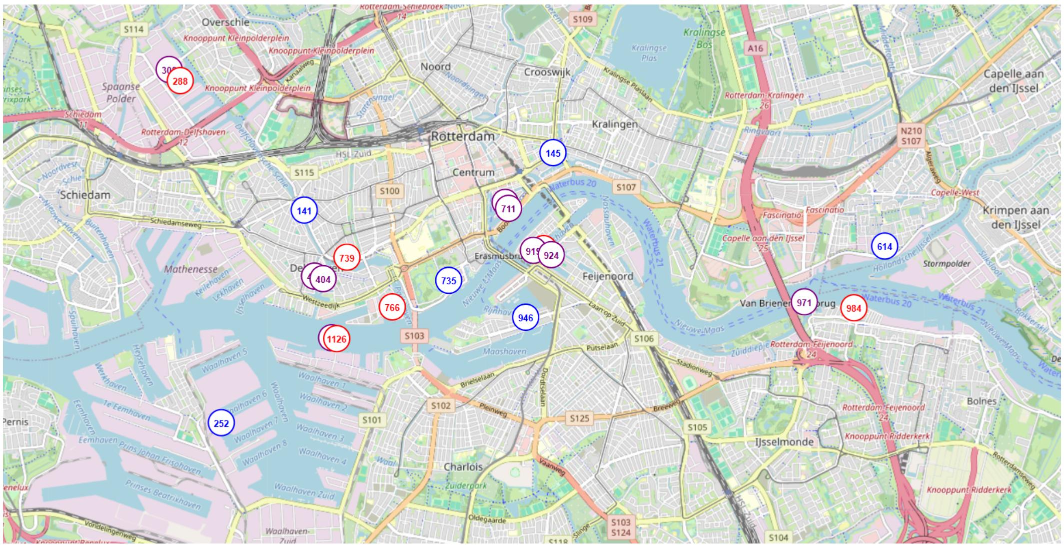

Figure B.1: Selected moorings in MILP and ALNS solutions for instance 2

Appendix C – Locations of the moorings

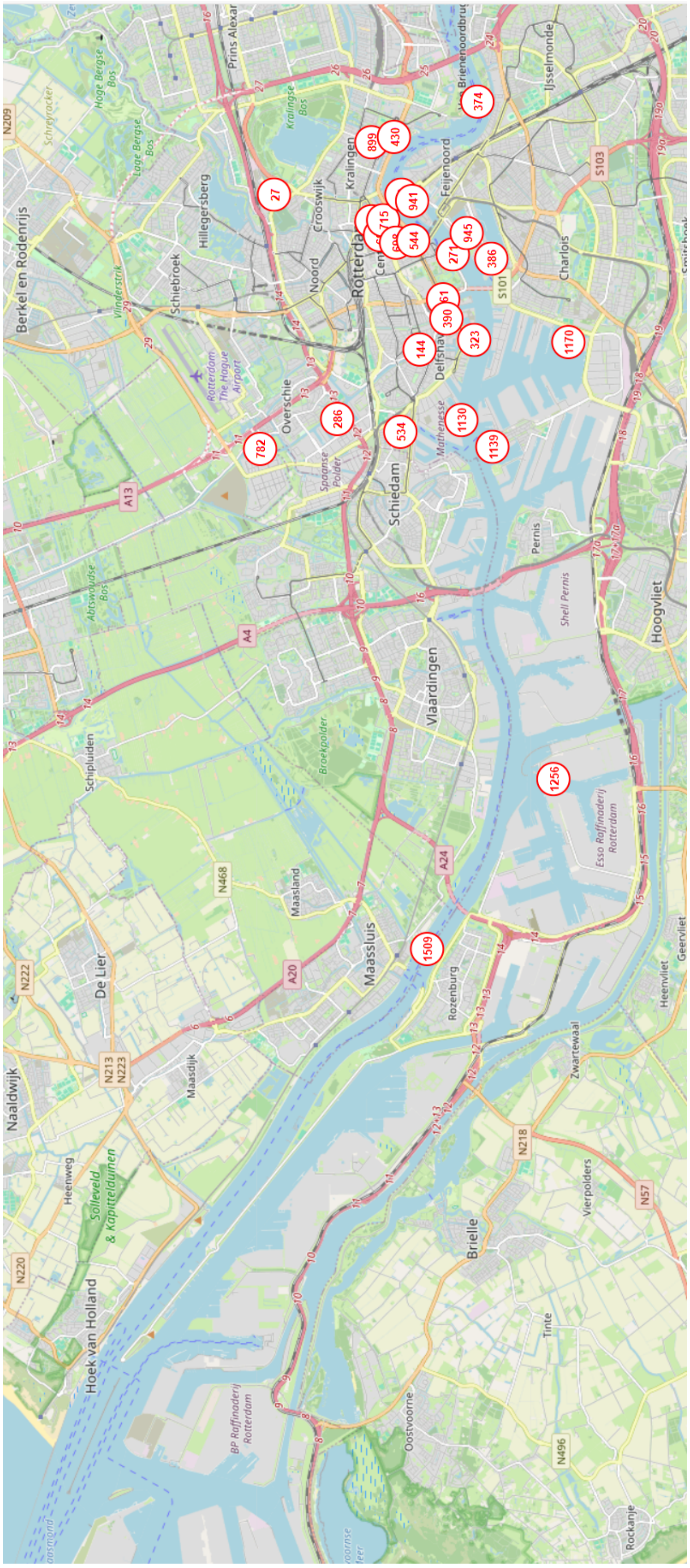

Figure C.1: Result of optimisation: recommended moorings in Rotterdam.