Optimization of the Location and Capacity of Shared Multimodal Mobility Hubs to Maximize Social Welfare

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Photo taken by the author

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This thesis presents a scientific but also personal story. It is the result of a 2-year journey at TU Delft. The cover pages of the different chapters are part of this story, starting from my first day in Delft to the different trips made during this exceptional period.

Preface

This thesis marks the end of my master's studies at TU Delft. A journey and passion that started 3196 km away from here, in Beirut. Circumstances often shape our outlook on things, and Beirut has marked its perspective pretty well with its deteriorated infrastructure and close to inexistent public transport. The charm of Beirut was marred by improper planning, awakening my interest in the direction of sustainable urban transportation. The T&P program nurtured this passion and provided me with knowledge about planning transport systems and networks through this thesis and the various courses. Working on this thesis was an enjoyable but also challenging process. I wouldn't have been able to achieve this without the support of many people whom I would take the opportunity to thank.

First, I want to express my gratitude to my thesis committee members. Thank you, Niels, for the help you have provided me during this master's and the memorable experience of recording the podcast. Goncalo, thank you for introducing me to the amazing field of Operation Research through your course, guiding me towards this path, and providing me with constructive feedback at every step of the way. Shadi, thank you for always pushing me to achieve more with your comments and suggestions and reminding me of the importance of looking at the bigger picture. Maaike, thank you for keeping me on the right path along the process, especially when I was confused about my choices. Your positivity and feedback constantly stimulated me. Finally, I would also like to thank Marieke for supporting me throughout the process by answering every question I had and finding a way to overcome every blocked road I was stuck in. The Thursday morning update meetings with Maaike and Marieke were my weekly motivation boost, especially when they used to express their satisfaction with the work done.

A round of appreciation goes to TNO - the company whose valuable resources and data made this thesis partly possible. My time at TNO has been very enriching on all levels. The cutting-edge research and breakthrough innovation, core to the TNO culture and practice, were an inspiration for my thesis and future works. My experience at TNO would not have been the same without the other interns, David, Maiara, Mukil, and Ruben. I have really enjoyed the many conversations we had during the breaks.

To my friends in the Netherlands, thank you for making these two years an unforgettable experience: Agnieszka, Aya, Dean, Gudrun, Jeronimo, Maddy, Marya, Nao, and Yara. Special thanks go to Monica for being an amazing assignment partner and friend, Blandine for being a supportive and amusing friend since the first day of this master's, Elias for always being there listening to my problems since high school, and finally, Marc, for all the support, fun times, and pieces of advice you gave me. Marc, your friendship felt like family - a home away from home. A special thanks to my friends from Lebanon: Denise, Ola, and Walid. Despite the distance, you always found ways to support me and cheer me up.

To my grandmother, who passed away during my first year of this master's, I am extremely grateful for what you have taught me. Your advice of always finishing tasks on time as perfectly as possible cascaded into every stage of this research.

I would also like to thank my family for their continuous support, including my aunts, uncle, and cousins. This success is undoubtedly dedicated to my parents. Thank you for your unconditional support, for shaping the person I am today, and for setting the compass in the direction of my dreams.

As this journey comes to an end, I hope that the knowledge acquired will help me contribute to sustainable, efficient, and equitable mobility options in the world and, hopefully, one day in my home country, Lebanon.

Stavros Xanthopoulos
Delft, July 2022

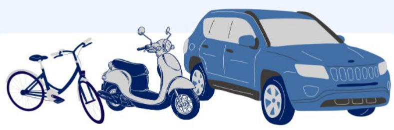
Abstract

Nowadays, urban areas are exposed to various challenges such as climate change, social inequalities, and congestion. Mobility hubs present the opportunity to reshape our cities and mitigate the previously mentioned problems by contributing to a more sustainable and equitable transport system. This thesis defines mobility hubs as places where shared cars, mopeds, and e-bikes are offered to improve connectivity and ameliorate mobility options. Given a limited budget, cities would like to optimize the locations of mobility hubs to maximize benefits. This problem is solved in this thesis by presenting an optimization model that allows the distribution of mobility hubs and allocation of shared cars, mopeds, and e-bikes to maximize social welfare. The algorithm can provide the optimal locations for the hubs and their respective capacity in terms of vehicles, while accounting for multimodal trips. It focuses on maximizing the utility of the population rather than the operators' profits. The model is divided into several modules: computational modules that calculate the number of people that would like to use a mobility hub; a mathematical optimization module to optimize the capacity, availability, and relocation of shared vehicles; and finally, a genetic algorithm that performs several iterations to find the optimal distribution of hubs. The model developed is applied in a case study for the city of Amsterdam. Several scenarios are performed to assess how the distribution of hubs varies depending on the budget provided to construct them. The results show that having more hubs with a lower number of shared vehicles is more beneficial than having fewer with more vehicles. Areas with higher population density are prioritized when lower budgets are invested in building the hubs. Additionally, the shift towards shared modes and the travel time savings are minimal. The benefits increase considerably when investments lead to complete coverage of the area by the network of mobility hubs. A modal split of 5% for the shared modes is expected when Amsterdam is fully covered by 288 hubs. From an environmental point of view, only 32 % of the shared trips replace trips previously made by car, leading to a limited CO_2 emissions reduction of 1.27%. To conclude, the model developed is one of the first models that optimizes the location and capacity of multimodal hubs to maximize social welfare by considering multimodal trips. It has the ability to quantify the benefits of introducing mobility hubs depending on the investments made.

Optimization of the Location and Capacity of Shared Multimodal Mobility Hubs to Maximize Social Welfare

The model developed includes the following features and elements:

Multimodal Paths
Shared Modes - Walking - Public Transport



3 Shared Modes
considered

Capacity
of mobility hubs modeled

The genetic algorithm is used to activate the mobility hubs from a set of candidate hubs. For each iteration the following steps are performed:

1

Compute the shortest path for each OD-pair and each mode combination

2

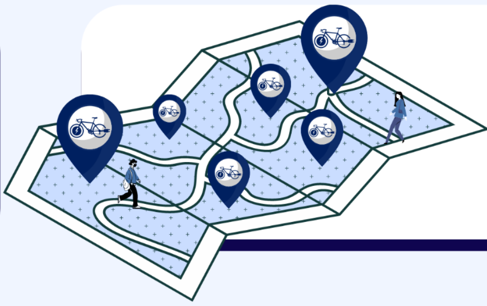
Compute the demand for each shared mode in the different mobility hubs

3

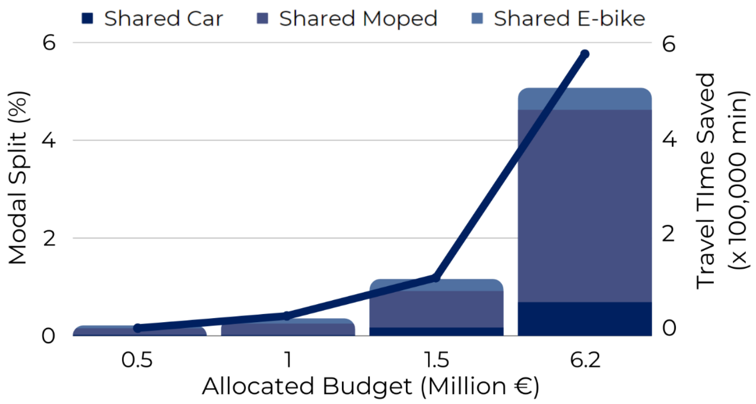
Optimize the capacity of the activated hubs and compute the ratio of satisfied demand

Amsterdam Case Study Results

Prioritize areas with higher population density



Install many small hubs rather than few big ones

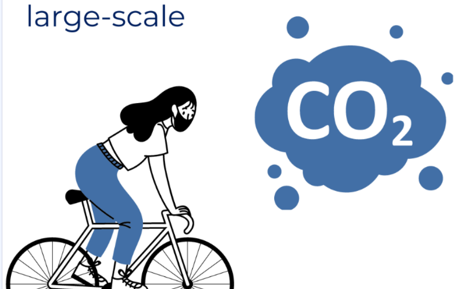


With lower allocated budgets, benefits are limited due to the fixed construction costs. When the budget is enough to cover all of Amsterdam, the benefits increase considerably: higher split for shared modes (stacked columns) and significant travel time gains (line graph)

A small number of trips combine shared modes and public transport due to high costs and good public transport coverage

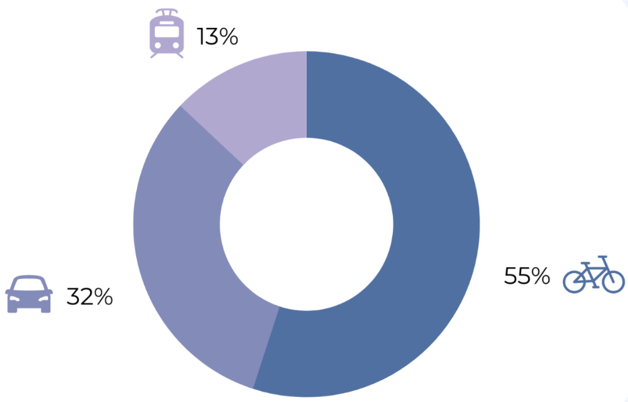
Shared Modes are combined with public transport for trips longer than 40 minutes

A maximum of 1.27% reduction* in CO_2 emissions is expected when shared modes are introduced on a large-scale



*compared to the case where no shared modes are available

If shared modes are introduced with the current policies in place, more than 65% of the trips performed using shared modes would substitute trips previously made by bike or public transport. This contradicts the common idea that shared modes substitute mainly polluting trips



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01 INTRODUCTION

Photo taken by the author – Delft, August 2020

1. Introduction

Nowadays, urban areas face multiple challenges such as climate change, social inequalities, and congestion. From the environmental point of view, transport is responsible for nearly 30% of the EU's CO_2 emissions, of which 60.7% comes from private car transport (European Parliament, 2019). Furthermore, from the inequality and accessibility aspects, transportation plays a significant role in creating or attenuating social inequalities. Therefore, the design of its systems contributes to the main goal of increasing the population's accessibility, regardless of their income, origins, or education. Currently, the whole concept of cities is being redefined, putting people rather than vehicles in the center of the design.

Mobility hubs present an opportunity to reshape our cities and contribute to a more sustainable and equitable transport system. Aono (2019) defines them as "a place where different sustainable transportation modes are integrated seamlessly to help promote connectivity". The list of modes at a mobility hub includes but is not limited to shared cars, shared mopeds, shared scooters, and shared bikes. Multimodal hubs have the potential to improve accessibility in urban areas by linking new emerging modes with the existing traditional public transport system. The emerging modes include but are not limited to shared micro-mobility (e-bikes, e-scooters, e-mopeds) and shared cars. In addition, mobility hubs can adapt over time to include new modes and services such as autonomous shuttles. Having all these modes in the same space would allow seamless intermodal travels by facilitating transfers and would open new opportunities to strengthen local neighborhoods and assemble commercial assets. Furthermore, the travel experience of many people would be enhanced by avoiding traffic jams and shifting towards more sustainable on-demand modes.

This modal shift would create new opportunities to repurpose public spaces, for example, by getting rid of car parking spaces and making the streets more suitable for active modes of travel. For these reasons, mobility hubs are gaining much momentum in European cities. Additionally, enhancing the multimodal links would lead to better social cohesion, connecting people from different socio-economic backgrounds to different opportunities. Areas where multimodal connections are absent, and people rely primarily on one mode suffer from several segregation issues. Hence, installing multimodal mobility hubs would partially heal the social fabric (Carpio-Pinedo, 2021).

Figure 1.1. Mobility hubs illustration (comouk, 2019)

1.1. Context

Many future mobility hubs will develop around existing transport nodes such as railway stations and bus stops. Their size can vary from a combination of bus stops and bike sharing parking to mega hubs at transport interchanges.

To distribute the multimodal mobility hubs, several decisions should be made about the location, offered mobility services, infrastructure, and capacity. Traditionally, the allocation of shared mobility mainly focused on maximizing the demand covered and the operator's revenues while neglecting aspects related to socio-economic equity, accessibility, and spatial distribution (Jaramillo et al., 2012). The focus on maximizing efficiency might favor specific social classes (especially higher-income ones) and disfavor areas with lower demand and population density. From the policymaker's point of view, accessibility is one of the ultimate goals set for any project, and locating mobility hubs should focus on increasing the social welfare of the citizens (Grengs, 2014). Hence, the decisions pertaining to the installation of mobility hubs are complex, and decision support tools are needed to assist decision-makers in their choices.

Qualitative and quantitative models have been developed to locate mobility hubs or shared mobility stations. Most of the models developed in the literature focus on locating stations for unimodal mobility services, mainly bike sharing services. The models aim to maximize profits for operators, maximize spatial coverage, or minimize travel costs for users by considering unimodal trips done using the shared modes. However, there is a lack of models focusing on maximizing users' multimodal accessibility and social welfare. Caggiani, Colovic, et al. (2020) considered accessibility in the objective function; however, they limited the analysis to bike sharing systems rather than multimodal mobility hubs. Frank et al. (2021) did not consider the users' behavior and generalized travel costs but focused on the travel time accessibility gains. Their model is mainly applied to a rural environment. Hence, no models optimized the location and capacity of multimodal mobility hubs to maximize social welfare while considering multimodal trips.

1.2. Objective and Research Scope

The previous sections highlighted the importance and possible effects of mobility hubs in providing a more sustainable mobility solution, improving the livability of urban spaces, and increasing the accessibility of different social groups. These benefits emphasize the importance of developing suitable and complete tools to locate mobility hubs and allocate the different services from a policy-makers point of view.

This thesis aims to develop an optimization model that would allow the distribution of mobility hubs and the allocation of shared modes to maximize social welfare. Hence, the model would be able to provide the optimal locations of mobility hubs and their capacity. All this while taking into account multimodal trips.

This thesis considers three shared modes: shared cars, mopeds, and e-bikes. The classifications of the hubs are not considered; the model sets the capacity of each hub without further classification per type or services provided. Although mobility hubs can provide other services, this thesis focuses only on the mobility services provided by the three shared modes mentioned previously.

1.3. Research Questions

The following research questions are answered in this thesis:

What is the most suitable model structure to find the optimal location and capacity of mobility hubs?

Finding the optimal locations and capacity of mobility hubs while considering multimodal trips presents several challenges in terms of computation power and acceptable assumptions. Hence, a model structure is presented in this thesis to determine the locations and capacity of mobility hubs to maximize social welfare. The model is divided into several modules: computational modules that calculate the utilities corresponding to the multimodal trips made using shared modes and the demand for shared modes; a mathematical optimization module to optimize the capacity, availability, and relocation of shared vehicles; and finally a genetic algorithm to iterate over the different activated mobility hubs to find the optimal distribution.

What are the optimal distributions of shared multimodal mobility hubs to maximize social welfare depending on the amount of investment allocated to build the hubs?

The budget allocated to build the mobility hubs is the primary determinant of the optimal number and location of mobility hubs in the system. Therefore, for each budget allocated, different results are obtained.

What are the impacts of additional investment to build mobility hubs on the service level and mobility indicators?

This thesis presents the effects of mobility hubs distributed by maximizing social welfare. Several indicators are analyzed, including the modal split, the total travel time experienced, the percentage of people covered by mobility hubs' service areas, and the reduction in emissions. These indicators vary depending on the investment allocated to build the hubs.

1.4. Thesis Outline

The following thesis includes in chapter 2 a literature review of the mobility hubs' definitions and the research conducted to locate mobility hubs or shared mobility stations. Then, in chapter 3, the methodology and model framework are detailed and explained. The developed model is then applied in a case study, presented in chapter 4. Next, the results and limitations are discussed in chapter 5. Finally, a conclusion is presented in chapter 6.

02

LITERATURE REVIEW

Photo taken by the author – Hamburg, July 2021

2. Literature Review

The following chapter presents a review of the literature. First, the definition and categorization of mobility hubs are presented. Second, the methodologies developed to locate shared mobility stations are presented.

2.1. Mobility Hubs Definition

A variety of definitions for mobility hubs have been used in the literature, all having common themes and keywords highlighting the ability to transfer between different transportation modes. These hubs are often perceived as a space where new transportation modes and technologies can be integrated to increase transportation options and enhance the overall experience. Aono (2019) defines mobility hubs as "A place where different sustainable transportation modes are integrated seamlessly to help promote connectivity". Alta (2020) defines mobility hubs as: "A location where mobility options are intentionally linked to one another and to amenities to make getting around more convenient, seamless, and enjoyable for the purpose of advancing mobility, climate, and equity goals". LA Urban Design Studio (2016) considers that "Mobility Hubs provide a focal point in the transportation network that seamlessly integrates different modes of transportation, multimodal supportive infrastructure and place-making strategies to create activity centers that maximize first-mile last-mile connectivity. An integrated suite of mobility services is provided at defined locations around existing and new transit stations, allowing transit riders to seamlessly access other modes of transportation once they arrive at the station" (LA Urban Design Studio, 2016).

The different keywords used in the reports and definitions of mobility hubs are processed to create the word cloud presented in Figure 2.1. The function of integrating different modes and presenting a "seamless" way to transfer between modes is one of the main characteristics of mobility hubs. Mobility hubs have the potential to increase accessibility by providing shared mobility options which would make the shift from the usage of personal vehicles more attractive. In the long run, this would enable more efficient usage of public space. These hubs can differ in their size and the services offered. The following section presents the different types and categories of mobility hubs.

Figure 2.1. Word cloud for the definitions of mobility hubs

2.1.1. Mobility Hubs Categorization

Mobility hubs are categorized according to their size, location, and purpose. Several reports classify mobility hubs similarly (APPM & Goudappel Coffeng, 2020; comouk, 2019; Steer, 2020). The types are presented below:

- Large city hubs: These hubs are designed to serve high passenger numbers traveling to the city or connecting between the different modes of transport. These hubs include main public transport links such as national and regional rail, tram, buses, taxis, and shared mobility modes. A significant challenge when designing such hubs is the limited space available in the inner city.
- Transport corridor hubs: These hubs link residents with public transport services by providing several first and last-mile options. Additionally, shared mobility provided in these hubs can fill the gaps in services to link the population with public transport.
- Neighborhood hubs: These hubs are located in the urban environment in combination with a small public transport stop or independently.
- Business park hubs: These hubs offer commuting links for the high density of users present at those locations.
- Suburbs hubs: These hubs are located on the city's outskirts, in areas with lower density and higher private car ownership. These hubs can also house national or regional railway, shared mobility, and car parking facilities, providing a seamless transfer between the different modes.
- Rural hubs: These hubs can provide a range of services since there is ample space available, as long as there is a critical mass to ensure the financial viability of services. These areas are usually underserved by traditional public transport modes. Mobility hubs can connect the service-limited areas to other areas using new mobility options.

Additionally, the hubs can be subdivided into categories depending on the scale at which they operate. The scale relates to the services provided and the willingness of the users to travel to reach them. APPM and Goudappel Coffeng (2020) subdivide the hubs into (Inter)national, (Inter)regional, City, and Neighborhood/village scales. APPM and Goudappel Coffeng (2020) present a figure to relate the different mobility hub types, geographical locations, and scales. The schematic is adapted to fit the previously discussed categorization and is presented in Figure 2.2.

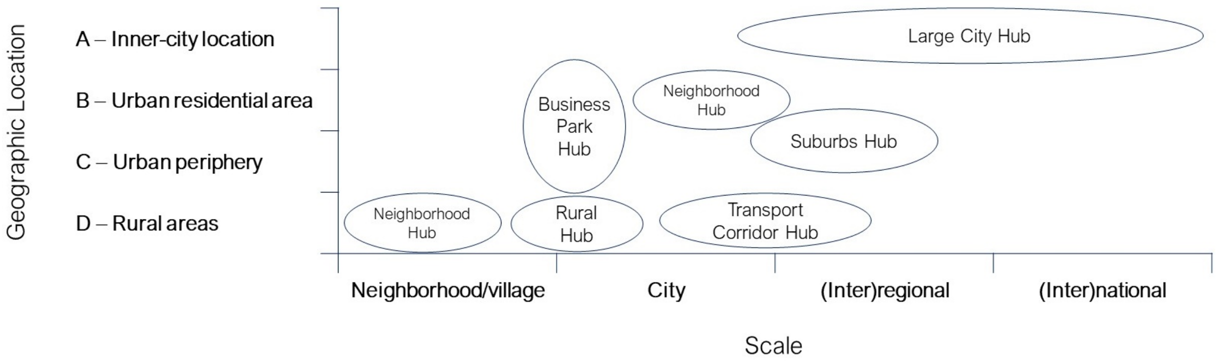

Figure 2.2. Categorization of mobility hubs (APPM & Goudappel Coffeng, 2020)

2.1.2. Available Modes at Mobility Hubs

Mobility hubs can house different transportation modes, traditional public transport modes, and emerging shared mobility. Traditional public transport modes include but are not limited to the railway, light rail, metro, tram, bus, and ferry. Roukouni and Correia (2020) presented a scheme summarizing the different shared modes. This scheme has been adapted to fit the mobility hub's definition adopted in this thesis, as seen in Figure 2.3. Only cars, mopeds, and e-bikes will be considered in this thesis. However, alternative transit and on-demand services are described in the following section since they can be incorporated into such a model in the future. Additionally, the system adopted in this thesis is a one-way station-based system which means that a user can only access these modes from designated hubs, but the pick-up and drop-off hubs can be different.

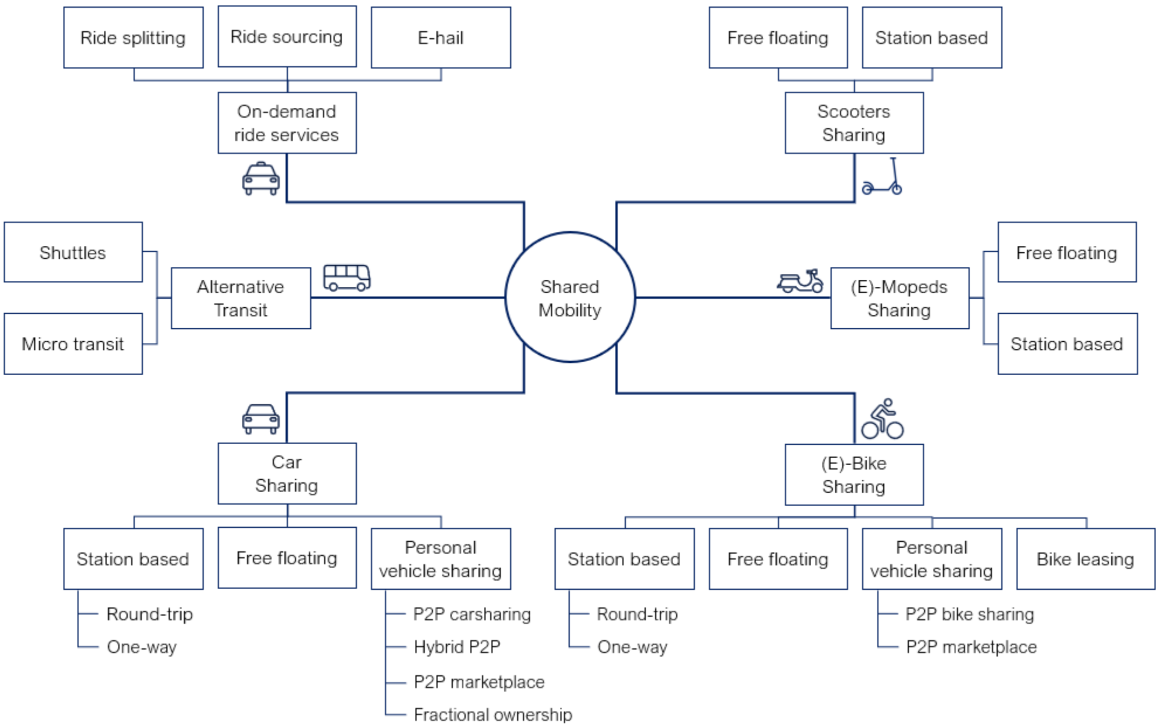

Figure 2.3. Shared mobility modes (Roukouni & Correia, 2020)

Car sharing

Car sharing systems allow individuals to use available cars on an on-demand basis and without owning them. The primary differentiation that can be made is whether the service is a business-to-consumer (B2C) service or a peer-to-peer (P2P) service. In the case of a B2C system, the shared cars are owned and operated by a car sharing company, while in the case of a P2P system, individual car owners rent out their private vehicles. This enables the service to be scaled up quickly with limited investments. In addition, the services can be either round-trip services which means that the trip must start and end at the exact location, or one-way services, which means that the trip can start and end in different locations. P2P systems are usually operated as round-trip services since the vehicles have to be brought back to their owner; the vehicles are parked in either private or public parking. In contrast, B2C systems can be either round-trip or one-way services. In the case of a round-trip service, the vehicle must be returned to the same facility after usage. One-way services can be station-based or free-floating (Shaheen et al., 2020).

Personal vehicle sharing is divided into several subtypes: peer-to-peer (P2P), hybrid P2P, P2P marketplace, and fractional ownership. In a P2P car sharing system, car owners make available their private vehicles to be used by the clients of a P2P carsharing company. Some companies choose to have private P2P carsharing and traditional carsharing services, classifying the services as hybrid P2P carsharing. In the case of the P2P marketplace, the vehicle owners provide the vehicles to the users while setting their terms and conditions; the company is just a platform that connects vehicle owners to users. Finally, fractional ownership refers to a vehicle owned by several individuals (Shaheen et al., 2020).

Bicycle sharing

Bicycle sharing is one of the first shared modes deployed in cities. Bicycle sharing can be station-based or free-floating. In the case of a station-based system, the operation might differ if a trip must start and end at the same station (round-trip), or it is possible to start a trip from a station and end it in another one (one-way). In the Netherlands, one of the most used bicycle sharing services is the OV-fiets. These bikes are unlocked at train stations and returned to the same station after usage. The aim of providing such a service is to expand the catchment area of train stations and provide a first-mile, last-mile solution to new and existing users. In the case of free-floating services, users can unlock and park the bicycle at any location in the operational zone (Roukouni & Correia, 2020; Shaheen et al., 2020). Lately, electric bicycles and electric cargo bicycles have been introduced. The electric engine allows users to travel longer distances with less effort. This benefit increases the competitiveness of bike sharing services. Additionally, providing cargo vehicles attracts new users such as families and users transporting goods.

On-demand ride services

Users can request on-demand ride services using digital applications. These applications connect drivers with passengers. On-demand ride services can be divided into ride sourcing, ride splitting, and e-hail. In the case of ride-sourcing, drivers transport passengers to the location specified by the passenger on the digital platform. Ride sourcing has been fast-growing during the last decade. The only difference between ride sourcing and ride splitting is that in the latter case, passengers having a similar origin and destination share the sourced ride to save on the fee. Finally, e-hail services allow users to ask for a taxi through an application. However, the price is fixed and is not demand-driven, as in the case of ride sourcing (Roukouni & Correia, 2020; Shaheen et al., 2020).

Shared scooters and mopeds

Multiple light electric vehicles can be shared, such as the e-scooters (e-steps) and e-mopeds. These modes can constitute a good mobility alternative for short and medium-length trips with a speed that can reach 25 km/h or 45 km/h for some e-mopeds.

Alternative transit services

Alternative transit services refer to either shuttle services or micro-transit. These services operate in parallel and complement public transport options. They can operate either on a fixed-route or demand-responsive basis providing high flexibility in itinerary and schedule (Shaheen et al., 2020).

2.1.3. Mobility Hubs Definition Adopted in this Thesis

The developed optimization model aims to choose which locations to install mobility hubs and how many vehicles to provide at each hub. The main focus of this thesis is the urban mobility hubs. These can be located near public transport stations, on the city's outskirts, or in different neighborhoods. Hence, there is no further differentiation in the type of mobility hub. The hub's sizes are then a result of the model developed rather than a parameter associated with the hub type. The maximum hub capacity set in this thesis is 33 vehicles which means that no major structures need to be constructed to accommodate them in the urban environment. Furthermore, this thesis does not consider additional facilities related to mobility hubs, such as parking spaces or package delivery points.

A one-way station-based system is considered, which means that the shared vehicle should be unlocked at a hub but does not have to be returned to the same facility after usage. The shared modes considered in this thesis are shared e-cars, e-mopeds, and e-bikes, as seen in Figure 2.4.

Figure 2.4. Shared modes considered in this thesis (Go Sharing, 2022)

2.2. Optimization Models for Planning Locations of Shared Mobility Services

Several models and approaches have been investigated to better design shared systems. The different approaches can be categorized depending on the method adopted, the objective, and the purpose of the model.

The first differentiation is done depending on the method adopted, whether a mathematical algorithm, multi-criteria decision making, or geographic information system. The second differentiation is done depending on the objectives of the model. Some papers focus on the system's profitability from an operator's point of view by maximizing, for example, the demand covered or the profits generated from the services. In contrast, few others assess the problem from a policy-maker point of view by focusing on maximizing spatial coverage, decreasing distribution inequality between zones, or minimizing travel costs for users. Any of the methods presented previously can be used to locate the stations, whether from an operator or policy-maker point of view.

In the following subsections, the models are divided based on their purpose into (1) planning new shared mobility systems and (2) improving the operations of existing systems.

2.2.1. Planning and Design of New Systems

A multitude of models has been developed for unimodal shared mobility services while considering the concerns of users and operators. The first category is the models that distribute and optimize the location of the bike sharing stations spatially using mathematical formulation. Caggiani, Camporeale, et al. (2020) developed a mathematical formulation to minimize the daily bike sharing costs, including operation, maintenance, and user's system costs. Constraints to satisfy the expected demand and ensure spatial equity were set. The second sub-constraint is achieved by setting limits on the difference between the districts regarding the available bikes per one demanded ride and the walking distances to and from the docking stations (Caggiani, Camporeale, et al., 2020). Frade and Ribeiro (2015) solved the design problem from the operator's perspective by maximizing the benefits in the design and operation processes. Lin et al. (2013) proposed a greedy heuristic method to find a near-optimal distribution of stations and inventory of bikes at each station. The objectives were to minimize total travel costs, minimize walking distance, and guarantee the availability of bicycles. Finally, Duran-Rodas et al. (2021) developed a heuristic model to distribute stations by maximizing spatial fairness, considering spatial equity, efficiency, and equality. Decision-makers input in the model weights for both demand and equity. An equity deprivation index was developed to assess the equity aspect. This index is a ratio of the percentage of the underprivileged population and the walking accessibility to essential opportunities (Duran-Rodas et al., 2021).

Guler and Yomralioglu (2021) developed a workflow that combines GIS and MCDM methods to determine the location of bicycle sharing stations and bike lanes, then applied it to the case of Istanbul, Turkey. The criteria used were the closeness to bus lines, parks, public transport stations, leisure, educational centers, population density, and land type. Similar methods have been applied to Catania, Italy, using as criteria the public transport accessibility, socio-economic data, and location of points of interest (Fazio et al., 2021). García-Palomares et al. (2012) used location-allocation models to distribute the stations and determine their capacity. The authors tested the model intending to maximize coverage, which means maximizing the number of people covered within a particular radius from the station, or to minimize impedance, which means minimizing the distance walked to reach the stations. It is essential to note the point that increasing the number of stations leads to an increase in the demand covered and the accessibility benefits, however with diminishing returns: the more developed the network is, the more significant increase in costs can be obtained with minimal improvements (García-Palomares et al., 2012).

Models were not only limited to the location of stations but also included the optimization of the number and size of carsharing depots (Correia & Antunes, 2012) or the rebalancing of vehicles between stations based on the demand (Huang et al., 2018; Jorge et al., 2014; Li et al., 2016; Nikiforiadis et al., 2021). In addition to that, several papers assessed the optimal number of docks, bikes, and trips per station. For example, Chou et al. (2019) optimized the location of the stations as well as the number of bikes by using train and bus operator's data. Wuerzer et al. (2012) performed an analysis that combines mathematical formulation and GIS to locate the stations and optimize the number of bikes. The parameters considered were the population density, the biking infrastructure, employment density, the public transport stations, and other points of interest.

Only a few models were developed to optimally locate multimodal mobility hubs. Nair and Miller-Hooks (2014) developed a bi-level framework to minimize total travel times and the installation costs of the multimodal hubs that include shared bicycles, cars, or electric vehicles. However, this model did not integrate public transport. Petrović et al. (2019) developed a methodology for planning the locations of urban intermodal terminals along a railway line. The first phase included finding the number of citizens in each catchment area using GIS. The second phase included optimizing the location while considering travel time, construction costs, and impact on the environment. However, this approach did not consider multimodal traveling. Steiner and Irnich (2020) introduce a model to optimize the use of line segments and hubs where on-demand mobility modes are provided. The goal of the model is to minimize total costs while considering the intermodal trips linking the on-demand legs to complement traditional links. However, the model developed does not differentiate between the on-demand modes. Caggiani, Colovic, et al. (2020) developed a model that distributes the bike sharing stations while considering the accessibility of the populations. A mathematical function has been developed, having as an objective the minimization of inequalities between advantaged and disadvantaged groups in terms of accessibility to public transport and intermodal travel itineraries while ensuring coverage. Frank et al. (2021) developed a decision support tool to locate multimodal mobility hubs in rural areas. The model aims to improve the accessibility to different points of interest by maximizing the number of points of interest categories that the residents can access within a certain travel time threshold and improving the accessibility to workplaces by maximizing the ratio of car travel time to intermodal travel time. The model includes decisions related to the location of the hubs, the required equipment, and the available on-demand modes per hub. Finally, Tran and Draeger (2021) developed an evaluation framework to assess the impacts of hubs in cities by considering three different scenarios of choosing ten mobility hubs to prioritize (1) current modal split, (2) high transit capacity, or (3) multimodal services.

2.2.2. Improvement of Existing Systems

Studies modeled how to improve existing bike sharing systems by locating additional stations and managing their capacity. Several indicators were used to demonstrate how to prioritize new locations for stations or other biking facilities (Kabak et al., 2018; Larsen et al., 2012). Banerjee et al. (2020) used a combination of GIS and mathematical formulation to identify the optimal location for new stations while considering the closeness to public transport, attractions, and existing bike stations. Kurniadhini and Roychansyah (2020) developed a model based on spatial multi-criteria analysis to identify the best location for new bike sharing stations in Yogyakarta, Indonesia. The model considered 13 criteria and aimed to induce a shift in the transport patterns of this city. Kanjanakorn and Piantanakulchai (2013) used experts' knowledge to rank suitable solutions and evaluate different parameters such as walkability to destinations and land type. Finally, Bhuyan et al. (2019) developed a spatial GIS approach that maps the areas according to the density-based bike equity index. This index includes disadvantaged demographic groups (youth, elderly, minorities, low-income, and zero-car households) and a level of traffic stress related to the safety of bikeable roads. The results help prioritize bike share infrastructure (Bhuyan et al., 2019).

Other methods include the utilization of mathematical formulations. For example, a mixed-integer linear programming model was used for a case in Beijing, China, to maximize the demand (Sun et al., 2019). Another objective was to minimize the distance traveled to reach the stations (Zuluaga et al., 2018) or minimize travel time and costs using a hybrid greedy evolutionary algorithm (Ali-Askari et al., 2017). Conrow et al. (2018) developed an approach that includes the use of GIS and a spatial bi-objective optimization model. The model aims to maximize potential user demand and total bicycle network coverage. Weights are assigned to each sub-objective, with a higher weight given to the potential user demand coverage to achieve equitable station siting (Conrow et al., 2018). Besides locating the stations, Jin et al. (2018) developed a model to find the optimal distribution of service sites for an operator in Fuzhou, China. Density-based clustering and ant colony algorithms were used to plan the shortest circuit between service sites while considering population density.

2.2.3. Summary

The literature review presented the different methods researchers have adopted to locate and distribute mobility hubs or shared mobility stations. The options used are the following: mathematical optimization, multi-criteria decision making, and GIS-based analysis. Most of the models developed in the literature focus on locating stations for unimodal mobility services, mainly bike sharing services. The models aim to either maximize profits for operators or maximize spatial coverage. There is a lack of models focusing on maximizing social welfare by considering travelers' costs in a multimodal network. Most of the models do not consider the relation with other traditional modes of transport, which might influence the choices made in the network and the overall traveler's welfare. The two options of multi-criteria decision making and GIS-based analysis do not adequately suit this thesis' purpose. Multi-criteria decision making can include more qualitative inputs such as the inputs of policy-makers and citizens' preferences without translating those inputs into quantitative mathematical values. This same advantage can also be considered a disadvantage due to the loss of precision and mathematical basis. GIS allows gathering and analyzing geographical data that includes demand, land use, and distances. An analysis based on GIS would allow relating the geographical data to the spatial distribution of the hubs, which would give more approximative results.

In conclusion, no model has been presented in the literature to optimize the location and capacity of multimodal mobility hubs in a multimodal network to maximize social welfare. The previously discussed studies that were performed in the field of locating shared bike and shared car facilities are summarized in Table 2.1. The abbreviations used in this table are presented below:

B: biking infrastructure, BS: bike sharing, CS: car sharing, ES: electric vehicle sharing, MH: multimodal mobility hubs

MO: mathematical optimization, GIS: geographic information system, MCDM: multi-criteria decision making

Table 2.1. Literature overview

Reference				Objective	Goal	Method			Case Study
	System	Planning	Operation			MO	GIS	MCDM	
(Ali-Askari et al., 2017)	BS		×	Minimize total costs, which include stations construction costs, lanes construction costs, bike holding costs, traveling costs, and penalty for missed demand	Distribution of new stations	×			Illustrative Example
(Banerjee et al., 2020)	BS		×	Location allocation model to maximize market share (considering existing stations and demand points) while considering a suitability score that includes the distance to attractions and restaurants	Distribution of new stations	×	×		Baltimore, US
(Bhuyan et al., 2019)	BS		×	Prioritizing new stations considering a bike equity index that includes parameters related to the age of the population, the car ownership levels, the presence of minorities, and the income levels	Distribution of new stations		×		Baltimore, US
(Caggiani, Camporeale, et al., 2020)	BS	×		Minimize the implementation, operations, and users' costs while balancing the level of service for all users	Distribution of stations, bikes, and racks	×			Illustrative Example
(Caggiani, Colovic, et al., 2020)	BS	×		Minimize the inequalities in bike-public transport mobility while maintaining levels of accessibility and coverage. Inequality is represented by the Theil index combined with multimodal BS-PT accessibility measure	Distribution of new stations	×			Illustrative Example

Reference	System	Planning	Operation	Objective	Goal	Method			Case Study
						MO	GIS	MCDM	
(Chou et al., 2019)	BS CS	×		Maximize the utilization rate of the system using transit data	Distribution of stations and bikes	×			Punggol, Singapore
(Conrow et al., 2018)	BS		×	Maximize total bicycle network coverage and potential user demand using a bi-objective weighted optimization	Distribution of stations	×	×		Phoenix, US
(Correia & Antunes, 2012)	CS	×		Maximize the profits of the operator	Distribution of depots	×			Lisbon, Portugal
(Duran-Rodas et al., 2021)	BS	×		Distribute the stations by weighing both demand and/or equity.	Distribution of stations	×			Munich, Germany
(Fazio et al., 2021)	B	×		Prioritizing locations based on a bicycle-oriented development index. The index considers socio-economic data, public transport accessibility, and attractiveness of points of interest	Distribution of stations		×	×	Catania, Italy
(Frade & Ribeiro, 2015)	BS	×		Maximize the demand covered with a budget constraint	Distribution of stations, bikes, and relocation	×			Coimbra, Portugal
(Frank et al., 2021)	MH	×		Improve the multimodal accessibility by: Maximizing the share of points of interest categories reachable within a certain time threshold Maximizing the ratio of travel time by car to travel time by multiple modes	Distribution of multimodal mobility hubs and availability of on-demand modes	×			Heinsberg, Germany
(García-Palomares et al., 2012)	BS	×		Location-allocation model to: Minimize impedance (costs to reach the stations) Maximize coverage within 200 m of each station	Distribution of stations and docks		×		Madrid, Spain
(Guler & Yomralioglu, 2021)	B	×		Ranking of locations using factors such as population density, slope, and proximity to points of interest, public transport, and bike lanes	Distribution of stations		×	×	Istanbul, Turkey
(Huang et al., 2018)	CS	×		Maximize operator's profit: the revenue is generated from the fees paid by the users; and the costs from the vehicles' fixed and variable costs, relocation costs, and parking spot rental costs	Distribution of stations, their capacity, and fleet size	×			Suzhou, China
(Jin et al., 2018)	BS		×	Cluster the bikes into service sites Identify the shortest circuit between the service sites using the ant colony algorithm	Distribution of service sites	×	×		Fuzhou, China

Reference				Objective	Goal	Method			Case Study
	System	Planning	Operation			MO	GIS	MCDM	
(Kabak et al., 2018)	BS		×	Ranking of locations using different spatial criteria	Distribution of new stations		×	×	Karsiyaka, Turkey
(Kanjanakorn & Piantanakulchai, 2013)	BS		×	Ranking of locations using factors such as land types, accessibility to biking infrastructure, walkability, and space availability	Distribution of new stations			×	Illustrative example
(Kurniadhini & Roychansyah, 2020)	BS		×	Ranking of locations using factors such as availability of biking infrastructure, public transport stations, points of interest, and population density	Distribution of new stations		×	×	Yogyakarta, Indonesia
(Li et al., 2016)	ES	×		Minimize construction, vehicle charging, and rebalancing costs	Distribution of stations and fleet	×			Illustrative example
(Lin et al., 2013)	BS	×		Minimize total costs, which include travel costs, setup costs for the bike stations and lanes, penalty costs for uncovered demand, investment costs, and bike safety costs	Distribution of stations and network structure of bike lanes	×			Illustrative example
(Nair & Miller-Hooks, 2014)	MH	×		Maximize revenues for the operator and minimize user travel and waiting times using a bi-level mixed-integer model	Distribution of stations, their capacity, and occupancy	×			Illustrative example
(Nikiforiadis et al., 2021)	BS	×		Maximize the demand and area coverage and minimize the need for redistribution throughout the day using a multi-objective optimization	Distribution of stations	×			Thessaloniki, Greece
(Petrović et al., 2019)	MH	×		Maximize the population covered by the service areas of the stations	Distribution of stations	×	×		Zagreb, Croatia
(Steiner & Irnich, 2020)	MH	×		Minimize operation costs for the operating fixed-route segments in addition to the variable and fixed costs for the on-demand mobility services	Determination of fixed-route network integrated with mobility-on-demand	×			Gottingen, Germany
(Sun et al., 2019)	BS		×	Maximize the satisfied user demand	Distribution of virtual stations and bikes	×			Beijing, China
(Wuerzer et al., 2012)	BS	×		Maximize an index that includes population covered, employment, availability of bike infrastructure, and availability of points of interest	Distribution of stations	×	×		Boise, US
(Zuluaga et al., 2018)	BS		×	Minimize the total access costs for users using a location-allocation problem	Distribution of new stations	×	×		Caldas, Columbia

03

METHODOLOGY

Photo taken by the author – Valencia, July 2021

3. Methodology

The model developed uses the outputs of a macroscopic transport model. A macroscopic model simulates the aggregate behavior of traffic flows. It aggregates the network's trips into several zones with similar attributes and properties. These zones are represented in the model as if all the characteristics are concentrated into single points called zone centroids. The centroids are not physical locations on the map but representative elements in space that are attached to the network using centroid connectors. The connectors represent the average costs to join the system (de Dios Ortúzar & Willumsen, 2011). They influence the route followed when using any mode and hence affect the total costs of traveling from an origin to a destination.

The attractiveness of different mobility alternatives is modeled using the concept of utility, which represents what an individual seeks to maximize. The utility includes two parts: the observable and random parts. The observable part is usually a linear combination of variables that represent attributes related to the mobility option, such as travel time, or to the individual, such as income. These variables are multiplied by coefficients that represent the contribution of these variables to the overall satisfaction produced by the alternative. The random part of the utility represents the particular tastes of each individual or parameters that are not considered in the model. The utility values of the different alternatives are contrasted and transformed into a probability of choosing a specific alternative (de Dios Ortúzar & Willumsen, 2011). The utilities are used to distribute the trips over different modes and routes to finally reach equilibrium in the system. The processes are not detailed in this paragraph since they are not the focus of this thesis. What is essential for this thesis are the exported elements from the transport model. In this case, the transport model allows obtaining the skim matrices representing the travel distance and travel time to go from an origin to a destination using a specific mode and the OD-matrix, which includes the number of trips performed between origin and destination centroids.

The model developed allows to optimally locate the mobility hubs and determine their capacity. The framework adopted for the development of the model is presented in Figure 3.1. The model is divided into several modules: computational modules that calculate the number of people that would like to use a mobility hub; a mathematical optimization module to optimize the capacity, availability, and relocation of shared vehicles; and finally, a genetic algorithm that performs several iterations to find the optimal distribution of hubs. In the initial *Utilities Computation* module, the utilities per mode and OD-pair are computed using skim matrices exported from a macroscopic transport model. The *Genetic Algorithm* activates some mobility hubs from a set of pre-chosen candidates. The utilities computed and the activated hubs are used in the *Path and Usage* module to find the multimodal shortest paths by maximizing utilities. As a result, the mobility hubs used by these paths are recorded. The utilities obtained for each OD-pair and path are used to compute the demand for each shared mode available at the hubs. This demand is inputted into the *Capacity* module to optimize the hubs' capacities and eventually obtain the ratio of satisfied demand. The objective function of the *Capacity* module is to maximize social welfare. This objective function also represents the fitness function used by the *Genetic Algorithm* to iterate over the different activated mobility hub locations. Hence, after several iterations, the optimal distribution and capacities of the mobility hubs are obtained. This framework is detailed in the following sections.

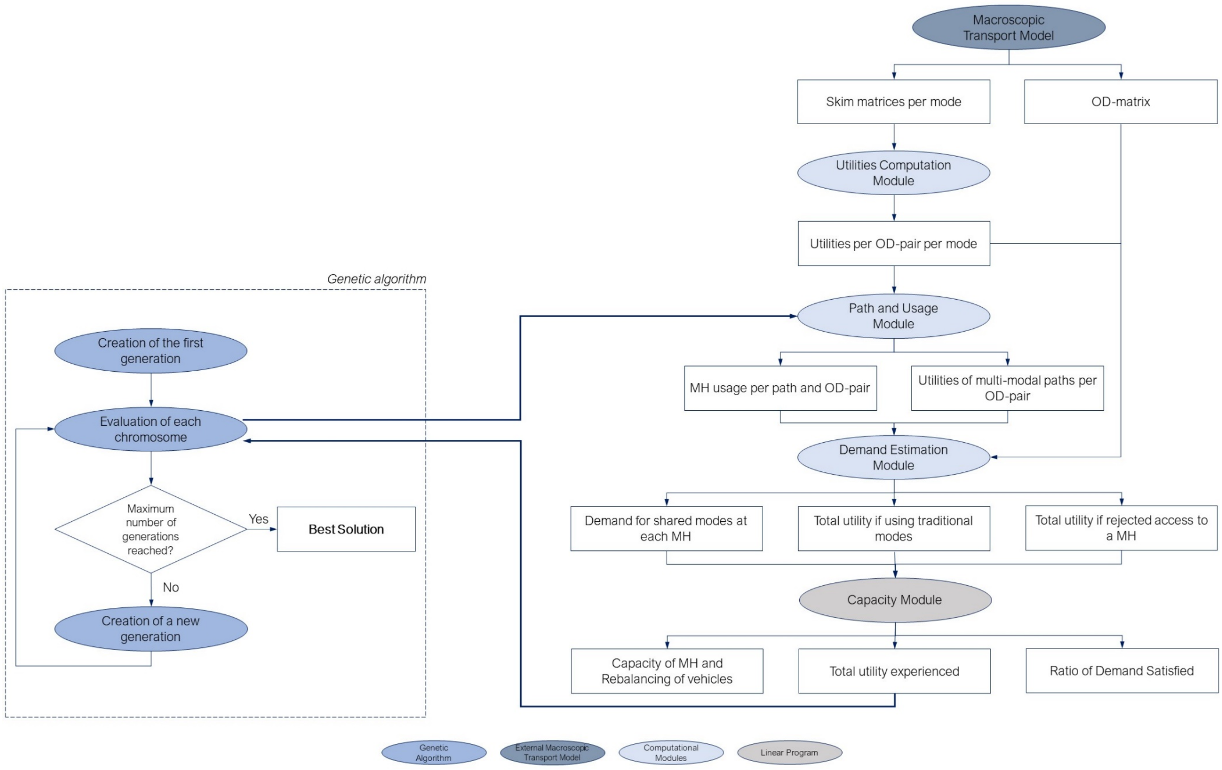

Figure 3.1. Model framework

3.1. Utilities Computation Module

In the initial step of the model, the skim matrices and the number of trips done per OD-pair are obtained from an existing transport model, in the case of this thesis *Urban Strategy*. *Urban Strategy* allows exporting the travel time and distance matrices per mode for the different OD-pairs. A more detailed description of *Urban Strategy* is presented in Appendix A. The advantage of using the skim matrices from a transport model is to reduce the complexity related to congestion and public transport modeling. The network is then simplified into a combination of centroids and links with specific travel times and distances depending on the modes. These matrices are used to compute the utilities to travel from an origin to a destination. The utilities are calculated for the traditional modes of transport, which include: walk, bicycle, car, public transport; and the shared modes, which include: shared cars, shared mopeds, and shared e-bikes. The following utility function is used for that purpose with different parameter values per mode:

$$U = (cost\_start + travel\_distance \times cost\_user\_per\_km) + (travel\_time \times value\_of\_time) \\ + (travel\_time \times cost\_user\_per\_hour) + mode\_specific\_constant$$

The parameters used in *Urban Strategy* are adopted in this thesis. These parameters were estimated using OViN data (Onderzoek Verplaatsing in Nederland), for example, the travel diary data of the Netherlands. However, shared mopeds and e-bikes do not have estimated parameters; hence they are approximated. The literature presents different parameters and elements to be included in utilities of shared modes, such as walking distance, searching time, pricing, battery levels, and availability (Li & Kamargianni, 2019, 2020; Papu Carrone et al., 2020; Reck et al., 2021; van Kuijk et al., 2021). However, a simplified utility structure is adopted to match the utilities used in the transport model *Urban Strategy.* Additionally, the parameters estimated in the literature for different cities can not be used for Amsterdam because of the differences in user behavior.

The data from the transport model is used to calculate the total number of trips per OD-pair which is used at a later stage to find the new modal split when the shared modes are introduced. The total number of trips done per OD-pair is computed by summing up the number of trips done per traditional mode for each OD-pair.

Assumptions: the assumptions made in this module are listed below:

- It is assumed that a simplified utility function sufficiently represents the individual's considerations when choosing to use shared modes.
- It is assumed that the parameters of the utility functions do not vary depending on the individual characteristics.

To summarize this module, the following inputs were used to generate the outputs used in the other modules:

- Inputs: Skim matrices per mode, trips per OD-pair per traditional mode.
- Outputs: Utility matrices per traditional mode, utility matrices between hubs per shared mode, total trips per OD-pair.

3.2. Path and Usage Module

This module aims to find the shortest paths for different mode combinations by maximizing the utilities of these paths. Additionally, for each path, the mobility hubs used are recorded. The traditional modes considered are walking, bicycle, car, and public transport. While the shared modes considered are shared mopeds, shared bikes, and shared cars. The utilities per OD-pair per mode, which are outputs of the previous module, are used to compute the total utilities for each multimodal path. These paths link OD-pairs by including also transfers at mobility hubs from one mode to another. In this thesis, a simplification is made by limiting the number of legs in a multimodal trip to three. Trips with more than three legs are considered rare (Wörle et al., 2021). Considering four traditional modes and three shared modes, the total possible alternatives for a three-leg trip is equal to 4 x 3 x 4 = 48. The different possible multimodal combinations are presented in Table 3.1. The mode combinations that are not considered are presented in a light font.

Table 3.1. Possible mode combinations for multimodal trips

1. Walk – Shared Bike – Walk	2. PT – Shared Bike – PT
3. Walk – Shared Moped – Walk	4. PT – Shared Moped – PT
5. Walk – Shared Car – Walk	6. PT – Shared Car – PT
7. Car – Shared Bike – Car	8. Bike – Shared Bike – Bike
9. Car – Shared Moped – Car	10. Bike – Shared Moped – Bike
11. Car – Shared Car – Car	12. Bike – Shared Car – Bike
13. Bike – Shared Bike – PT	14. PT – Shared Bike – Bike
15. Bike – Shared Moped – PT	16. PT – Shared Moped – Bike
17. Bike – Shared Car – PT	18. PT – Shared Car – Bike
19. Bike – Shared Bike – Car	20. Car – Shared Bike – Bike
21. Bike – Shared Moped – Car	22. Car – Shared Moped – Bike
23. Bike – Shared Car – Car	24. Car – Shared Car – Bike
25. Car – Shared Bike – PT	26. PT – Shared Bike – Car
27. Car – Shared Moped – PT	28. PT – Shared Moped – Car
29. Car – Shared Car – PT	30. PT – Shared Car – Car
31. Walk – Shared Bike – PT	32. PT – Shared Bike – Walk
33. Walk – Shared Moped – PT	34. PT – Shared Moped – Walk
35. Walk – Shared Car – PT	36. PT – Shared Car – Walk
37. Walk – Shared Bike – Bike	38. Bike – Shared Bike – Walk
39. Walk – Shared Moped – Bike	40. Bike – Shared Moped – Walk
41. Walk – Shared Car – Bike	42. Bike – Shared Car – Walk
43. Walk – Shared Car – Car	44. Car – Shared Car – Walk
45. Walk – Shared Moped – Car	46. Car – Shared Moped – Walk
47. Walk – Shared Car – Car	48. Car – Shared Car – Walk

It is essential to mention that other access/egress legs might be included in the public transport leg since the transport model considers walking, for example, as an access/egress mode to public transport, as seen in Figure 3.2. Considering all the 48 possible combinations of modes for a three-leg trip is computationally heavy. Hence, the combinations that are less probable or more complex to model are not considered in the case study. The mode combinations 2, 4, and 6 are not considered since using shared mobility between two public transport trips is relatively rare; people would prefer to transfer using public transport. Combinations 7 to 12 that have the car or bike as access/egress to the shared modes are disregarded because such encounters are rare.

The person should then have two vehicles located at different places, which is possible but constitutes a negligible amount of trips. The previously mentioned combinations can be modeled easily; however, they are disregarded to reduce computation time. Finally, all the combinations that include a car or a bike as access or egress are not considered due to the increase in complexity and computation time to model the vehicle ownership and its spatial availability. However, disregarding the paths that have the car as access or egress excludes the cases where the person parks the car on the city's outskirts and uses public transport or shared modes to access or leave the city. Hence, the cases where the hub is used as a park and ride facility are not considered in this thesis, especially that the case study focuses on the urban area of Amsterdam.

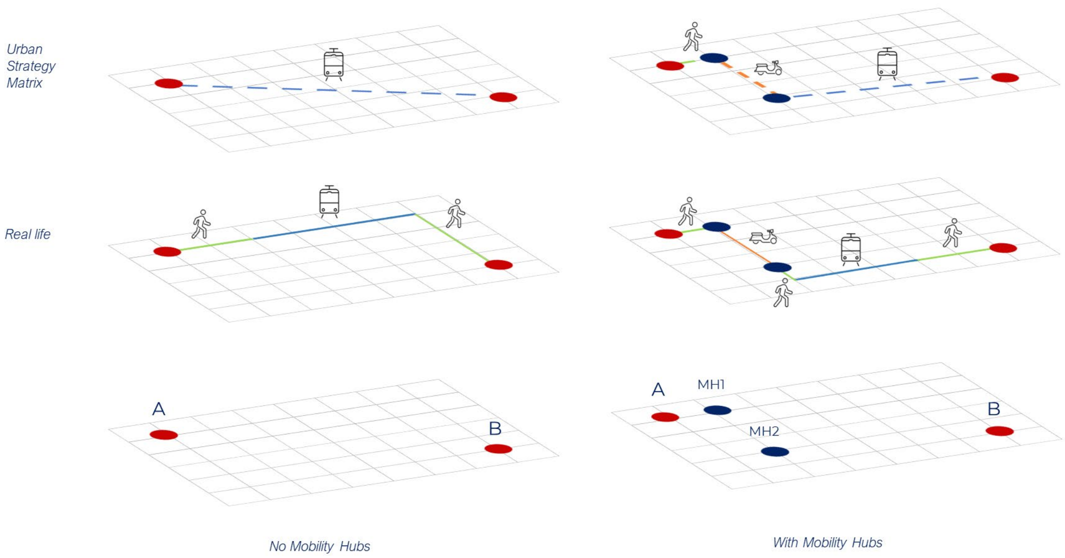

Figure 3.2. Comparison between real-life multimodal paths and Urban Strategy paths used

To compute the shortest path between OD-pairs while considering shared modes, the location of mobility hubs for the specific iteration should be inputted into this module from the heuristic. The shortest path computation varies depending on the mobility hubs activated. The utilities are used to find these shortest paths. For the mode combinations 1, 3, and 5 (mode combinations in which the first and last legs are walking and a shared mode is considered the main mode), the closest mobility hubs to the origin and destination are found for each OD-pair. The utility of the whole path is computed by adding the utilities of the walking legs and the shared modes. It is essential to note that the walking leg can be equal to zero if the centroid is also an activated hub. In the case of the mode combinations 31 to 36 (mode combinations that include public transport), the shortest path is found by maximizing the total utility of the path. The latter is computed by adding the utility of the walking, shared mode, and public transport legs. Adding the different utilities for the different legs of the trip is inspired by the super network concept (Carlier et al., 2002). A supernetwork comprises networks specific to different modes interconnected using transfer links (Carlier et al., 2002).

Mode-specific constants can be included in the path's utility depending on the role of the mode in the entire trip (van Eck et al., 2014). Hence, for the paths that include only walking and a shared mode, the mode-specific constant for the walking legs is not considered since it is not the main mode. Likewise, for the mode chains that include walking, shared modes, and public transport, only the mode-specific constant of the public transport is considered since it is the main mode in this path, and the other two modes are just access or egress modes.

Assumptions and Limitations: the assumptions made and limitations present in this module are listed below:

- When computing the utility of the multimodal paths, only the shortest path is considered in this model. However, in real life, the shortest path is not always used while using active modes (Koch et al., 2021). Additionally, other parameters affect the choice of which mobility hub to use, such as the services and shared modes present at that hub (Nogal & Jiménez, 2020). It is essential to mention that the legs forming the shortest path consider congestion (before introducing shared modes) since they are exported from the transport model.
- Only the mode-specific constant of the main mode is considered when computing the total utility of the multimodal path. Due to the lack of stated or revealed preference data, a new mode-specific constant for the mode combination is not estimated.
- It is assumed that trips with more than three legs are rare and are disregarded.
- Only nine multimodal paths are considered. The combinations that include a bike or car as an access or egress mode are disregarded due to the increased complexity of modeling personal vehicles' ownership and spatial availability.
- It is assumed that the congestion is not affected by the shift from traditional modes of transport to shared modes. This assumption is made because it is computationally heavy to compute the congestion for the whole network at each iteration. Hence, the skim matrices of the initial state are used for all the iterations. Many studies have proved that the effect of shared modes is limited; in some cases, there is either a minor increase or a decrease in congestion (Fan & Harper, 2022).

To summarize this module, the following inputs are used to generate the outputs used in the other modules:

- Inputs: Utilities per mode and OD-pairs, set of activated mobility hubs.
- Outputs: Utilities per multimodal path and OD-pair; and mobility hubs usage per path and OD-pair (record of which hubs are used per path for each OD-pair).

3.3. Demand Estimation Module

The *Demand Estimation* module estimates the travel demand per shared mode for every pair of mobility hubs. For each OD-pair k, the utilities U of all the paths $p \in \mathcal{P}$ are used to compute the ratio of trips performed using a multimodal path p. The utilities are multiplied by a logit parameter β. The equation of the logit ratio used for this purpose is presented below:

$$r_p^k = \frac{\exp\left(-\beta \times U_p^k\right)}{\sum_{p \in \mathcal{P}} \exp\left(-\beta \times U_p^k\right)}$$

However, the logit model assumes that all alternatives are independent, which is not the case when considering different paths that include public transport. Several solutions are presented in the literature to overcome this problem.

The first one is using a probit model. The utilities are decomposed into observed and unobserved parts. In the probit model, it is considered that the unobserved part follows a normal distribution with a specific variance. Hence, every path alternative would have a different variance, and this variability allows to find the distribution of individuals over the different paths (Train, 2009). However, the probit model can not be computed analytically (Hoogendoorn-Lanser & Bovy, 2007). This makes probit computationally heavy, especially since several iterations need to be performed for every OD-pair.

Another solution is to use a nested model. In such a model, public transport is treated as the main mode with a shared mode and walking as the access/egress mode (Krajzewicz et al., 2018). However, in that case, several nesting parameters need to be estimated, which is difficult, especially if no data is available. Furthermore, the nests only consider the correlation between the choices without considering the length of the correlated paths. Additionally, the computation of the probabilities with the nesting parameters needed consumes much CPU time, making it critical for a model with many OD-pairs (Krajzewicz et al., 2018).

The third option is using a path size overlap factor. The path size overlap factor is used to increase the disutility of an alternative in case of overlap. It varies between 0 and 1. If the path of an individual is unique, then the path size factor is equal to 1; hence the utility remains constant. On the other hand, if there is partial overlap, then the path size factor is smaller than 1, leading to an increase in disutility and a decrease in the attractiveness of this path (Hoogendoorn-Lanser & Bovy, 2007). The probability of choosing path p is given by the following equation:

$$r_p^k = \frac{\exp\left(-\beta \times \left(U_p^k + \beta_{overlap} \ln PS\right)\right)}{\sum_{p\in\mathcal{P}} \exp\left(-\beta \times \left(U_p^k + \beta_{overlap} \ln PS\right)\right)}$$

Where,

$$PS = 1 - \frac{l_{PT\ (in\ SM\ paths)}}{N \times l_{SM\ path}}$$

$l_{PT\ (in\ SM\ paths)}$ corresponds to the length of the public transport leg in the path that includes shared modes, N corresponds to the total number of paths that include public transport legs, and $l_{SM\ path}$ corresponds to the length of the whole path that includes walking, shared mode, and public transport. The logarithm of the path size factor appears to account for statistical and behavioral overlaps effects (Hoogendoorn-Lanser & Bovy, 2007). To properly model how the overlap affects choice behavior, a parameter $\beta_{overlap}$ is needed. This parameter is estimated from obvservations (Hoogendoorn-Lanser & Bovy, 2007). Since no data is available to estimate $\beta_{overlap}$, it is approximated. The impact of the parameter $\beta_{overlap}$ on the modal split and hubs usage is analyzed in the case study. A positive $\beta_{overlap}$ is chosen to reflect that the overlap would lead to a disutility, meaning that a path overlapping with public transport is not as attractive as if the same path was considered an independent one. Dixit et al. (2021) found a positive perception of route overlap for public transport due to the availability of alternative travel options in case of disruptions. However, in the case of this thesis, the overlap is assumed to be negatively perceived. It adds to the disutility due to the assumed identical paths used.

A significant issue is that in the case where the mode combination “walk – shared mode – public transport” and the path of public transport are compared together, it might happen that the public transport leg used is not physically the same in both cases. The macroscopic model uses the public transport lines available to compute the travel time and distance between the OD-pair but does not provide which paths are used. In this case, the path size overlap parameter is used to account for the physical and modal overlap, although the physical overlap is not sure due to the inability to check which lines are used by the model for each OD-pair. As seen in Figure 3.2, other public transport lines can be used.

The split of trips over the multimodal paths is multiplied by the total number of trips per OD-pair to obtain the demand for shared modes. Finally, the demand for shared modes per OD-pair is combined with the usage matrix to obtain the number of trips demanding the use of the different mobility hubs and shared modes. The usage matrix provides information on which mobility hubs are used for each path and OD-pair and is the output of the previous module.

If individuals want to use a shared mode, but no vehicles are available, then it is assumed that they are rejected access and are redistributed over traditional modes of transport. The utility $U^k_{TradRej}$ is the utility experienced by the individuals of OD-pair k that have been rejected access to mobility hubs. It is computed by multiplying the logit ratio of each traditional mode $m' \in \mathcal{M}'$ by the utility of using it. $\mathcal{M}'$ includes the four traditional modes of transport.

$$U^k_{TradRej} = \sum_{m' \in \mathcal{M}'} \frac{\exp\left(-\beta \times U^k_{m'}\right)}{\sum_{m'' \in \mathcal{M}'} \exp\left(-\beta \times U^k_{m''}\right)} \times U^k_{m'}$$

Assumptions: the assumptions made in this module are listed below:

- It is assumed that the path size overlap factor can translate the individual's perception of overlaps in paths.
- It is assumed that the OD matrix that includes the number of trips done between each OD-pair does not vary when the shared modes are introduced to the network. In a more advanced model, the OD matrix should be computed again in an iterative manner using the skim matrices of all the available modes.

To summarize this module, the following inputs are used to generate the outputs used in the other modules:

- **Inputs:** Utilities per mode path and mobility hubs usage per OD-pair.
- **Outputs:** Number of trips using the different mobility hubs and shared modes per OD-pair, number of trips using traditional modes of transport, and the total utility experienced by each OD-pair when using shared modes, traditional modes, or in the case they are rejected access to shared modes.

3.4. Capacity Module

The *Demand Estimation* module generates the demand for each shared mode and each mobility hub pair. The demand is then inputted into the linear optimization model that maximizes social welfare. Social welfare can be effectively modeled by using the utilities experienced by the individuals in the system (Wu et al., 2012). In this model, social welfare is represented by the sum of utilities for the trips using shared modes and the trips using traditional modes. The latter include the trips that are using traditional modes initially and the trips that are rejected the use of shared modes due to the lack of available vehicles. It is assumed that the individuals who are rejected access to one shared mode at a mobility hub are redistributed over the traditional modes of transport without considering the other shared modes or mobility hubs as options. The model's basis is inspired by models developed for carsharing systems (Correia & Antunes, 2012; Huang et al., 2018) and bike sharing systems (Frade & Ribeiro, 2015). The model notation and description are presented in Table 3.2.

Table 3.2. Model Notation

Sets	
$\mathcal{K}$	Set of OD-pairs
$\mathcal{M}$	Set of available shared modes (shared cars, shared mopeds, and shared e-bikes)
$\mathcal{N}$	Set of centroids
$\mathcal{T}$	Set of timesteps
Parameters	
B_{inv}	Investment budget
C_{fixed}	Fixed investment costs to build a mobility hub
C_{dock}^{m}	Investment cost to construct or install a dock for shared mode $m \in \mathcal{M}$
C_{op}^{m}	Operational cost per vehicle of type m per year
C_{reloc}^{m}	Relocation cost per vehicle of type m per timestep
C_{veh}^{m}	Investment cost to acquire a vehicle of type m
d_{ij}^{mk}	Demand for vehicles of type m needed for OD-pair $k \in \mathcal{K}$ from mobility hub $i \in \mathcal{N}$ to mobility hub $j \in \mathcal{N}$
M	Big number
p^{t}	Demand fraction at time step $t \in \mathcal{T}$
R^{m}	Revenue generated per vehicle of type m per timestep
T_{ij}^{m}	Timesteps needed to travel from mobility hub i to mobility hub j using shared mode m
U^{mk}	Total utility experienced by the OD-pair k using shared mode m
$U_{Total\ Trad}$	Total utility experienced by all the OD-pairs using traditional modes of transport
$U_{TradRej}^{k}$	Total utility experienced by the OD-pair k that have been rejected access to a shared mode due to lack of capacity and used traditional modes instead
y_{max}^{m}	Maximum number of docks or spaces for shared mode m per mobility hub
y_{min}^{m}	Minimum number of docks or spaces for shared mode m per mobility hub
z_i	Binary: 1 if mobility hub is activated at node i, which is the chromosome obtained from the genetic algorithm
Decision variables	
r_{ij}^{mt}	Number of repositioned or relocated vehicles of type m from mobility hub i to mobility hub j at the beginning of time step t
v_{i}^{mt}	Number of vehicles of shared mode m present at timestep t in mobility hub i
x_{i}^{mt}	Ratio of satisfied demand for shared mode m at timestep t in mobility hub i
y_{i}^{m}	Number of docks or spaces for shared mode m available in mobility hub i

Objective Function

$\max C$

$$C = \sum_{i\in\mathcal{N}} \sum_{m\in\mathcal{M}} \sum_{t\in T} \left(x_i^{mt} \times \sum_{j\in\mathcal{N}} \sum_{k\in K} d_{ij}^{mk} \times p^t \times U^{mk} \right) + \sum_{i\in\mathcal{N}} \sum_{m\in\mathcal{M}} \sum_{t\in T} \left(\left(1 - x_i^{mt}\right) \times \sum_{j\in\mathcal{N}} \sum_{k\in K} d_{ij}^{mk} \times p^t \times U_{TradRej}^{k} \right) + U_{Total\ Trad} \tag{3.1}$$

Subject to

$$v_i^{m(t+1)} = v_i^{mt} - x_i^{mt} \times \sum_{j\in\mathcal{N}} \sum_{k\in K} d_{ij}^{mk} \times p^t + \sum_{j\in\mathcal{N}} \sum_{t'\in\mathcal{T} \mid t'+T_{ji}^{m}=t} \sum_{k\in K} x_j^{mt'} \times d_{ji}^{mk} \times p^{t'} - \sum_{j\in\mathcal{N}} r_{ij}^{mt} + \sum_{j\in\mathcal{N}} \sum_{t'\in\mathcal{T} \mid t'+T_{ji}^{m=0}=t} r_{ji}^{mt'} \quad \forall\, i \in \mathcal{N}, m \in \mathcal{M}, t \in (\mathcal{T}-1) \tag{3.2}$$

$$v_i^{mt} \geq x_i^{mt} \times \sum_{j\in\mathcal{N}} \sum_{k\in K} d_{ij}^{mk} \times p^t \quad \forall\, i \in \mathcal{N}, m \in \mathcal{M}, t \in \mathcal{T} \tag{3.3}$$

$$\sum_{j\in\mathcal{N}} r_{ij}^{mt} \leq v_i^{mt} \qquad \forall\, i \in \mathcal{N}, t \in \mathcal{T}, m \in \mathcal{M}_{SM} \tag{3.4}$$

$$r_{ii}^{mt} = 0 \qquad \forall\, i \in \mathcal{N}, m \in \mathcal{M}, t \in \mathcal{T} \tag{3.5}$$

$$r_{ij}^{mt} \leq M \times z_j \qquad \forall\, i \in \mathcal{N}, j \in \mathcal{N}, m \in \mathcal{M}, t \in \mathcal{T} \tag{3.6}$$

$$r_{ij}^{mt} \leq M \times z_i \qquad \forall\, i \in \mathcal{N}, j \in \mathcal{N}, m \in \mathcal{M}, t \in \mathcal{T} \tag{3.7}$$

$$y_i^{m} \leq y_{max}^{m} \times z_i \qquad \forall\, i \in \mathcal{N}, m \in \mathcal{M} \tag{3.8}$$

$$y_i^{m} \geq y_{min}^{m} \times z_i \qquad \forall\, i \in \mathcal{N}, m \in \mathcal{M} \tag{3.9}$$

$$v_i^{mt} \leq y_i^{m} \qquad \forall\, i \in \mathcal{N}, m \in \mathcal{M}, t \in \mathcal{T} \tag{3.10}$$

$$x_i^{mt} \leq z_i^{m} \qquad \forall\, i \in \mathcal{N}, m \in \mathcal{M}, t \in \mathcal{T} \tag{3.11}$$

$$\sum_{i\in\mathcal{N}} \sum_{m\in\mathcal{M}} y_i^{m} \times C_{dock}^{m} + \sum_{i\in\mathcal{N}} z_i \times C_{fixed} \leq B_{inv} \tag{3.12}$$

$$\sum_{i\in\mathcal{N}} \sum_{m\in\mathcal{M}} \sum_{t\in T} R^{m} \times x_i^{mt} \times \sum_{j\in\mathcal{N}} \sum_{k\in K} d_{ij}^{mk} \times p^t \times T_{ij}^{m} - \sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{N}} \sum_{m\in\mathcal{M}} \sum_{t\in T} C_{reloc}^{m} \times r_{ij}^{mt} \times T_{ij}^{m} - \sum_{i\in\mathcal{N}} \sum_{m\in\mathcal{M}} v_i^{m(t=0)} \times \left(\frac{1}{\text{LifeExp} \times \text{TimePeriod}} \times C_{veh}^{m} + \frac{1}{\text{TimePeriod}} \times C_{op}^{m} \right) \geq 0 \tag{3.13}$$

The objective function is to maximize social welfare by maximizing the total travel utility experienced by the individuals in the system. It is divided into three elements: the first represents the sum of utilities for the trips using a shared mode and are satisfied by the available vehicles. The second part of the objective function represents the sum of utilities for the trips which are rejected access to the shared modes due to lack of capacity. These trips are then split over the traditional modes of transport and experience the utilities of the traditional modes. Finally, the utilities of the trips performed using the traditional modes of transport are added to compute the total social welfare. The model is subject to 13 constraints that are detailed below.

Constraint 3.2 is an equilibrium constraint. It represents the conservation constraint of available shared vehicles of type m over timestep t at mobility hub i. The number of vehicles of type m at timestep $t+1$ is equal to the number of present vehicles at timestep t minus the number of vehicles that leave the mobility hub at timestep t, plus the number of vehicles that arrive at timestep t from any mobility hub to hub i, minus the number of vehicles relocated from mobility hub i to any other hub at timestep t, plus the number of vehicles relocated from any mobility hub to hub i arriving to hub i at timestep t. To find the arrival times of the used shared vehicles, the travel time for each shared mode m from OD-pairs j to i is used. However, to find the arrival times of the relocated shared vehicles, the travel time for a car is used since all the shared modes are relocated using the road network with travel times similar to the car.

Constraint 3.3 ensures that a higher number of vehicles of type m is present at mobility hub i at moment t than the demand satisfied. This constraint is translated by the need to have more vehicles present at a mobility hub compared to the number of vehicles leaving from that hub. It is essential to mention that the ratio of satisfied demand x is a variable related to the mobility hub i rather than the OD-pairs. Hence, all the OD-pairs that use mobility hub i have the same ratio of satisfied demand. This is more logical than finding a ratio of demand satisfied for each OD-pair since the operator can not choose which trips to serve. Therefore, everyone that arrives at the exact moment to the mobility hub has the same chance of using the shared modes regardless of their origin or destination.

Constraint 3.5 ensures that no vehicles are rebalanced within the same mobility hub to avoid relocations that are not needed in the system. Constraints 3.6 and 3.7 ensure that no vehicles of type m are rebalanced from mobility hub i to j if those hubs are not activated. Constraints 3.8 and 3.9 ensure that no active hubs house more (or less) docks or spaces than the set limits. Constraint 3.10 guarantees that the model does not assign more vehicles of shared mode m than the available docks or spaces at a mobility hub i. Constraint 3.11 ensures that the ratio of satisfied demand is lower than one if the mobility hub is activated or is zero if it is not activated.

Finally, constraints 3.12 and 3.13 are budget constraints. The first one ensures that the investment costs are smaller than the investment budget. It computes the costs of installing the docks/spaces and the fixed costs of constructing a mobility hub. These costs are found by multiplying the installation costs per dock/space for shared mode m by the number of docks needed, plus the number of mobility hubs activated times their construction costs. The second constraint ensures that the operation of the services is profitable. These profits are computed by subtracting the operator's costs from their revenues. The latter are computed from the total trips performed, which are found by multiplying the duration of the trips performed by the rate of using the shared mode. The operational costs equal the sum of relocation costs, the vehicle's acquisition costs, and maintenance costs. The relocation costs are computed by multiplying the timesteps needed to relocate by the cost of relocation per timestep, while the total acquisition and maintenance costs are computed by multiplying the total number of vehicles by their acquisition and maintenance costs. The acquisition costs are divided by the time period in which the vehicles will operate. For example, if the modeled period is a 2 hours interval, and the vehicles are assumed to be operational 20 hours per day, then the time period used is 365 days/year x 20 hours/day /2 hours = 3650, and their life expectancy is 5 years. While the maintenance costs are divided by the time period to convert the yearly costs into 2-hour costs.

Assumptions: the assumptions made in this module are listed below:

- It is assumed that rebalancing can happen at each timestep. However, other constraints such as the availability of employees and trucks might limit the ability to rebalance at every timestep.
- It is assumed that the trips that are not satisfied due to the unavailability of vehicles are distributed back to traditional modes of transport. However, in real life, when individuals are rejected access to a shared mode due to its unavailability, they might consider several alternative options of which: shifting to another shared mode or walking to another mobility hub, for example.
- Individuals have a particular learning experience. For example, suppose there are no vehicles to satisfy their trips in a particular mobility hub. In that case, using this hub might not be considered in the following days, or this will discourage those individuals from using shared modes again. Hence, this model does not consider long-term behavior and choice changes.
- The pricing is set as a value per travel time. However, many operators are proposing subscriptions that allow the users to get further discounts. In this thesis, the subscriptions are not taken into consideration.
- No discount rates are considered when converting all the costs to costs per period.

To summarize this module, the following inputs are used to find the capacity of the mobility hubs and compute the objective function :

- **Inputs:** Parameters and data mentioned in Table 3.2.
- **Outputs:** Capacity of mobility hubs, number of vehicles of each type in each mobility hub at different timesteps, percentage of satisfied demand at each timestep, objective function, and the rebalancing performed during the period.

3.5. Genetic Algorithm

Two elements must be inputted to compute the utility of each multimodal path in the *Path and Usage* module: the utilities matrix per mode and the activated mobility hubs. The utilities are computed in the *Utilities Computation* module presented previously. While the hubs are activated from a set of candidate locations by a heuristic. According to different pieces of literature, the genetic algorithm is one of the most suitable heuristics to perform such a task. Most papers that use a heuristic to locate shared modes stations use a genetic algorithm (Caggiani, Colovic, et al., 2020; Liu et al., 2015; Nair & Miller-Hooks, 2016; Romero et al., 2012). Chen et al. (2015) proposed a genetic simulated annealing algorithm to locate urban refueling stations. Ali-Askari et al. (2017) mention different genetic algorithm applications, such as the location-allocation problem of shared modes stations. In this thesis, a genetic algorithm is used to find the optimal distribution of hubs due to its ability to search for the best solution probabilistically.

The genetic algorithm is inspired by the theory of evolution. It is mainly based on the idea of the survival of the fittest. Individuals with better traits will survive and inherit those traits through the generations, while individuals with less adaptive traits have a lower chance of survival. Over the different generations, the traits that enable the individuals to survive become more frequent, leading to the evolution of the population (Mirjalili, 2019). The genetic algorithm is initiated by generating a population of N individuals which represents a set of solutions. The fitness of each individual is assessed using a specific objective function. Pairs of individuals from the initiated population are selected to be the parents and reproduce the next generation of the population. The children are generated by taking genes from both parents in a process named crossover and by randomly modifying some genes in a process named mutation. Having a small part of genes changed randomly increases the algorithm's exploratory behavior and maintains diversity in the population. Then the fitness of the new individuals is assessed using the objective function in a cyclic process until the stopping criteria are met. Like natural selection, this algorithm allows one to obtain better solutions over the generations, bringing it closer to the optimum (Mirjalili, 2019).

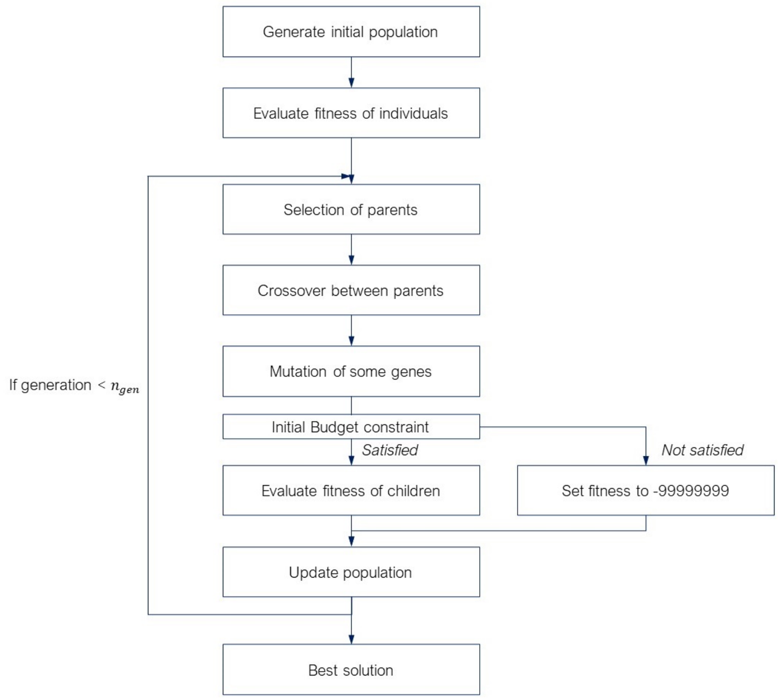

Figure 3.3. Genetic algorithm steps

The genetic algorithm is implemented in this thesis by following the steps below (Mirjalili, 2019; Romero et al., 2012).

1. In the initial phase, a set of n' possible mobility hub locations is identified, taking different parameters into account, such as spatial availability and spatial coverage. The initial population is generated with a size of N individuals. Each individual is constituted of an array of 1s and 0s representing whether a mobility hub is active at a specific location or not. This array is identified as a *chromosome* with a length of n'. The chromosome of each individual is initially generated completely randomly or with a certain proportion of 1s and 0s. Setting a certain proportion of 1s and 0s in each chromosome depending on the available budget leads to faster convergence. Several initialization mechanisms are presented in the literature (Hassanat et al., 2018). These are used to create a custom initialization mechanism in the case study.
2. Each individual's fitness is computed using the objective function explained in the *Capacity Module*. The individual with the best fit is saved as the *Best Solution*.
   Two conditions are set to avoid computing for each individual, the objective function, and avoid excessive computational time. If one of the conditions is met, then the fitness value is set to – 99999999. The first condition checks whether the solution proposed exceeds the budget set even if the minimum number of vehicles is allocated to each hub. Hence the following equation should be satisfied to set the fitness to –99999999 and avoid performing all the computations:
   $$\sum_{i\in\mathcal{N}} z_i \times \left(C_{fixed} + \sum_{m\in\mathcal{M}} y_{min}^m \times C_{dock}^m \right) > B_{inv}$$
   The second condition set checks whether the solution maximizes benefits with the available resources. Since adding mobility hubs and shared vehicles always increases the social welfare, the number of vehicles should be maximized using the budget allocated. In the case where the costs of installing the maximum number of vehicles plus the fixed costs are less than the budget with the buffer of having one station filled less than the minimum, then the fitness is set to – 99999999:
   $$\sum_{i\in\mathcal{N}} z_i \times \left(C_{fixed} + \sum_{m\in\mathcal{M}} y_{max}^m \times C_{dock}^m \right) < B_{inv} - \sum_{m\in\mathcal{M}} y_{min}^m \times C_{dock}^m$$
3. The following steps are repeated n_{gen} times :
   a. Two parents are selected to generate a child using a tournament selection procedure. In this procedure, two individuals are chosen randomly from the population. Then the fittest individual is selected as the first parent. The same procedure is repeated to select the second parent. Two individuals are chosen randomly from the population, and the fittest is selected as the second parent. The advantage of performing a tournament-based selection is that its implementation is efficient while preserving the diversity of the population, which is essential to explore the different solution spaces (Yadav & Sohal, 2017). The tournament method is presented in Figure 3.4. In this example, the aim is to maximize the objective function. Hence, from each two randomly chosen individuals, the one with a fitness of -500 is selected as the first parent, and the one with a fitness of -750 is selected as the second parent.

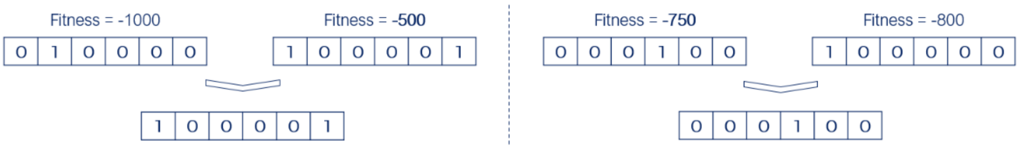

Figure 3.4. Tournament example

b. A child solution is generated by crossing over the selected parents. The crossover function takes two parents and the crossover rate. A crossover procedure is performed with a probability equaling the crossover rate; otherwise, the parents are copied to the next generation. If a crossover is to be performed, a split point is randomly chosen to take p bits from the first parent and $n' - p$ from the second parent. A high crossover is generally used to allow the creation of diverse children. In this thesis, a crossover rate of 0.9 is used since it provides better performance (Mirjalili, 2019).
Another method of crossover is also considered, which is a two-point crossover. If a crossover is to be performed, two split points are randomly chosen, and the contents between these points are exchanged between the selected parents (Kaya et al., 2011). The crossover methods are presented in Figure 3.5.

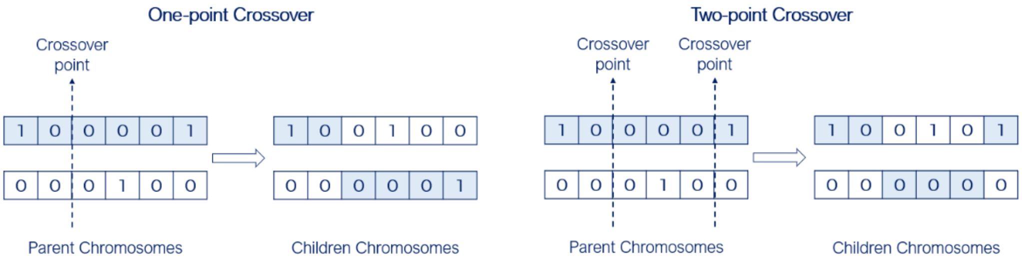

Figure 3.5. Crossover methods

c. For each generated child, a mutation procedure occurs. For each bit from the chromosome, there is a probability r_{mut} inputted initially that the bit is modified.
d. The population is then updated with the new children generated and their fitness computed as described in step 2. If one of the individuals has a better fitness than the *Best Solution*, then it becomes the *Best Solution.*
One possibility that is also considered is to transfer the best 10% of the individuals to the next generation. The elites are transferred to the next generation to preserve valuable individuals leading to faster convergence (Rani et al., 2019).

To summarize this module, the following inputs are used to generate the outputs used in the other modules:

- **Inputs:** Set of potential mobility hub locations, genetic algorithm parameters.
- **Outputs:** Activated mobility hubs for each iteration; at the end of the iterations, the optimal distribution of hubs is obtained.

04

CASE STUDY

Photo taken by the author – London, September 2021

4. Case Study

In the following chapter, the methodology proposed previously is applied in a case study for the city of Amsterdam. Section 4.1 presents a description of the city of Amsterdam. Section 4.2 presents how the potential locations of mobility hubs are generated. Section 4.3 presents the parameters inputted in the model. The model developed and presented previously is run for the different scenarios in section 4.4, and the results obtained are presented in section 4.5. A sensitivity analysis is performed in section 4.6 to assess the impact of the assumptions and parameters chosen. Finally, a validation is performed in section 4.7 to check whether the genetic algorithm can converge toward a global optimum.

4.1. The City of Amsterdam

This thesis aims to find the optimal location and capacity of mobility hubs in the city of Amsterdam. The distribution of trips and modal adoption is unique in the world. Each household in Amsterdam has an average of 1.98 bicycles. In addition to that, a high share of trips is made using active modes: 38% and 10% of the residents' and visitors' trips, respectively, are made using a bicycle with an average modal split for the bicycle of 28% (Gemeente Amsterdam, 2021). This is also stimulated due to the presence of a well-developed cycling infrastructure with more than 2336 km of isolated cycling and shared paths. While the share of mopeds is growing but is still limited to 2%. However, the city is also facing rapid growth, which increases pressure on public spaces and reduces accessibility. To curb these issues, the municipality of Amsterdam is working on improving traffic flow by diverting traffic from the center to the outskirts of the city. In addition to that, the municipality aims to make the city more livable by reducing the space available for personal cars to move from individual to collective forms of mobility. In its 2030 mobility plan, the city will work on improving the already-extensive bike network by introducing new cycle bridges and completing missing sections of cycle routes (Gemeente Amsterdam, 2021).

Hence, the main public goals are to improve mobility while decreasing the pressure on public spaces. Mobility hubs are a good solution to achieve the goals mentioned since they decrease reliance on personal vehicles and shift mobility from owning to sharing. It is essential then to assess how these mobility hubs will be installed and how they will be distributed in the city to maximize accessibility and improve mobility while creating a more livable and sustainable city.

(Felyx, 2022)

4.2. Potential Location of Mobility Hubs

Mobility hubs can have different sizes and include different modes, as previously discussed in paragraph 2.1. The main focus of this thesis is urban mobility hubs, whether neighborhood mobility hubs or mobility hubs associated with public transport stations. One of the main goals of the model developed is to distribute the hubs to maximize social welfare rather than just focusing on the profitability of the service. Therefore, it is essential to have potential locations that do not include any bias when establishing the optimal locations. Considering the demand and attractions while generating the candidate locations creates a bias that the optimization model would accentuate. Hence, as a starting point, the public transport stations and stops are considered potential locations for mobility hubs. First, all the stops are inputted, and the ones that overlap due to the presence of multiple modes are cleaned to have only one stop at each location. This results in obtaining 589 points. The next step is to assess whether it is spatially possible to construct mobility hubs in these locations using Google Street View. If there is insufficient space to install a mobility hub, this point is deleted or moved to a parallel street. It is essential to note that any bias in the distribution of stations and stops should be avoided. So the 250, 500, and 750 m service areas of the hubs are generated using ArcGIS Pro. Then the service areas are overlayed on top of the 100m x 100m population density map. If the service areas generated do not cover a part of the population from the map, potential mobility hub locations are added. The potential locations generated consider the different possibilities of locating mobility hubs independently in neighborhoods, or in combination with major mobility points such as train stations, or in the city's outskirts in combination with a park and ride facility. The service areas of the final potential mobility hub locations are presented in Figure 4.1. It is essential to note that the service areas are not uniform since the walking distance is computed using the available road network.

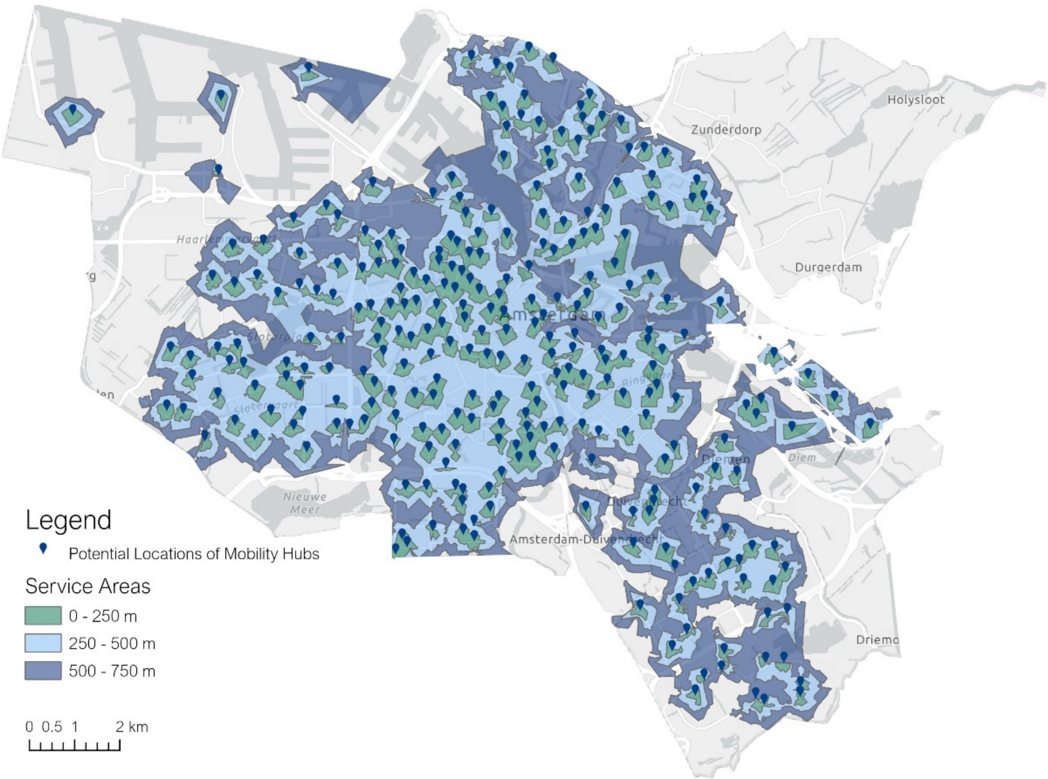

Figure 4.1. Service areas of potential mobility hub locations

To model the mobility hubs and obtain the skim matrices needed, either new centroids can be added to the transport model or available ones are used. The latter option of using the available centroids is adopted for the following reasons. First, the Amsterdam transport model has a high density of centroids with over 3,035 centroids (as seen in Figure 4.2), allowing the association of the suggested mobility hub locations to respective centroids without increasing the walking time. Associating the possible mobility hub locations to an already available centroid is a logical solution since the centroid already aggregates several trips. However, a disadvantage of this technique compared to adding new centroids is that the walking distances between the population centroids and the proposed mobility hub locations might affect the results. To decrease the variation in this parameter, the possible mobility hub locations are only associated with centroids within a distance of 150 m. This decreases the discrepancies between the actual walking distances and the computed ones using the model. Some centroids are dummy centroids used only to model parking demand and patterns. Hence, the mobility hub locations are associated with non-dummy centroids. If no centroids are available within 150 m from a proposed location of mobility hubs, then this location is moved within the neighborhood. After associating all the proposed mobility hub locations to the respective centroids, the service areas are computed again to ensure that the mobility hubs' service areas cover all of the population. If some areas are not covered, then a mobility hub is added.

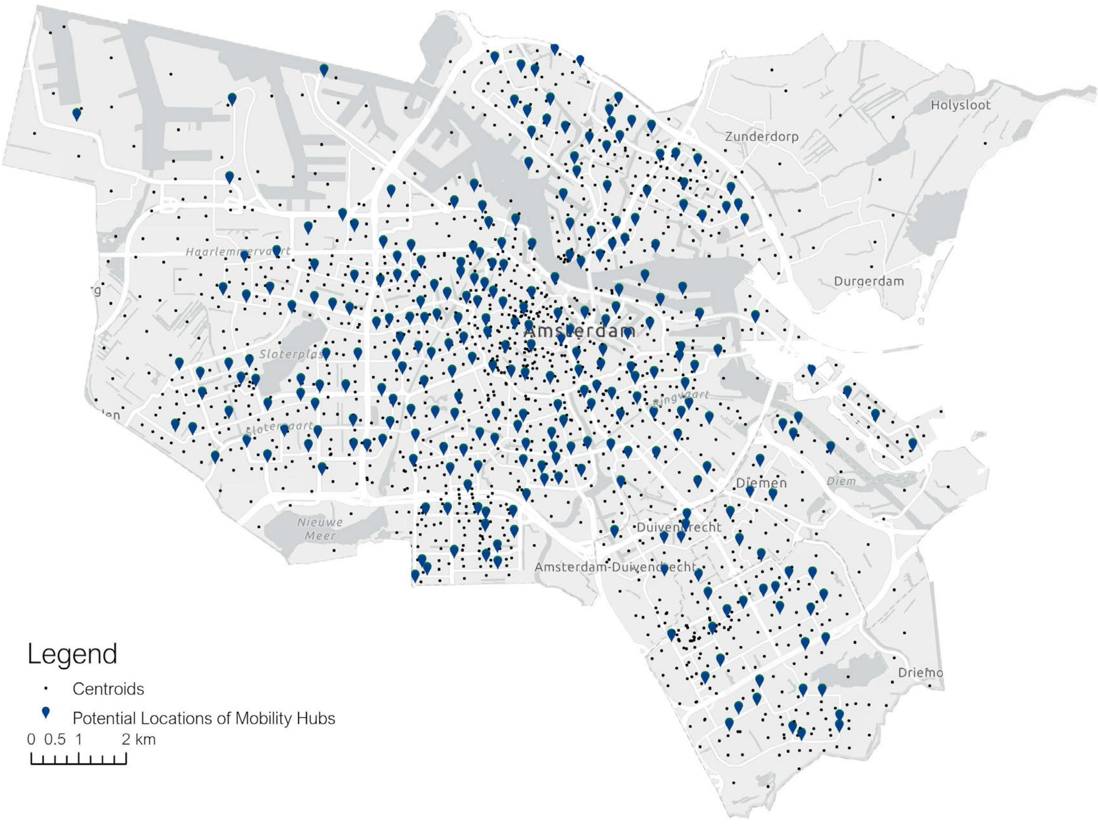

Figure 4.2. Centroids and potential locations of mobility hubs

The steps performed to generate the potential mobility hub locations are summarized in Figure 4.3.

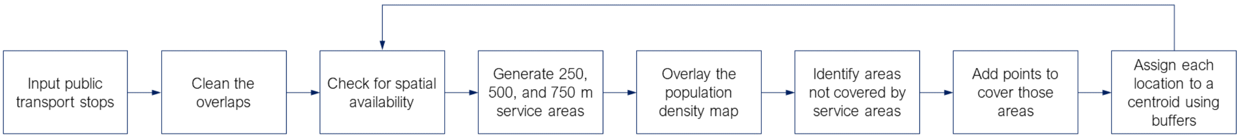

Figure 4.3. Potential mobility hub locations generation steps

After performing the presented steps, 288 possible mobility hub locations are proposed as potential ones for the case study.

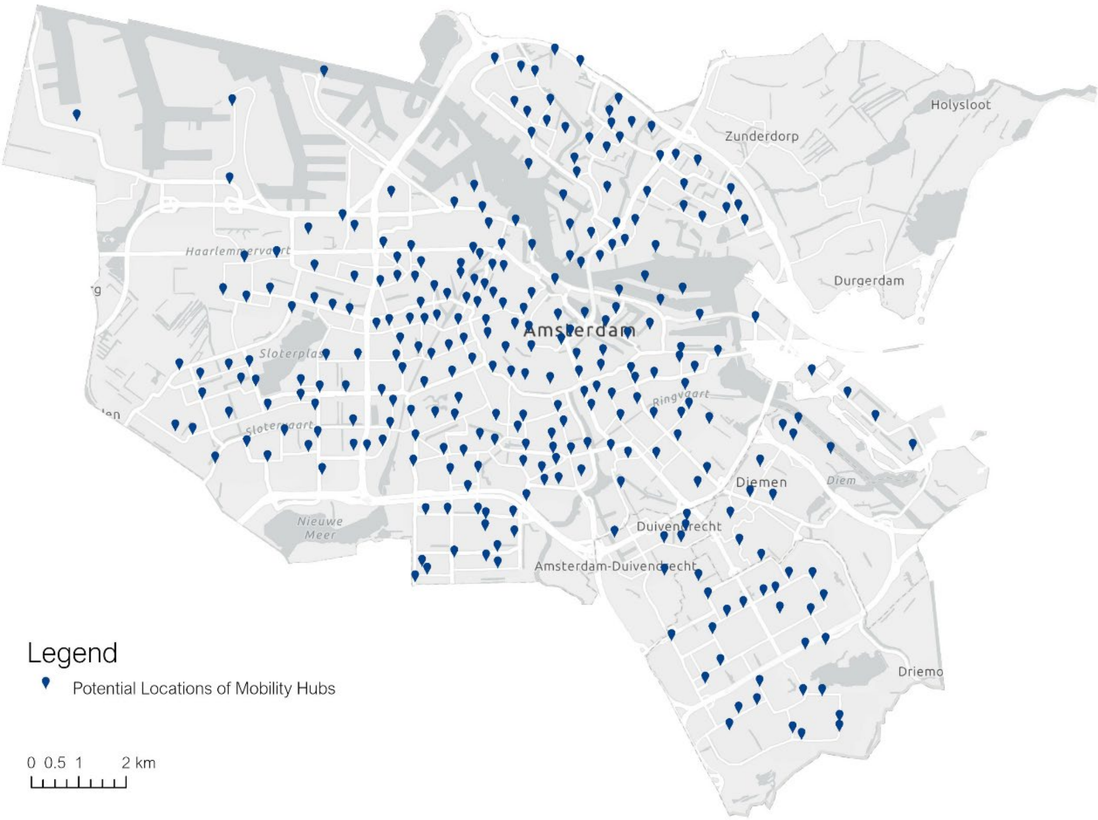

Figure 4.4. Final potential mobility hub locations

4.3. Model’s Parameters

The model parameters used to perform the case study for the city of Amsterdam are presented in the following section. The 2030 morning peak transport data is used for the runs.

4.3.1. Utilities

The following utility function is used with different parameter values per mode:

$$U = (cost\_start + travel\_distance \times cost\_user\_per\_km) + (travel\_time \times value\_of\_time) + (travel\_time \times cost\_user\_per\_hour) + mode\_specific\_constant$$

The utilities of traditional modes and shared cars are present in the transport model *Urban Strategy* and have been estimated using transport data. However, the utilities for shared mopeds and shared e-bikes are missing. As previously mentioned, several studies have estimated the utilities’ parameters for these modes in different cities by using revealed or stated preference data. However, the parameters are approximated to match the utility functions already present in *Urban Strategy* for this case study.

The bicycle's mode-specific constant is used to estimate the parameters for the shared moped and shared e-bike. The value of time parameter used for these modes is 7.5€/hr, which is the value of time adopted in the LMS national model for an electric bicycle (Rijkswaterstaat, 2021). The user costs per hour are estimated by examining the rates set by the operators in Amsterdam and the Netherlands. The following prices are obtained: Go Sharing prices 0.23€ per minute for the shared e-bike services, Felyx and GoSharing prices 0.3€ per min and 0.29 € per minute respectively for shared mopeds. For this case study, no subscriptions are considered.

The different parameter values for each mode are presented in Table 4.1. The travel time and distance for the traditional modes (walk, bicycle, car, and public transport) are obtained from the transport model. The car travel times and distances are used for the shared car, while for the shared moped and e-bike, the bicycle’s travel distances are used. However, for the travel time, the bicycle’s travel times are divided by 3 and 2 for the moped and e-bike, respectively. The average speed of the bike used in the model is 10 km/h. For the moped and e-bike, it is assumed to be 30 km/h and 20 km/h, respectively.

Table 4.1. Utilities parameters

Mode	Cost start	Cost user per km	Cost user per hour	Value of time	Mode-specific constant
Walk	0	0	0	9	2
Bicycle	0	0	0	9	9.5
Car	0	0.17	0	9	0
Public Transport	0.87	0.142	0	6.75	10.5
Shared Car	0	0.6	0	9	5
Shared Moped	0	0	17.7	7.5	9.5
Shared e-Bike	0	0	13.8	7.5	9.5

4.3.2. Overlap Parameter

As previously mentioned in the *Demand Estimation* module, the overlap factor is used to account for the disutility related to overlapping legs. It is assumed that in the case of this thesis, overlapping paths are less attractive than independent paths. The probability of choosing path p is given by the following equation:

$$r_p^k = \frac{\exp\left(-\beta \times \left(U_p^k + \beta_{overlap} \ln PS\right)\right)}{\sum_{p \in \mathcal{P}} \exp\left(-\beta \times \left(U_p^k + \beta_{overlap} \ln PS\right)\right)}$$

The same logit parameter $\beta = 0.5$ adopted in *Urban Strategy* is used in this case study. To choose the overlap parameter $\beta_{overlap}$, a sensitivity analysis is conducted. The sensitivity analysis allows to assess the impact of $\beta_{overlap}$ on the modal split and the demand distribution over the mobility hubs. However, it is impossible to conduct a sensitivity analysis on the overall model due to the long computation time. Hence, it is performed when all the mobility hubs are activated. The impact of the overlap parameter is assessed on the demand modal split by varying it between 0 and 19.5. The graph presented in Figure 4.5 highlights the effect of the overlap parameter on the modal split of each shared mode. It is essential to mention that the modal split presented is the demand for shared modes rather than the trips satisfied. Hence, the real modal split is smaller than what is presented in this graph. The main paths that are affected by this change are the paths that include public transport since only the overlap with public transport is considered. The overlap parameter has a negligible effect on the split over the paths that only include a shared mode combined with walking. Increasing the overlap parameter from 0, which means that the overlap is not considered, to 20, decreases the modal split of shared modes-public transport combinations from 0.6% to 0.18%, as seen in Figure 4.5.

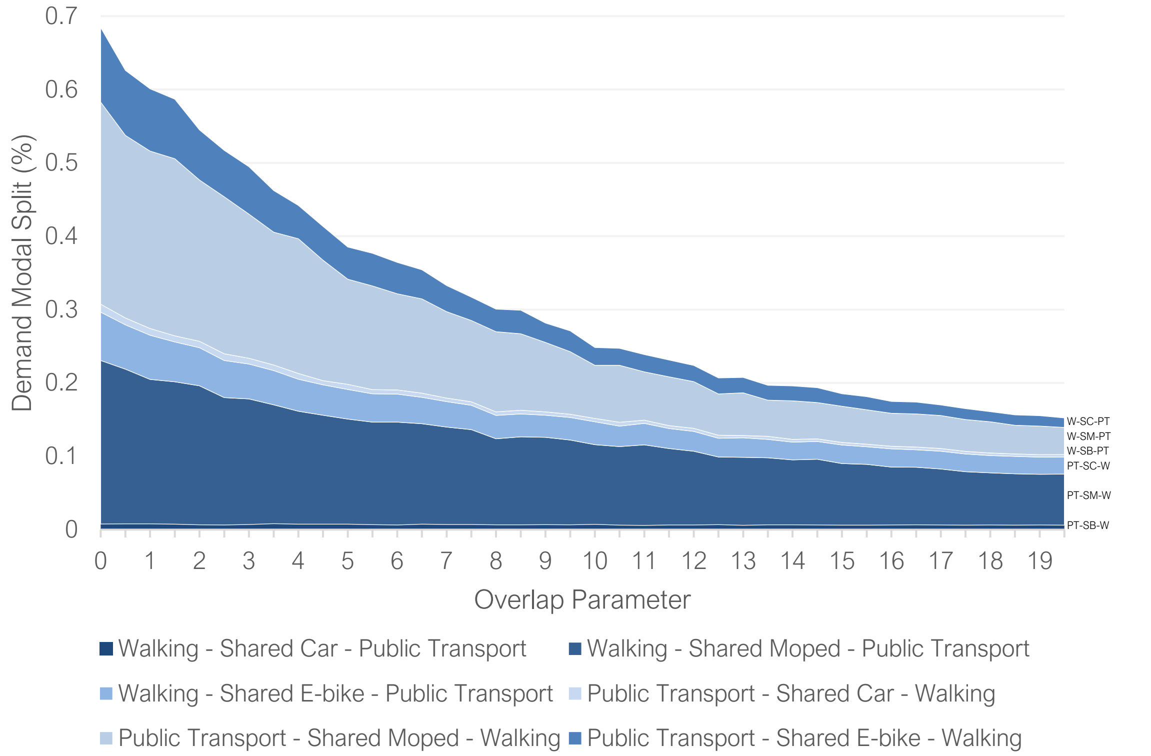

Figure 4.5. Effect of the overlap factor on the demand modal split

The overlap parameter chosen is 15 due to the stability seen after that point and the smaller slope in the interval 15 – 19.5 compared to the interval 0 – 15. To conclude, the overlap parameter is predicted to have a negligible effect on the results of optimal locations since the demand split for the public transport – shared modes combinations is minimal, and only a split of it will be served.

The change in demand distribution over the mobility hubs is assessed depending on the change in the overlap parameter. This gives a better understanding of the effects of the overlap parameter on the results. The average and standard deviation of the change in demand over the mobility hubs is presented in Figure 4.6 for the three shared modes. When the overlap parameter is increased from 0 to 20, the average change in the demand for shared cars for all the mobility hubs is approximatively constant, around 0.1%, with a maximum standard deviation of 2%. This means that the variation in the overlap parameter leads to a uniform change in demand for shared cars over the different mobility hubs. In the case of shared mopeds, the change in overlap parameter leads to a maximum of -1.5% decrease in demand for all the mobility hubs. In the case of the shared mopeds, the maximum standard deviation of the change in demand is higher, around 5%. This means that not all the mobility hubs are affected in the same way. However, since the average change is small and the standard deviation is also small, then the effects on the results are minimal. In the case of the shared e-bikes, both the average change and standard deviation are more affected than the other shared modes. Since the share of the paths that include shared bikes is less than 0.07% (Figure 4.5), then the effect of this variation on the final results is negligible.

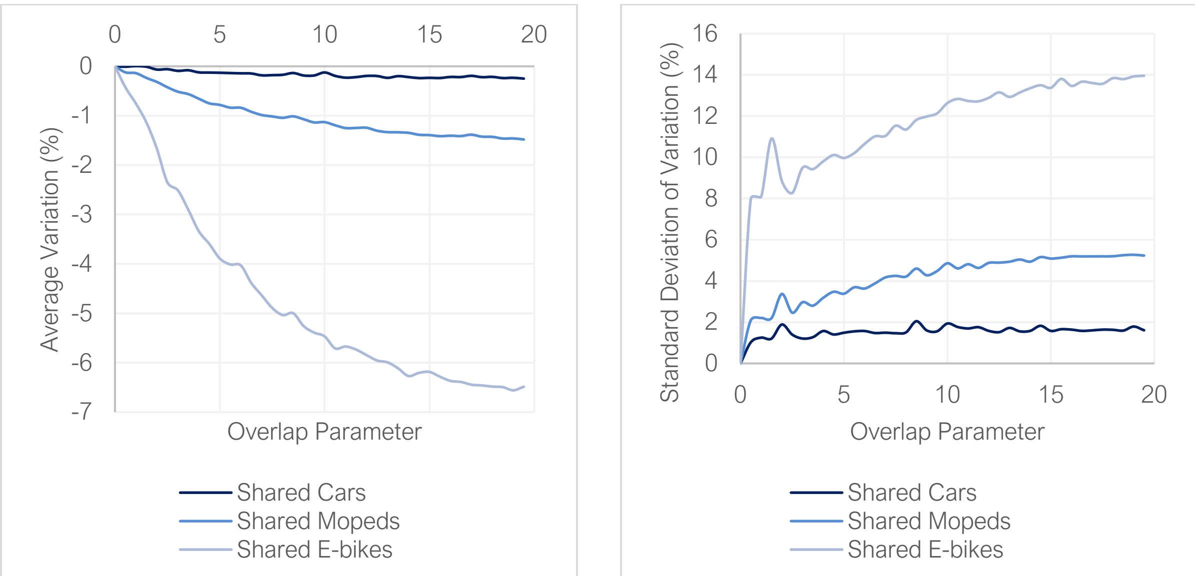

Figure 4.6. Effect of the overlap factor on the demand for mobility hubs

The *Capacity* module is also run with the different overlap parameters. As seen in Figure 4.7, the social welfare decreases by 0.017 % when the overlap factor is increased from 0 to 20. This is mainly because the number of trips that include a combination of public transport and shared modes are limited (less than 0.7%), and the results are mainly affected by the most significant part of the demand related to the combination of shared modes and walking which is independent of the overlap factor. To conclude, it is essential to include the overlap parameter to account for the disutility of overlapping paths. However, the value of the overlap parameter is not expected to have a significant effect on the final results since all the mobility hubs have a similar decrease in demand for the shared cars and mopeds, while the split of shared bikes – public transport is negligible.

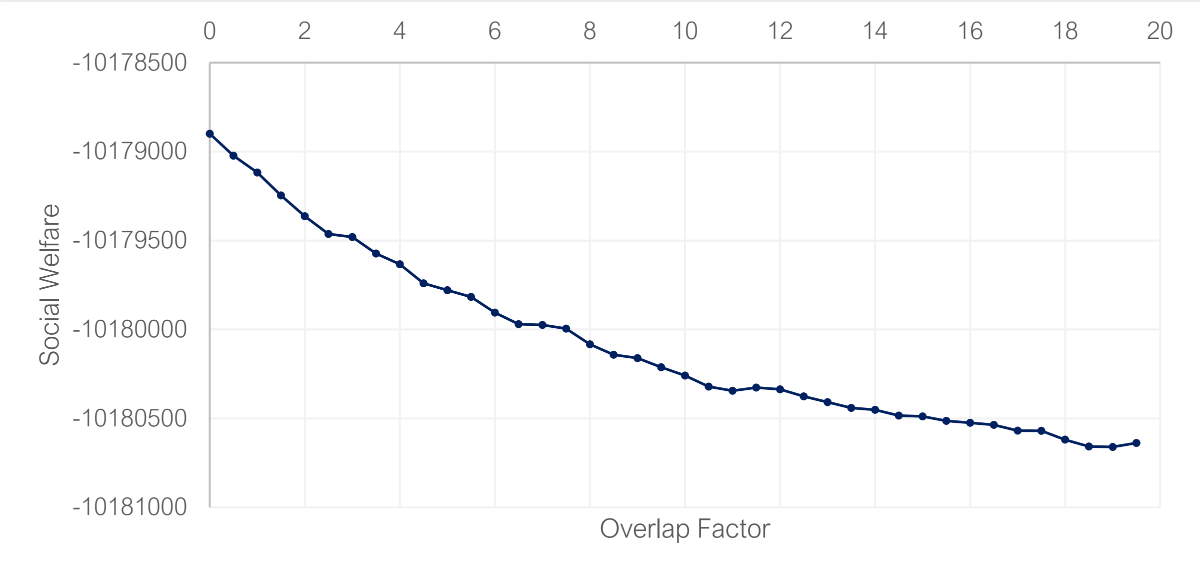

Figure 4.7. Effect of the overlap factor on the social welfare when all mobility hubs are activated

4.3.3. Capacity Module's parameters

The *Capacity* module needs several parameters to be inputted, primarily related to the costs of constructing mobility hubs, acquiring the vehicles, and operating the system. First, the fixed construction costs (C_{fixed}) are set to be 5000 € per mobility hub. These costs include the installation of signs and information related to the hub and services offered, the standard amenities of bus stations are used for this estimation (SMARTNET). The costs to construct/install a dock or space for all the shared modes (C_{dock}^{m}) are set to 500€/space (Frade & Ribeiro, 2015). It is assumed that the charging will not be done on-site; hence, no significant installations are needed, mainly repurposing the space and applying surface painting. Regarding the revenue generated for each shared mode (R^{m}), the following prices are used:

- For the shared car services, the Sharenow price is used (0.28 € per minute)
- For the shared moped services, the average of Felyx (0.3€ per minute) and GoSharing (0.29 € per minute) prices is used.
- For the shared e-bike services, the Go Sharing price is used (0.23€ per minute)

The revenue parameters are inputted in the model in euros per timestep, which is 10 minutes. Hence, the parameters inputted are 2.8 €, 2.95 €, and 2.3 € per timestep for the shared car, moped, and e-bike, respectively.

The shared car's relocation costs per hour are assumed to be equal to the average hourly wage in the Netherlands (Correia & Antunes, 2012). The relocation costs for the shared scooters and e-bikes equal a tenth of the average hourly wage, assuming that each employee can take ten vehicles in a truck. The average wage in the Netherlands is assumed to be 20 € per hour, considering the salary and allowances. This brings the relocation costs to 3.33 € per 10 minutes per shared car relocated and 0.33 € per 10 minutes per shared moped or e-bike relocated. The operational costs of e-vans and electricity consumption are considered in the operational costs presented below.

To find the capital costs needed to initiate an e-moped sharing company, Wortmann et al. (2021) simulated the usage of e-mopeds in Berlin and combined it with the user's data. For an active fleet of 2,500 vehicles, the capital costs totaled 15,612,793 €. This amount includes the costs related to acquiring the e-mopeds (71.5%), the additional batteries in the depot (14.8%), marketing costs (5.9%), e-vans (2.7%), the charging infrastructure (0.9%), the helmets (0.7%), the app development (0.5%), the e-cargo bikes for battery swapping (0.4%), and finally other costs (0.2%). Some of the costs included in the capital costs are fixed costs such as the app development. However, it is assumed that the capital costs for one active e-moped are equal to the total lifetime capital costs divided by the size of the active fleet, which gives 6,245 € per e-moped. Additionally, it is assumed that the same parameters hold for the users in Berlin and Amsterdam.

To compute the investment costs for the e-bikes, a methodology close to the one used by Wortmann et al. (2021) is adopted by modifying only the cost of buying an e-bike. It is assumed that a shared e-bike costs 750 €, which is the average price of the e-bikes currently available in the market. The ratio of the total fleet over the active fleet is assumed to be the same for e-bikes and e-moped, in that case, 1.35 (Wortmann et al., 2021). This is due to decay, vandalism, and theft. Hence the total capital costs per active e-bike are the sum of the acquisition of 1.34 e-bikes and the fixed costs, which brings it to 2800 € per e-bike. For both e-mopeds and e-bikes, no salvage value is considered.

To compute the investment costs for the shared car, it is assumed that the car is an average electric car costing 20,000 € and can be salvaged after five years for a value of 26.5 % of the initial investment, which gives a present value of 14,700 € (Belastingdienst, 2022). The fixed investment costs accounted for in the calculation of the e-mopeds are added to the present value. These costs include the marketing costs (5.9% of 6245 €), the charging infrastructure (0.9% of 6245 €), the app development (0.5% of 6245 €), and finally, other costs (0.2% of 6245 €). This brings the total investment costs for a shared car to 15,170 €.

Regarding the operational costs, Wortmann et al. (2021) calculate the yearly operational costs for an active fleet of 2,500 e-mopeds to be 4,757,641 € which brings it to 1900 € per year per moped, assuming that the fixed costs can be distributed evenly over the vehicles. This operational cost includes the costs for the personnel (68.3%), the electric consumption of the e-mopeds (8%), the maintenance (7.4%), connectivity fee (7.3%), office rent (2.7%), e-moped insurance (2.2%), e-moped decay (2%), warehouse rent (1.3%), app infrastructure (0.5%), electric consumption of the e-vans (4%), and other elements (0.03%). The costs related to the personnel constitute the majority of the operating costs. It is assumed that the operator incurs the same operational costs for all the shared modes, 1900 € per year. Although the shared e-car has higher maintenance and insurance costs, it is assumed that these costs can be compensated by the decrease in costs related to the warehouse and e-vans.

A maximum number of docks/spaces is set to limit the spatial usage of the mobility hubs. The maximum capacity is 3 shared cars and 15 shared mopeds and e-bikes. Most of the suggested mobility hub locations can house this number of vehicles, corresponding to approximately six car parking spaces. A minimum number of docks/spaces is also set to avoid having a mobility hub with a capacity of 1 or 2 vehicles. The minimum capacity is 1 shared car and 3 shared mopeds and e-bikes per mobility hub.

The parameters used in the *Capacity* module are summarized in Table 4.2.

Table 4.2. Capacity module's parameters

	Fixed	Shared Car	Shared Moped	Shared E-bike
C_{fixed}	5,000 €			
C_{dock}^{m}		500 €	500 €	500 €
C_{op}^{m}		1900 €/year	1900 €/year	1900 €/year
C_{reloc}^{m}		3.33 €/10 min	0.33 €/10 min	0.33 €/10 min
C_{veh}^{m}		15,170 €	6,245 €	2,800 €
R^{m}		2.8 €/10 min	2.95 €/10min	2.3 €/10 min
y_{max}^{m}		3	15	15
y_{min}^{m}		1	3	3

4.3.4. Demand Distribution

The model at hand is a macroscopic model that aggregates the trips spatially and temporally. The 2030 transport data is exported from *Urban Strategy* to perform the analysis because this is a long-term planning problem, and mobility hubs will be implemented in the following years. Since the optimization model distributes the vehicles and simulates how the shared vehicles are located in space and time, the aggregated trips obtained from *Urban Strategy* should be divided into smaller time intervals. The case study is performed for the 2-hour morning peak with timesteps of 10 minutes. Hence, the demand distribution every 10 minutes during the 2 hours is needed. This demand distribution is inputted in the *Capacity* module as p^t.

The ratio of demand per timestep is found using the ODiN data. ODiN (Onderweg in Nederland) is a yearly questionnaire sent out by the Central Bureau of Statistics to around 60,000 respondents. Respondents record their travel behavior on one particular day of the year. The collected data is corrected according to background characteristics and additional non-response among holidaymakers (CBS, 2022).

The 2019 ODiN data is used to find the demand distribution in the morning peak. First, to assess the departure time of the whole trip, only the trips are selected, not the trip legs. Then, the trips with departure times between 7:00 and 9:00 AM are selected. Finally, the trips originating from a postal code within the region of Amsterdam are selected (between longitudes 52.272359 – 52.467305 and latitudes 4.715881 – 5.068130). After filtering the trips needed, the demand distribution over the morning peak is found and presented in Figure 4.8. Although the 2030 transport data is inputted to run the model, the 2019 temporal demand distribution is used to divide the aggregated data into smaller time intervals. Hence, it is assumed that the temporal demand distribution does not vary between 2019 and 2030.

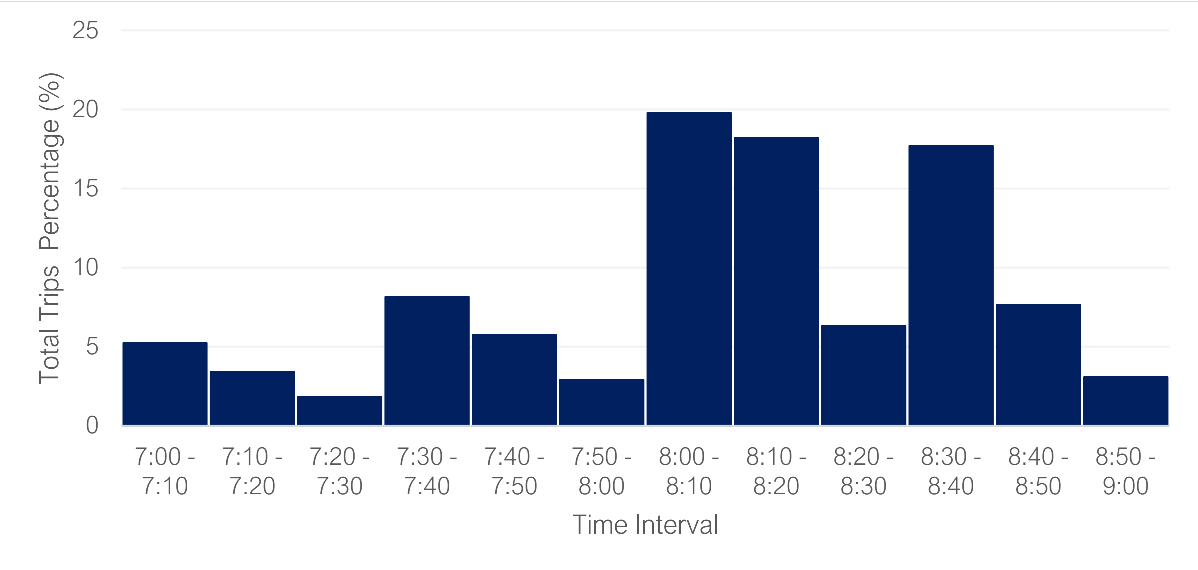

Figure 4.8. Demand distribution over the morning peak

4.4. Model Runs

The genetic algorithm includes several parameters that affect the algorithm's ability to explore the solution space. Therefore, different genetic algorithm parameters have been modified while keeping the inputs related to the budget constant to assess which combination leads to a convergence towards optimality. The parameters modified are the following: the mutation rate, the mechanism of initiation of the population, and the introduction of elitism.

In the initial runs, a budget of 1 M€ is used with mutation rates of 0.1 and 0.3. When running the genetic algorithm with higher mutation rates, it is clear that it does not converge towards any optimum. Increasing the mutation rate to 0.1 and 0.3 leads to a more randomized search, which has the advantage of finding other solutions that are not in the current local solution space of the optimum found, but this leads to losing the strong traits of the individuals. The graphs presented in Figure 4.9 show the evolution of the best solutions over the different generations. A higher mutation rate allows reaching a solution that meets the conditions to compute the fitness (mentioned in section 0 point 2) faster than when a lower mutation rate of 0.1 is used. The first solution that meets the conditions set is found at generations 17 and 33 for the mutation rates 0.3 and 0.1, respectively. However, in this case study, a higher mutation rate led to the shift towards a randomized search of solutions. After 35 generations, the whole population has a fitness of -99999999 which means that the search became random and that a high mutation rate does not suit this problem. The fitness of these random solutions was not assessed since they did not satisfy the conditions mentioned previously. This is why it is possible to assess 1000 generations rapidly without computing any fitness function.

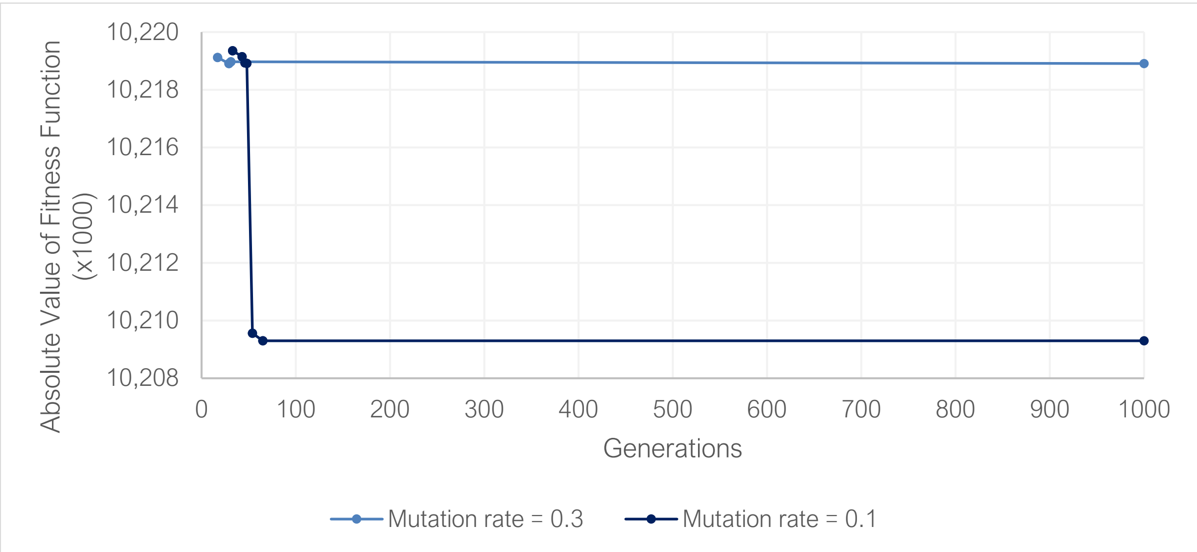

Figure 4.9. Evolution of the best solutions over the generations with different mutation rates

The previous runs present clearly that a lower mutation rate is needed. Therefore, a 0.01 mutation rate is used for the case study. This choice is proved to be the right one since the algorithm can converge toward feasible solutions. In addition to that, two crossover methods (one-point and two-point) are tried, but the convergence rate is not affected. Hence, a one-point crossover method is adopted due to minor savings in computation time compared to a two-point crossover. The population size used in all the runs is 50 individuals. The limited population size is due to the requirement of limiting computation time. After several trials and short runs, a 10%

elitism is used in the subsequent runs since it can conserve the best solutions (5 in that case) through the generations, which avoids losing the best traits. In some cases where elitism is not used, the population diverges toward solutions with a fitness of -99999999.

Four computers and servers are used to perform the runs. The computation time for each individual varies mainly depending on the device used and the number of hubs activated. The specifications of the devices used are presented below, along with the average computation time per individual:

- I9 – 9900X CPU @3.5 GHz 20 Logical cores, 64 GB RAM with a 24 GB NVIDIA Titan RTX GPU. The average computation time is 180 seconds per individual.
- Google Collab Pro Servers, 25 GB RAM with K80, T4, or P100 GPU. The average computation time is 220 seconds per individual.
- I7 – 9750H CPU @ 2.6 GHz 12 Logical cores, 16 GB RAM with a 4 GB NVIDIA Quadro P2000 GPU card. The average computation time is 305 seconds per individual.
- I7 – 6820 HK CPU @ 2.7 GHz 8 Logical cores, 16 GB RAM with a 1 GB NVIDIA GeForce GTX 980M. The average computation time is 330 seconds per individual.

The computations performed at each iteration are heavy since the different paths, utilities, and demands are computed for more than 9 million OD-pairs. However, the computation time has been severely reduced and optimized to reach the above values. The *Path and Usage* and *Demand Estimation* modules are performed on the GPU, which reduces that computation time by an order of 10^4. Additionally, all the sums present in the *Capacity* module are processed on the GPU to save computation time and then inputted into the Xpress library as variables. Furthermore, the centroids that can not use any shared mode because they are only dummy centroids are not part of the shortest path computation, which saves computation time. It is essential to mention that the computation time also varies depending on the number of activated hubs. The computation time can sometimes reach more than 3000 seconds per individual solution. Before introducing those measures, the computation time of each individual was around 55 days, leading to a total computation time of hundred years for the overall algorithm. Hence, taking advantage of GPU computing technology offers substantial benefits. For each scenario, the convergence is reached after approximately 150 generations, with each generation having 50 individuals. Considering the average computation times per individual, each scenario took around 20 days to run.

Three scenarios are run with different budgets of 0.5, 1, and 1.5 million euros. For each scenario, two runs are performed to assess whether they converge towards the exact optimum. That way, the chance of being stuck at a local optimum is reduced, and it can be considered that the optimum reached is a global optimum. It is essential to mention that the two runs have the same parameters but are initiated with different populations. In some cases, the two runs do not converge to the same value due to minor rounding errors in the computation.

The first run is performed by initiating a population constituted of the first half with entirely random individuals and the second with random individuals following a certain proportion of activated hubs. The proportion of activated hubs is set depending on the budget used. It is equal to the number of hubs that can be activated with the set budget if a maximum of shared cars are assigned to each hub: $\frac{Budget}{C_{dock}^{0} \times y_{max}^{0} + C_{fixed}}$. The choice of shared mode in the initiation process does not affect the result; it just orients the genetic algorithm towards a solution space that meets the preliminary conditions to compute the fitness function. The second run is performed by initiating a completely random population. The evolution of the best solutions over the different generations is presented in Figure 4.10. The algorithm is assumed to converge toward the optimal solution since a plateau has been observed over the last 70 generations. It is important to note that when the initiated population is entirely random, the convergence rate is slower (28 days) than when half of it is initiated with a certain proportion of activated hubs (19 days).

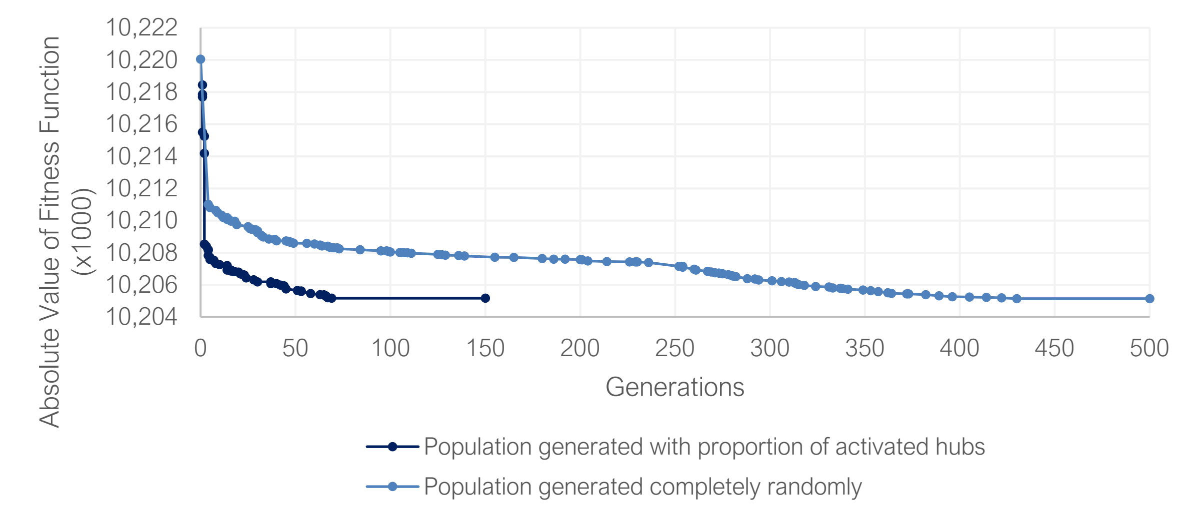

Figure 4.10. Evolution of the best solutions over the generations for a budget of 1 M€

In the previous run, it is proven that initiating a population with a certain proportion of activated hubs leads to faster convergence. Hence, the same initiation procedure is adopted in the other scenarios. For the second scenario with a lower budget of 0.5 M€, the evolution of best solutions over the different generations is presented in Figure 4.11. The algorithm is assumed to converge towards the optimal solution since a plateau is observed for both runs over the last 79 and 111 generations. This scenario takes approximately 17 days to run.

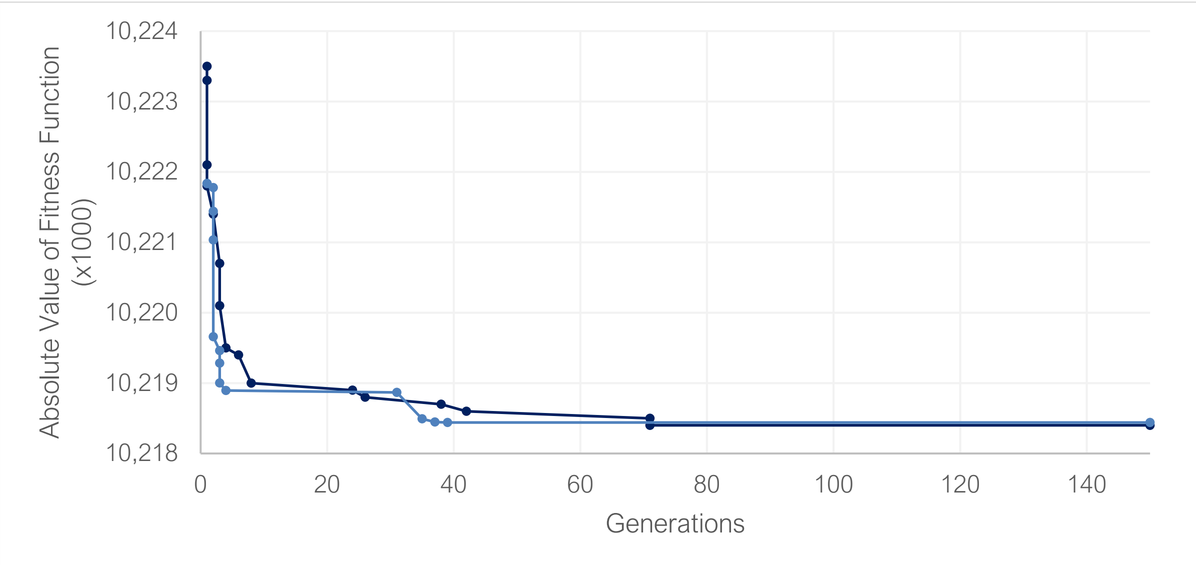

Figure 4.11. Evolution of the best solutions over the generations for a budget of 0.5 M€

For the third scenario with a higher budget of 1.5 M€, the evolution of best solutions over the different generations is presented in Figure 4.12. Again, the algorithm is assumed to converge towards the optimal solution since a plateau has been observed for both runs over the last 81 and 73 generations. This scenario takes approximately 25 days to run.

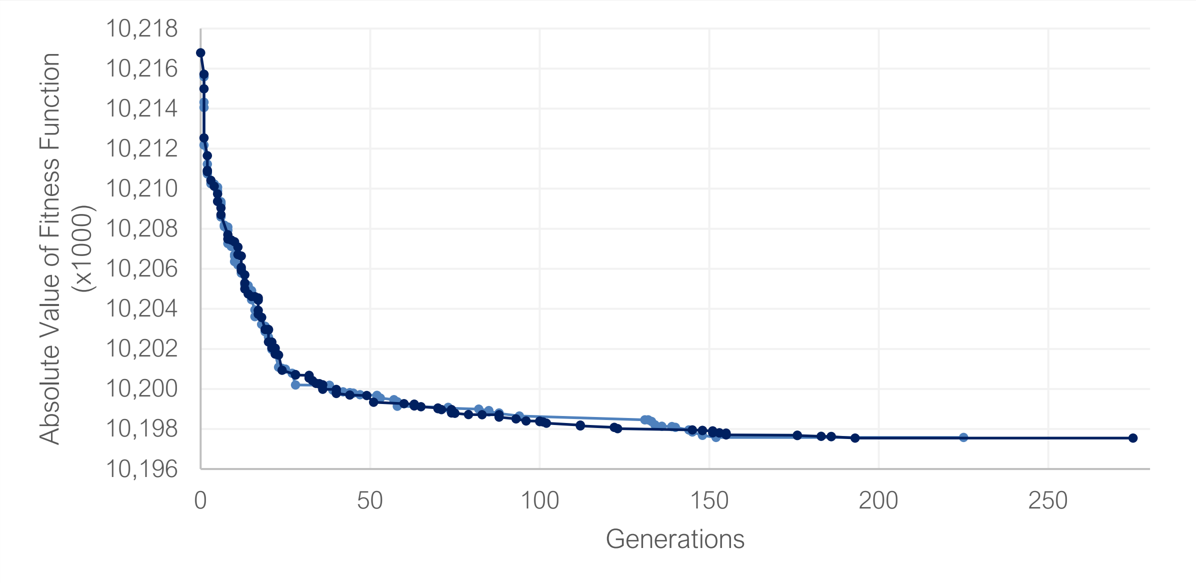

Figure 4.12. Evolution of the best solutions over the generations for a budget of 1.5 M€

4.5. Results

After running the algorithm for several generations, it is assumed that the global optimum is reached. The distribution of hubs obtained for a budget of 1 M€ is presented in Figure 4.13. The buttons under the figure can be used to check maps that include the respective service areas, the average neighborhood income, the population density, the locations of train stations, and the capacities of the hubs. The algorithm activates 116 hubs and distributes them uniformly over the different neighborhoods. More hubs are located in the central part of Amsterdam compared to Amsterdam South-East, North, and West. The distribution of activated hubs is compared with the population density map (Figure B.7) and the average neighborhood's income (Figure B.4). It can be seen that a considerable number of mobility hubs are activated mainly in highly dense areas having an average yearly income smaller than 60,000 €. Another important indicator is that the model locates the mobility hubs near main train stations, as seen in Figure B.10. Except for some stations in Amsterdam South-East (Amsterdam-Zuidoost).

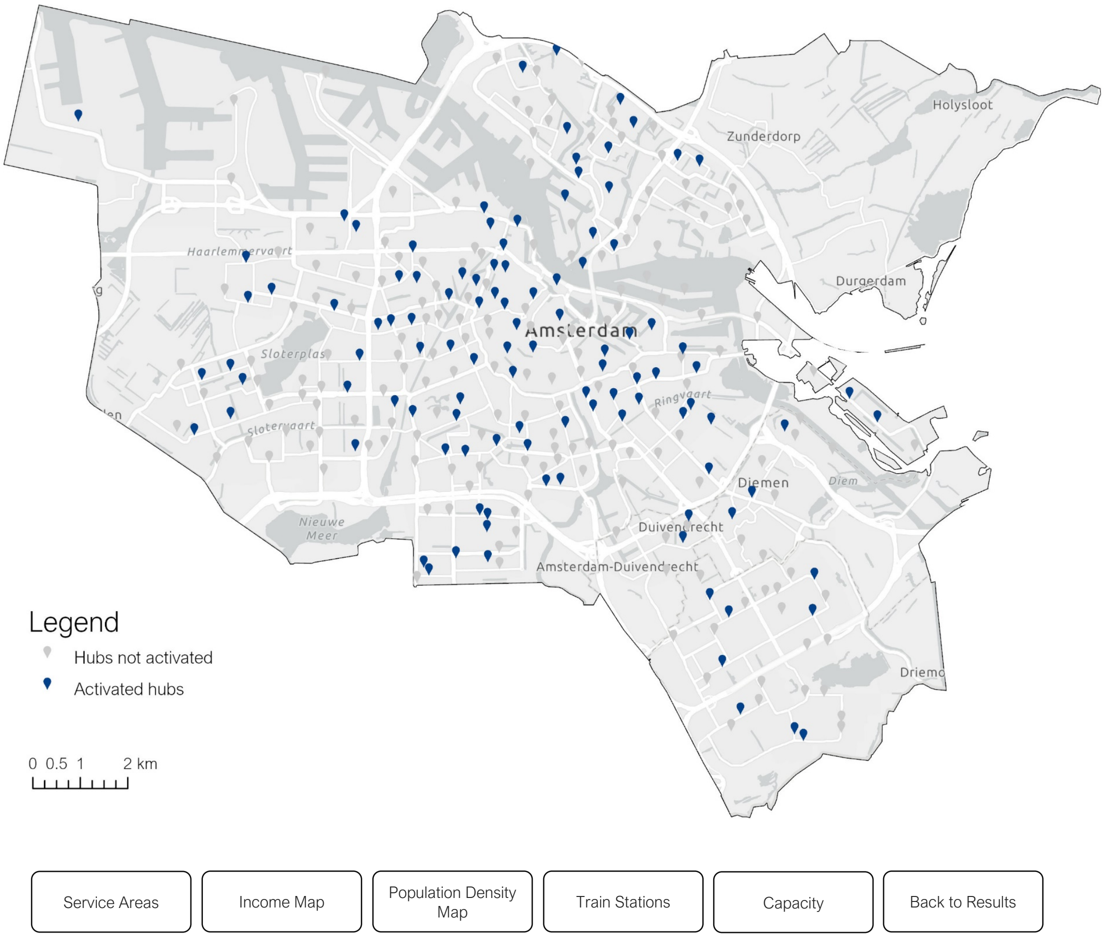

Figure 4.13. Distribution of activated mobility hubs for a budget of 1 M€

For a lower budget of 0.5 M€, the algorithm activates 58 hubs, as seen in Figure 4.14. The service areas cover mainly the areas in the central part of Amsterdam, as seen in Figure B.2. The same pattern of activating the hubs in dense areas and lower to medium-income neighborhoods is seen in Figure B.5 and Figure B.8.

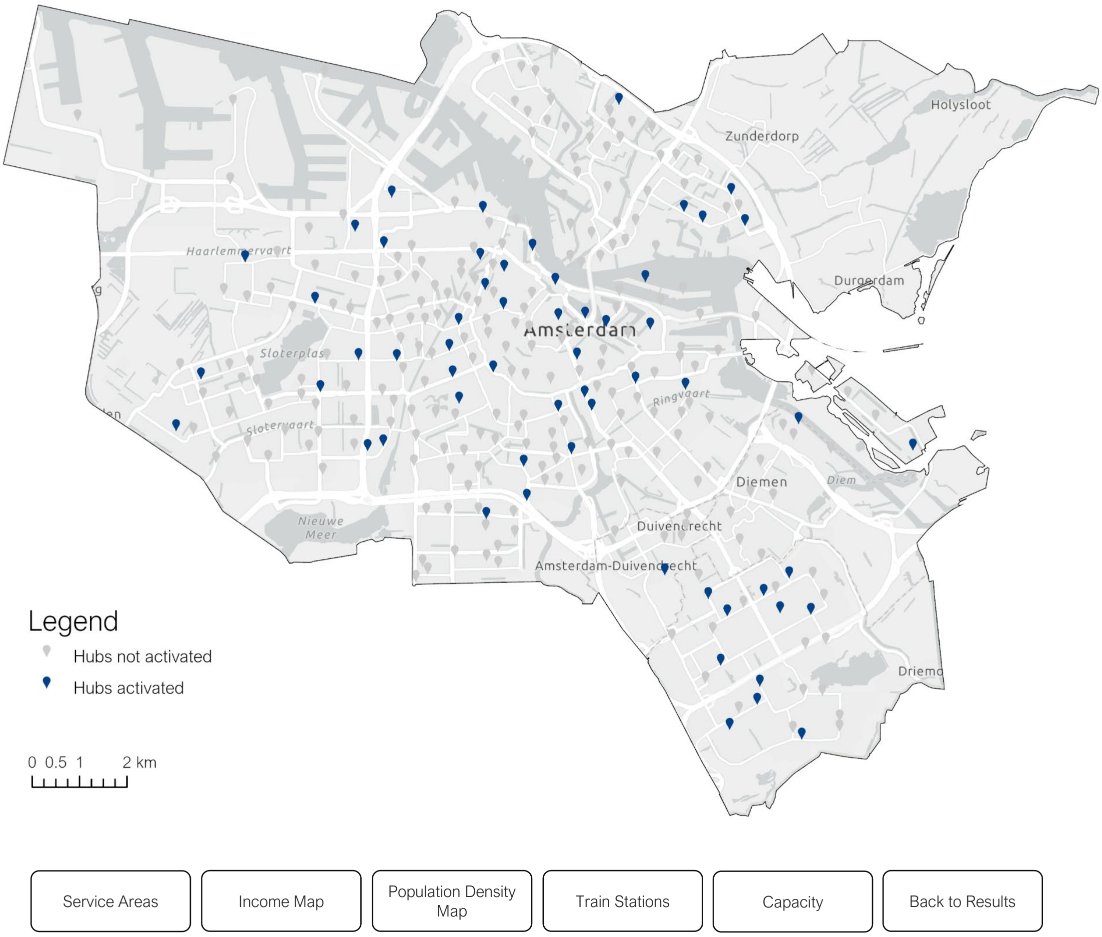

Figure 4.14. Distribution of activated mobility hubs for a budget of 0.5 M€

The distribution of hubs obtained for an allocated investment budget of 1.5 M€ is presented in Figure 4.15. This investment leads to extensive coverage of the Amsterdam area while distributing the hubs evenly.

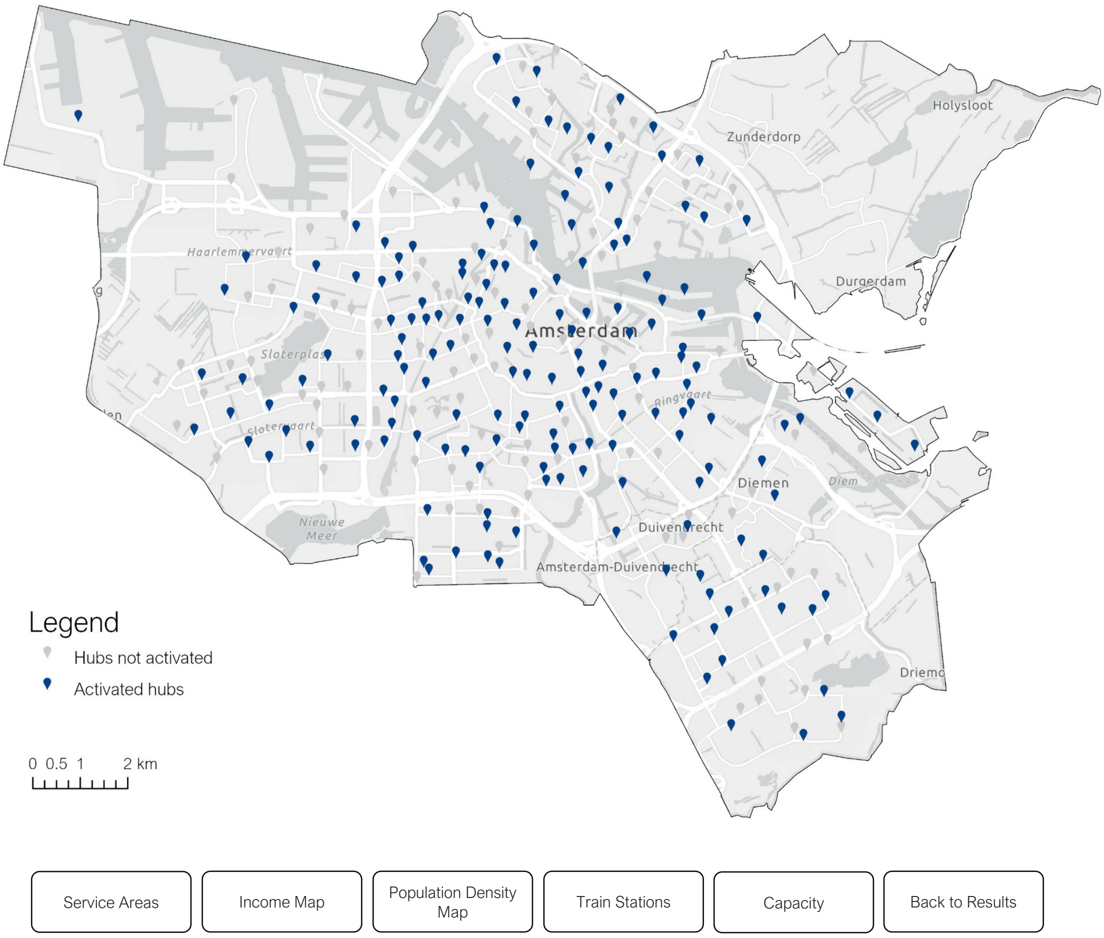

Figure 4.15. Distribution of activated mobility hubs for a budget of 1.5 M€

The variation in the capacity of the mobility hubs is presented in Table 4.3. In all the scenarios, the hubs have capacities close to the minimum capacities set for each shared mode. This is also reflected in the averages obtained. Few hubs have capacities exceeding the minimum. Higher capacities are set for the shared mopeds compared to the shared e-bikes.

Table 4.3. Statistics of the mobility hubs' capacities depending on the budget allocated

	Budget (M€)	0.5	1	1.5
Shared Car	Average	1.16	1.12	1.01
	Minimum	1	1	1
	Maximum	3	3	2
Shared Moped	Average	3.14	3.06	3.13
	Minimum	3	3	3
	Maximum	11	5	13
Shared E-bike	Average	3.00	3.07	3.05
	Minimum	3	3	3
	Maximum	3	8	9

The algorithm provides the distribution of mobility hubs that maximizes social welfare for the different budgets. This distribution is used to compute the following indicators: the modal split, the total travel time experienced, the kilometers traveled per mode, the percentage of people covered by mobility hubs' service areas, the average income of the population covered by the mobility hubs' service areas, the ratios of demand satisfied, and the reduction in emissions. This allows having a better understanding of the impact of mobility hubs and how the indicators vary depending on the allocated budget to install the mobility hubs.

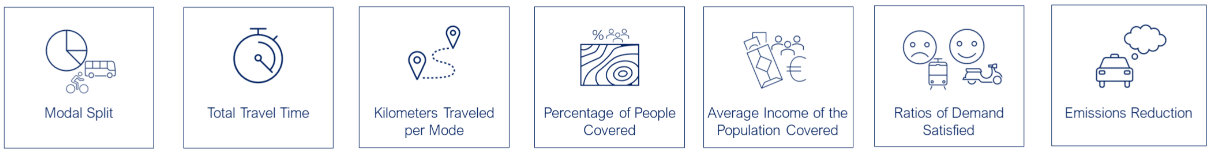

Figure 4.16. Indicators assessed

The indicators are computed for five scenarios: the first one with no mobility hubs activated, the following three scenarios with an allocated budget of 0.5, 1.0, 1.5 M€, and a final scenario with all the 288 mobility hubs activated, which needs a budget of 6.192 M€. It is essential to note that the indicators related to the base scenario, where no mobility hubs are activated, are computed using the skim matrices and OD-matrix rather than exported directly from *Urban Strategy*. This is because *Urban Strategy* considers some variation between population groups, making the comparison with other scenarios less reliable.

The modal splits for the five scenarios are presented in Table 4.4 and Figure 4.17. When installing mobility hubs with different allocated budgets, there is a decrease in the modal split of the bike, car, and public transport, while the walking modal split remains the same. The most significant decrease is seen for the bike: around 0.11 % and 3% for allocated budgets of 0.5 M€ and 6.2 M€, respectively. This result is logical since shared modes can substitute bike trips and provide faster means of transport. The second highest decrease is seen for the personal cars: around 0.07% and 1.55% for budgets of 0.5 M€ and 6.2 M€ respectively. Finally, the public transport split decreases by 0.027% and 0.523% for budgets of 0.5 M€ and 6.2 M€. Around 55%, 32%, and 13 % of the trips made using shared modes replace trips previously made using bike, car, and public transport, respectively (as seen in Figure C.1).

Table 4.4. Modal split (%) for the different budget scenarios

Budget (M€)	0	0.5	1	1.5	6.2
Walk	20.758	20.758	20.758	20.758	20.758
Bike	28.321	28.211	28.117	27.634	25.329
Car	43.757	43.691	43.649	43.419	42.208
Public Transport	7.164	7.137	7.116	7.035	6.641
Shared Car	-	0.021	0.018	0.167	0.683
Shared Moped	-	0.125	0.223	0.730	3.859
Shared E-bike	-	0.036	0.090	0.212	0.410
Shared Car + Public Transport	-	<0.001	<0.001	0.001	0.006
Shared Moped + Public Transport	-	0.003	0.004	0.012	0.066
Shared E-bike+ Public Transport	-	0.018	0.025	0.032	0.041

Shared moped takes the largest share of trips (0.13% and 3.92% for allocated budgets of 0.5 and 6.2 M€, respectively) since they are faster than e-bikes and the fare difference is relatively small. The modal split for the shared cars slightly decreases when comparing the scenarios with budgets of 0.5 and 1 M€. This is explained by the fact that mobility hubs serve fewer shared car trips, but those served are longer, as seen in Figure C.6. The modal split for the shared modes is relatively small for the scenarios with lower budgets of 0.5 and 1 M€. However, it increases significantly when higher investments are made.

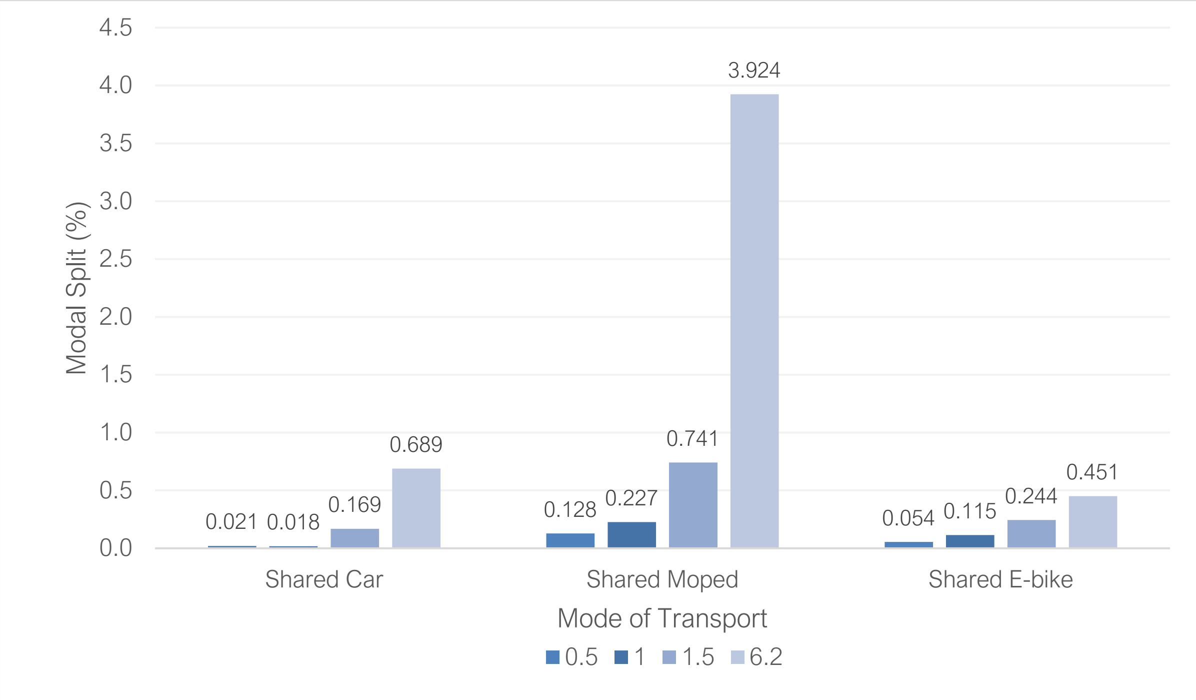

Figure 4.17. Comparison of modal splits of shared modes for different budget scenarios

The significant benefits gained by higher investments are also highlighted in Figure 4.18. The higher reductions in total travel time are seen with investments higher than 1 M€. The same effect is confirmed when looking at the total traveled kilometers using shared modes in Appendix C (Figure C.6. - Figure C.8).

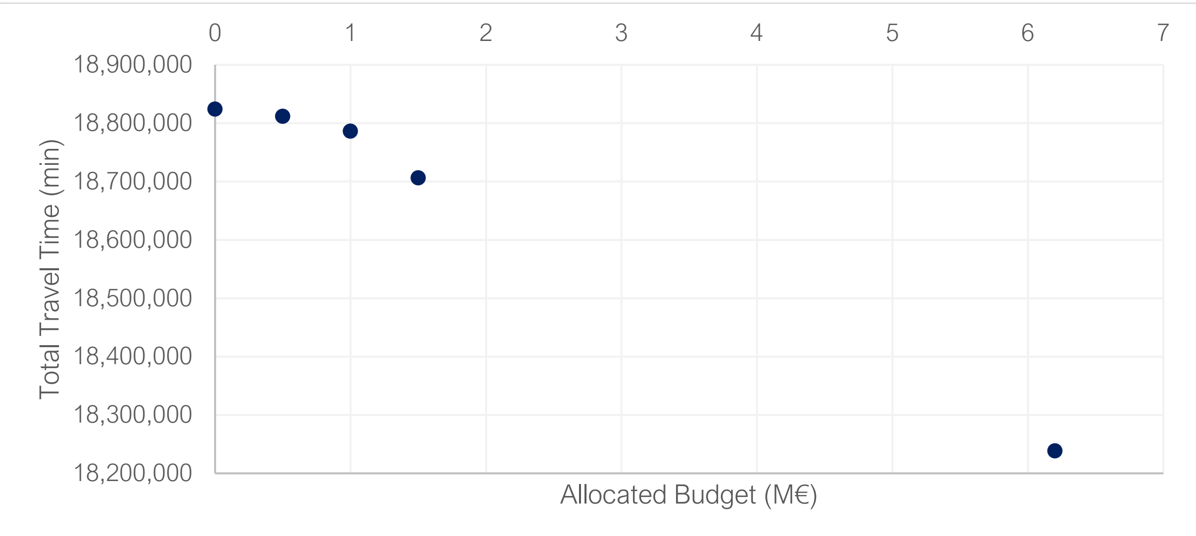

Figure 4.18. Decrease in total travel time depending on the budget allocated to build the mobility hubs

Another interesting indicator to assess is the average percentage of demand satisfied over the different time periods, presented in Table 4.5. The average percentage of demand satisfied decreases between the scenario of 0.5 and 1 M€ since increasing the budget increases the demand that can be satisfied. The mobility hubs might not be able to satisfy this increase in demand. Nevertheless, an overall trend can be noticed: increasing the allocated budget leads to higher percentages of demand satisfied. The high standard deviation proves a high fluctuation between the different time periods, which is also highlighted by the extremums (0 and 100%).

Table 4.5. Statistics of the percentages of demand satisfied depending on the budget allocated

	Budget (M€)	0	0.5	1	1.5	6.2
Shared Car	Average	-	5.6	4.8	26.9	71.3
	Standard Deviation	-	16.0	16.7	30.6	36.9
	Minimum	-	0.0	0.0	0.0	0.0
	Maximum	-	100.0	100.0	100.0	100.0
Shared Moped	Average	-	9.6	7.4	16.7	61.6
	Standard Deviation	-	13.8	10.7	15.6	40.4
	Minimum	-	0.0	0.0	0.0	0.0
	Maximum	-	99.6	95.5	100.0	100.0
Shared E-bike	Average	-	87.4	82.7	92.1	90.3
	Standard Deviation	-	31.6	36.8	24.3	28.7
	Minimum	-	0.0	0.0	0.0	0.0
	Maximum	-	100.0	100.0	100.0	100.0

To assess whether the shared modes are used for short or long trips, the percentages of trips traveled using a shared mode for each travel time interval are presented in Figure C.9 to Figure C.16. First, the weighted average travel time is computed prior to introducing the shared modes for each OD-pair. Next, the number of trips performed using a shared mode is computed for each OD-pair. Then the percentages of trips performed using a shared mode are computed for each travel time interval and each scenario. In all the scenarios, the same patterns are seen. Shared modes are combined with public transport, mainly when the average initial trip length is higher than 40 minutes. 60% of the trips combining shared modes and public transport are longer than 40 minutes. In contrast, shared modes are used independently for trips between 10 and 50 minutes. Shared mopeds cover the highest percentage of trips having a travel time between 20 and 30 minutes. In comparison, shared cars and shared e-bikes cover the highest percentage of trips with a travel time between 10 and 20 minutes.

After assessing the effects of mobility hubs using mobility indicators, the spatial distribution of the hubs is analyzed. The percentages of residents covered by the 0 – 250 m, 250 – 500 m, 500 – 750 m, and higher than 750 m are presented in Figure 4.19. It is clear that when increasing the budget allocated to mobility hubs, a higher percentage of the population is closer to a mobility hub. It is also interesting to note how the percentage of the population within 250 m of a mobility hub is equal to 17% for a budget of 1.5 M€ and 30% for a budget of 6.2 M€ which means that initial budgets (lower than 1.5 M€) focus on maximizing coverage and additional investments have diminishing returns in terms of coverage. For the service area of 250 – 500 m, the increase in budget always increases the coverage. However, it is not the case for the service area of 500 – 750 m. Increasing the budget from 0.5 to 1 M€ shifted a percentage of people that were outside of the 750 m service area to the area within 500 to 750 m of a mobility hub. While maximizing the budget leads to a decrease in the population covered by a service area larger than 500 m since a high percentage is now 500 m away from a mobility hub.

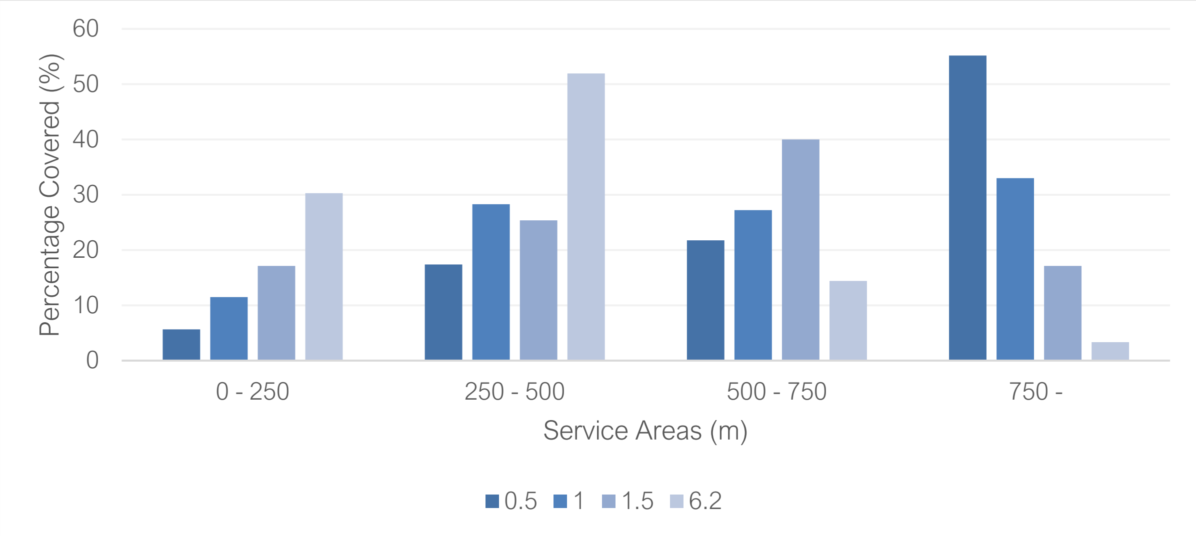

Figure 4.19. Comparison of the percentage of residents covered by the mobility hubs' service areas depending on the budget allocated

Further insights can be obtained when relating the spatial coverage with the current socio-economic data of the neighborhoods. The average income for the residents covered by the 0 – 250 m, 250 – 500 m, 500 – 750 m, and higher than 750 m are presented in Figure 4.20. When the budget is maximized, the average yearly income of the population covered decreases which means that the service areas of the mobility hubs cover more lower-income areas. Increasing the budget always decreases the average income of the population covered by the 250 m service area. In contrast, this is not always the case for the service areas between 250 and 750 m. This can be explained by the fact that increasing the allocated budget leads to higher coverage of areas that might have a higher average income. In most scenarios, the population not covered by a 750 m service area always has a smaller income than the population within 500 m of a mobility hub.

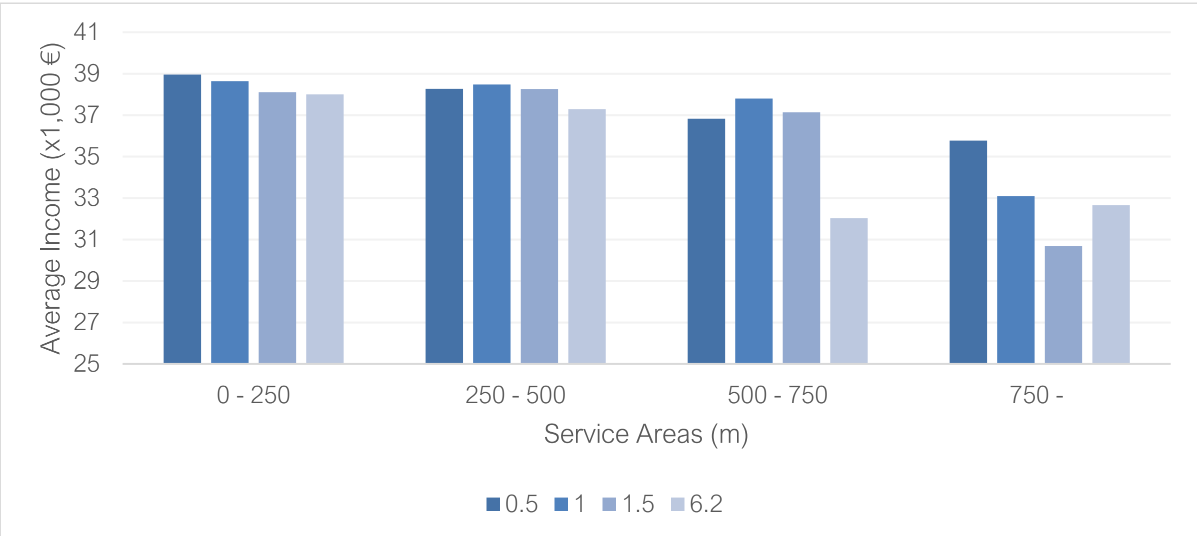

Figure 4.20. Comparison of the average income of the population covered by the mobility hubs' service areas depending on the budget allocated

Finally, the effect of the mobility hubs on the environment is assessed. To compute the net reduction in emissions for the different scenarios, the emissions generated by the shared modes from the traveled kilometers and relocation operations are added. Then the emissions generated from the reduction in traditional modes of transport are subtracted. The emissions are obtained by multiplying the kilometers traveled by the CO_2 emissions per mode per passenger-kilometer. These values are obtained from the "Effect of shared electric mopeds on CO_2 emissions" report (CE Delft, 2021). For the relocation operations of shared cars, the emissions of an electric car are used. While for the relocations of shared mopeds and shared e-bikes, the emissions for an electric van are used, and it is assumed that each van can relocate ten vehicles at a time (as mentioned in paragraph 4.3.3). The CO_2 emissions per mode might vary depending on the assumptions made in the calculation process. The assumptions can be related to the vehicle type, speed traveled, the electricity generation mix, the usage patterns of the vehicles, and the vehicle's occupancy (OECD/ITF, 2020). The reduction in emissions is computed for all the scenarios by comparing them to the base scenario with no mobility hubs. It is calculated for two cases; the first one considers that the electric cars constitute 8 % of the total fleet of cars and the electric buses 50% of the total fleet of buses. In contrast, the second case considers that all vehicles are electric.

It can be concluded that the reductions in CO_2 emissions are limited, with a maximum of 1.27% for the case where all mobility hubs are activated, and a mixed composition of cars is still available. The reduction is even more limited when all the vehicles traveling in Amsterdam are electric. The results obtained refer to the emissions while using the vehicles.

Table 4.6. Reduction in emissions per scenario

	CO_2 emissions per mode (CO_2 -eq g/pkm)	Budget (M€)			
		0.5	1	1.5	6.2
Traveled kilometers (km)					
Shared cars	80	390	426	4014	17587
Shared mopeds	16	6374	10948	35588	199653
Shared e-bikes	6	1531	3123	6815	12871
Relocated vehicles.kilometers (veh.km)					
Shared cars	80	369	530	283	5853
Shared mopeds	106	457	722	2688	47876
Shared e-bikes	106	803	1797	4879	9741
Variation in kilometers traveled using traditional modes of transport (km)					
Walk	0	+704	+857	+3200	+8716
Bike	0	-4364	-8382	-27405	-129453
Car	217 (80 for all electric)	-7286	-9821	-24094	-106445
Public Transport	88 (84 for all electric)	-3132	-4451	-10232	-41520
Emissions Reduction					
Total Reduction in Emissions (CO_2 – eq T)		-1.67	-2.23	-5.10	-21.02
Percentage reduction in CO_2 emissions (%)		-0.10	-0.14	-0.31	-1.27
Total Reduction in Emission for the case where all vehicles are electric (CO_2 – eq T)		-0.66	-0.86	-1.75	-6.23
Percentage reduction in CO_2 emissions for the case where all vehicles are electric (%)		-0.04	-0.05	-0.11	-0.38

However, the net emission variation differs if the life-cycle emissions are considered. Therefore, the average values presented by OECD/ITF (2020) are used to compute these life-cycle emissions. OECD/ITF (2020) presents central values estimates of life-cycle greenhouse gas emissions for urban transport modes. These include vehicle, fuel, infrastructure, and operational components. The values used are the following: for shared cars: 125 CO_2-eq g/pkm, for e-mopeds: 79, for e-bikes: 83, for all relocation operations: 125, for personal bikes: 17, for personal cars: 135, for public transport: an average of 72. Using these values leads to a reduction in CO_2 emissions of 0.05% for the scenarios with budgets of 0.5 to 1.5 M€. In comparison, introducing shared modes on a large scale (scenario with a budget of 6.2 M€) leads to an increase of 0.09 % in life-cycle CO_2 emissions. The life-cycle emissions numbers are not precise since the values used to compute them are global averages with an average energy mix rather than the Dutch energy splits.

4.6. Sensitivity Analysis

The model includes several parameters that might affect the model's results. A sensitivity analysis is performed on the operation costs (C_{op}^{m}), relocation costs (C_{reloc}^{m}), and vehicle acquisition costs (C_{veh}^{m}). It is impossible to assess the parameters' impact on the results due to the high computational time. Hence, to perform the sensitivity analysis, all the mobility hubs are activated, and the different parameters are modified accordingly. The relocation costs have been varied between 2, 2.5, 3, 3.33, 4, 4.5 € per 10 minutes timestep for shared cars and between 0.20, 0.25, 0.30, 0.33, 0.40, 0.45 € per 10 minutes timestep for shared e-bikes and mopeds. Hence, 36 instances are computed to assess the impact of the relocation costs on the social welfare and ability to relocate. All the instances have fitness functions varying between -10,180,460 and -10,180,553. The variation is negligible, which means that this parameter does not influence the results. The same method is adopted to assess the impact of the acquisition costs by varying those costs between 15000, 17000, 19000, 21000 € per shared car and 5000, 6000, 6245, 7000 € per shared moped and 1500, 2000, 2811, 3500 € per shared e-bike. Hence, 64 instances are computed and the fitness function varies between -10,180,462 and 10,180,555. The operational costs are also varied to obtain the same result: these parameters do not affect the results and distribution of vehicles. The main reason behind these results is that the revenue generated from these services is considerably higher than the costs. In addition, the positive net revenue (presented in constraint 3.13) is a sum of the net revenues for all the services provided; hence if one of the shared modes is not profitable, the other shared modes can compensate for these losses to keep the net revenue positive. This explains that varying the parameters presented does not affect the final results.

To assess how much the costs can be increased without impacting the final results, an additional variable is subtracted from constraint 3.13. This variable represents the gross profit that the operator receives. The initial constraint 3.13 has the general form of Revenues – Costs≥0; the gross profit corresponds to the amount of money the operator makes, which is added as a separate variable to obtain the following general constraint: Revenues – Costs – Gross Profit≥0. The sensitivity analysis is performed on the gross profit by adopting the same procedure of activating all the mobility hubs. The results obtained show that social welfare remains constant if the gross profit varies between 0 and 80% of the total revenues. However, the problem becomes not feasible if the gross profit surpasses 81%. This shows that there is a high margin to increase the costs assumed in the model, which means that even if additional costs are added, the results are not affected. It is essential to note that a gross profit of 80% does not mimic a real-life situation. However, no additional costs are added since having additional costs would decrease the relocation of vehicles to a relatively same degree in all the runs, which is not expected to change the results of optimal locations.

4.7. Convergence Validation

A significant challenge when applying the genetic algorithm is ensuring that the algorithm is not stuck on a local optimum. This problem is mainly associated with the fact that the population loses genetic diversity, which leads to a focus on one solution space. A mutation rate of 0.01 is used in the case study to overcome this challenge, which means that each bit has a 1% probability of being changed. Hence, 2 to 3 bits from the 288-bit chromosome are mutated for each individual. Two checks are performed to ensure that the genetic algorithm developed reaches the global optimum. The first one is by running each scenario twice and ensuring that the algorithm converges towards the same solution. The second check is performed by creating a case where a specific distribution of hubs is imposed as the best one and ensuring that the genetic algorithm reaches it.

For this purpose, the same network of Amsterdam and the 288 potential mobility hub locations are used. Keeping all the modules and interactions in the model makes it impossible to impose an optimal solution. Hence, the model is modified to impose one solution as the optimal one. 160 from the 288 mobility hubs are randomly chosen and stored in an array. All the OD-pairs using the other 128 mobility hubs ($\mathcal{N}_{rejected}$) are always rejected access to shared modes, and the utility of traditional modes is applied. The fitness function used is the following:

$$C = \sum_{i\in\mathcal{N}}\sum_{m\in\mathcal{M}}\sum_{t\in T}\left(x_i^{mt} \times \sum_{j\in\mathcal{N}}\sum_{k\in K} d_{ij}^{mk} \times p^t \times U^{mk}\right) + \sum_{i\in\mathcal{N}}\sum_{m\in\mathcal{M}}\sum_{t\in T}\left(\left(1 - x_i^{mt}\right) \times \sum_{j\in\mathcal{N}}\sum_{k\in K} d_{ij}^{mk} \times p^t \times U_{TradRej}^{k}\right) + U_{Total\,Trad}$$

The following constraints are added:

- $x_i^{mt} \leq z_i^m$ (Constraint to ensure that the ratio of satisfied demand is one if the mobility hub is activated or is zero if the mobility hub is not activated)
- $x_i^{mt} = 0$ for $i \in \mathcal{N}_{rejected}$ (Constraint to ensure that the OD-pairs using the 128 chosen mobility hubs are always rejected access to shared modes)
- $x_i^{mt} \in \{0,1\}$ (Constraint to ensure that the ratio of demand satisfied is either one or zero)

Although the capacity module is not included in this trial, the size and variation in the fitness function are similar to the model developed. Hence, it is possible to prove that the algorithm effectively converges. The evolution of the solution is presented in Figure 4.21. After 252 generations, the algorithm reaches the imposed optimal solution. Many generations are needed to converge towards the imposed optimal solution since the population was generated entirely randomly. Additionally, the algorithm reaches solutions close to the global optimum within 120 generations and spends an equal number of generations to reach the exact global optimum. It is clear from the evolution of the best solutions that no intermediate plateaus are present, which gives additional confirmation that the global optimum is reached in the case study. It is also essential to note that the fitness function is smaller than in the previous scenarios since this convergence validation does not consider capacity.

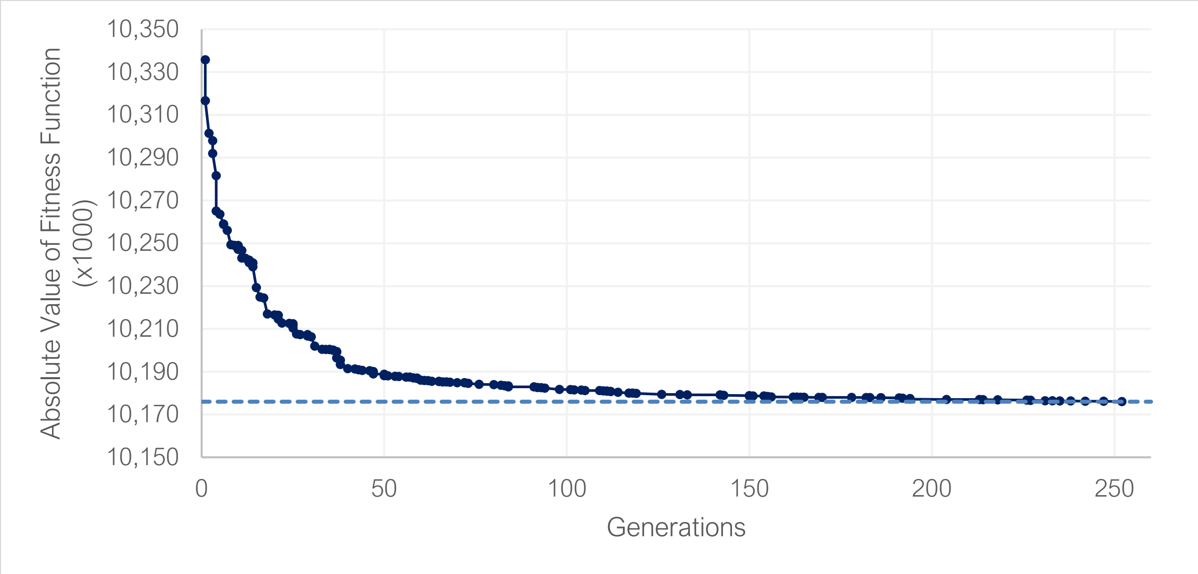

Figure 4.21. Evolution of the best solutions over the generations to reach the imposed optimal solution

05

DISCUSSION

Photo taken by the author – Paris, December 2021

5. Discussion

In the following chapter, the results obtained for the case study are discussed in section 5.1. Next, the model's limitations and the impact of the assumptions made are discussed in section 5.2. Finally, the generalizability of the model and results is discussed in section 5.3.

5.1. Discussion of Results

The model developed is used to distribute the mobility hubs for different investment budgets to maximize social welfare. When a low budget is set, the algorithm suggests an even distribution of hubs in Amsterdam, with more hubs located in the center. After comparing the solution with the population density map, it is concluded that the model prioritizes distributing hubs in highly dense areas. More hubs are then located in less dense areas when increasing the budget. From the results obtained and the number of hubs activated for a budget of 0.5 M€, the algorithm prioritizes activating many hubs with lower capacities rather than larger ones with higher capacities. This can be explained by the fact that increasing the mobility hubs' coverage leads to covering more demand, serving more OD-pairs, and providing more utility gains. However, activating many smaller hubs leads to higher fixed costs, which means fewer vehicles are available to satisfy the demand. This is reflected by the low travel time gains and modal split for the shared modes when smaller budgets are invested. A more extensive network of hubs provides the ability to serve more trips leading to substantial gains in terms of travel time and trips served. With smaller budgets, the benefits are limited compared to when the investments are increased. Increasing marginal returns are associated with the benefits mentioned. When investing 0.5 M€ in building mobility hubs, the travel time savings are equal to 49 minutes per 1,000 € invested, while when increasing the budget from 1 M€ to 1.5 M€, the travel time saved accounts for 160 minutes per 1,000 € (as seen in Figure 4.18). After providing complete city coverage, the marginal returns are expected to become constant since every euro invested would be used for additional vehicle capacity rather than building a new hub. Therefore, the same amount of money can have different benefits depending on the total investment made.

To understand the reasons behind the algorithm's choices, the demand for each hub and the average utility gains per trip are mapped in Figure B.16. These parameters are mapped when all the 288 mobility hubs are activated; hence, they are subject to change for a different distribution of mobility hubs activated. However, this map gives a good overview of the relation between the demand, the utility gains, and the results obtained. In the scenarios with an allocated budget of 0.5 M€, it can be visually deduced that hubs with higher utility gains are chosen. In some cases, adjacent hubs are chosen since the utility gains might vary depending on the network of activated hubs. When higher budgets are allocated, both utility gains and demand play a role in selecting the optimal distribution of hubs and capacities. It can be seen that many hubs located on the outskirts of Amsterdam are activated since they provide significant benefits per trip. In the scenario of 1.5 M€, the largest hub in terms of capacity is located in Java-eiland. This can be explained by the fact that the utility gains per trip are considerable. When checking on Google Maps, a trip from Java-eiland to Rijksmuseum, for example, takes around 17, 21, and 30 minutes by bike, car, and public transport, respectively. Hence, shared modes can shorten travel times considerably for such trips due to their speed and ease of access.

The results related to the distribution of hubs are then used to assess the shift towards shared mobility and its impact on the environment. The trips made using shared modes mainly replace trips made initially by bike, car, and public transport. Around 55%, 32%, and 13% of the trips made using shared modes were to be made by bike, car, and public transport, respectively, if shared modes were not introduced. These percentages match with some of the percentages found in the literature. Many papers found that more than half of the electric micromobility trips seem to substitute public transport and active modes (Liao & Correia, 2022). The shift percentages vary depending on the city assessed and the method adopted to measure them (Wang et al., 2022), with conflicting evidence on whether shared modes predominantly substitute biking or walking (Liao & Correia, 2022). In the Amsterdam case study performed, a negligible number of trips shifted from walking to shared modes. This can be explained by the fact that there is a high reliance on bikes in Amsterdam, and individuals that want to make their trips faster would have shifted previously to biking. Hence shared modes seem a better substitution for bikes than walking trips in the case of Amsterdam. The higher percentage shift to shared modes from the bike and public transport compared to cars leads to lower emissions benefits. The CO_2 emissions reductions for lower allocated budgets are limited (around 0.1%), while for the higher allocated budget of 6.2 M€, the emissions decrease by 1.27% compared to the base scenario. This reduction is even smaller (around 0.38%) when considering the case where all vehicles replaced are electric. Hence, the argument that shared modes lead to a significant reduction in CO_2 emissions is debatable. When considering the central estimates of life-cycle greenhouse gas emissions rather than just the emissions produced while traveling, the introduction of shared modes on a large scale (budget of 6.2 M€) leads to an increase of 0.09% in total emissions. An increase in life-cycle emissions was also obtained for a case study applied in Zurich when shared modes were introduced (Reck et al., 2022). However, it is essential to keep in mind that the numbers used to compute the life-cycle emissions are global averages which hinder the precision of the life-cycle emissions obtained. This highlights the need to perform further studies to accurately compute the life-cycle emissions of shared modes. The shared modes are expected to decrease the NO_x and CO_2 emissions; however, only the CO_2 emissions are calculated in this thesis and the reduction is estimated to be limited to a maximum of 1.27%. Although the CO_2 reductions benefits might be limited, the goal of shifting from personal to shared means of transport can be achieved, which allows reshaping the urban fabric by, for example, repurposing parking spaces and creating more livable cities. The reduction of CO_2 emissions can become more significant in the case where shared modes are introduced with other policies that discourage the use of personal vehicles.

For all the scenarios analyzed, the modal split for the mode combinations that include shared modes and public transport is negligible. Depending on the scenario, around 3 to 10% of the shared modes trips are performed in combination with public transport. This is mainly because shared modes do not offer significant advantages to access public transport compared to walking or cycling. Additionally, the public transport network in Amsterdam is extensive and has good coverage of most areas, limiting the benefits that shared modes can provide as access or egress modes. Shared modes are mainly used as access/egress modes to public transport for trips longer than 40 minutes. Many papers argue whether shared modes complement or compete with public transport. It is challenging to come up with generalized conclusions about the relationship between shared modes and public transport. Many parameters affect this relationship: public transport coverage, level of service, and the population's mobility behavior. In the case of Warsaw, Nawaro (2021) concluded that e-scooters provide limited support to public transport, especially in areas with high public transport usage. Similar results were obtained for the case of Indianapolis; Luo et al. (2021) conclude that shared e-scooters can compete with buses in areas with high bus coverage and can complement public transport where there is no good coverage. These two cases can be compared to the results obtained in the case of Amsterdam, where good public transport services cover most parts of the city. The combination of shared modes and public transport is not attractive, mainly due to the high fares and lower travel time benefits for most OD-pairs when associating shared modes with public transport. This highlights the need for better policies to integrate shared modes and public transport since such a combination would have several benefits on the social and economic levels. Better fare integration between shared modes and public transport might increase the appeal of performing such multimodal trips. In the future, if the adoption rate of shared modes increases, then new public transport infrastructure can be designed to accommodate the new way of traveling that combines public transport and shared modes. The latter can increase the catchment areas of public transport stations, allowing the design of new systems with fewer stations and higher speed of services. Further studies can assess the factors affecting the attractiveness of combining shared modes and public transport to develop policies and strategies that improve modal integration among different social groups.

Regarding equity and equal distribution, the model aims to maximize social welfare by maximizing the utility experienced by the population. Therefore, the model can distribute the hubs equitably. To explain this notion, two groups are taken into account, the first one is the better-off group and the second one is the disadvantaged group. The better-off group experiences higher accessibility levels, and introducing shared modes would provide this group with minor individual utility benefits. In contrast, the disadvantaged group would benefit more from shared modes with higher utility benefits. Hence, it is possible to maximize benefits for the exact vehicle and amount of time by providing many better-off individuals with minor utility benefits or a few disadvantaged individuals with significant utility benefits. The model does not have any constraint that might induce a stronger preference for one of the groups, which means that the distribution can be considered equitable. In addition to that, the ratio of demand satisfied is relative to the mobility hub rather than the OD-pair; hence, all the OD-pairs using the same mobility hub have an equal probability of accessing shared modes whether they are disadvantaged or better-off individuals. This can also be seen in the results obtained, where hubs are activated in the outskirts of Amsterdam. These hubs provide significant utility gains per trip but serve a smaller demand. In further studies, modeling the actual users of the shared modes would provide better insights into the social equity of the services provided. Constraints can then be included in the developed model to limit the benefits discrepancies between zones or population groups.

A special scenario is presented in Appendix D to highlight the impact of different policy measures that the municipality of Amsterdam can take. The scenario models the case where the municipality focuses only on one neighborhood. Investing 1 M€ in developing hubs in only one neighborhood (in this case, Amsterdam-Noord) provides fewer overall benefits than investing the same amount in developing hubs in all of Amsterdam. However, higher modal splits for shared modes are obtained when looking only at the trips of the neighborhood. Hence, the municipality can invest in installing hubs in one neighborhood to ameliorate the accessibility and provide better mobility alternatives. However, it is essential to keep in mind that investing the same amount in all of Amsterdam might provide more overall benefits.

5.2. Discussion of Assumptions and Limitations

Several assumptions are made in the model to simplify it. These assumptions and their impact on the results are discussed in the following section.

The utilities used for the different modes are simplified versions of what individuals in real life consider when making their choices. Other parameters specific to the mode like safety perception or specific to the environment like the weather might impact the choices made in the system. The use of other utilities would affect the modal split. It might increase or decrease the demand for shared mobility depending if these added parameters would make shared mobility more or less attractive. For example, in the current model, the personal car always has a better utility than shared cars. However, if the parking costs are included in the utility, this might not be the case anymore, possibly making the shared vehicles more attractive. An increase in demand does not affect the results obtained in this case study since the hubs are already not satisfying all the demand. However, if other time periods are modeled, an increase in demand might affect the results. In addition to the simplified structure considered, the same utility functions are used for all individuals regardless of their characteristics. Varying the utilities depending on the income might lead to a smaller demand for shared modes from lower-income individuals than richer ones. This will also affect the distribution of mobility hubs if the demand is too small in lower-income areas. Additionally, the value of time of disadvantaged individuals might be smaller than well-off individuals, which leads to fewer hubs activated in lower-income neighborhoods due to the limited utility gains compared to higher-income neighborhoods. The literature describes this problem as the income effect of travel time savings, creating an implicit advantage for higher-income groups by assigning higher values for their time (Martens & Ciommo, 2017). However, in the case of this study, since the same utilities are used for all individuals, no inequalities result from the use of utilities to maximize social welfare. Hence, even if a specific mobility hub provides significant travel time benefits for only a few individuals, the model may activate this hub. It is essential then to estimate the utility parameters for the individuals in the specific city to have a more accurate representation of the individual’s behavior while considering the inequalities created due to the reliance solely on the utility maximization approach.

Another limitation that can be noted is that the case study is only performed during the 2 hours morning peak. Suppose the other periods have symmetrical demand patterns (for example, morning and evening peak hours). In that case, the distribution and capacity of mobility hubs should not be affected since the hubs already have space to accommodate the morning peak trips. However, modeling the off-peak hours might lead to different results if there are significant changes in the demand distribution between work and leisure trips.

In the model developed, the only access or egress mode for the shared modes is walking. Hence, the instances where individuals would park their cars or bikes in a parking facility at a mobility hub are disregarded. This means that the distribution of hubs might differ if those trips are taken into account. If the car and bike are added as access/egress modes, a possible impact would be that the model would activate more mobility hubs on the city's outskirts. This would allow individuals to park their cars and reach the city using a shared mode. However, modeling such trips is beyond the scope of this thesis since it needs to have an understanding of the car ownership and movement through space and time, in addition to the availability of parking spaces in the city and the mobility hubs.

Several modeling assumptions that affect the distribution of demand over the different mobility hubs are made of which: always choosing the shortest path when deciding which mobility hub to use, not considering the change in congestion levels, not taking into account the latent demand, and finally, assuming that individuals that do not have access to a shared mode due to the lack of available vehicles shift back to traditional modes of transport.

First, regarding the shortest path, it is assumed that the individuals choose the paths with the smallest disutility to access mobility hubs. However, other parameters affect the choice of mobility hubs of which the services present at the hub and the availability of shared modes. A future research topic would be to assess what parameters influence the route choice to access or use shared modes. If the research proves that individuals tend not to choose the closest mobility hub, then this would have implications on the demand distribution computed in the model. In addition to that, using the centroids to compute the shortest path might lead to an overestimation of the disutility faced when traveling using multiple modes. However, since Amsterdam's public transport network is very dense, then it is considered that no major detours result from this computation.

Second, the model only considers the congestion when no mobility hubs are introduced. However, a more precise approach would be to assess the congestion for each iteration. The literature presented some analysis to affirm that the reduction in congestion is not significant when introducing shared modes (Fan & Harper, 2022), making this assumption acceptable. If the congestion increases, then an increase in the share of modes not using the road network would be seen. However, if the variation is negligible, the shared modes will not be affected since mobility hubs only satisfy a part of the demand in all the scenarios considered. This means that even if the demand varies, the actual usage of shared modes will remain the same.

Third, the number of trips between OD-pairs is assumed to be constant. However, introducing an attractive mobility option possibly leads to an increase in trips. Hence, the OD matrix should be computed again in an iterative manner using the skim matrices of the modes introduced. If shared modes provide a considerably more attractive mobility option compared to traditional modes of transport to travel between certain OD-pairs, then it is expected that demand will be induced between this OD-pair. However, in this case study, since only the morning peak is considered and no mobility hubs satisfy all the demand, increasing the number of trips does not affect the results; this would only lead to a higher ratio of unsatisfied demand. Eventually, this unsatisfied demand would increase the pressure on the traditional modes of transport, which might reduce the traffic and environmental benefits associated with shared modes.

Fourth, this model assumes that the people who are rejected access are redistributed to the traditional modes of transport rather than them searching for another shared mode available. In real life, people might have access to real-time information, which gives them the ability to choose which mobility hub to use depending on the availability of the vehicles rather than just choosing the closest one. If the shared modes satisfy all the demand and some vehicles are left unused, this would positively affect the redistribution. However, since all the vehicles in the hubs are used, this does not affect the results except for the increased ratio of unsatisfied demand. Additionally, the individuals will learn which mobility hubs and vehicles are available in the long term. Therefore, their behavior might adapt, which decreases the demand and the ratio of unsatisfied demand. Hence, the availability of vehicles can also be included in the utility function of the shared modes, which leads to a decrease in the attractiveness of shared modes if they are not available.

To conclude this sub-section, all the modeling assumptions presented might affect the demand distribution. However, since the morning peak is modeled in this case study, the ratios of demand satisfied are low, which means that a variation in the demand does not affect the final output of the model. Any variation would impact the final results if other periods are also modeled and the shared modes can satisfy all the demand.

In addition to the modeling assumptions, the inputted parameters might affect the results. The sensitivity analysis was performed previously to assess their impact. It proved that varying the relocation, acquisition, and maintenance costs do not affect the results. However, a sensitivity analysis for the construction costs was not performed due to the high computation time. The construction costs might affect the results of the model developed. If the fixed costs are higher, this might lead to having fewer mobility hubs activated and activating larger mobility hubs. If the fixed costs are smaller than those used, this might lead to having more small hubs activated, providing higher coverage. In the case where the costs of installing a dock are smaller than the ones used, then it would be possible to activate more hubs with the same budget. It is essential to mention that the results are not altered when the fixed costs of installing a hub, variable construction costs per dock, and budget are multiplied by the same number. For example, the same results are obtained if the three parameters are set to 2500 €, 250 €, and 0.5 M€ or 5000 €, 500 €, and 1 M€.

The algorithm developed can provide the optimal distribution of mobility hubs. It optimizes the location and capacity of mobility hubs to maximize social welfare by looking at the travel costs of the population. However, when looking at the evolution of the solutions found, two solutions might have very close fitness functions but a completely different distribution of hubs. Therefore, qualitative parameters can also be considered when comparing different solutions to avoid only focusing on the fitness function as an objective. When deciding where to install the hubs in a city, decision-makers should consider several other qualitative parameters, such as the residents' preference, the attractiveness of the areas, and the spatial distribution of assets in the urban fabric. In addition to that, the model developed is very computationally heavy and takes around 20 days to run. Hence, another application of the model developed can be to compare different distributions of mobility hubs. The municipality can first assess the qualitative aspects and present different distributions of hubs. Then, the proposed options can be quantitatively assessed using the developed model to obtain the best distribution of hubs from the options presented.

5.3. Generalizability of the Model and Results

The model developed is flexible and can be adapted for different scenarios, policies, and locations. First, it can use the output of any macroscopic transport model to optimize the location and capacity of shared multimodal mobility hubs and compute the effects of the shared modes. In this thesis, the output of *Urban Strategy* was used to perform the case study; however, any other model can be used for this purpose. The structure of the developed model would remain the same; only the data format needs to be adapted. However, it is essential to note that the macroscopic model needs to preferably have a high density of centroids to avoid creating significant detours, leading to increased travel costs. Second, the change in behavior and policies can be included by modifying the utility functions. Suppose the effect of new policies needs to be modeled, for example, increasing parking costs. In that case, the utilities should be modified directly in the macroscopic transport model and the developed model to account for these adjustments. Third, If other mobility hub candidates need to be chosen or the analysis needs to be done on a smaller scale, the candidate mobility hub locations can be modified directly.

In addition to the model developed, some results are generalizable to other cases and cities. The result of prioritizing the installation of many hubs with lower capacities rather than larger ones with higher capacities can be considered valid in other cases or cities. This leads to locating hubs closer to the origins and destinations, which provides higher utility gains, especially when demand is spread across the city. In the case where demand is concentrated between an origin and a destination, then smaller hubs might not be the preferred option. In addition, the increasing marginal returns related to the travel time saving can be associated with such investments and be generalized due to the fact that fixed costs limit the benefits and vehicles available if a low budget is invested. The hubs considered in this thesis are limited to 33 vehicles, with no significant construction needed. If cities want to look into larger hubs, then the limits set for the capacities can be modified, but the distribution is not guaranteed to be the same.

Furthermore, it is possible to generalize the result that trips combining shared modes and public transport are limited when the public transport network is extensive since this combination is not that attractive. However, if the public transport network does not cover the whole population, then the shared modes might help complement this network. Finally, it is possible to generalize that most shared trips substitute public transport and active modes in cities having similar public transport coverage and car policies to Amsterdam.

06

CONCLUSION

Photo taken by the author – Dublin, February 2022

6. Conclusion

To conclude, an algorithm was developed in this thesis to optimize the location and capacity of multimodal mobility hubs to maximize social welfare while considering multimodal paths. The model developed fills the gap that was present in the literature by combining the following three main features:

- It considers multimodal trips that combine walking, shared modes, and public transport and computes the demand based on a logit ratio while considering overlaps. Most of the models developed in the literature consider the demand as a fixed input rather than a variable input based on the activated hubs.
- It considers three shared modes present at each mobility hub. Most papers consider unimodal shared stations rather than multimodal hubs.
- It relates mobility and service level indicators to the budget allocated to construct the hubs.

In the following chapter, the answers to the research questions are presented in section 6.1. Finally, recommendations for the municipality of Amsterdam and future works are presented in sections 6.2 and 6.3, respectively.

6.1. Answers to the Research Questions

In the following section, the different research questions are presented and answered.

Question 1: What is the most suitable model structure to find the optimal location and capacity of mobility hubs?

The developed model optimizes the location of mobility hubs and distributes the vehicles among them to maximize social welfare. A genetic algorithm activates the different mobility hubs from a set of candidate hubs at each iteration. The *Path and Usage* module computes the utilities experienced by all the users after introducing the activated hubs. These utilities vary depending on the mode combination considered. The multimodal paths can be constituted of walking, shared modes, and public transport legs. The utilities previously computed in the Demand Estimation module are used to find the demand (number of trips) for each shared mode at each mobility hub. Finally, the *Capacity* module optimizes the capacity of the activated hubs, the rebalancing of the vehicles to obtain the ratio of demand satisfied by maximizing the total travel utility experienced by the users. The total utility experienced corresponds to the fitness function of the genetic algorithm. The algorithm mimics the natural selection process to obtain, after several generations, the distribution of mobility hubs that maximizes social welfare. The model's structure is presented in Figure 3.1.

Question 2: What are the optimal distributions of shared multimodal mobility hubs to maximize social welfare depending on the amount of investment allocated to build the hubs?

The algorithm was run for different allocated budgets to build the mobility hubs (0.5, 1, and 1.5 M€). Different distributions of hubs are obtained for each scenario as presented in Figure 4.13 to Figure 4.15. The algorithm prioritizes locating many smaller hubs first rather than a few larger ones. With smaller allocated budgets, the hubs are evenly distributed in the Amsterdam area, with a higher concentration in the central part of Amsterdam, specifically in areas with higher population densities. The algorithm also activates hubs in the outskirts where significant utility gains can be achieved. The biggest hubs in terms of capacity are not located in main transport stations but mostly in areas where they can provide utility gains for the population served.

Question 3: What are the impacts of additional investment to build mobility hubs on the service level and mobility indicators?

The mobility indicators and service level of the mobility hubs differ depending on the budget allocated to build them. The algorithm activates as many hubs as the budget allows when lower budgets are allocated. Most of the hubs have a capacity equal to the minimum capacity set. Since activating hubs leads to high fixed costs, fewer vehicles are available when lower budgets are invested, hence, lower benefits in terms of travel time saving. Increasing marginal returns are associated with the modal split and travel time benefits: higher benefits are obtained after crossing the bar of the 1 M€ invested, with higher modal splits and travel time saved. Hence every euro invested after initializing a relatively complete network of hubs leads to more advantages in terms of travel time savings compared to the same euro invested in the range of 0 to 1 M€. For a budget of 0.5 M€, 1 M€, 1.5 M€, and 6.2 M€, the total modal splits for the shared modes are 0.2%, 0.35%, 1.15%, and 5%, respectively. When looking at the level of service, coverage increases significantly with lower investment budgets but does not increase at the same rate when investments above 1 M€ are allocated in Amsterdam. To conclude, investments to construct mobility hubs are associated with increasing marginal returns in terms of benefits and travel time savings but diminishing returns in terms of spatial coverage.

6.2. Recommendations for the Municipality of Amsterdam

The results obtained in this thesis allow presenting the following recommendations to the municipality of Amsterdam. Some of these recommendations can be generalized to other cities having similar mobility patterns.

If the municipality has lower budgets allocated for installing mobility hubs, it must not only focus on using this budget to build large mobility hubs. This thesis has proven that installing smaller ones distributed in the city provides more benefits to maximize social welfare. Suppose the municipality decides to invest a small budget in installing smaller hubs. In that case, it should keep in mind that the benefits might be limited, which might not be convincing to invest such amounts if the current societal cost-benefit analysis is used to make the decisions. However, benefits can be substantial if larger investments are made since increasing marginal returns are associated with the investments made. The thesis confirmed the common idea of locating the hubs in dense areas. However, it is essential to keep in mind that mobility hubs located in the city's outskirts and less accessible areas can provide significant utility gains to the population. These hubs are usually omitted in typical allocation decisions. Hubs in less accessible areas are even more essential than those located next to major public transport stations. Another point that should not be forgotten is considering qualitative parameters in the mobility hub’s location choice. Quantitative assessment can then be performed using the model developed to assess the best distributions among a set of options.

If the money available from the municipality is limited, another solution could be to create virtual mobility hubs. Mobility hubs do not always have to be physical stations; municipalities can choose to have virtual ones. The shared modes providers would impose on their customers to park the vehicles in specific spaces, which can be monitored through the GPS signal emitted by the vehicles. The municipality can choose the location of these virtual stations using a model similar to the one developed in this thesis. Therefore, this would bring together several modes at distinctive points in the city with no significant investments needed from the municipality in terms of racks or facilities other than providing the space for this purpose. Adopting such strategies allows for better organization of the public space. It avoids the chaos that some cities have faced with free-floating micro-mobility vehicles without investing significant amounts of money.

Installing shared modes in the city looks very beneficial on paper and stimulates a behavior change. However, this is not sufficient. Many policies should accompany such an introduction to induce positive change correctly. Many experts talk about stick and carrot measures, especially when looking at the shift from personal to shared usage of vehicles. These measures are a combination of “punishments” and “rewards” to induce the desired behavior. The stick measures can discourage private car ownership by reducing the parking spaces available, reducing the speed limits, and flipping the urban planning priorities by focusing on the users of active modes and public transport rather than private cars. It is more essential to induce a shift from private cars to shared modes rather than active modes or public transport to shared modes, especially in terms of spatial occupancy and sustainability. This is not an easy task and can not be implemented immediately. Instead, it is a long-term plan also outlined in Amsterdam’s 2030 mobility plan. Looking at the carrot measures, these can be incentives for the users to use shared modes. These incentives can be financial ones by providing a bonus for citizens to shift from personal cars to shared modes. However, such incentives might be limited to a particular group of people. To widen the range of people covered by carrot measures, better integration between shared modes and public transport can be imposed on the operators. For example, by reducing the fares for the individuals using shared modes as access or egress modes to public transport; or using the OV-card (or any other future system) to unlock the shared vehicles. This might encourage people from lower-income and less-educated backgrounds to use shared modes due to the ease of access. Hence, when looking at the city's mobility transition, it is essential to take a holistic approach, combining mobility and spatial policies to induce the desired shift and make the city more livable.

6.3. Recommendations for Future Research

Several assumptions were made in this model mainly related to the behavior of the individuals and the parameters considered when making choices associated with the use of mobility hubs and shared modes. These assumptions can be relaxed in future studies to have more accurate results. One of the points to work on is to accurately model the choices made by users of shared modes and the factors influencing which mobility hub to choose, especially in areas where biking and public transport are predominant such as Amsterdam. If more specific behavior can be modeled, optimal pricing schemes can be found to encourage combining shared modes with public transport. In addition, there is still a gap in the literature related to the route choice for the access/egress legs to the mobility hubs and the main shared modes legs. On another note, in the developed model, it is considered that travelers are homogeneous; therefore, future studies can consider the heterogeneity of the population, which might present interesting results, especially if the demographics are linked with the demand patterns. Finally, it is also interesting to model the behavior of the individuals in the longer term to assess the impact of introducing shared modes on car ownership and eventually on the use of public space.

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Photo taken by the author – Brussels, March 2022

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Appendix A. Urban Strategy Description

The *Urban Strategy Digital Transport Twin*, developed by TNO, can model different measures (or so-called interventions) to accurately understand their effects. In this appendix, an overview of *Urban Strategy* is provided.

Urban Strategy includes several modules that interact together to quantify the impact of different interventions. The modules included in this digital transport twin are the following: the demand module that is related to the generation of trips, the new mobility modeler that is used to re-estimate mode choice, the traffic module that performs traffic assignment for both cars and bikes, the public transport module that performs public transport assignment, and finally the air and noise modules that determine air and noise quality. Using *Urban Strategy,* different elements can be modified to simulate scenarios and assess their impact on the transport network and travel behavior. The different interventions can be subdivided into several domains:

- Mobility domain: Different mobility interventions can be modeled of which a change in road capacity, speed limits, or the presence of accidents. The effects are quantified by assessing the traffic flows, travel times, and other traffic indicators.
- Demand domain: The effects of increasing housing, jobs, and services can be quantified in terms of change in zonal attractions and variation in traffic indicators.
- Public transport domain: The effect of changing line frequencies on passenger intensities can be assessed.
- Modal costs: The effects of varying travel parameters such as travel costs on the mode choice, traffic intensities, and other parameters can be computed.
- Environment: Other interventions such as the closure of roads, the effect of physical barriers on the environment, and noise can also be assessed.

All interventions, even if done in one specific domain, can impact other modules of *Urban Strategy*. For example, when the user costs for personal cars are increased, the mode choice is recalculated using the new mobility modeler. The resulting traffic flows are assigned to the network using the Traffic and Public Transport Modules.

The Traffic and Public Transport modules are discussed to understand the model's considerations. First, the trips are aggregated into centroids (or centers of gravity) of traffic zones. Then, the Traffic module allocates trips to the network. It uses the OD matrix as an input for different modes of which car, freight, and bikes. This OD matrix includes the number of trips allocated to the modes between the OD-pairs for the relevant time period. In addition to that, the road network and its characteristics are needed. The characteristics are specific to each link in the network and include the capacity and the maximum speed per mode. Junction delays per direction are also used. Finally, the Traffic module computes the shortest path from one origin to a destination iteratively to reach equilibrium. The results are the traffic intensities, travel times, and distances per link and mode.

The Public Transport module allocates trips to the public transport network. It uses as an input the OD-matrix for public transport. This OD-matrix includes the number of trips allocated to public transport between each origin and destination for each relevant time period. In addition to that, the public transport network connected to the traffic network is needed. This network includes details about each transit line, such as the maximum speed of the mode serving this line, the frequency, and the transit stops served.

The travel times, distances, and demand between OD-pairs are used in this thesis as an initial input to the model developed, as discussed in chapter 3. These elements are output from the modules previously discussed, starting from the demand module to estimate the number of trips performed, to the new mobility modeler to obtain the modal split, then finally obtaining the travel times and distances using the Traffic and Public Transport Modules.

Appendix B. Mapping of Results

The mobility hubs activated for each budget scenario are presented in the maps below. Figure B.1 to Figure B.3 present the service areas of the activated mobility. They show which zones can access mobility hubs by walking 0 to 250 m, 250 to 500 m, or 500 to 750 m. Figure B.4 to Figure B.6 allow comparing the location of the activated mobility hubs with the average neighborhood's average income. Figure B.7 to Figure B.9 allow comparing the location of the activated mobility hubs with the population density map. Figure B.10 to Figure B.12 allow assessing whether the activated mobility hubs are located in the vicinity of the train stations. Finally, the capacity of the chosen mobility hubs is presented in Figure B.13 to Figure B.15.

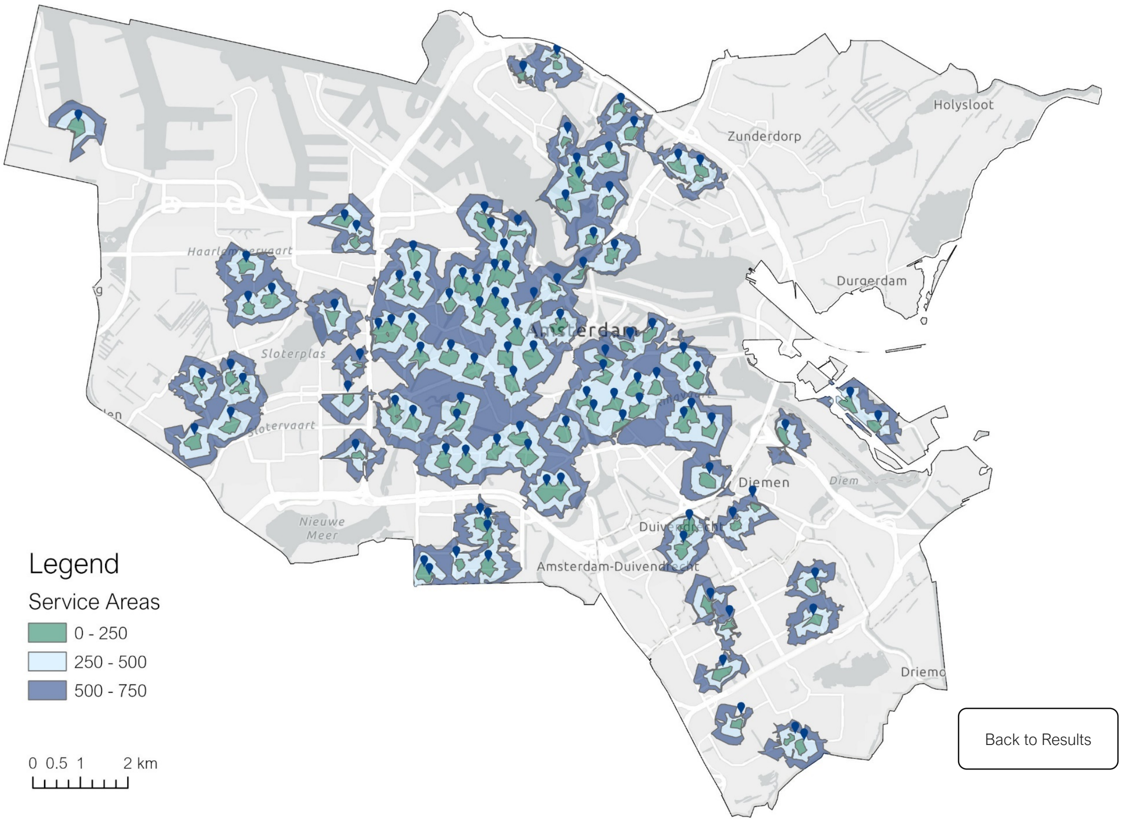

Figure B.1. Service areas of activated mobility hubs for a budget of 1 M€

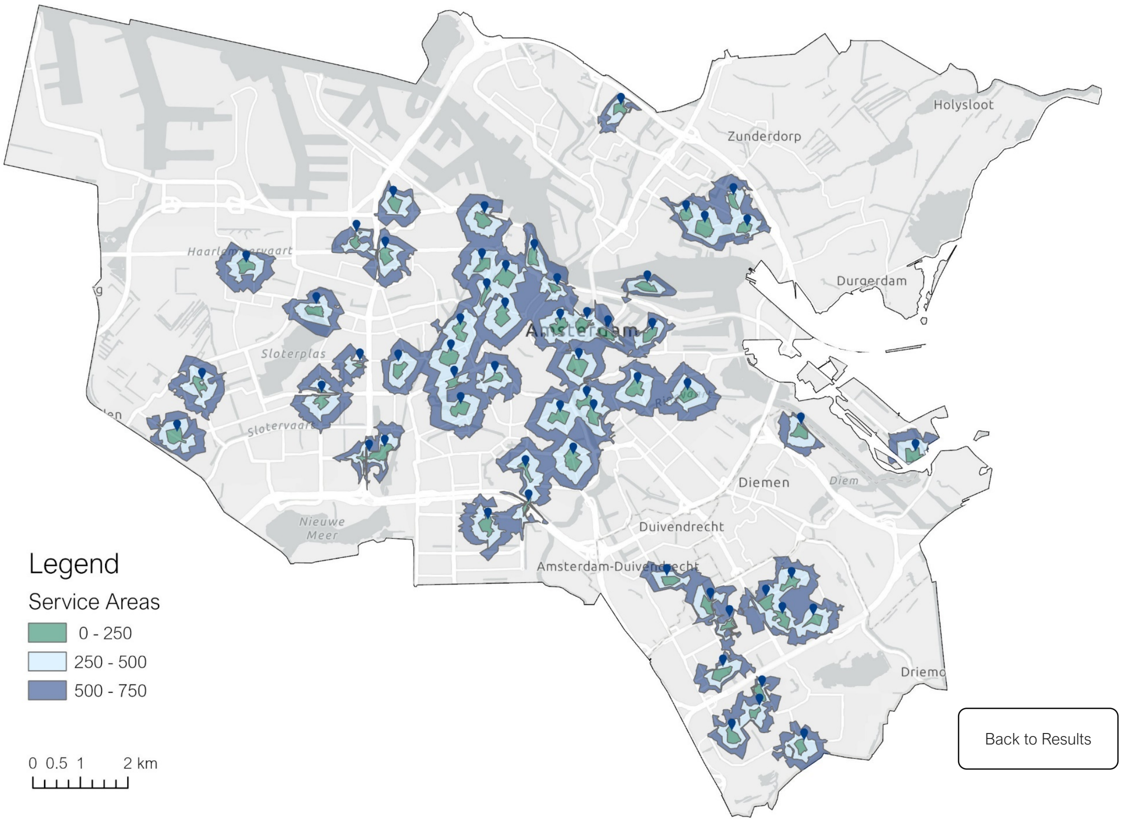

Figure B.2. Service areas of activated mobility hubs for a budget of 0.5 M€

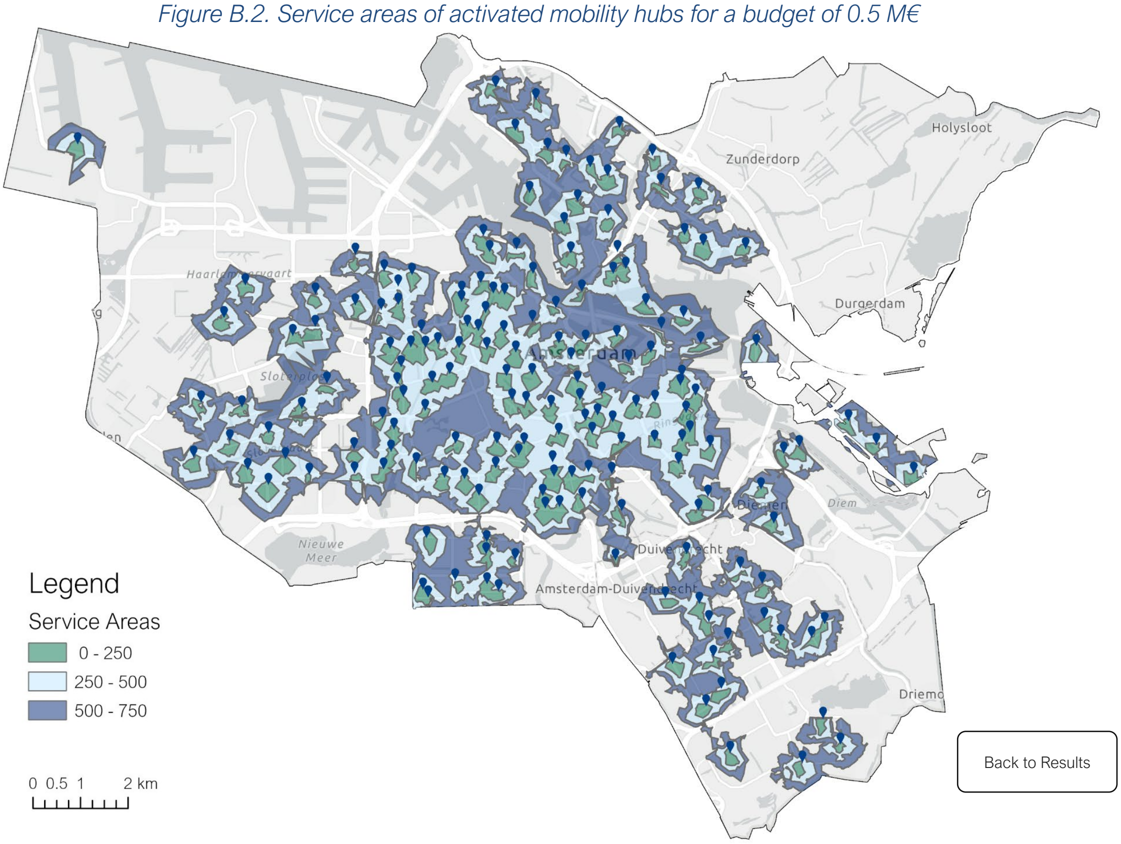

Figure B.3. Service areas of activated mobility hubs for a budget of 1.5 M€

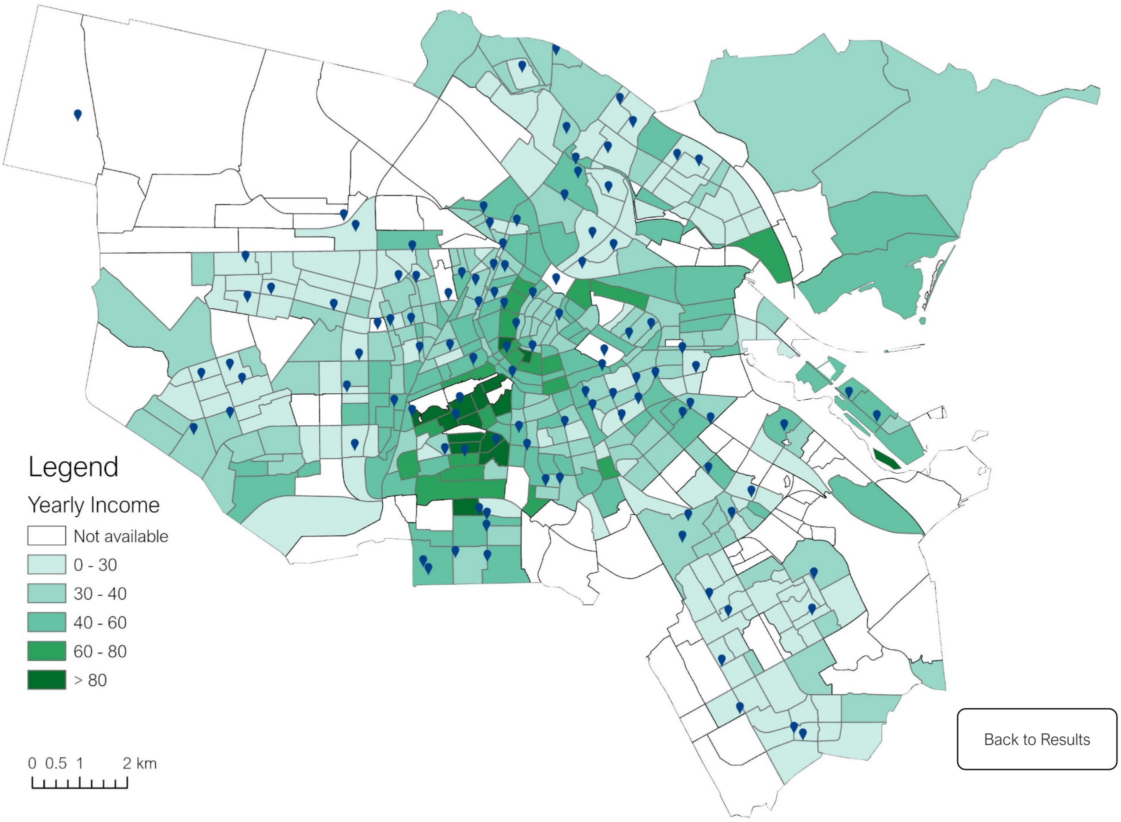

Figure B.4. Distribution of activated mobility hubs for a budget of 1 M€ with the average yearly income distribution

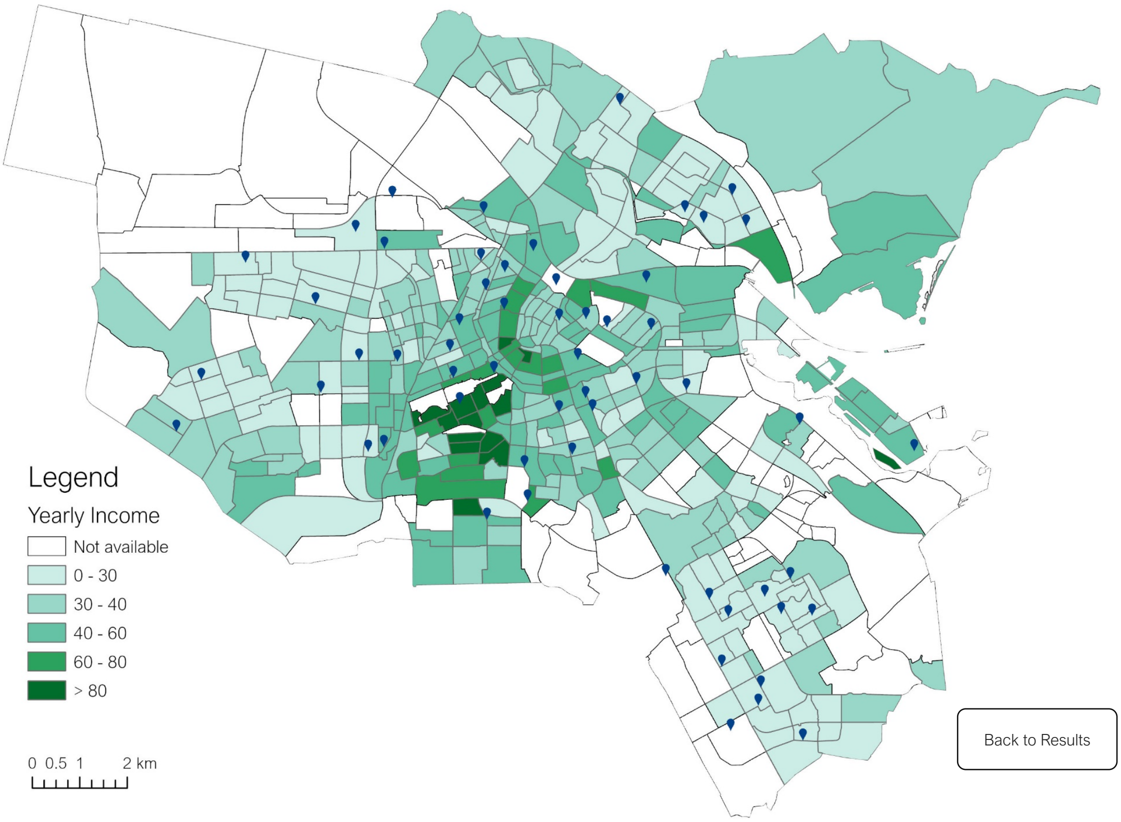

Figure B.5. Distribution of activated mobility hubs for a budget of 0.5 M€ with the average yearly income distribution

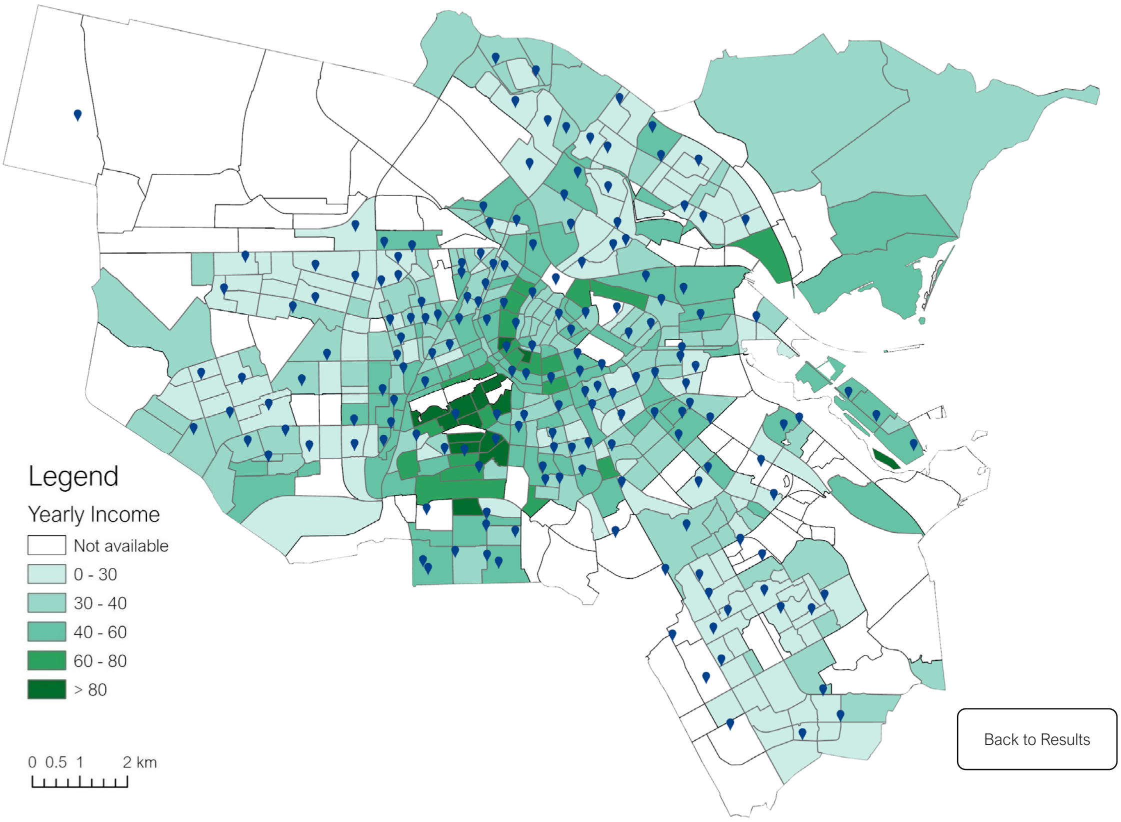

Figure B.6. Distribution of activated mobility hubs for a budget of 1.5 M€ with the average yearly income distribution

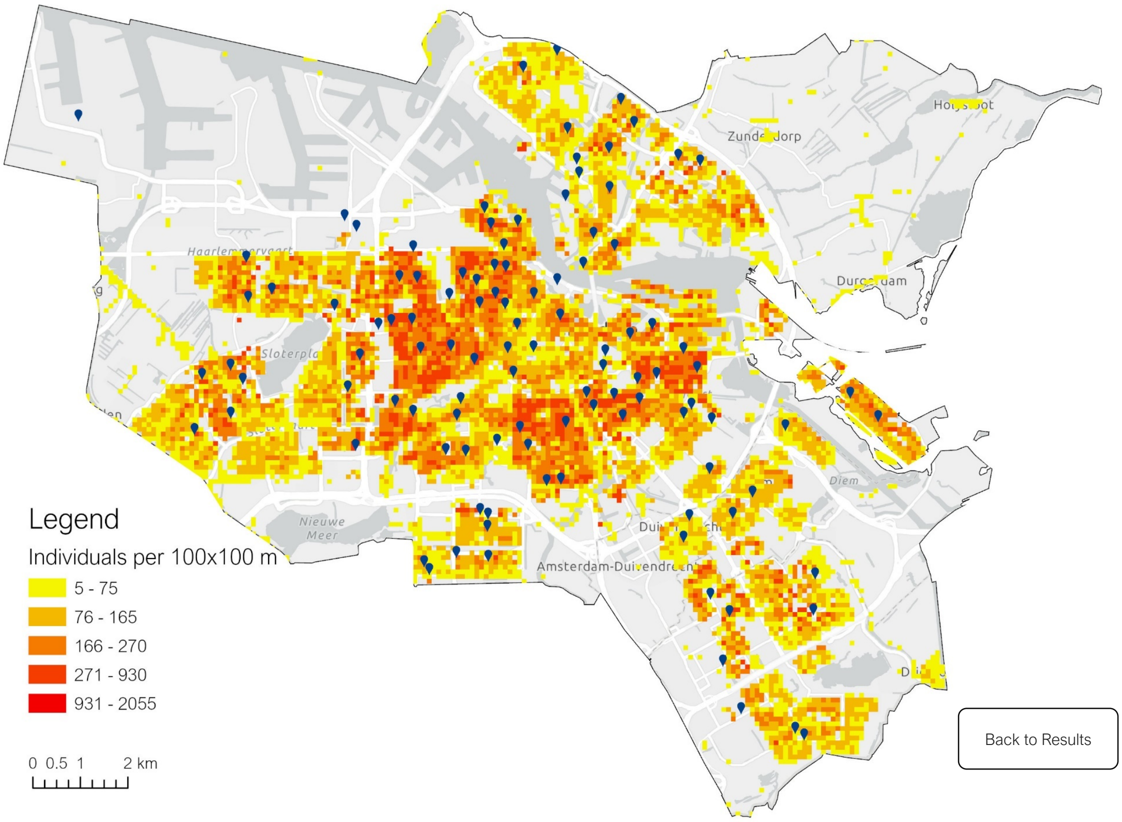

Figure B.7. Distribution of activated mobility hubs for a budget of 1 M€ with the population density map

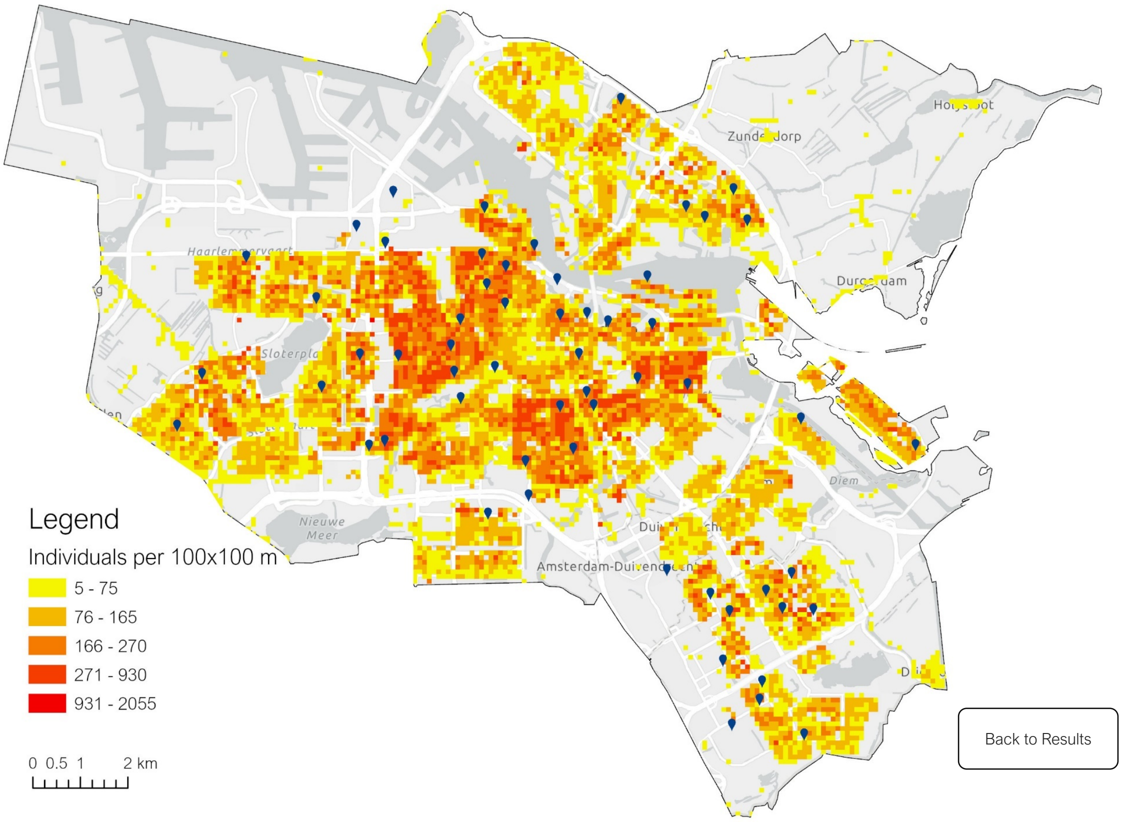

Figure B.8. Distribution of activated mobility hubs for a budget of 0.5 M€ with the population density map

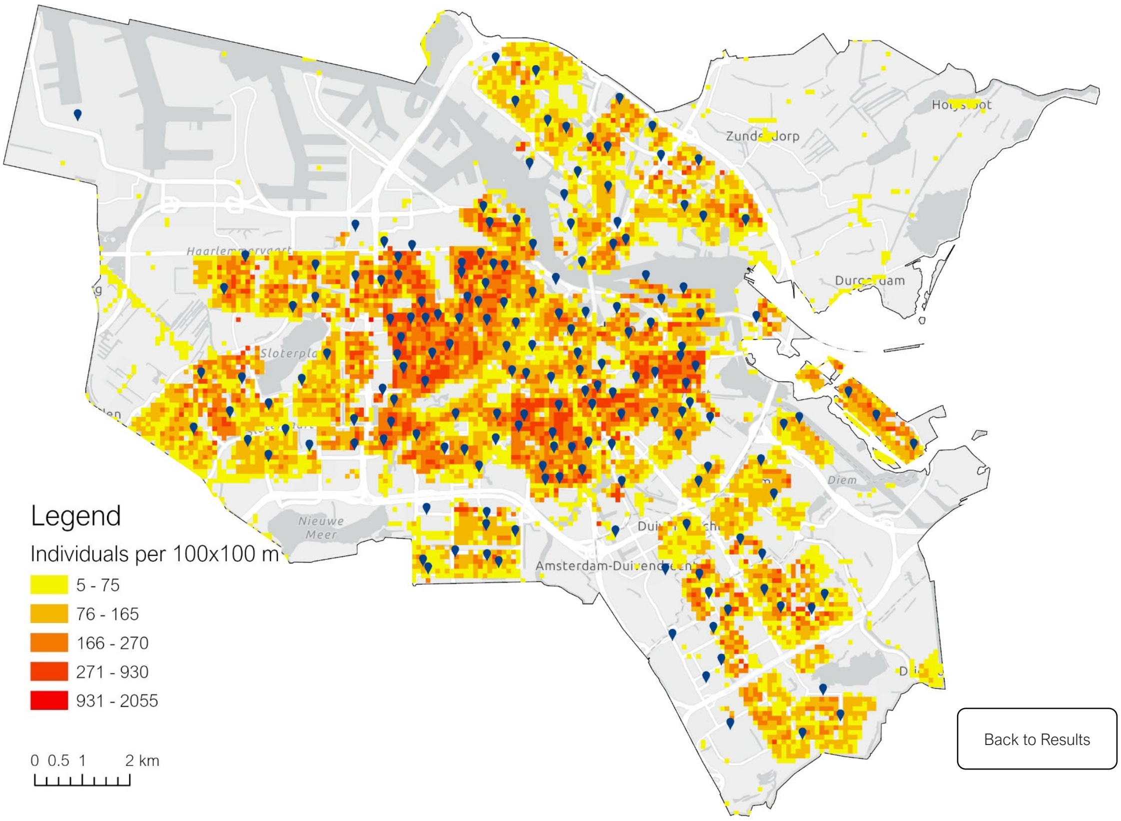

Figure B.9. Distribution of activated mobility hubs for a budget of 1.5 M€ with the population density map

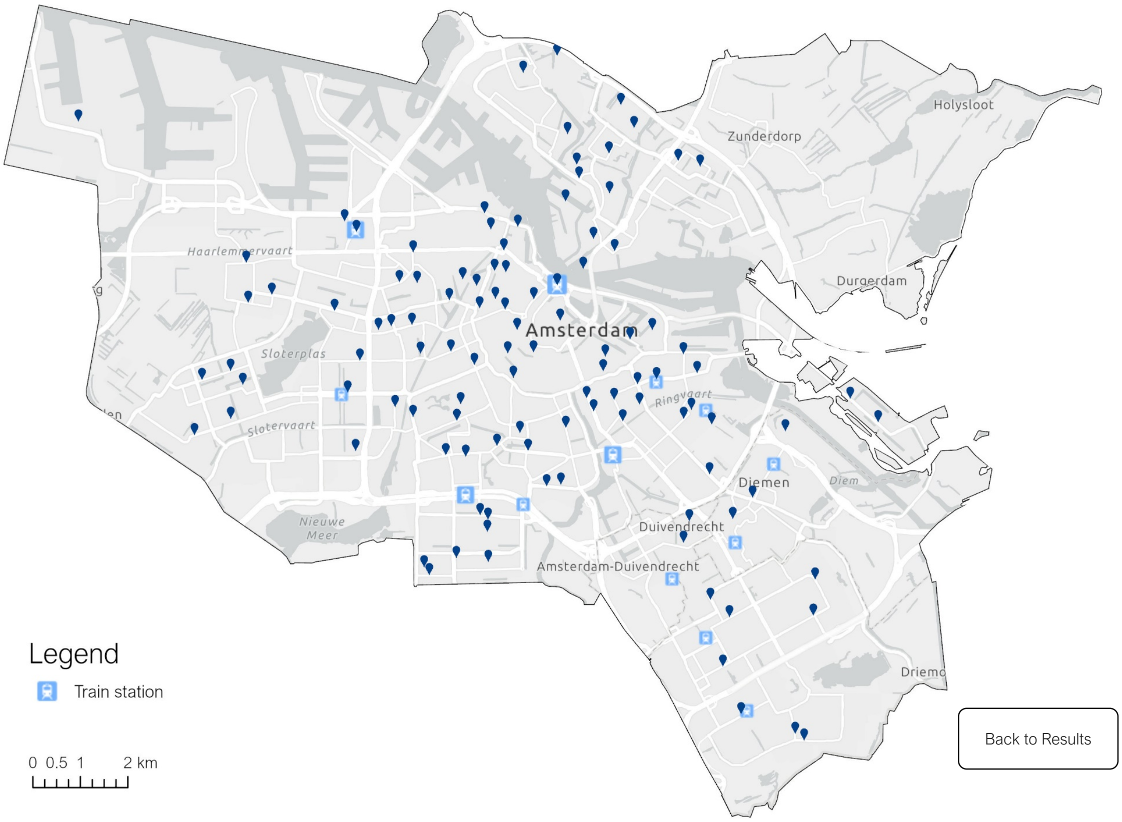

Figure B.10. Distribution of activated mobility hubs for a budget of 1 M€ with the train stations

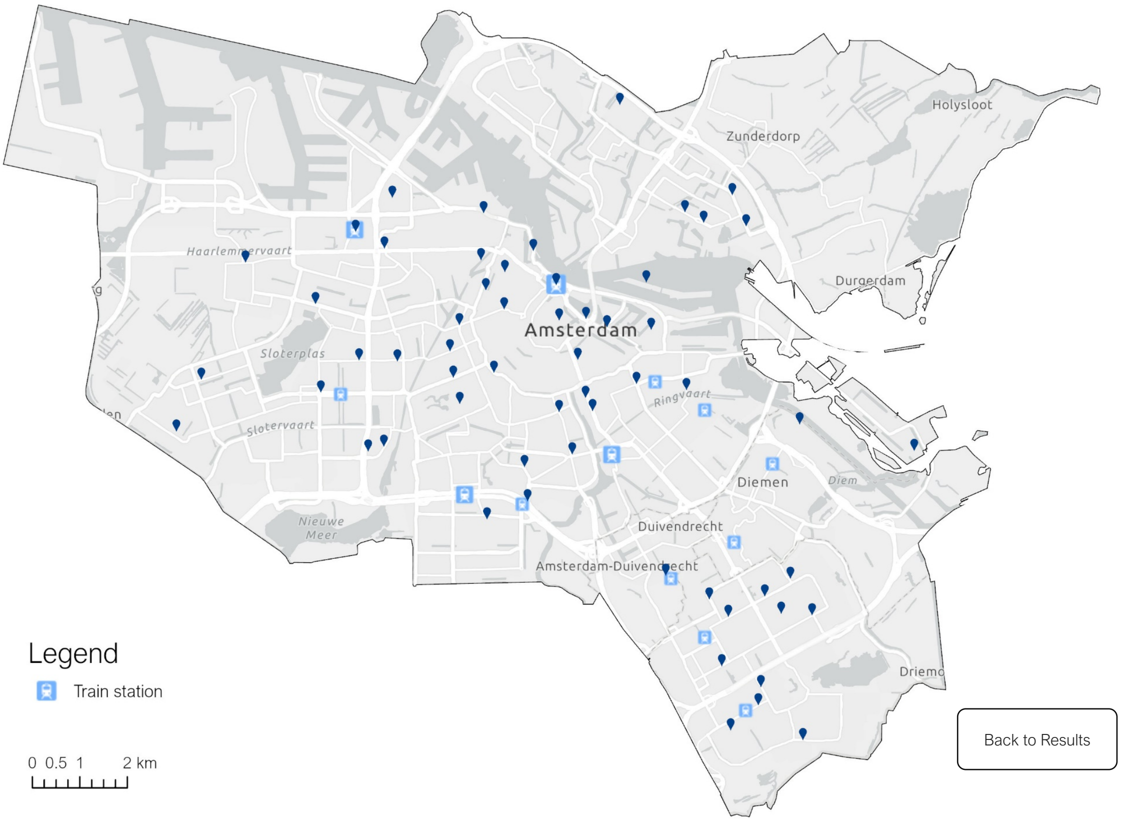

Figure B.11. Distribution of activated mobility hubs for a budget of 0.5 M€ with the train stations

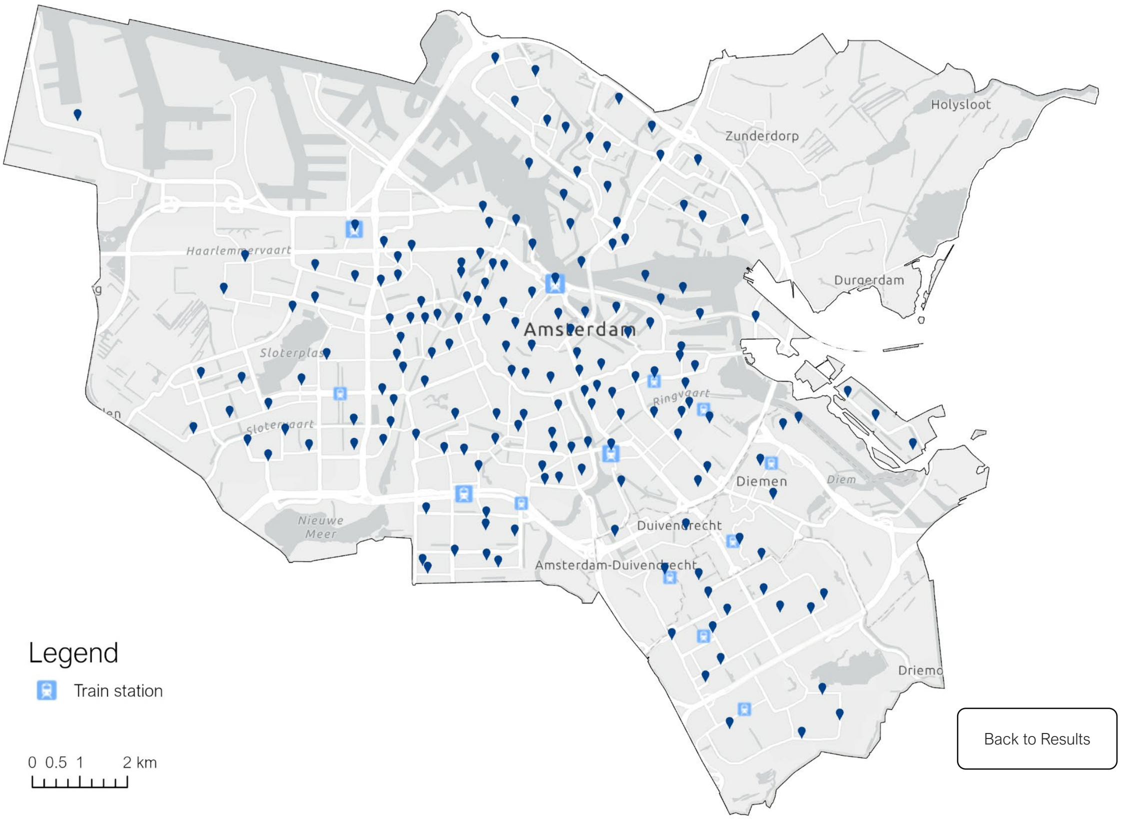

Figure B.12. Distribution of activated mobility hubs for a budget of 1.5 M€ with the train stations

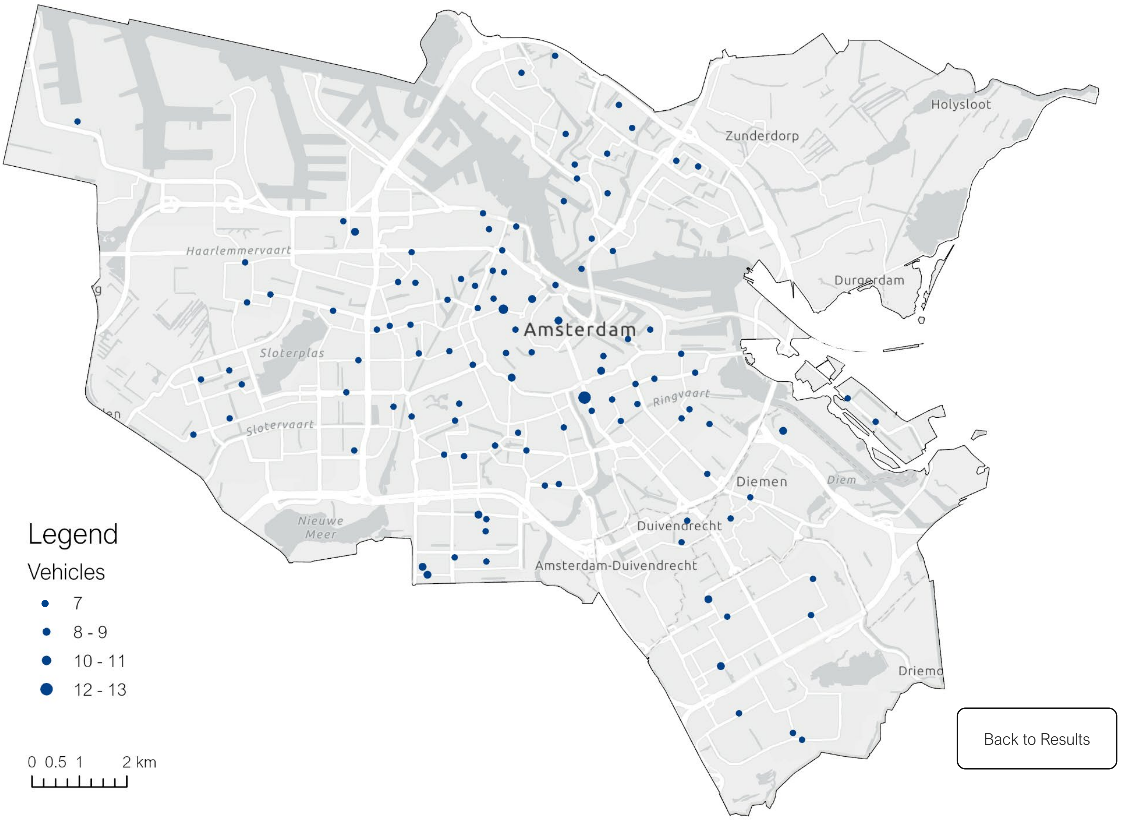

Figure B.13. Capacity of activated hubs for a budget of 1 M€

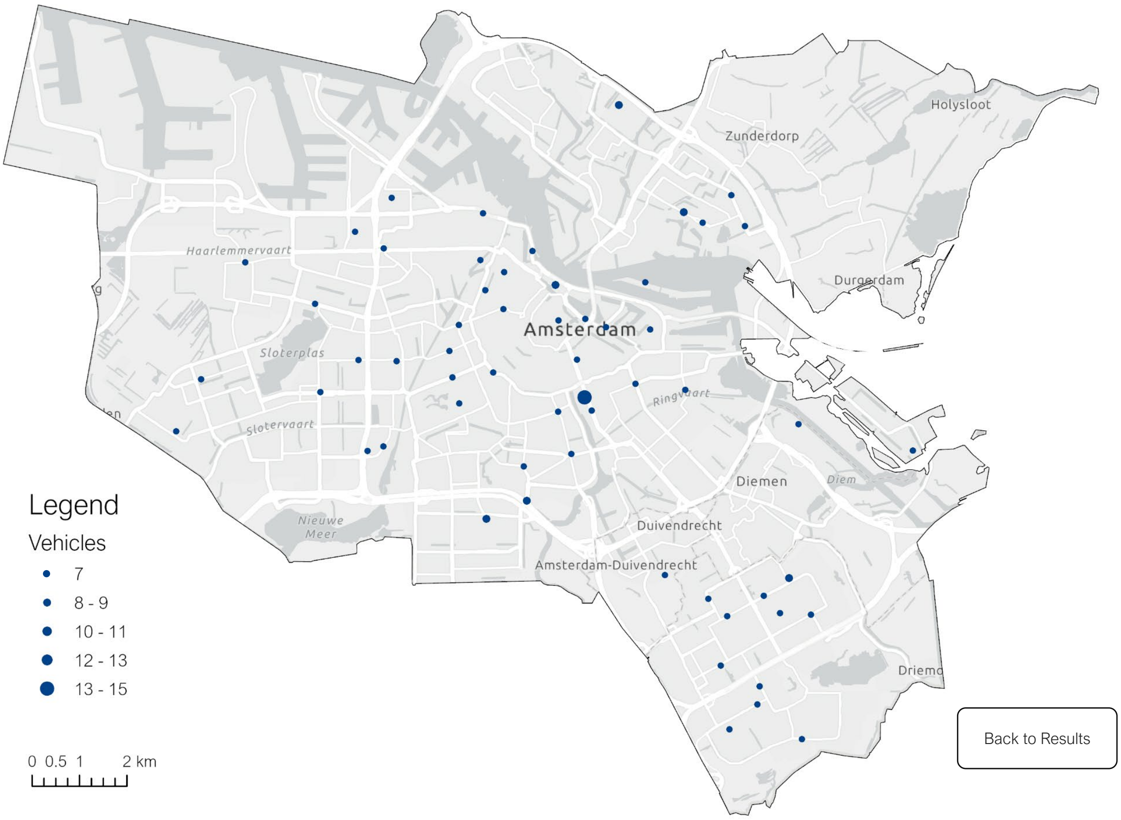

Figure B.14. Capacity of activated hubs for a budget of 0.5 M€

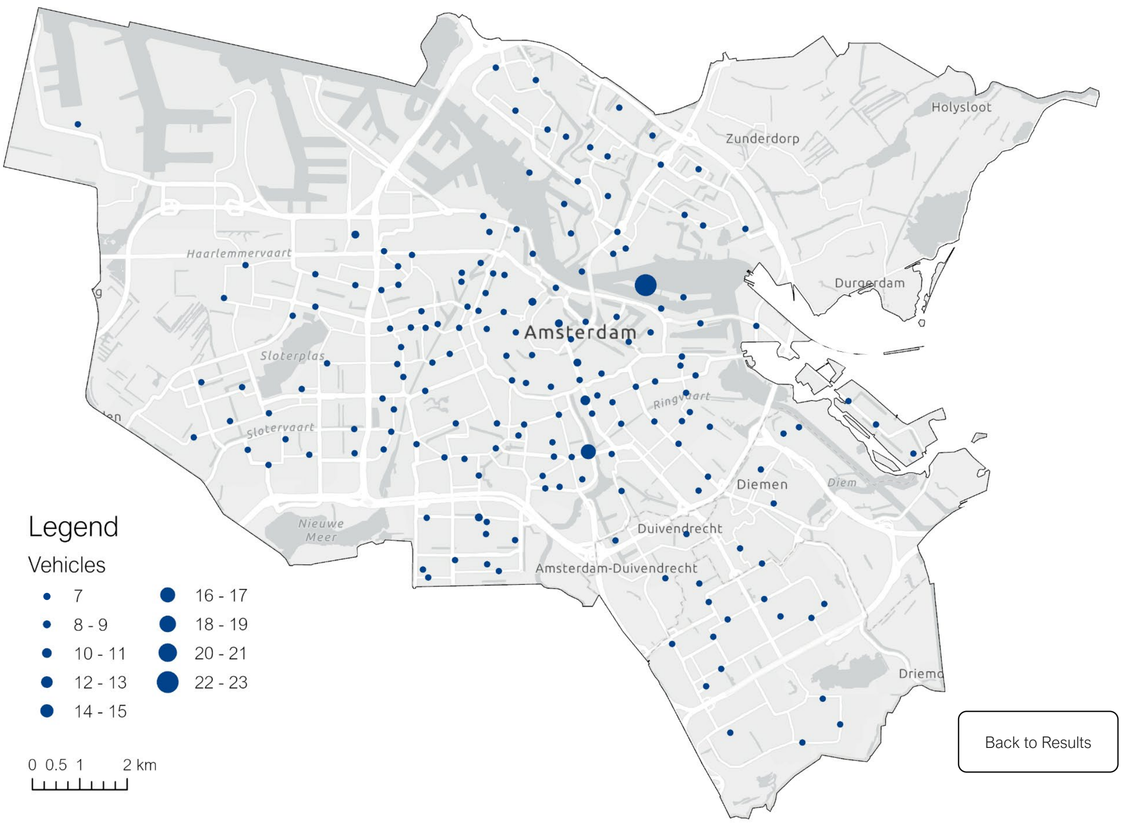

Figure B.15. Capacity of activated hubs for a budget of 1.5 M€

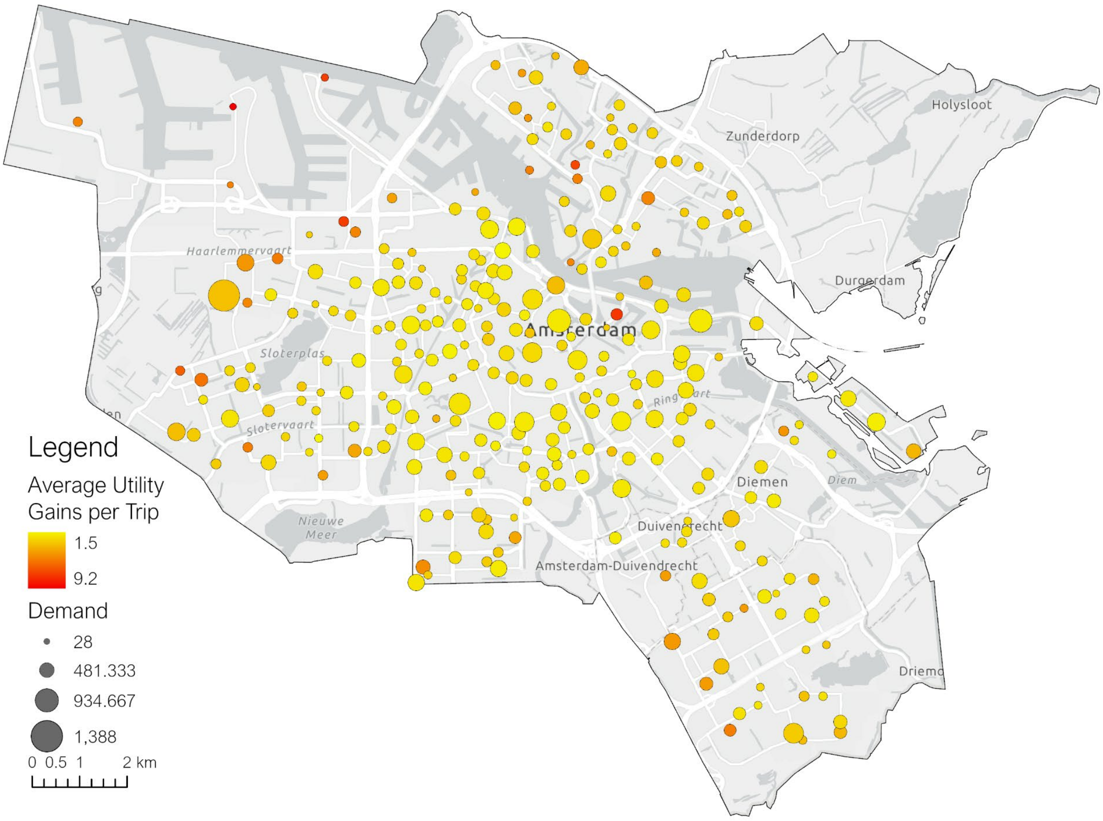

Figure B.16. Distribution of demand and average utility gains per mobility hub

Appendix C. Graphical Results

The percentage of trips displaced from traditional modes of transport towards shared modes is presented in Figure C.1.

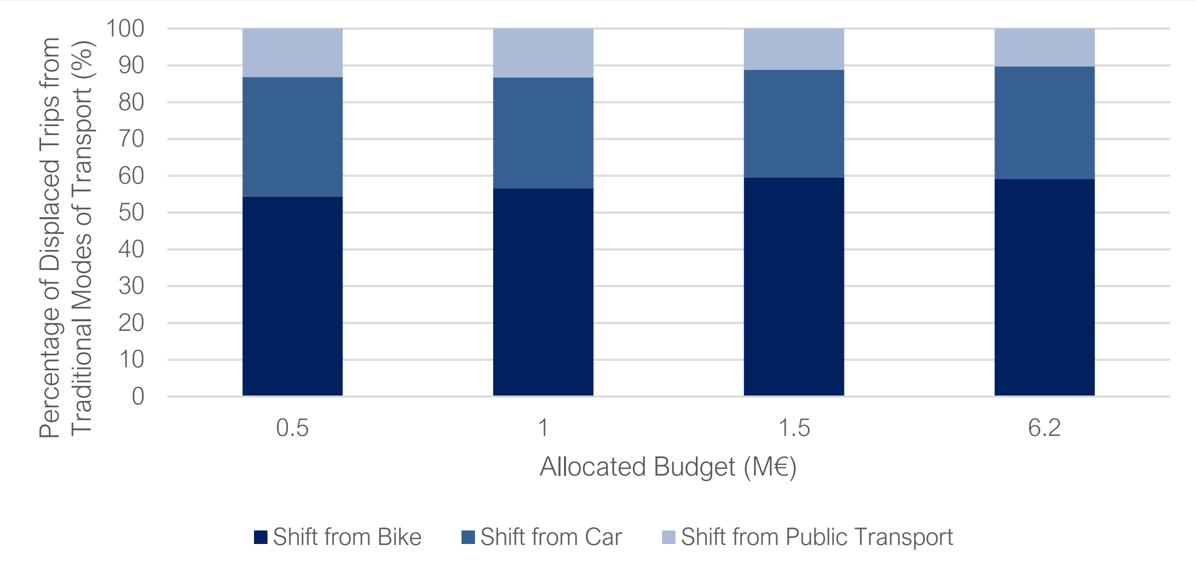

Figure C.1. Percentage of trips displaced from traditional modes of transport towards shared modes

The kilometers traveled per mode are presented in Figure C.2 to Figure C.8. The distance traveled per mode varies depending on the budget allocated to install the mobility hubs.

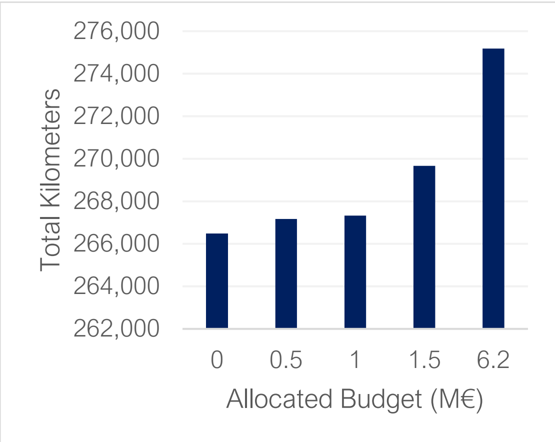

Figure C.2. Total kilometers walked depending on the budget allocated

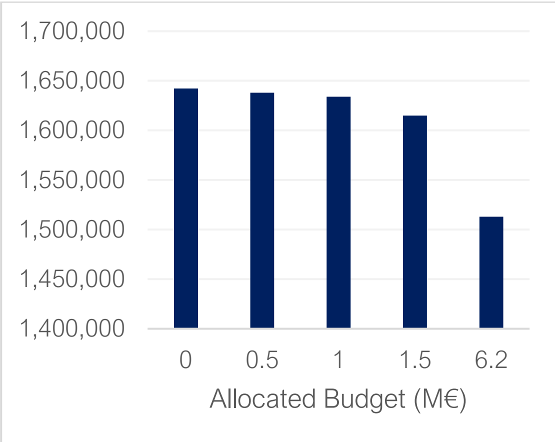

Figure C.3. Total kilometers biked depending on the budget allocated

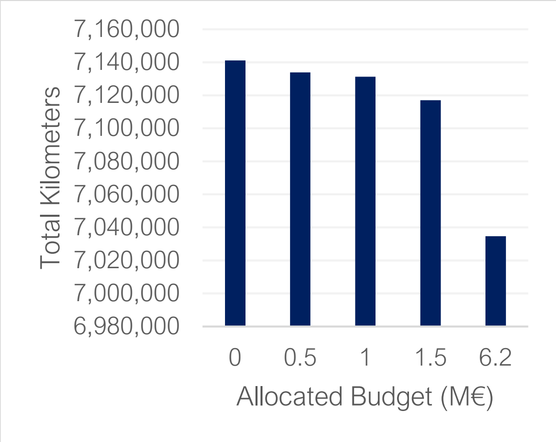

Figure C.4. Total kilometers traveled using a car depending on the budget allocated

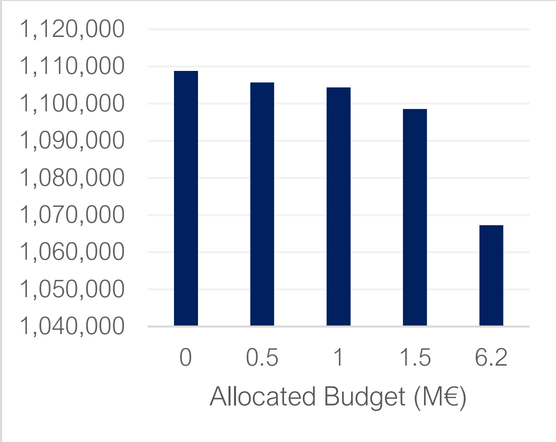

Figure C.5. Total kilometers traveled using public transport depending on the budget allocated

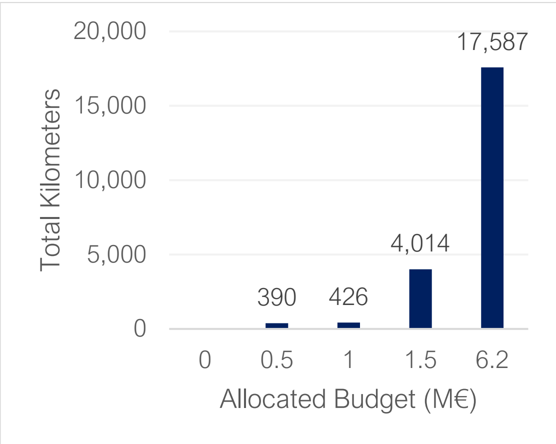

Figure C.6. Total kilometers traveled using shared car depending on the budget allocated

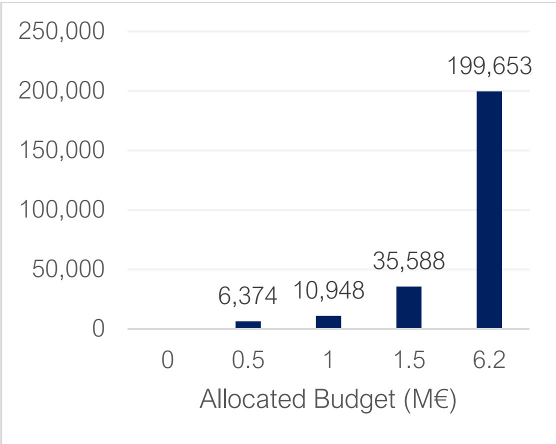

Figure C.7. Total kilometers traveled using shared mopeds depending on the budget allocated

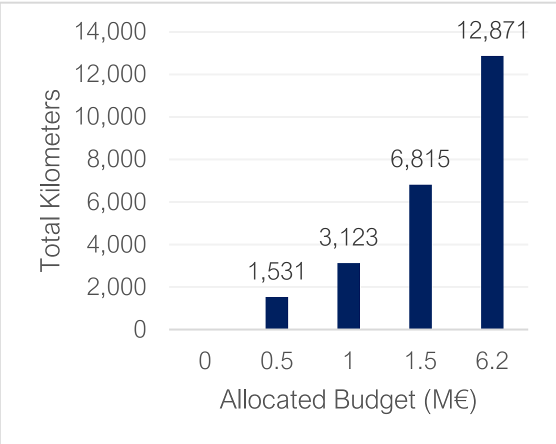

Figure C.8. Total kilometers traveled using shared e-bikes depending on the budget allocated

To assess which type of trips the shared modes serve, the percentages of trips traveled using a shared mode for each initial travel time interval are presented in Figure C.9 to Figure C.16.

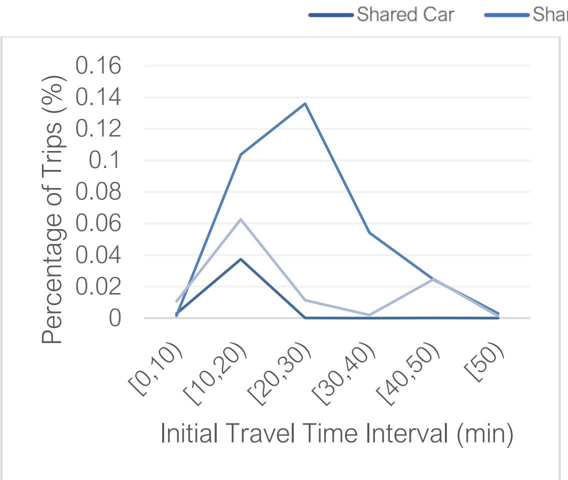

Figure C.9. Percentage of trips traveled using shared modes per travel time interval for an allocated budget of 0.5 M€

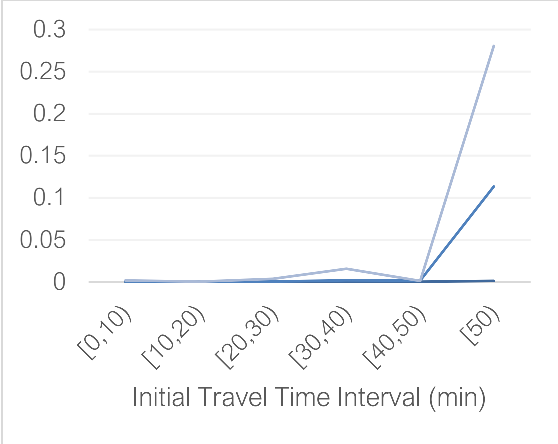

Figure C.10. Percentage of trips traveled using the mode combinations "shared mode – public transport" per travel time interval for an allocated budget of 0.5 M€

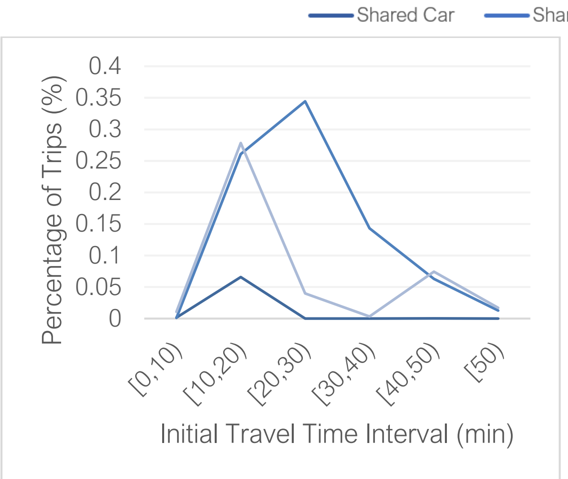

Figure C.11. Percentage of trips traveled using shared modes per travel time interval for an allocated budget of 1 M€

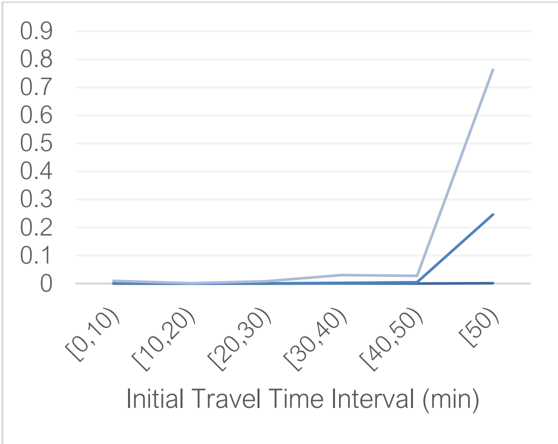

Figure C.12. Percentage of trips traveled using the mode combinations "shared mode – public transport" per travel time interval for an allocated budget of 1M€

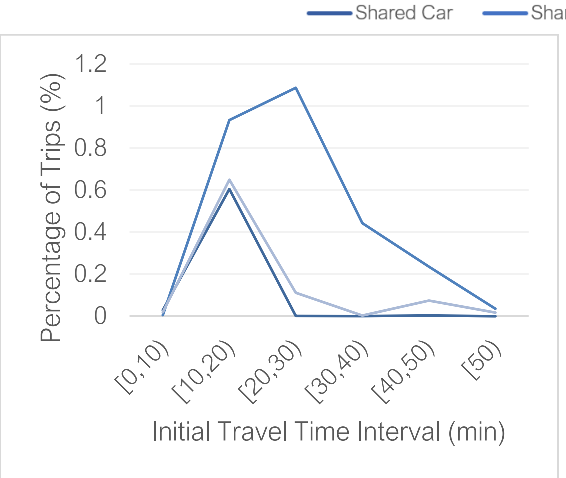

Figure C.13. Percentage of trips traveled using shared modes per travel time interval for an allocated budget of 1.5 M€

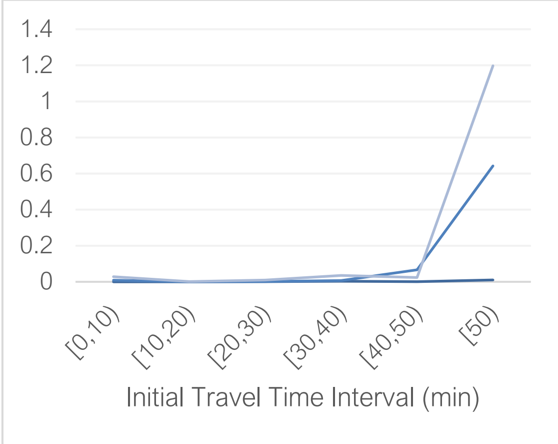

Figure C.14. Percentage of trips traveled using the mode combinations "shared mode – public transport" per travel time interval for an allocated budget of 1.5 M€

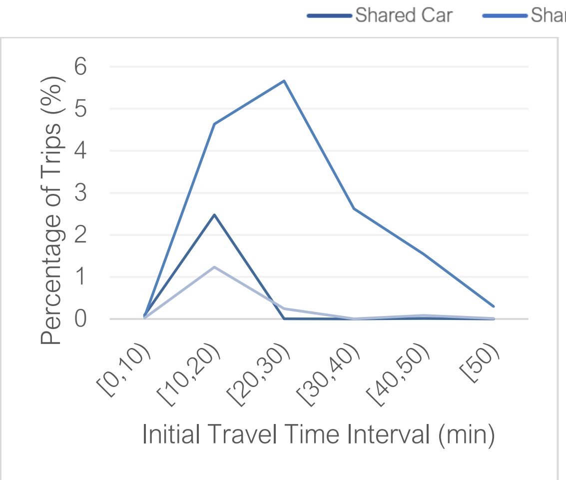

Figure C.15. Percentage of trips traveled using shared modes per travel time interval for an allocated budget of 6.2 M€

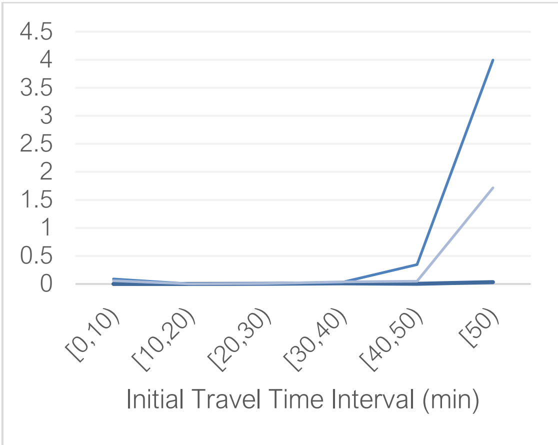

Figure C.16. Percentage of trips traveled using the mode combinations "shared mode – public transport" per travel time interval for an allocated budget of 6.2 M€

Appendix D. Amsterdam – Noord Focus Scenario

In the following appendix, another scenario is performed. This scenario aims to better understand the effects of a policy that aims to install mobility hubs only in Amsterdam North (Amsterdam – Noord). This region is chosen since public transport has the lowest share of trips (Gemeente Amsterdam, 2021). A budget of 1 M€ is used to perform this scenario. The budget of 1 M€ allows activating all the candidate mobility hubs in the district, as seen in Figure D.1, with the maximum capacity of 3 shared cars, 15 shared mopeds, and 15 shared e-bikes each.

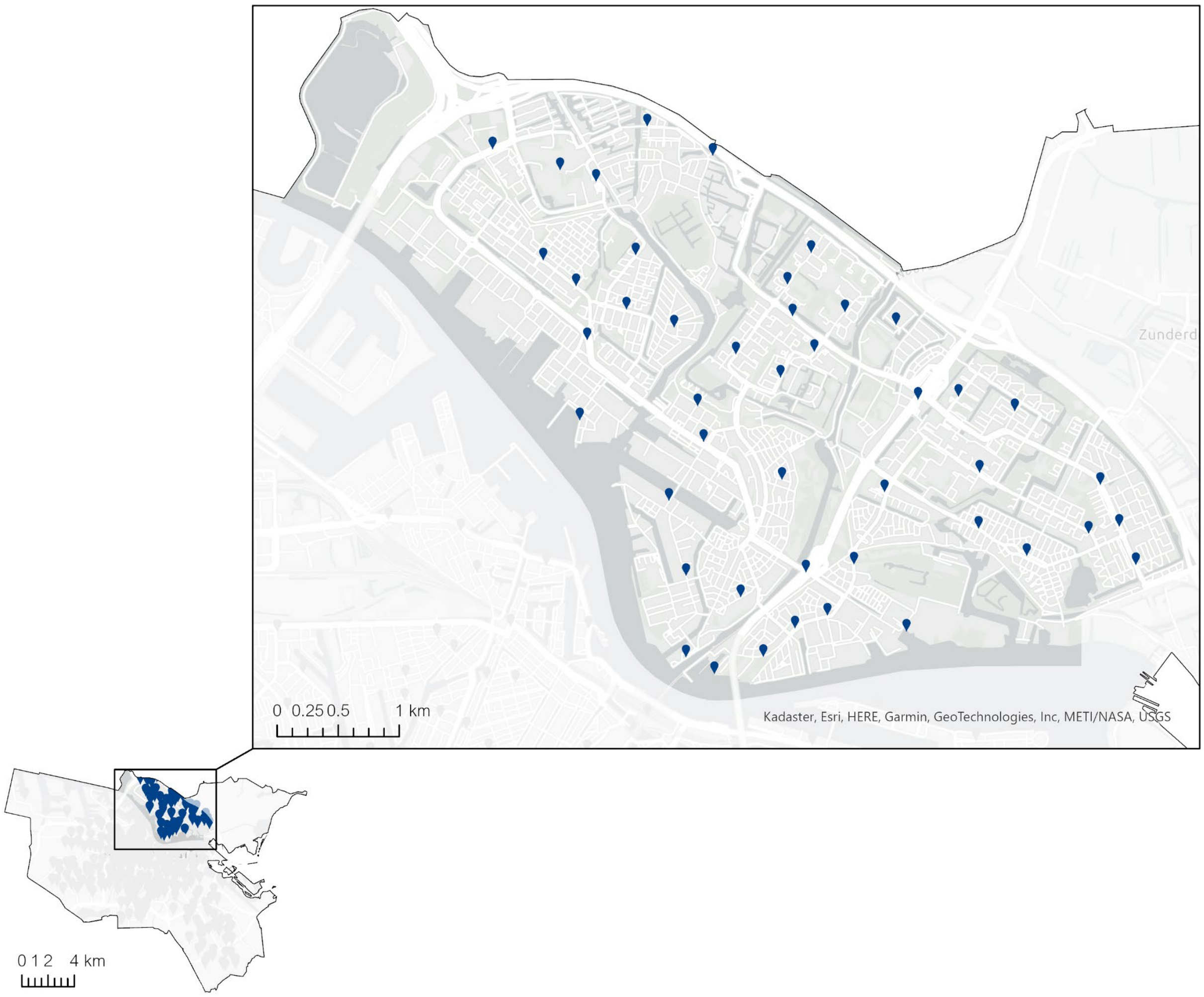

Figure D.1. Mobility hubs activated in Amsterdam-Noord

When considering the trips that have an origin or a destination in Amsterdam Noord, the modal split for the shared modes is considerable, around 1.2%, 2.5%, and 0.4% for the shared cars, shared mopeds, and shared e-bikes, respectively, as seen in Figure D.2. The 4.15% split for shared modes is accompanied by an approximate decrease of 1%, 0.4%, and 2.7% for personal cars, bicycles, and public transport, respectively, as seen when comparing Figure D.2 and Figure D.3.

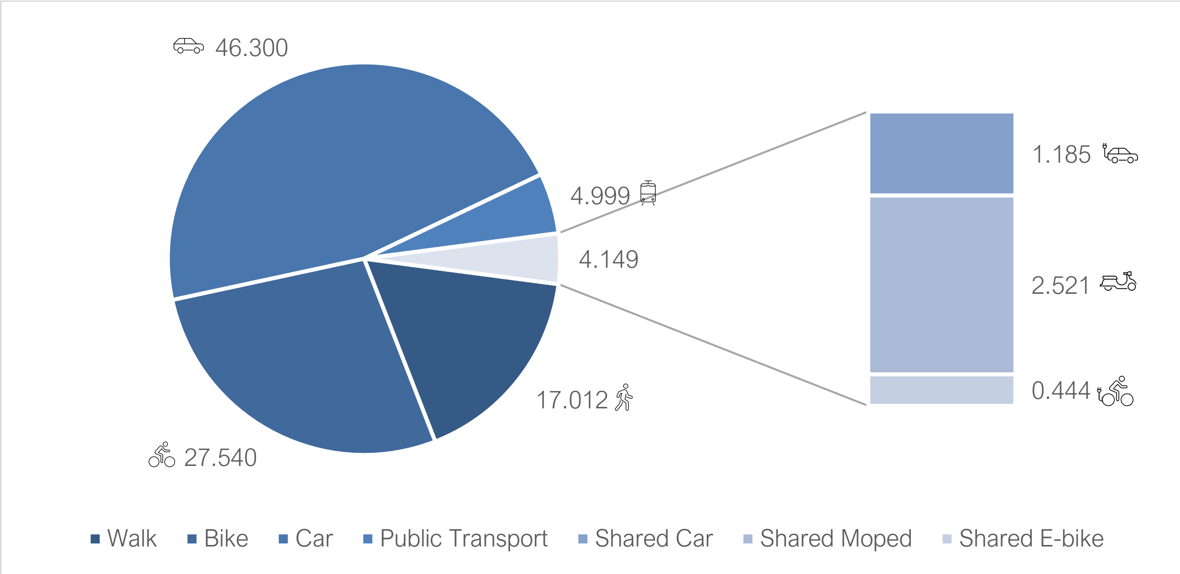

Figure D.2. Modal split of the trips performed in Amsterdam-Noord after installing the mobility hubs

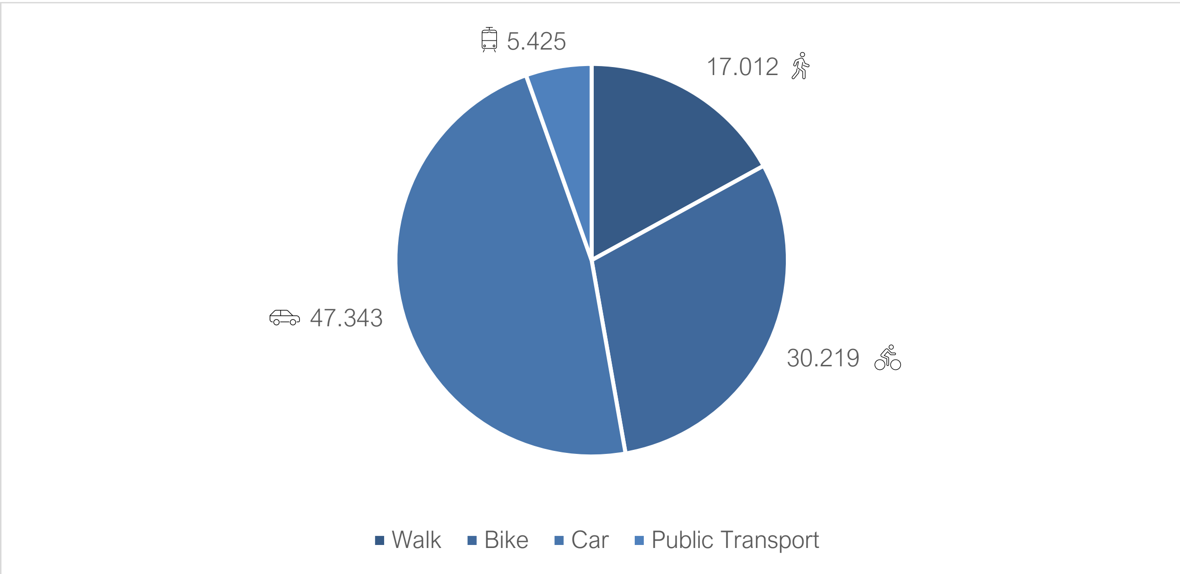

Figure D.3. Modal split of the trips performed in Amsterdam-Noord before the installation of the mobility hubs

The modal splits of the trips performed in Amsterdam are compared between the scenarios of installing hubs in one area and installing hubs in all of Amsterdam using the same budget of 1M€. Installing hubs in all of Amsterdam using the budget of 1 M€ leads to a higher modal split for the shared modes (Figure D.4) and hence higher benefits compared to only focusing on one area (Figure D.5).

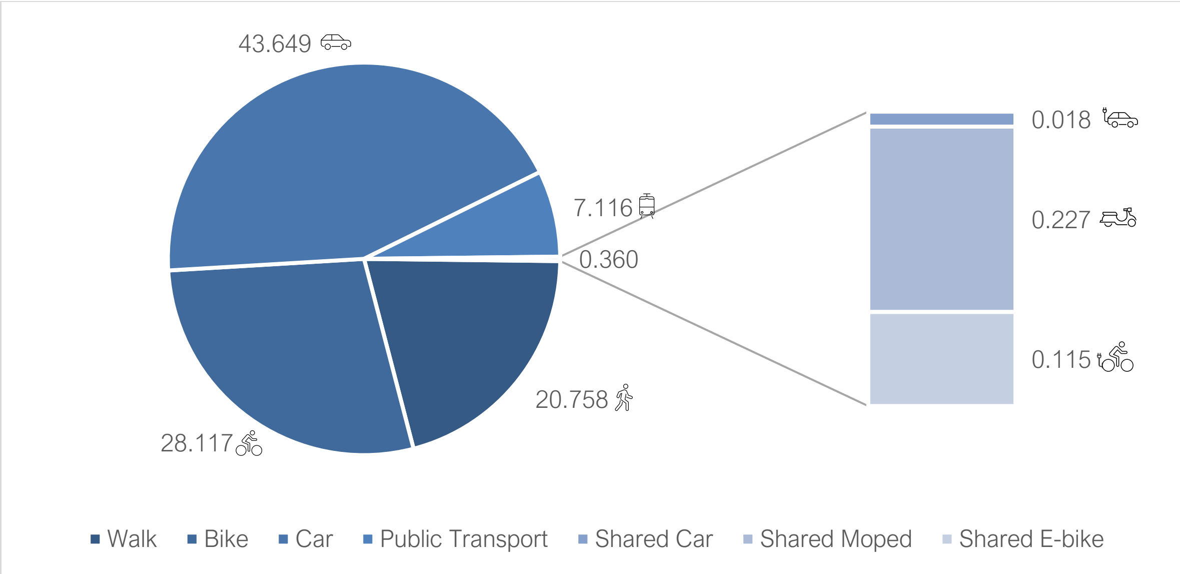

Figure D.4. Modal split of the trips performed in all of Amsterdam when 1 M€ are invested in constructing hubs in all of Amsterdam

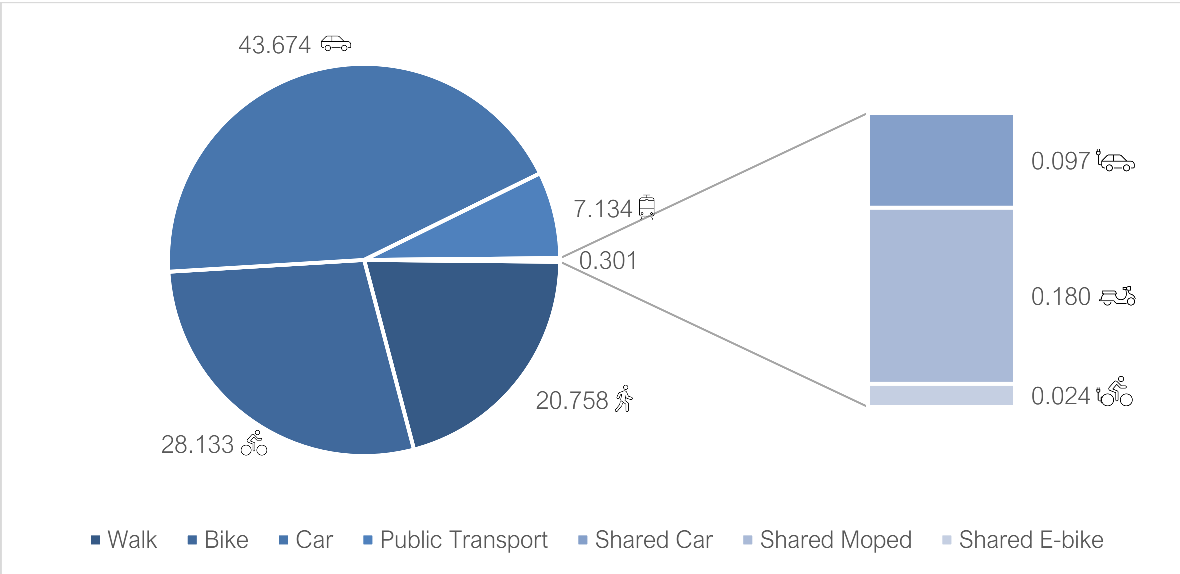

Figure D.5. Modal split of the trips performed in all of Amsterdam for a mobility hub's investment of 1 M€ focused on Amsterdam-Noord

In the case of distributing the hubs in all of Amsterdam, the 1 M€ is used to install 116 mobility hubs. While in the case where the main focus of the intervention is Amsterdam-Noord, then the 1 M€ is used to install 47 hubs. As a result, more vehicles are available at each hub in the second case, and a higher percentage of the demand is satisfied, as seen in Table D.1.

Table D.1. Comparison of the percentage of demand satisfied between the two scenarios

		All of Amsterdam	Only Amsterdam Noord
Shared Car	Average	4.8	76.0
	Standard Deviation	16.7	36.5
	Minimum	0.0	0.0
	Maximum	100.0	100.0
Shared Moped	Average	7.4	98.8
	Standard Deviation	10.7	9.0
	Minimum	0.0	0.0
	Maximum	95.5	100.0
Shared E-bike	Average	82.7	99.3
	Standard Deviation	36.8	7.2
	Minimum	0.0	0.0
	Maximum	100.0	100.0

Although it is more beneficial to use the budget of 1 M€ in all of Amsterdam, other parameters need to be considered when making such a decision from a policy point of view. For example, the municipality may want to focus on ameliorating the mobility options of one area, although this measure does not lead to the best quantitative outcome. So this focus scenario proves that focusing on one area might provide significant shifts and benefits for one zone but using this money for a larger area leads to a better global optimum with higher benefits achieved.