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Optimization of the location and capacity of shared multimodal mobility hubs to maximize travel utility in urban areas

Stavros Xanthopoulos [a], Marieke van der Tuin [b], Shadi Sharif Azadeh [a], Gonçalo Homem de Almeida Correia [a], Niels van Oort [a], Maaike Snelder [a,b,*]

[a] *Department of Transport & Planning, TU Delft, Delft 2628 CN, the Netherlands*
[b] *TNO, The Hague 2595 DA, the Netherlands*

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ABSTRACT

Nowadays, urban areas are exposed to various challenges such as climate change, social inequalities, and congestion. Shared mobility hubs present the opportunity to reshape our cities and mitigate the previously mentioned challenges by contributing to a more sustainable transport system. These are places where shared cars, mopeds, and e-bikes are offered to improve connectivity in urban areas. In this paper, we investigate the impact of efficiently allocating multimodal shared mobility hubs on modal split, service level, and environmental factors while assuring economic feasibility. Given a limited budget, cities would like to optimize the hubs' locations to maximize the population's benefits. For that purpose, we introduce a multi-stage design algorithm model that distributes the hubs and allocates fleets of shared cars, mopeds, and e-bikes to maximize travel utility for all the population traveling using traditional and/or shared modes while accounting for multimodal trips. The model is divided into several modules: computational modules that calculate the demand for the hubs; an optimization module to optimize the hubs' capacities, availability, and relocation of shared vehicles; and finally, a genetic algorithm to find the optimal hub distribution. Our proposed model is one of the first that optimizes the location and capacity of multimodal hubs by considering multimodal trips in a large network. Additionally, it allows to assess mobility, spatial, and environmental impact of shared modes. The model is applied to the case of Amsterdam, the capital of The Netherlands, with around 800,000 inhabitants. After running several scenarios with different budgets allocated to build the hubs, results show that having more hubs with a lower number of shared vehicles is more beneficial than having fewer hubs with higher capacity. That is because the travel time savings increase considerably when investments lead to complete coverage of the area by the hubs network. A modal split of 5% for the shared modes is expected when Amsterdam is covered by 288 hubs. From an environmental point of view, only 32% of the shared trips replace trips previously made by ICE and electric cars, leading to a limited CO2 emissions reduction of 1.27%. Hence, introducing shared modes and mobility hubs without push measures for the use of private cars appears to offer limited benefits to decrease the negative impacts of private car usage.

* Corresponding author.
E-mail addresses: S.Xanthopoulos@tudelft.nl (S. Xanthopoulos), marieke.vandertuin@tno.nl (M. van der Tuin), S.SharifAzadeh@tudelft.nl (S. Sharif Azadeh), G.Correia@tudelft.nl (G.H.A. Correia), N.vanOort@tudelft.nl (N. van Oort), M.Snelder@tudelft.nl (M. Snelder).

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1. Introduction

Nowadays, urban areas face multiple challenges regarding sustainability, pollution, livability, accessibility, and social inequality, which are partly related to the design of the mobility system. Since mobility hubs present an opportunity to reshape our cities and contribute to a more sustainable, livable, accessible, and equitable transport system, many local and regional governments throughout the world are focusing their policies on the introduction of mobility hubs (Weustenenk & Mingardo, 2023). A hub is defined as "a place where different sustainable transportation modes are integrated seamlessly to help promote connectivity" (Aono, 2019). Multimodal hubs have the potential to improve accessibility in urban/suburban areas by linking new emerging shared modes with the existing traditional public transport. Allowing seamless intermodal trips would enhance the population's travel experience by mitigating traffic jams and shifting towards more sustainable mobility solutions. This modal shift would create new opportunities to repurpose public spaces, for example, by reducing car (parking) space and making the streets more suitable for active modes of travel (Stam et al., 2021). Given a limited budget, cities need to optimize the location of mobility hubs to maximize the benefits for their citizens.

Facility locations can be selected efficiently using facility location models, a specific sort of optimization model whose decision variables correspond to the location and capacity of these facilities. This problem has been extensively studied for various types of facilities, of which shared mobility stations (Frade & Ribeiro, 2015). However, most of the models developed in the literature focus on locating stations for unimodal mobility services such as bike and car sharing services. 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. This paper aims to introduce a multi-stage design algorithm that optimizes the hubs' location and the allocation of shared vehicles to maximize utility given a certain budget restriction while considering multimodal trips in a real size urban area.

Mobility hubs can differ in their size and services offered. The focus of this paper is urban shared mobility hubs that offer shared e-mopeds, e-bikes, and e-cars and that do not need the construction of major structures. 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 hub's type. The hubs' sizes are then a result of the model developed rather than a classification of the hub type. A one-way station-based system is considered, which means that the shared vehicles should be unlocked at a hub but do not have to be returned to the same hub after usage (Mounce & Nelson, 2019).

This paper contributes to the scientific literature by presenting a model framework to optimize the locations and the capacities of multimodal shared mobility hubs (i.e. number of shared e-mopeds, e-bikes, and e-cars offered) in large-scale realistic multimodal networks to maximize travel utility for all individuals traveling using traditional and/or shared modes. This model is one of the few that considers multimodal trips which highly affect the results. A case study for the municipality of Amsterdam in the Netherlands illustrates how the model can be used to develop policies for the design of a network of hubs. The case study also shows what is the impact of the introduction of mobility hubs on the modal split, vehicle kilometers traveled, total travel time, emissions, percentage of shared mobility demand satisfied over different time periods, and spatial coverage. The study also provides a deeper understanding of the relationship between shared modes and public transport. The paper is structured as follows. In the following section, we present a literature review of the research conducted to locate mobility hubs or shared mobility stations. Then, the methodology is detailed and explained. In the next section, the model is applied in a case study for the city of Amsterdam. This is followed by a discussion on the results. The paper ends with the main conclusions that can be taken from the study.

2. Related literature

Several models and approaches have been investigated to better design shared mobility 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, a geographic information system, or a combination of methods is applied. This categorization is not meant to be exclusive, and it does not seek to rigidly classify models into separate compartments. Instead, the aim is to discuss the advantages and limitations of various methodological approaches used in the literature and acknowledge that these approaches can often be combined or applied together to address the problems effectively. The second differentiation is done on the objective 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, only a 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. This literature review focuses mainly on algorithms developed to distribute unimodal and multimodal mobility hubs. The literature review was conducted by searching for relevant studies and articles using online databases such as Google Scholar, ScienceDirect, and IEEE Xplore. Various keywords and combinations such as "shared mobility", "station location", "capacity optimization", and "mobility hubs" were used. References within the articles found were also examined to identify additional sources. The selected studies were then analyzed and synthesized to draw insights and recommendations on the topic.

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 bike sharing stations using mathematical programing. Caggiani et al. (2020a) developed a linear mathematical problem to minimize the daily bike sharing costs, including operation, maintenance, and user system costs. Constraints to satisfy the expected demand and ensure spatial equity were set. The equity 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 et al., 2020a). 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. 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). Caggiani et al. (2020b) developed a model that distributes 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.

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 the number of people covered, or to minimize 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 stations (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.

Other 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

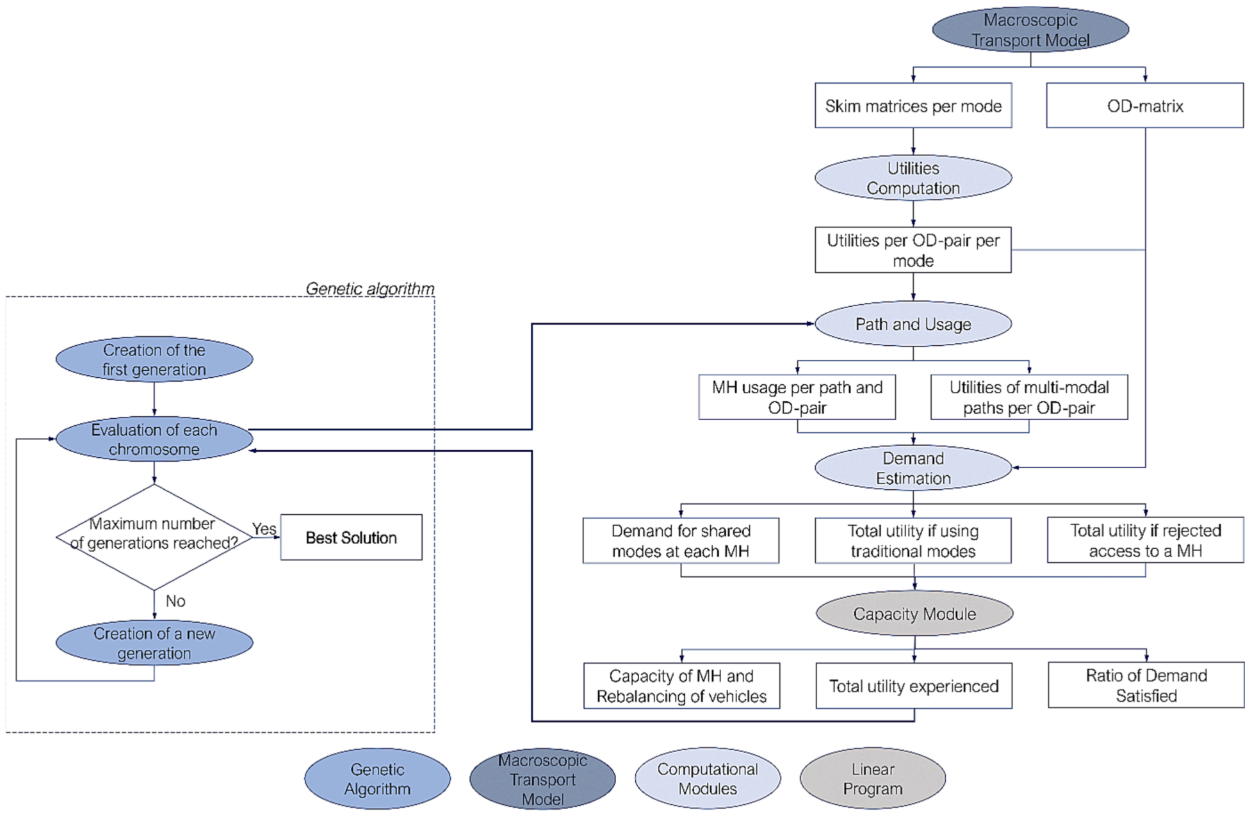

Fig. 1. Model framework.

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 in order to prioritize bike sharing infrastructure. 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.

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 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 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. Frank et al. (2021) developed a decision support tool to locate multimodal mobility hubs in rural areas. The model aims to improve accessibility to points of interest by increasing the number of categories accessible within a certain travel time threshold; and 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.

Most of the models developed so far focus on locating stations for unimodal mobility services. The models aim to either maximize profits for operators or maximize spatial coverage. There is a lack of models considering travelers' costs in a multimodal network. Most of the models do not consider the relation with other traditional modes of public transport, which might lead to unrealistic results and inaccurate assessments. In conclusion, no model has been presented in the literature to optimize the location and capacity of multimodal mobility hubs in a large multimodal network to maximize utility. This paper aims to fill a gap in the literature by proposing a model that optimizes the location and capacity of shared multimodal mobility hubs while maximizing travel utility in urban areas, accounting for multimodal trips.

3. Methodology

The model proposed in this paper has as its main objective to locate shared mobility hubs and determine their fleet capacity. The framework adopted for the model is presented in Fig. 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.

The model developed uses the outputs of a macroscopic transport model for a certain area of interest. A macroscopic model simulates the aggregate behavior of traffic flows. It aggregates the network's trips into several zones with similar attributes and properties (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. Some examples of macroscopic modelling packages include AIMSUN, PTV VISUM, Cube Voyager, EMME, and Omnitrans (Calvert et al., 2016).

Fig. 1 outlines the structure of the proposed model. In our initial Utility Computation Module, the utilities per mode and OD-pair are computed using skim matrices exported from a macroscopic strategic traffic and transport model. A Genetic Algorithm activates some mobility hubs from a set of pre-chosen candidates.

To determine the candidate mobility hub locations, candidates are distributed in the city by ensuring full coverage of the population. Literature has shown that users are willing to walk 200 to 400 m to access a shared mobility system (Duran-Rodas et al., 2021). If the city has a good coverage of public transport stops, these stops can be used as candidate mobility hub locations. However, if parts of the population are not covered by the candidate hubs' 400 m service areas, other locations are added to cover the whole population to prevent any bias and avoid favoring specific neighborhoods or demographics. Only locations that have sufficient space to install a hub are selected by checking them using Google Street View or conducting a field visit. In the case where the city lacks a robust public transport system, then the candidate locations can be distributed in the city by iterating while ensuring the space availability and coverage of the population by the 400 m service areas.

The utilities computed in the Utility Computation Module and the activated hubs are used in the Path and Usage Module to find the multimodal paths that maximize utility. As a result, the mobility hubs used in these paths are recorded, being those multi or uni-modal. The utilities obtained for each OD-pair and path are used in a logit model that accounts for path overlaps. This logit model computes 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 travel utility and it is the same as the fitness function used in the Genetic Algorithm to iterate over the different hub locations. After several iterations leading to the fitness function's convergence, the (assumed) optimal distribution and capacities of the mobility hubs are obtained. As is the case with all metaheuristics, they can yield highly satisfactory solutions to the problem, but there is no guarantee of achieving optimality. In the following sections, the term "optimal" solution refers to the solution at which a certain level of convergence of the fitness function has been reached since mathematical proof of optimality is not provided. All the sub-models within the framework are further explained in detail in the following sections.

3.1. Utilities computation module

In the initial step of the model, the skim matrices and the number of trips made per OD-pair in the case study region are obtained from a macroscopic transport model. Hence, the congestion and public transport modeling are performed by the macroscopic transport model rather than one of the developed modules, reducing the computation complexity. The resulting travel times and travel distances per OD-pair per mode (skim matrices) are used to compute the utilities to travel from an origin to a destination per traditional and shared mode. The current more traditional modes considered are walking, private bicycle, private car, and public transport; while the shared modes considered are the shared e-car, e-bike, and e-moped. The literature presents several factors to be included in the utility of the 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., 2022). However, in this paper, a simplified utility structure is adopted to match the utilities used in the macroscopic transport model. The utility function (U) is presented in Equation (1).

$$U = -(cost\_start + travel\_distance \times cost\_user\_per\_km) - (travel\_time \times value\_of\_time) - (travel\_time \times cost\_user\_per\_hour) - mode\_specific\_constant \quad (1)$$

The utility function (U) includes several variables. The initial costs incurred by the user are represented by the *cost_start* variable. The distance traveled is represented by *travel_distance*, while the cost per kilometer is represented by *cost_user_per_km*. The time spent traveling from their origin to the destination is represented by *travel_time* (for the shared modes, 2 additional minutes are included in the travel time to unlock and lock the vehicle), while the user's value of time is represented by *value_of_time*. Additionally, the cost per hour incurred by the user for using the specific mode is represented by *cost_user_per_hour*. Finally, a mode-specific constant value is included in the equation.

Inputs/outputs summary of the module:

- **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 shared modes usage module

This module aims to find the highest utility paths, for different mode combinations. Additionally, for each path, the mobility hubs that are used are also recorded. To compute the highest utility paths between OD-pairs while considering shared modes, the hubs' locations for a specific iteration of the genetic algorithm (to be explained later in section 3.5) should be inputted into this module. At each iteration, the metaheuristic activates different hubs from a set of candidate locations, e.g., current transit stops. The highest utility paths are naturally going to vary depending on the hubs that have been activated. The utility of a whole path is computed by adding the utilities of the different legs, which is inspired by the concept of a super network whereby this comprises networks specific to different modes interconnected by transfer links (Carlier et al., 2002). However, the mode-specific constants are not summed. Mode-specific constants are included in the path's utility depending on the role of the mode in the entire trip (van Eck et al., 2014). Due to the lack of stated or revealed preference data, a new mode-specific constant for the mode combination is not estimated. Hence, in this case, only the mode-specific constant of the main mode is included. It is also possible to add a transfer penalty to account for the disutility generated by transferring between modes. It is important to mention that the legs forming the highest utility path consider congestion (before introducing shared modes) since they are exported from the macro transport model. However, no further iterations are performed to compute the new congestion levels that may be affected by the introduction of shared vehicles. 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.

We assume in the modeling framework that multimodal trips have a maximum of three modal legs. The legs for the traditional modes are extracted from a transport model, which means that each leg can encompass multiple underlying trips. For instance, a public transport leg may involve a combination of bus and tram trips. Limiting the number of main legs to three is deemed acceptable for Amsterdam, given its high population density and the fact that longer trips typically do not exceed three modal legs. While it is feasible to consider more legs, doing so would significantly increase computational time.

Taking four traditional modes and three shared modes, the total number of alternatives for a three-leg trip is equal to $4 \times 3 \times 4 = 48$. From these 48 options, the following 9 combinations have been considered in this paper: walk – shared car – walk; walk – shared moped – walk; walk – shared bike – walk; walk – shared car – public transport; walk – shared moped – public transport; walk – shared bike – public transport; public transport – shared car – walk; public transport – shared moped – walk; public transport – shared bike – walk. Some combinations that are less probable or more complex to model are not considered in the case study. For example, the mode combinations that include a shared trip between two public transport trips are not considered. These trips might be candidates for shared mobility however they represent a marginal number of shared mobility trips when compared to the effort of modeling them. Finally, all the combinations that include a car or a private bike as access/egress modes to mobility hubs are not considered due to the increase in complexity and computation time to model the vehicle ownership and 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 study, especially since the case study focuses on the urban area of Amsterdam. To locate regional shared mobility hubs, Blad et al. (2022) proposed a multi-criteria decision analysis.

Inputs/outputs summary of the module:

- **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 computes the travel demand per shared mode for every pair of hubs. To compute this demand, a logit model is used including a path size (*PS*) overlap factor to correct for overlap in paths. The *PS* is a continuous value that varies between 0 and 1. If the path 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 a decrease in utility and a decrease in the attractiveness of this path (Hoogendoorn-Lanser & Bovy, 2007). Public transport and walking are the only traditional modes that are combined with shared modes in the developed model. Therefore, there may be overlaps between the public transport or walking legs when they are combined with shared modes and the corresponding uni-modal public transport or walking trips. To address this overlap, we use an overlap factor for the overlapping public transport leg. However, it is assumed that a relatively small walking leg is combined with shared mode trips, and as a result, we do not consider the overlap between the walking leg in the shared trip and the uni-modal trip done solely by foot. This approach allows to appropriately account for the main overlaps while maintaining simplicity and accuracy in the analysis. It is important to note that alternative methods exist in the literature for handling dependent paths, including probit and nested models. However, these models are computationally intensive. Probit models, for instance, cannot be computed analytically and demand numerous iterations for each OD-pair (Hoogendoorn-Lanser & Bovy, 2007). Nested models involve nesting parameters that complicate computations, particularly for numerous OD-pairs (Krajzewicz et al., 2018). Additionally, parameter estimation in these models is challenging, especially in the absence of sufficient data. Hence, for each OD-pair k, the utilities U of all paths p, a logit parameter β, and overlap parameter $\beta_{overlap}$ are used to compute the ratio r of trips performed using a multimodal path p as shown in Equation (2).

$$r_p^k = \frac{\exp\left(\beta \times \left(U_p^k + \beta_{overlap}\ln PS\right)\right)}{\sum_{p\in\mathscr{P}}\exp\left(\beta \times \left(U_p^k + \beta_{overlap}\ln PS\right)\right)} \tag{2}$$

Where,

$$PS = 1 - \frac{l}{N \times L}$$

PS corresponds to the path size overlap factor, l (in km) 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 (in km) 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, the parameter $\beta_{overlap}$ is needed. 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 study, the overlap is assumed to be negatively perceived thus adding disutility due to the assumed identical paths used.

The share of trips over the multimodal paths is multiplied by the total number of trips per OD-pair to obtain the demand for shared modes. The use of the total number of trips per OD-pair that result from the macroscopic model provides a direct depiction of the population's mobility behavior in the area. As a result, there is no need to rely on proxy variables such as points of interest or other demand attraction factors to estimate the number of trips. Finally, to obtain the number of trips demanding the use of the different hubs and shared modes, the demand for shared modes per OD-pair is combined with the usage matrix that contains information on which hubs are used for each path and OD-pair (the output of the previous module). It is assumed that the number of trips between each OD-pair does not vary when shared modes are introduced to the network. In a more advanced methodology, the OD matrix should be computed again in an iterative way using the skim matrices of all the available modes since there might be new trips generated or old ones redistributed when an alternative is introduced. This would make the model harder to solve.

If individuals want to use a shared mode but no vehicles are available (the capacity will be obtained in the next module), it is assumed that they are rejected and thus redistributed over traditional modes. The utility W^k 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-computed share of each traditional mode (walking, bicycle, private car, and public transport) by the utility of using it and summing them all up.

Inputs/outputs summary of the module:

- **Inputs:** Utilities per mode path and mobility hubs usage per OD-pair, total number of trips 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 for each shared mode and each pair of hubs computed in the Demand Estimation module is inputted into a linear optimization model, presented in this section, that maximizes utility by optimizing the number of docks or spaces for shared modes, the number of shared vehicles, the number of relocated vehicles between the hubs, and the ratio of demand satisfied. In this model, the objective function 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 access to the shared mobility system 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. This is a

Table 1
Model Notation.

Sets	
$\mathscr{K}$	Set of OD-pairs
$\mathscr{M}$	Set of available shared modes (shared cars, shared mopeds, and shared e-bikes)
$\mathscr{N}$	Set of centroids
$\mathscr{T}$	Set of time-steps
Parameters	
B	Investment budget for building hubs
C_f	Fixed investment costs to build a mobility hub
C_d^m	Investment cost to construct or install a dock for shared mode $m \in \mathscr{M}$
C_o^m	Operational cost per vehicle of type m per year
C_r^m	Relocation cost per vehicle of type m per time-step
C_v^m	Investment cost to acquire a vehicle of type m
d_{ij}^{mk}	Demand for vehicles of type m needed for OD-pair $k \in \mathscr{K}$ from mobility hub $i \in \mathscr{N}$ to mobility hub $j \in \mathscr{N}$ (output of the *Demand Estimation* module)
F	Big number: in that case max $(2 \times y_{max}^m)$ with $m \in \mathscr{M}$
p^t	Demand fraction at time-step $t \in \mathscr{T}$ (discussed in the Model's Parameters section)
R^m	Revenue generated per vehicle of type m per time-step
T_{ij}^m	Time-steps needed to travel from mobility hub i to mobility hub j using shared mode m
U^{mk}	Utility experienced by OD-pair k using shared mode m
Q	Total utility experienced by all OD-pairs using traditional modes of transport. Q is obtained by multiplying the utility per OD-pair for each traditional mode (computed in the utilities computation module) by the number of trips using each traditional mode per OD-pair (computed in the demand estimation module) and summing the results for all OD pairs
W^k	Utility experienced by 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, greater than 0
z_i	Binary variable equal to 1 if mobility hub is activated at node i, and 0 otherwise. It 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 time-step t in mobility hub i
x_i^{mt}	Ratio of satisfied demand for shared mode m at time-step t in mobility hub i
y_i^m	Number of docks or spaces for shared mode m available in mobility hub i

Objective Function

$$\max(\mathrm{S}) = \sum_{i\in\mathscr{N}}\sum_{m\in\mathscr{M}}\sum_{t\in T}\left(x_i^{mt} \times \sum_{j\in\mathscr{N}}\sum_{k\in K}d_{ij}^{mk} \times p^t \times U^{mk}\right) + \sum_{i\in\mathscr{N}}\sum_{m\in\mathscr{M}}\sum_{t\in T}\left(\left(1 - x_i^{mt}\right) \times \sum_{j\in\mathscr{N}}\sum_{k\in K}d_{ij}^{mk} \times p^t \times W^k\right) + Q \tag{3}$$

Subject to

$$v_i^{m(t+1)} = v_i^{mt} - x_i^{mt} \times \sum_{j\in\mathscr{N}}\sum_{k\in K}d_{ij}^{mk} \times p^t + \sum_{j\in\mathscr{N}}\sum_{t'\in\mathscr{T}|t'+T_{ji}^m=t}\sum_{k\in K}x_j^{mt'} \times d_{ji}^{mk} \times p^{t'} - \sum_{j\in\mathscr{N}}r_{ij}^{mt} + \sum_{j\in\mathscr{N}}\sum_{t'\in\mathscr{T}|t'+T_{ji}^{m=0}=t}r_{ji}^{mt'}\ \forall i \in \mathscr{N}, m \in \mathscr{M}, t \in (\mathscr{T} - 1) \tag{4}$$

$$v_i^{mt} \geq x_i^{mt} \times \sum_{j\in\mathscr{N}}\sum_{k\in K}d_{ij}^{mk} \times p^t\ \forall i \in \mathscr{N}, m \in \mathscr{M}, t \in \mathscr{T} \tag{5}$$

$$\sum_{j\in\mathscr{N}}r_{ij}^{mt} \leq v_i^{mt} \quad \forall i \in \mathscr{N}, t \in \mathscr{T}, m \in \mathscr{M}_{SM} \tag{6}$$

$$r_{ii}^{mt} = 0\ \forall i \in \mathscr{N}, m \in \mathscr{M}, t \in \mathscr{T} \tag{7}$$

$$r_{ij}^{mt} \leq F \times z_j\ \forall i \in \mathscr{N}, j \in \mathscr{N}, m \in \mathscr{M}, t \in \mathscr{T} \tag{8}$$

$$r_{ij}^{mt} \leq F \times z_i\ \forall i \in \mathscr{N}, j \in \mathscr{N}, m \in \mathscr{M}, t \in \mathscr{T} \tag{9}$$

$$y_i^m \leq y_{max}^m \times z_i\ \forall i \in \mathscr{N}, m \in \mathscr{M} \tag{10}$$

$$y_i^m \geq y_{min}^m \times z_i\ \forall i \in \mathscr{N}, m \in \mathscr{M} \tag{11}$$

$$v_i^{mt} \leq y_i^m \quad \forall i \in \mathscr{N}, m \in \mathscr{M}, t \in \mathscr{T} \tag{12}$$

$$x_i^{mt} \leq z_i^m \quad \forall i \in \mathscr{N}, m \in \mathscr{M}, t \in \mathscr{T} \tag{13}$$

$$\sum_{i\in\mathscr{N}}\sum_{m\in\mathscr{M}}y_i^m \times C_d^m + \sum_{i\in\mathscr{N}}z_i \times C_f \leq B \tag{14}$$

$$\sum_{i\in\mathscr{N}}\sum_{m\in\mathscr{M}}\sum_{t\in T}R^m \times x_i^{mt} \times \sum_{j\in\mathscr{N}}\sum_{k\in K}d_{ij}^{mk} \times p^t \times T_{ij}^m - \sum_{i\in\mathscr{N}}\sum_{j\in\mathscr{N}}\sum_{m\in\mathscr{M}}\sum_{t\in T}C_r^m \times r_{ij}^{mt} \times T_{ij}^m - \sum_{i\in\mathscr{N}}\sum_{m\in\mathscr{M}}v_i^{m(t=0)} \times \left(C_v^m + C_o^m\right) \geq 0 \tag{15}$$

simplification based on the notion that people would like to stick with the mode that they prefer among these new alternatives.

While the model does not explicitly reflect the disutility experienced by travelers who are rejected access to a mobility hub, it should be emphasized that it is assumed that travelers have full visibility of the available vehicles through a dedicated app or platform before leaving their origin. Hence, they can make informed decisions based on the availability of vehicles, and no disutility is assumed in terms of effort or inconvenience caused by lack of vehicle availability. However, it is worth mentioning that the mere absence of available shared vehicles can also be considered a form of disutility, even if no efforts were involved. Nevertheless, for the purpose of the model, this aspect is disregarded.

The mathematical model structure is inspired by models developed for car sharing (Correia & Antunes, 2012; Huang et al., 2018) and bike sharing systems (Frade & Ribeiro, 2015). The model notation and description are presented in Table 1.

The objective function is to maximize the total travel utility experienced by the individuals in the system. It has three components: the first represents the sum of utilities for the trips using a shared mode; the second represents the sum of utilities for the trips that were rejected access to the shared modes due to lack of capacity; the third represents the utilities of the trips performed using the traditional modes. The model is subject to 13 constraints that are detailed below.

Constraint 4 is an equilibrium constraint. It represents the conservation constraint of available shared vehicles of type m over time-step t at mobility hub i. The number of vehicles of type m at time-step $t+1$ is equal to the number vehicles present at time-step t minus the number of vehicles that leave the hub at time-step t to be used or relocated, plus the number of vehicles, used or relocated, that arrive at time-step t from any hub at hub i. To find the arrival times of the relocated shared vehicles, the travel time for a shared car ($m = 0$) is used since all the shared modes are relocated using the road network with travel times similar to the car.

Constraint 5 ensures that a higher number of vehicles of type m is present at 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 that hub. It is important to mention that the ratio of satisfied demand x is a variable related to the mobility hub i rather than each OD-pair. Hence, all the OD-pairs that use mobility hub i have the same ratio of satisfied demand. Therefore, everyone that arrives at the same moment at the hub has the same chance of using the shared modes regardless of their origin or destination.

Constraint 6 ensures that fewer vehicles of type m are relocated from hub i than the available vehicles in this hub. Constraint 7 ensures that no vehicles are rebalanced within the same mobility hub to avoid unnecessary relocations. Constraints 8 and 9 ensure that no vehicles of type m are rebalanced from mobility hub i to j if those hubs are not activated. In this model, it is assumed that rebalancing can happen at each time-step. However, we do recognize that other constraints such as the availability of employees and trucks might limit the ability to rebalance vehicles at every time-step (Santos & de Almeida Correia, 2019). Constraints 10 and 11 ensure that no active hubs house more (or fewer) spaces than the set limits. Constraint 12 guarantees that fewer vehicles of shared mode m are assigned to mobility hub i than the available spaces. Constraint 13 ensures that the ratio of satisfied demand is lower than one if the mobility hub is activated or zero if it is not activated.

Finally, Constraints 14 and 15 are budget constraints. The first one ensures that the investment costs are lower than the budget. It computes the costs of installing the docks/spaces and the fixed costs of constructing a hub. The second constraint ensures that the operation of the service is profitable. These profits are computed by subtracting the operators' costs from their revenues. The latter are computed by multiplying the duration of the trips by the price of using the shared mode. The costs equal the sum of relocations, vehicles' depreciation, and vehicle maintenance costs normalized to the study period.

Inputs/outputs summary of the module:

- **Inputs:** Parameters and data mentioned in Table 1.
- **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. Metaheuristic for the location problem: Genetic algorithm

The entire process described above assumes the existence of a network of hubs solution to be evaluated. Formulating the above mathematical problem with the location problem simultaneously leads to a very difficult problem to solve (Correia & Antunes, 2012), especially in a context of multiple modes available for traveling. A metaheuristic is proposed to search for a good configuration solution for the hubs' network. For each network - a set of activated mobility hubs out of the candidate locations - it is possible to compute the utility of each multimodal path in the *Path and Usage* module and run all the other modules described above to estimate the performance of that particular set of active hubs.

According to the literature, the genetic algorithm is one of the most suitable metaheuristics to perform such a task (Caggiani et al., 2020b; Liu et al., 2015; Nair and Miller-Hooks, 2016; Romero et al., 2012). Genetic algorithms are inspired by the theory of evolution. Over the different generations, the traits that enable the individuals to survive (perform better according to a performance function) become more frequent, leading to the population's evolution (Mirjalili, 2019). The initial population is generated with several individuals. Each individual is constituted of an array or *chromosome* of 1 s and 0 s representing whether a mobility hub is active at a specific candidate location or not. The fitness of each individual is assessed using the *Capacity* module's objective function which requires running all the prior modules as explained before. Pairs of individuals from the initiated population are selected to be the parents and reproduce the next generation of the population by taking genes from both parents in a crossover process and randomly modifying some genes in a mutation process. Then the fitness of the new individuals is assessed using the objective function in an iterative 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 but not guaranteeing it (Mirjalili, 2019).

Inputs/outputs summary of the module:

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

4. Case study

The method has been applied to the case study city of Amsterdam, capital of the Netherlands (approximately 800,000 inhabitants), to evaluate the methodology and simultaneously get insights into the optimal locations and capacities of the mobility hubs. Each household in Amsterdam has an average of 1.98 bicycles which shows a great interest in this mode. In fact, 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). While the bike modal split to train stations is close to 50 % (Shelat et al., 2018). This is also stimulated by the presence of a well-developed cycling infrastructure with more than 2336 km of segregated cycling and shared paths. 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 private cars thus pushing people to use collective forms of mobility as well as active modes. Mobility hubs are a good solution to achieve the mentioned goals since they decrease reliance on personal vehicles and shift mobility from owning to sharing, making the usage of cars an option, not an obligation. It is therefore a challenge to propose good reliable and robust methods for the city of Amsterdam to scale up these hubs into a proper network that maximizes accessibility and improves mobility while creating a more livable and sustainable city. This is a goal of Amsterdam but also of other cities worldwide as they move to cut carbon emissions in this decade.

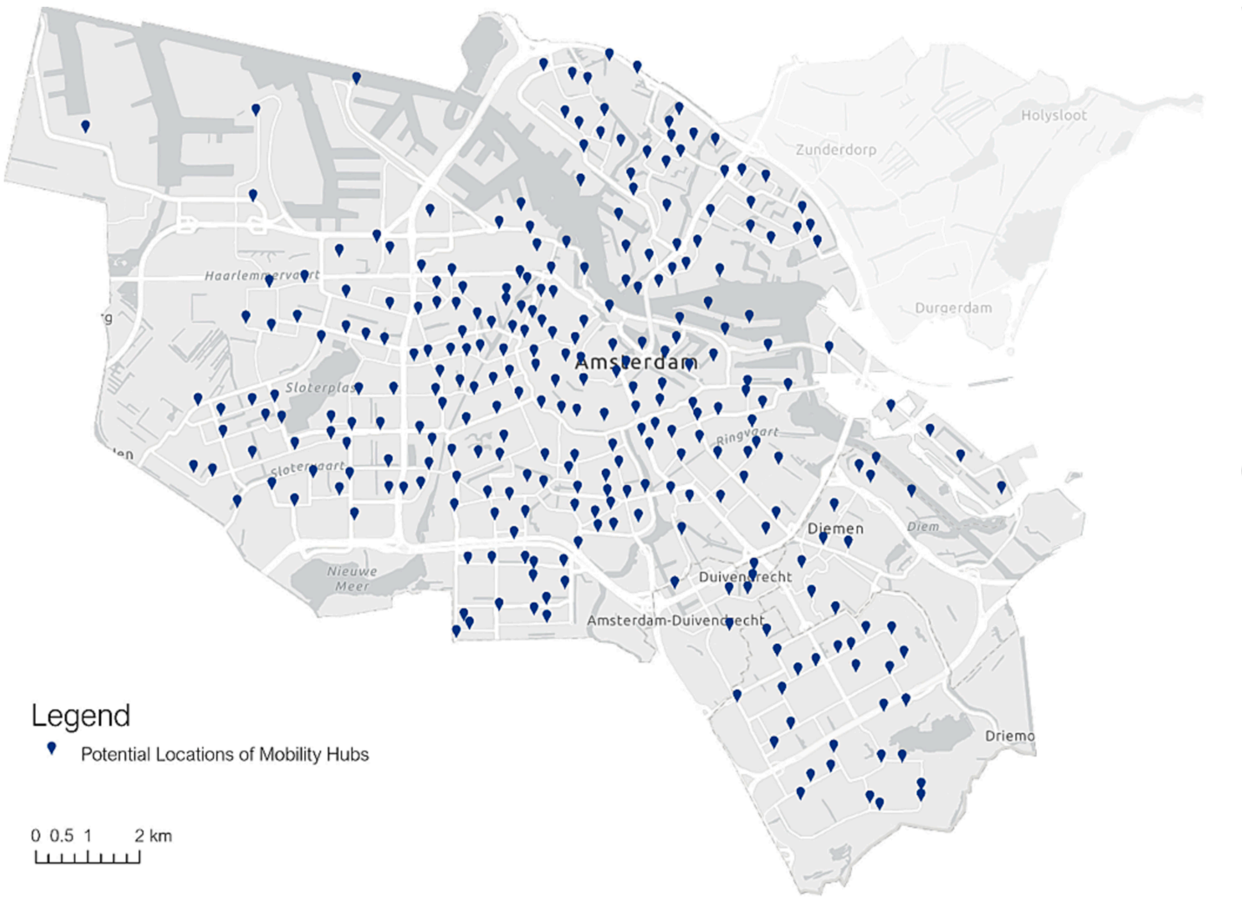

Fig. 2. Final potential mobility hub locations.

4.1. Potential location of mobility hubs

To generate solutions for the problem one must start by generating a list of candidate locations. As previously mentioned in section 3, public transport stops are initially considered as candidate hubs. To ensure comprehensive coverage and avoid biases, additional candidate hubs are included to cover the entire population with 400 m service areas. All hubs, including both public transport stops and additional candidate locations, were checked using Google Street View to visually evaluate whether there is enough space available, equivalent to approximately four car parking spots, on the road, sidewalk, or other empty areas. Only locations that have sufficient space to install a hub have been selected.

To model the mobility hubs and obtain the skim matrices needed, the candidate hub locations are associated with centroids from an existing macroscopic traffic and transport model of Amsterdam which has a high density of centroids (TNO, 2022). The main focus area of this study is the city of Amsterdam, and smaller villages in the metropolitan area, particularly those located in the north-east beyond the highway (e.g., Zunderdorp), have not been included. In the end, a total of 288 potential candidate mobility hub locations have been selected for the case study, as seen in Fig. 2. These potential candidate hubs cover more than 99 % of the population in the area under consideration.

4.2. Parameters

The model parameters used to perform the case study for Amsterdam are presented in this section. The forecasted 2030 morning peak transport data is used for the runs since it is assumed that the network of hubs will be ready by then.

4.2.1. Utilities' parameters

The utility function presented in Equation (1) is used with different costs and parameter values per mode (see Table 2). The utilities of traditional modes and shared cars are present in Amsterdam's transport model and have been estimated using transport demand data (TNO, 2022). However, since shared mopeds and shared e-bikes are not included in that model, these parameters have been derived based on expert judgment. The mode-specific constant for shared mopeds and shared e-bikes is set equal to the mode-specific constant of regular bikes. The value of time parameter used for these modes is 7.5€/hr, which is the value of time adopted in the Dutch 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.

No transfer penalties are included in the calculation of utilities for the case study. The reason for this is that mobility hubs are associated with the centroids of the transport model, as mentioned in section 4.1. As a result, the model generates many detours that do not occur in real life. Therefore, each transfer is inherently accompanied by a certain detour due to the modeling approach adopted, which can be considered as a type of penalty. Hence, while explicit transfer penalties are not utilized, the detours generated by the model inherently account for the disutility generated by transferring between modes.

4.2.2. Overlap parameter

As previously mentioned in the *Demand Estimation* module section (3.3), the overlap factor is used to account for the disutility related to overlapping legs. It is assumed that in the case of this study, overlapping paths are less attractive than independent paths. The probability of choosing path p is given by Equation (2).

To determine the value for the overlap parameter $\beta_{overlap}$, there are three possible options: estimating it based on available data, borrowing it from existing literature, or performing a sensitivity analysis. In this specific research, the first two options were not accessible and were considered out of scope. Therefore, a sensitivity analysis of this parameter is conducted on the modal split and the demand distribution over the mobility hubs. Since long computation times do not allow for a sensitivity analysis on the overall model, the analysis is performed when all the candidate mobility hubs are activated. The overlap parameter is varied between 0 and 20 to assess its impact on the modal split. The graph presented in Fig. 3 highlights the effect of the overlap parameter on the modal split of each shared mode. It is important to mention that the modal split shown in the chart is the demand for shared modes rather than the actual trips satisfied. Hence, the real modal split can be smaller than what is presented in this graph due to vehicle unavailability. 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. An increase in the overlap parameter results in a higher disutility, causing a decrease in the modal split for shared modes-

Table 2
Utility 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

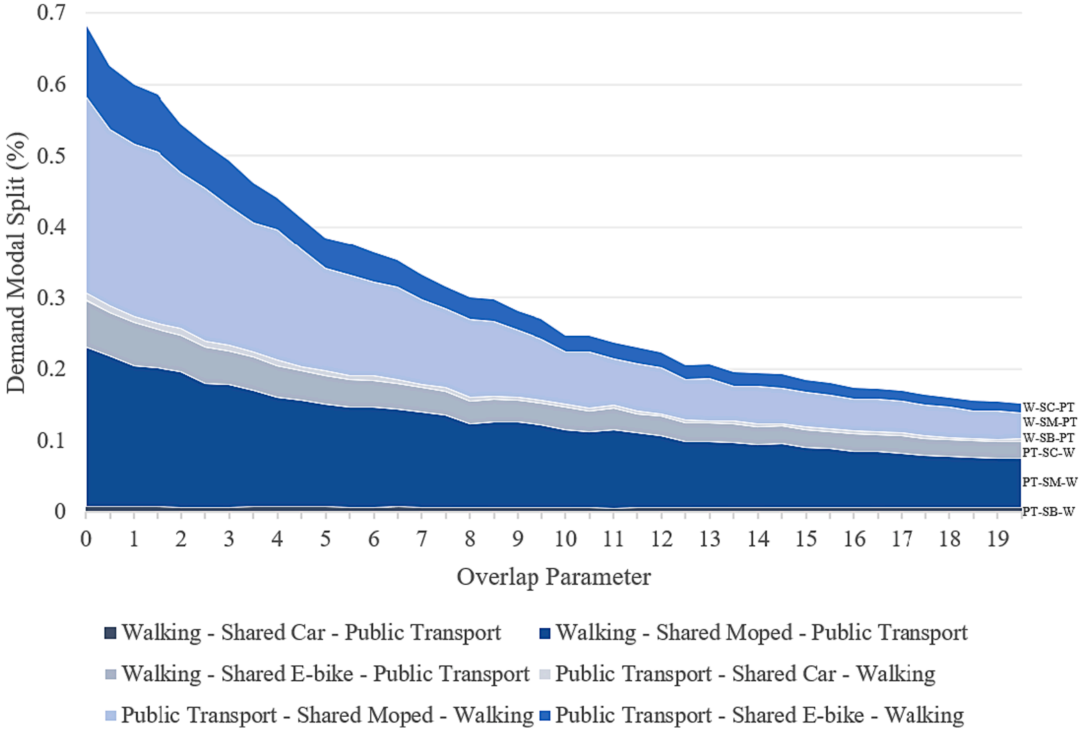

Fig. 3. Effect of the overlap factor on the demand modal split.

public transport combinations. As the overlap parameter continues to grow, the demand modal splits of the shared modes-public transport combinations approach zero. Increasing the overlap parameter from 0 (0 means that the overlap is not considered) to 20, decreases the modal split of the shared modes-public transport combinations from 0.6 % to 0.18 % of the overall trips in the system, as seen in Fig. 3. This percentage is relatively small and only a split of it will be satisfied by the available shared modes. A parameter value of 15 is chosen, because in the interval 0 – 15, the modal split exhibited more significant fluctuations, indicating higher sensitivity to changes in the overlap parameter. Beyond the value of 15, the slope decreased, suggesting that the results became less sensitive to further increases in the overlap parameter. The selected value of 15 offers a balance between stability and impact, making it a suitable choice. Additionally, few OD-pairs were chosen to represent cases for which the combination of shared modes and public transport was either expected to be beneficial or not. Modal splits were computed for various overlap parameters, and in consultation with local mobility experts, 15 was estimated as the value most closely representing the real-world scenarios for these OD-pairs. Because of the absence of behavioral data, the parameter choice could not be validated and was instead approximated. Future research could improve accuracy by estimating this parameter using choice models. Importantly, it is worth mentioning that the sensitivity analysis showed that the overlap parameter had a negligible effect on the overall results, and the chosen value does not significantly alter the main conclusions drawn from the research.

4.2.3. Parameters for the capacity module

The *Capacity* module is dependent on several parameters which are primarily related to the costs of constructing the mobility hubs, acquiring the vehicles, and operating the system. First, the fixed construction costs (C_f) are set to be 5000€ per hub, according to experts at TNO working in the field in close cooperation with the municipality of Amsterdam. The costs to construct/install a dock or space for all the shared modes (C_d^m) are set to 500€/space (Frade & Ribeiro, 2015). It is assumed that the charging will not be done on-site but in a specialized facility; hence, no significant installations are needed, mainly repurposing the space, and applying surface painting. Regarding the revenue generated (R^m), the average service prices in Amsterdam are used: 0.28€, 0.295€, and 0.23€ per minute 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 are equal to a tenth of the average hourly wage, assuming that each employee can take ten vehicles in a truck. This brings the relocation costs to 3.33€ per 10 min per shared car relocated and 0.33€ per 10 min per shared moped or e-bike relocated. When considering the relocation costs, it is assumed that full capacities of the vehicles are always utilized. This simplification allows for easier modeling of the system, but it may not fully capture real-world variations in vehicle occupancy. The operational costs of e-vans and electricity consumption are considered in the operational costs presented below.

The capital costs needed to initiate a shared mobility company are estimated based on a study performed by Wortmann et al. (2021)

for e-mopeds usage in Berlin. The capital costs used for this case study are 6,245€ per moped, 2,800€ per e-bike, and 15,170€ per car. Regarding the operational costs, it is assumed that the operator incurs the same operational costs for all the shared modes and that the fixed costs can be distributed evenly over the vehicles, which brings it to 1,900 € per year per vehicle (Wortmann et al., 2021).

A maximum number of docks/spaces is defined to limit the spatial usage of the mobility hubs due to the spatial limitations present in the city. The maximum capacity is 3 shared cars, 15 mopeds, and 15 e-bikes per hub. Most of the suggested mobility hub locations can house this number of vehicles, corresponding to approximately six car parking spaces. The minimum capacity set in the model is 1 car, 3 mopeds, and 3 e-bikes per hub.

The parameters used in the *Capacity* module are summarized in Table 3.

4.2.4. Share of demand in each time interval

The Amsterdam transport model at hand is a macroscopic model that aggregates trips spatially and temporally into a 2-hour peak. However, the demand fraction (p^t) every 10 min during the 2 h is needed to divide the aggregated data into smaller time intervals. The ratio of demand per time-step is found using the ODiN data, which is a yearly nation-wide questionnaire of around 60,000 respondents in the Netherlands (CBS, 2022). After filtering the trips, the demand distribution over the morning peak is presented in Fig. 4.

4.3. Model runs

Three scenarios are run with different budgets of 0.5, 1.0, and 1.5 million euros to build the shared mobility hubs. The computer used to perform the runs has the following specs: I9 – 9900X CPU@3.5 GHz 20 Logical cores, 64 GB RAM with a 24 GB NVIDIA TitanRTX GPU. 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 by taking advantage of the GPU computing technology 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 python library as variables. For each scenario, the convergence is reached after approximately 150 generations, with each generation having 50 individuals. The average computation time is 180 s per individual. Hence, each scenario takes around 20 days to run which is deemed acceptable for a hard planning problem such as this.

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. Additionally, for each scenario, two runs with different initial populations are performed to assess whether they converge towards the same optimum. Running the model twice is not intended to demonstrate that it produces the true optimal solution. Instead, it serves the purpose of assessing the convergence of the process. By running the model multiple times, it can be verified whether the achieved convergence is due to mere chance or if the results are consistently stable. The aim is to avoid obtaining vastly different results concerning the objective function when running the model again. This stability check provides additional confidence in the reliability of the outcomes. In some cases, the two runs do not converge exactly to the same absolute value of the fitness function due to minor rounding errors in the computation. For the scenario with a budget limit of 1.0 M€, 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 vehicles are assigned to each hub:

$$\frac{B}{C_f + \sum_{m\in\mathscr{M}} C_d^m \times y_{max}^m} \tag{16}$$

The proportion of activated hubs set 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 Fig. 5. The algorithm is assumed to converge toward the optimal solution since a plateau has been observed over the last 70 generations.

In the run presented in Fig. 5, it is proven that initiating a population with a certain proportion of activated hubs leads to faster convergence as opposed to starting the procedure with zero hubs or all hubs on. Hence, the same initiation procedure is adopted in the

Table 3
Capacity module's parameters.

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

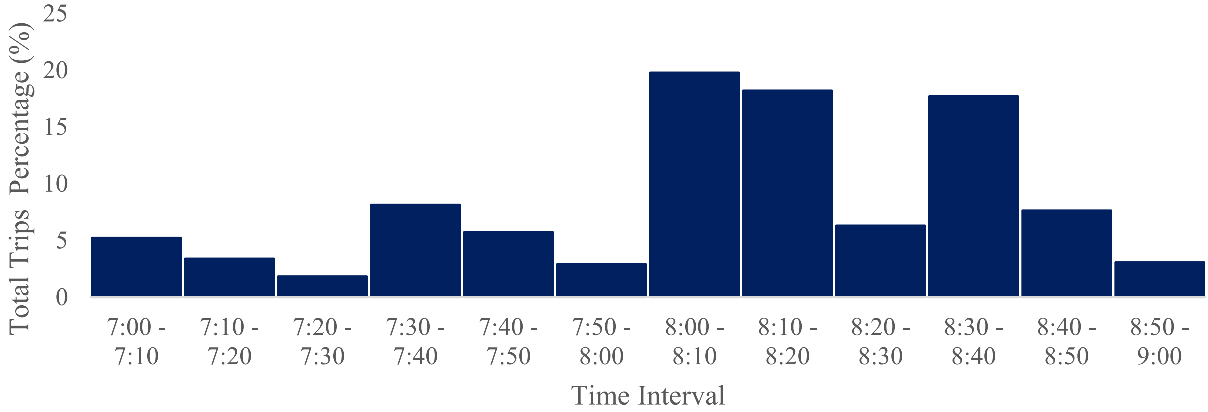

Fig. 4. Demand distribution over the morning peak.

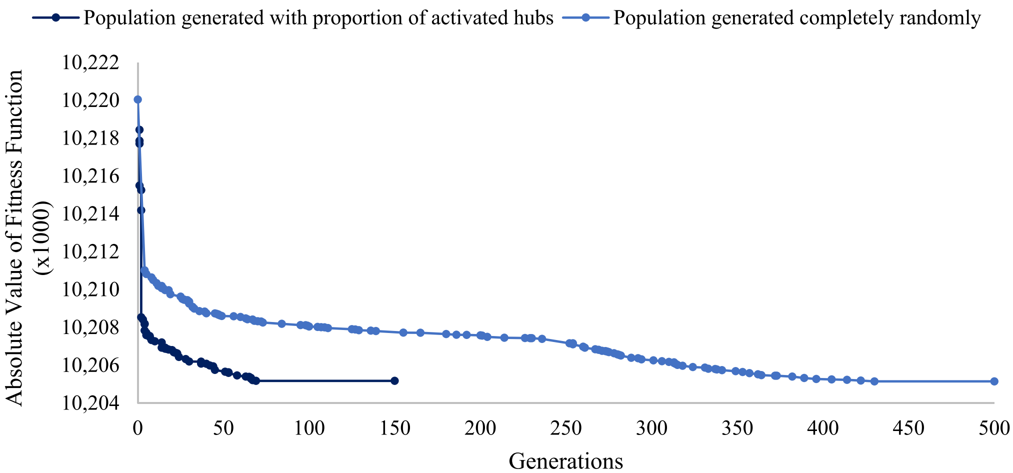

Fig. 5. Evolution of the best solutions over the generations for a budget of 1.0 M€.

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 Fig. 6. 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. For the third scenario with a higher budget of 1.5 M€, the evolution of best solutions over the different generations is presented in Fig. 7 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

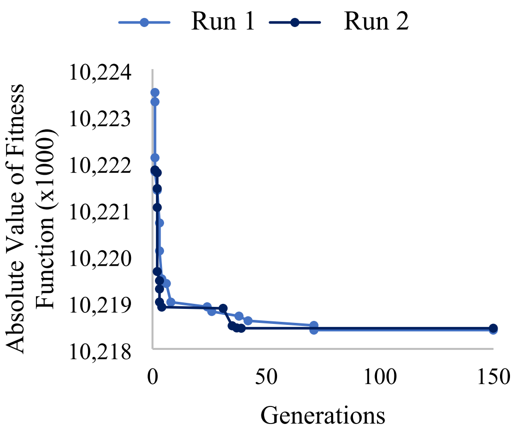

Fig. 6. Evolution of the best solutions over the generations for a budget of 0.5 M€.

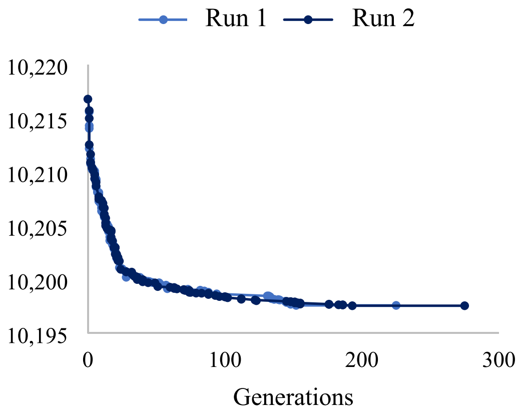

Fig. 7. Evolution of the best solutions over the generations for a budget of 1.5 M€.

approximately 25 days to run.

In addition to performing two runs, another check is performed to have higher confidence in the convergence reached 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. By keeping all the modules and interactions in the model intact, it would have been impossible to impose an optimal solution. Hence, for this trial, the capacity module which optimizes capacities of the hubs at each generation is not included, and a specific hub distribution is imposed 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 are not given access to shared modes, and the utility of traditional modes is applied. The selection of 160 hubs is made through a random process with the expectation that running the algorithm will naturally lead to convergence toward the imposed optimal solution. It is essential to emphasize that this selection is exclusively reserved for the additional verification trial and is not a standard practice in the typical model execution, serving to augment the degree of confidence in the convergence outcomes. Although the capacities are not considered in this trial, the size and variation in the fitness function are similar to the model developed. Hence, it is possible to show that the algorithm effectively converges. After 252 generations, the algorithm reaches the imposed optimal solution, which gives additional confidence regarding the results obtained with regards to the case study.

4.4. Results

Different 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€, respectively, and a final scenario with all 288 hubs activated, which requires a budget of 6.192 M€. For the five scenarios, the following results are presented:

- Mobility indicators: modal split, total travel time spent, percentage of demand satisfied.
- The spatial distribution of hubs, their capacities, and the population coverage.
- Environmental implications in terms of emissions.

4.4.1. Mobility indicators

First, the modal splits for the five scenarios are presented in Table 4. 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

Table 4
Modal split (cut at < 0.001 %) for the different budget scenarios.

Budget (M€)	0	0.5	1.0	1.5	All hubs activated (6.2)
Walk	20.76 %	20.76 %	20.76 %	20.76 %	20.76 %
Bike	28.32 %	28.21 %	28.12 %	27.63 %	25.33 %
Car	43.76 %	43.69 %	43.65 %	43.42 %	42.21 %
Public Transport	7.16 %	7.14 %	7.12 %	7.04 %	6.64 %
Shared Car	–	0.02 %	0.02 %	0.17 %	0.68 %
Shared Moped	–	0.16 %	0.22 %	0.73 %	3.86 %
Shared E-bike	–	0.04 %	0.09 %	0.21 %	0.41 %
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 %

logical since shared modes can substitute bike trips and provide faster means of transport. The second highest decrease is seen for 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, private car, and public transport, respectively.

Shared moped takes the largest share of trips since they are faster than e-bikes, and the fare difference is relatively small. The modal split for the shared modes is small for the scenarios with budgets of 0.5 and 1 M€. However, it increases significantly when higher investments are made. The significant benefits gained by higher investments are also highlighted in Fig. 8. The analysis comprises a limited number of data points due to the significant computation time required for each scenario. However, if more data points were added, it is likely that an S-shaped graph would be generated. This trend can be explained by the allocation of lower budgets primarily towards constructing smaller hubs with limited capacity and hence limited benefits. As the budget increases, more resources are dedicated to expanding the capacity of the extensive hub network. This allows a larger number of users, particularly those located in areas where the highest gains can be achieved, to benefit from the system. Consequently, investments exceeding 1 M€ result in more substantial reductions in total travel time per euro invested, contributing to the steeper slope observed in the S curve. However, there comes a point where the additional capacity and newly added hubs do not provide significant benefits compared to other transportation modes. This explains the flatter slope of the curve and the smaller returns per euro invested. The locations where the additional hubs and vehicles are provided may not offer substantial advantages to users compared to traditional modes, explaining the limited benefits achieved beyond a certain threshold.

Shared modes are combined with public transport, mainly when the average initial trip length is large. 60 % of the trips combining shared modes and public transport are longer than 40 min. In contrast, shared modes are used independently for trips between 10 and 50 min. Shared mopeds cover the highest percentage of trips having a travel time between 20 and 30 min. In comparison, shared cars and shared e-bikes cover the highest percentage of trips with a travel time between 10 and 20 min.

Another interesting indicator to assess is the average percentage of demand satisfied over the different time periods. For the shared car, it varies between 5.6 % and 71.3 % for budgets of 0.5 and 6.2 M€, respectively. While for the shared moped, it varies between 9.6 and 61.6 %, and for the shared e-bike between 87.4 and 90.3 %. This shows that the hubs do not satisfy all the demand, especially with lower investment budgets.

4.4.2. Spatial distribution of hubs

After assessing the hubs' effects on mobility indicators, their spatial distribution and capacity are analyzed. For a lower budget of 0.5 M€, the algorithm activates 58 hubs, as seen in Fig. 9.

While for a budget of 1 M€, the 116 activated hubs are presented in Fig. 10.

The distribution of hubs obtained for an allocated investment budget of 1.5 M€ is presented in Fig. 11. This investment leads to extensive coverage of Amsterdam while distributing the hubs evenly.

The variation in the capacity of the mobility hubs is presented in Table 5. In all 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.

The percentage of residents covered by the 0–250 m service areas is equal to 5.7, 11.5, 17.1, and 30.3 % for budgets of 0.5, 1, 1.5, and 6.2 M€, respectively. It is clear that when increasing the budget allocated to build 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 hub is equal to 17 % for a budget of 1.5 M€ and 30 % for a budget of 6.2 M€. This signifies that investments have diminishing returns in terms of coverage. The rationale behind this observation is twofold. Firstly, there is a focus on areas with higher population densities. This strategic approach ensures that a larger portion of the population resides in proximity to the mobility hubs, maximizing utility for a significant number of

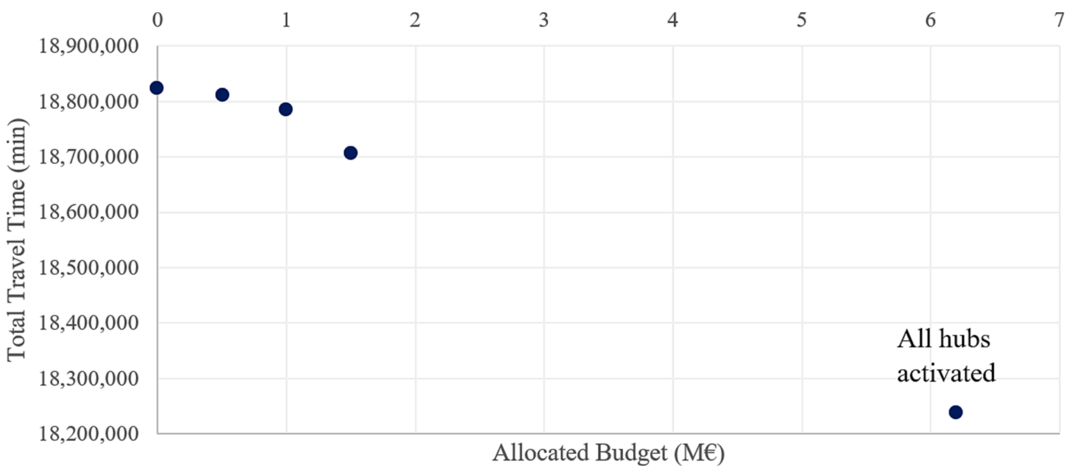

Fig. 8. Total travel time depending on the budget allocated to build the hubs.

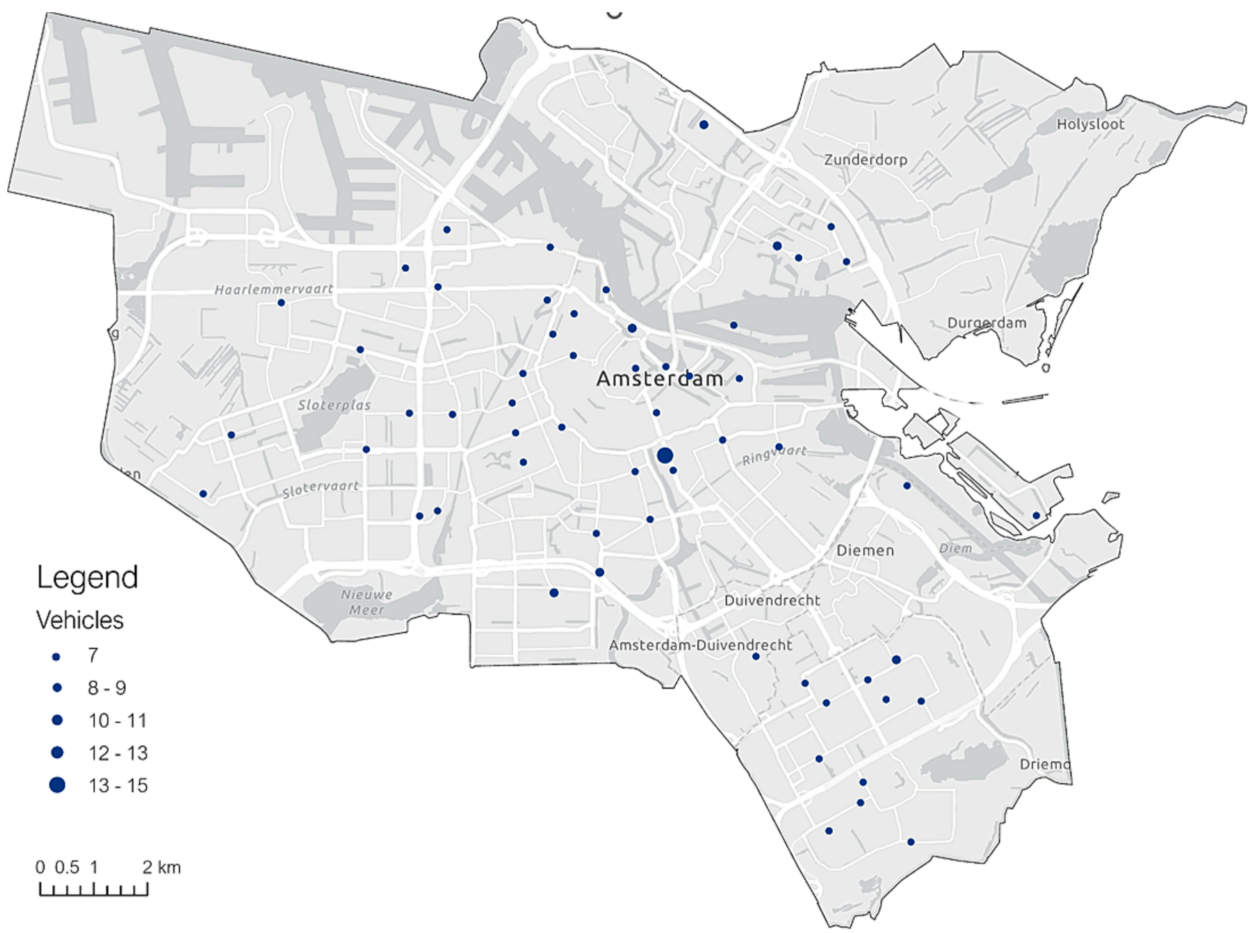

Fig. 9. Activated hubs for a budget of 0.5 M€.

people. Secondly, the implementation with lower budgets involves installing more hubs with smaller capacities. This approach allows for a wider coverage area, as activating numerous hubs ensures that a larger portion of the population is within reach of a mobility hub.

The hubs distribution obtained for a budget of 1 M€ along with the population density map is presented in Fig. 12. It can be observed that more hubs are activated in high-density areas and Amsterdam's central part compared to other regions, reflecting both the focus on higher population densities and the initial installation of hubs with smaller capacities.

4.4.3. Environmental implications

Finally, the effect of the mobility hubs on the environment is assessed. First, the emissions generated by the shared modes from the traveled kilometers and relocation operations are added to compute the net reduction in emissions. Then the emissions generated from the reduction in traditional modes are subtracted. The emissions are obtained by multiplying the kilometers traveled by the CO_2 emissions per mode per passenger-kilometer (CE Delft, 2021). For the relocations of shared mopeds and shared e-bikes, the emissions of an electric van are used, and it is assumed that each van can relocate ten vehicles at a time. 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 (Table 6). It is calculated for two cases; case 1 considers that electric cars constitute 8 % of the total fleet of cars and electric buses 50 % of the total fleet of buses. In contrast, case 2 considers that all vehicles are electric. With these assumptions, it can be concluded that the reductions in CO_2 emissions, measured in tons of CO_2 equivalent (CO_2 – eq T), 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 vehicles traveling in Amsterdam are considered to be electric. The results obtained refer to the emissions while using the vehicles so there is no life cycle analysis performed.

4.5. Sensitivity analysis

The model includes several parameters that might affect the results. A sensitivity analysis is performed on the operation costs (C_o^m),

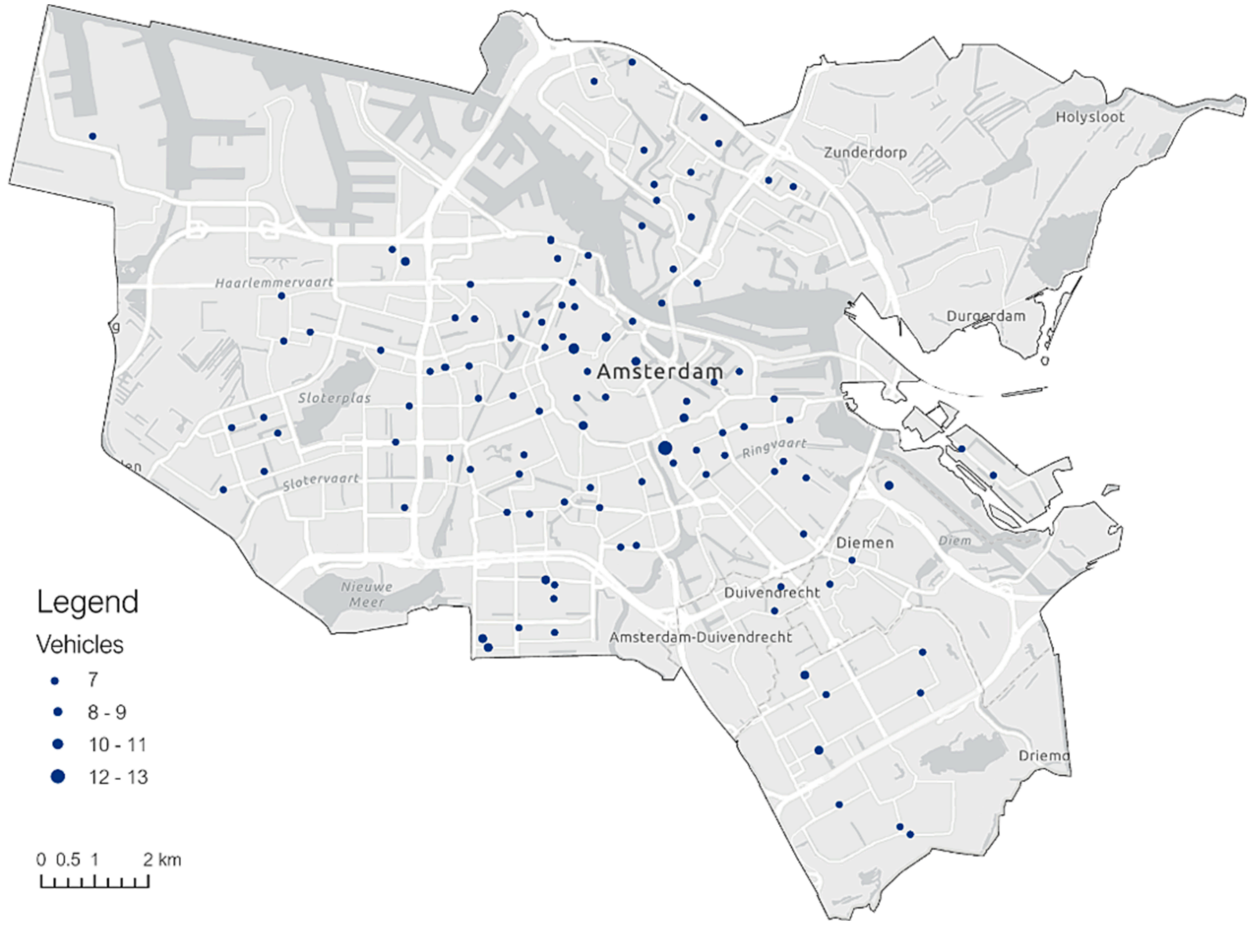

Fig. 10. Activated hubs for a budget of 1.0 M€.

relocation costs (C_r^m), and vehicle acquisition costs (C_v^m). Nevertheless, due to the computational time, it is impossible to assess the parameters' impact on the results for all scenarios. Hence, to perform the sensitivity analysis, all the mobility hubs are activated, and the different parameters are modified accordingly.

The relocation costs were varied between 2 and 4.5 € per 10 min timestep for shared cars and between 0.20 and 0.45 € per 10 min timestep for shared e-bikes and mopeds. All the instances have fitness functions varying by less than 0.001 %. 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 in the intervals of 15000–21000 € per shared car and 5000–7000 € per shared moped and 1500–3500 € per shared e-bike. Hence, the fitness function varies by less than 0.001 %. 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 15) 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.

5. Discussion of results and policy implications

In this section, the model's implementation challenges and the results obtained are discussed. The results include: the hubs' spatial distribution, their environmental impact, the modal split achieved for the shared modes, and finally, the policy aspects related to the introduction of shared modes.

The implementation of the developed model presents two challenges: high data requirements and computational intensity. Data unavailability or delays in computational processing can hinder the development and deployment of the model for timely policy decisions. These challenges can be overcome with the implementation of specific strategies enhancing the model's applicability.

Firstly, the model necessitates a substantial volume of data, which may not always be available for different cities. While the model itself is adaptable to diverse areas, as it can utilize the output of any macroscopic transport model with the structure remaining

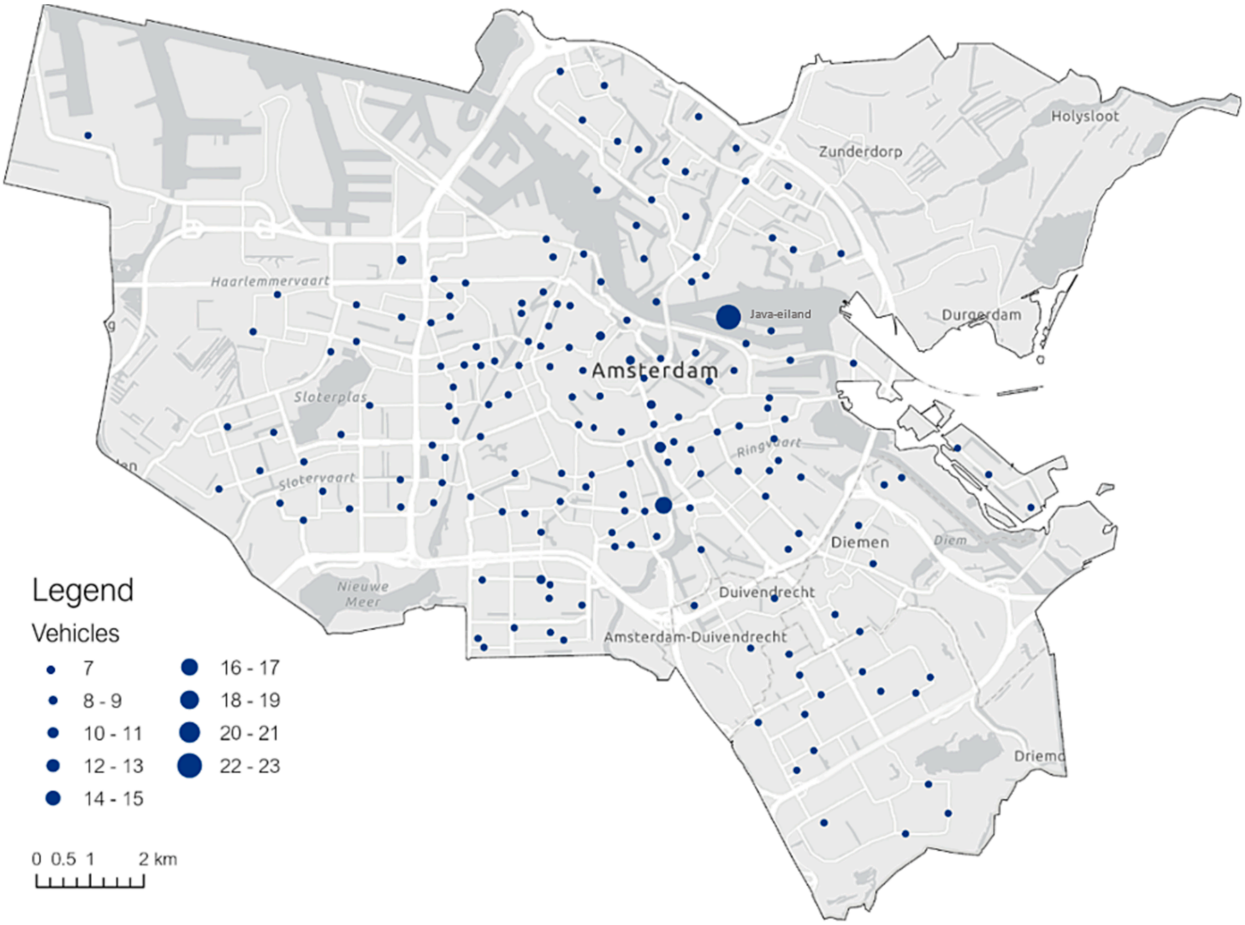

Fig. 11. Activated hubs for a budget of 1.5 M€.

Table 5
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

unchanged and only the data format needing adaptation, the primary limitation arises from the need for comprehensive and accurate data to ensure reliable results. In cases where fine-grained data is unavailable, but neighborhood-level data is accessible, the model can still serve as a valuable tool. It can estimate capacity requirements and hub allocation for these neighborhoods. While the level of accuracy may not match that of the case study, this approach remains useful for urban planners seeking more efficient resource allocation within a city. Additionally, addressing data constraints is possible through the use of imputation methods, which include statistical and machine learning techniques. These methods help bridge data gaps, ensuring model robustness even when confronted with incomplete datasets.

Secondly, there is a computational limitation as the model is resource-intensive when evaluating numerous paths, utilities, and demands for over 9 million OD-pairs in the large urban area of Amsterdam. The practical implementation of the model in different contexts may face hindrances due to the availability and affordability of computational resources. While the model has already been applied to a large area, scaling it up for larger contexts with increased OD-pairs or generations would be possible but would require

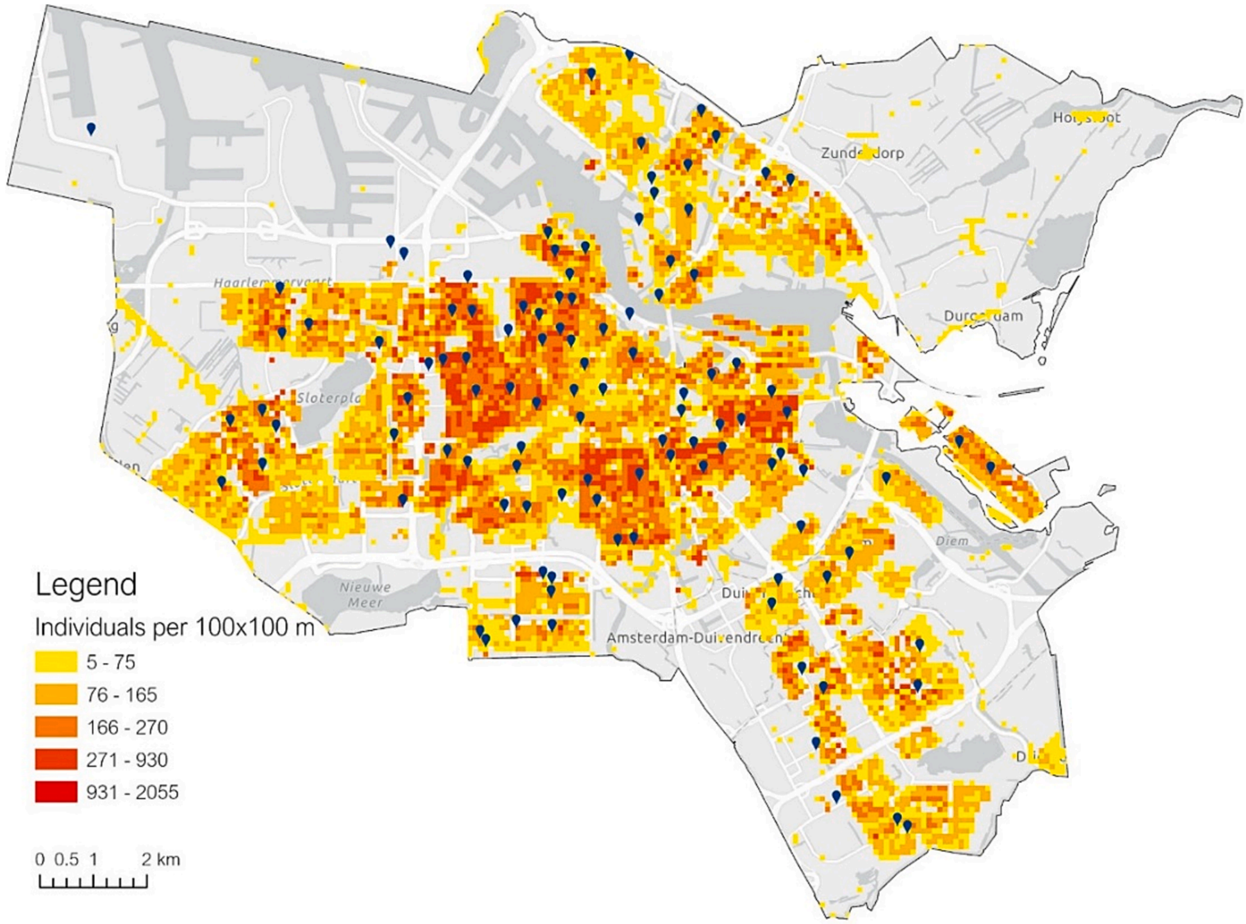

Fig. 12. Activated hubs for a budget of 1 M€ with the population density map.

Table 6
Variation in emissions per scenario.

	Budget (M€)			
	0.5	**1**	**1.5**	**All hubs activated (6.2)**
Traveled kilometers (km)				
Shared cars (80 CO_2-eq g/pkm)	390	426	4014	17,587
Shared mopeds (16 CO_2-eq g/pkm)	6374	10,948	35,588	199,653
Shared e-bikes (6 CO_2-eq g/pkm)	1531	3123	6815	12,871
Relocated vehicles.kilometers (veh.km)				
Shared cars (80 CO_2-eq g/pkm)	369	530	283	5853
Shared mopeds (106 CO_2-eq g/pkm)	457	722	2688	47,876
Shared e-bikes (106 CO_2-eq g/pkm)	803	1797	4879	9741
Variation in kilometers traveled using traditional modes of transport (km)				
Walk (0 CO_2-eq g/pkm)	+704	+857	+3200	+8716
Bike (0 CO_2-eq g/pkm)	−4364	−8382	−27405	−129453
Car (217 CO_2-eq g/pkm for case 1, 80 CO_2-eq g/pkm for case 2)	−7286	−9821	−24094	−106445
Public Transport (88 CO_2-eq g/pkm for case 1, 84 CO_2-eq g/pkm for case 2)	−3132	−4451	−10232	−41520
Emissions Reduction				
Case 1: Total Reduction in Emissions (CO_2 – eq T)	−1.67	−2.23	−5.10	−21.02
Case 1: Percentage reduction in CO_2 emissions (%)	−0.10	−0.14	−0.31	−1.27
Case 2 (where all vehicles are electric): Total Reduction in Emission (CO_2 – eq T)	−0.66	−0.86	−1.75	−6.23
Case 2 (where all vehicles are electric): Percentage reduction in CO_2 emissions (%)	−0.04	−0.05	−0.11	−0.38

higher computational resources to keep the time as it is. To mitigate this challenge, several options are available. One approach involves considering a reduction in the number of shared modes: instead of optimizing for three shared modes, limiting it to two or even one could significantly reduce the computational load. Additionally, in many cities, certain modes, such as bikes, do not constitute a significant portion of the modal split and could be excluded from the model, resulting in substantial computation time savings. Another viable option would be to run the model on a neighborhood level instead of a fine-grained level, as discussed earlier. These strategies can enhance the feasibility and accessibility of the model across a wider range of contexts. In future research, a heuristic could be developed to solve concurrently the capacity module, currently formulated as a mathematical model, and the module that activates the hubs, currently performed by the genetic algorithm. This approach would allow for simultaneous optimization, potentially reducing the computation time.

The model developed is used to distribute the mobility hubs for different investment budgets to maximize travel utility. When a low budget is set, the algorithm suggests locating more hubs in the center and highly dense areas compared to the outskirts. From the results obtained 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 hubs' coverage leads to covering more demand, providing more utility gains, and enabling to take advantage of the network effect whereby the presence of more hubs enables increased connectivity and accessibility between mobility hubs. This allows for greater opportunities for travel between these hubs and maximizes the overall benefits and utility gains for users. 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. Increasing marginal returns are associated with the benefits mentioned. When investing 0.5 M€ in building mobility hubs, the travel time savings during the 2-hour morning peak are equal to 49 min per 1,000 € invested, while when increasing the budget from 1.0 M€ to 1.5 M€, the travel time saved accounts for 160 min per 1,000 € (as seen in Fig. 5). After providing complete city coverage, the marginal returns are expected to be higher 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 results, the demand for each hub and the average utility gains per trip are mapped in Fig. 13. These parameters are mapped when all 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 (Fig. 11). 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 (in the center of Amsterdam), for example, takes around 17, 21, and 30 min 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.

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. Many papers found that more than half of the electric micromobility trips substitute public transport and active modes (Liao & Correia, 2022). van Marsbergen et al. (2022) also describe this substitution effect but also stressed the increased option set for passengers, enabling a less car-dependent lifestyle. The shift percentages vary depending on the city assessed and the method adopted to measure them. In the Amsterdam case study, 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 this city. 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 reduction for lower allocated budgets is limited (around 0.1 %), while for the higher 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 if not accompanied by other push policies.

For all scenarios, 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 accessing 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 min. Many authors ask if shared modes complement or compete with public transport. It is challenging to come up with a general answer to that question. Many parameters affect this relationship: public transport coverage, level of service, and the population's mobility behavior. van Mil et al. (2021) found about 40 factors in their literature review. 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

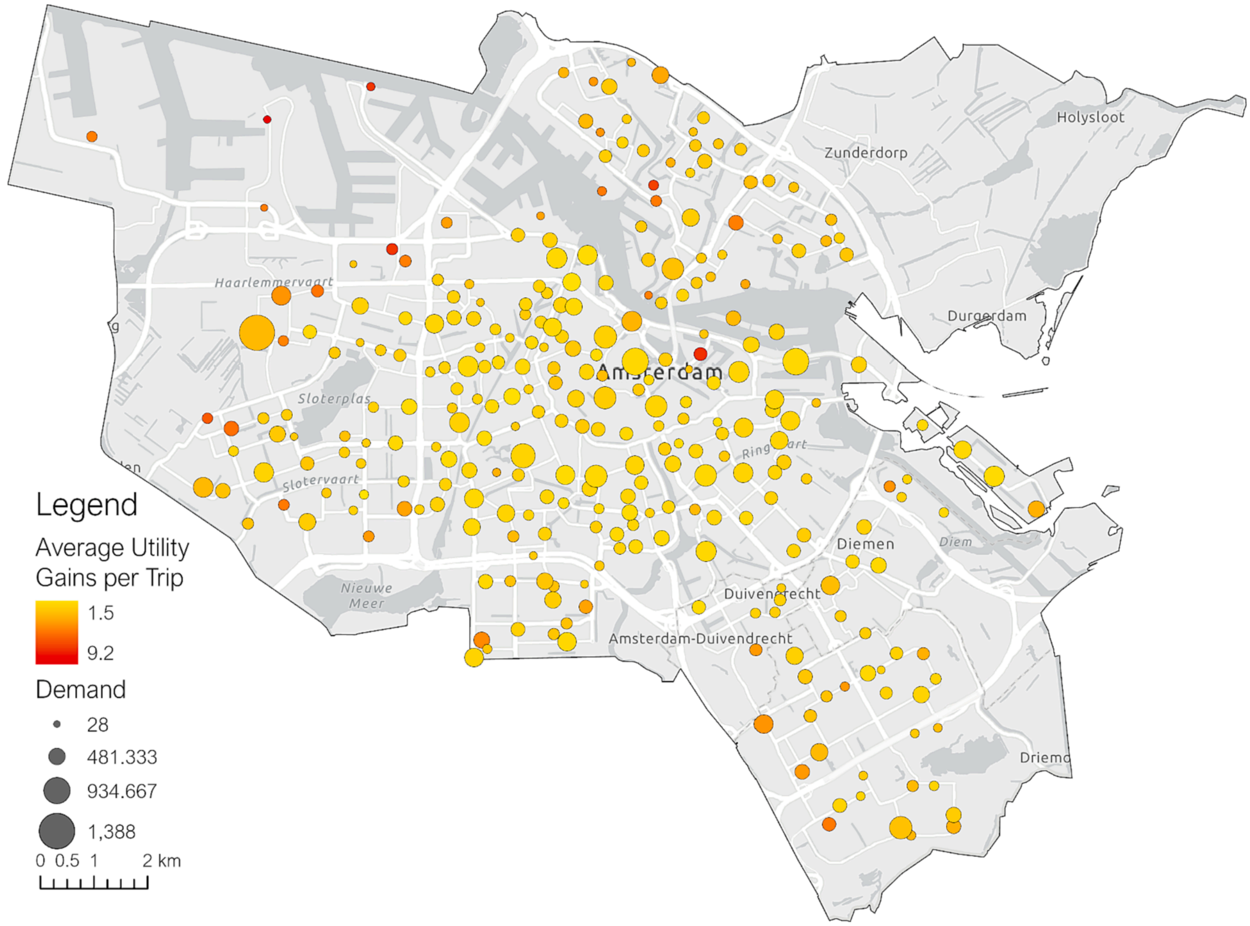

Fig. 13. Distribution of demand and average utility gains per mobility hub.

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.

If the municipality has lower budgets allocated for installing shared mobility hubs, it must not only focus on using this budget to build large mobility hubs. This study has proven that installing smaller ones distributed in the city provides more benefits to maximize utility. The construction of the mobility hubs can be divided into phases starting from a lower budget to a higher one after several years. An adaptive design of hubs would allow first to install a network of smaller mobility hubs, then add other hubs and upgrade the capacity of the existing ones in line with the higher budget designs.

If the budget 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 study. 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 and stimulates behavior change. However, 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 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 cannot be implemented immediately. Instead, it is a long-term plan also outlined in Amsterdam's 2030 mobility plan (Gemeente Amsterdam, 2013). 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 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. Conclusions

In this paper, we proposed a model to optimize the location and capacity of multimodal mobility hubs to maximize the total utility experienced by individuals traveling using traditional and/or shared modes, all while considering multimodal trips in large urban networks. It fills the gap that is currently present in the literature by considering multimodal trips that include shared modes, public transport, and walking. Finally, it relates mobility, environmental, and service level indicators to the budget allocated to construct the network of hubs.

We conclude that the model is flexible and can be adapted for different scenarios, policies, and locations. It can use the output of any macroscopic transport model to optimize the location and capacity of shared multimodal mobility hubs and compute their effects. When implementing the model for a new location, the specific characteristics of that region's transport system and the choices made by its population can be translated into the model through the development of new choice models and utility functions. This customization ensures that the model, with its current structure, accurately reflects the unique factors influencing transportation preferences in the new location. Different policy measures can also be implemented to push for the shift towards sustainable modes and translated in the model. For instance, increasing parking costs, decreasing speed limits, reducing the cost of shared modes and public transport, and enhancing road safety are all strategies that can be integrated into the model by adjusting the utility functions. Parking costs can be incorporated into the car mode costs parameter, speed limits can be factored in by modifying the calculation of travel time, the cost of sustainable modes can be adjusted by changing their associated costs in the utility functions, and the safety of infrastructure can be accounted for by modifying the constants attributed to the different modes. It is essential to note that these parameters should be re-estimated through various choice models, as the stated preferences data cannot be repurposed for a substantially different use case. Nevertheless, the general framework for defining utilities remains consistent across these adaptations.

The algorithm was run for different allocated budgets to build the mobility hubs (0.5, 1.0, and 1.5 M€, respectively). Different hub distributions are obtained for each scenario. The algorithm prioritizes locating many smaller hubs in the city center 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 areas with higher population densities. The algorithm also activates hubs in the outskirts where significant utility gains can be achieved. 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. 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.

The implementation of mobility hubs can be phased for optimal results. Initially, multiple smaller hubs can be installed in areas with high population densities, leveraging the network effect and proximity to origins and destinations. In subsequent phases, additional hubs can be strategically added to areas with significant utility gains, and the capacity of the hubs installed in the initial phase can be expanded if required. Adopting a multi-stage approach allows cities to benefit from incremental development, refining the network over time. This strategy offers flexibility, adaptability, and the opportunity to evaluate and make necessary adjustments at each stage. Ultimately, it facilitates the transition to a final hub configuration that maximizes benefits, travel time savings, and spatial coverage, effectively meeting the diverse transportation needs of residents and visitors. 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, the model proves that most shared trips in Amsterdam would substitute public transport and active modes, around 32 % and 55 % respectively, leading to limited environmental benefits. In the case that electric cars constitute 8 % of the total fleet of personal cars and electric buses 50 % of the total fleet of buses, the CO_2 emissions reduction for lower allocated budgets is limited (around 0.1 %), while for the higher budget of 6.2 M€, the emissions decrease by 1.27 % compared to the base scenario.

Future research efforts should dwell on validating empirically the results of the model. This validation could be achieved by comparing the model's results with the actual usage metrics of hubs in cities where such hubs are already implemented. This comparison would involve analyzing data from shared mobility operators or conducting mobility surveys to assess trip combinations, modal split, and the total number of trips performed.

Furthermore, it is recommended to do a comparative analysis with state-of-the-art or state-of-practice methods for the same case study. This can involve using solely a facility location problem or multi-criteria analysis to provide insights into the model's ability to outperform or at least match existing approaches. The effectiveness of the model can be evaluated through various metrics, including service level, operational and fixed costs under different demand scenarios. These scenarios can range from an underutilized system to a highly saturated network. By subjecting the model to a spectrum of demand conditions, its robustness and adaptability can be assessed.

Future research can also focus on improving or extending the various sub-models within the presented framework. Firstly, by analyzing in more depth which factors influence the usage of shared modes, hub and route choices. Secondly, in the developed model, it is considered that travelers are homogeneous; therefore, future studies can consider the population's heterogeneity, which might present interesting results especially if the demographics are linked to the usage patterns. It would also allow optimizing the location of mobility hubs and shared services to provide equitable mobility options. Finally, it is 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.

CRediT authorship contribution statement

Stavros Xanthopoulos: Conceptualization, Methodology, Software, Formal analysis, Data curation, Investigation, Writing – original draft, Visualization. **Marieke van der Tuin:** Conceptualization, Methodology, Investigation, Validation, Writing – original draft. **Shadi Sharif Azadeh:** Conceptualization, Methodology, Investigation, Validation, Writing – review & editing. **Gonçalo Homem de Almeida Correia:** Conceptualization, Methodology, Investigation, Validation, Writing – review & editing. **Niels van Oort:** Conceptualization, Validation, Writing – review & editing, Supervision. **Maaike Snelder:** Conceptualization, Methodology, Investigation, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

References

Aono, S. (2019). *Identifying Best Practices for Mobility Hubs*. https://sustain.ubc.ca/sites/default/files/Sustainability%20Scholars/2018_Sustainability_Scholars/Reports/2018-71%20Identifying%20Best%20Practices%20for%20Mobility%20Hubs_Aono.pdf.

Banerjee, S., Kabir, M.M., Khadem, N.K., Chavis, C., 2020. Optimal locations for bikeshare stations: A new GIS based spatial approach. Transport. Res. Interdisciplinary Perspect. 4, 100101. https://doi.org/10.1016/J.TRIP.2020.100101.

Bhuyan, I. A., Chavis, C., Nickkar, A., & Barnes, P. (2019). GIS-Based Equity Gap Analysis: Case Study of Baltimore Bike Share Program. *Urban Science 2019, Vol. 3, Page 42*, *3*(2), 42-42. 10.3390/URBANSCI3020042.

Blad, K., de Almeida, H., Correia, G., van Nes, R., Anne Annema, J., 2022. A methodology to determine suitable locations for regional shared mobility hubs. Case Studies on Transport Policy 10 (3), 1904–1916. https://doi.org/10.1016/j.cstp.2022.08.005.

Caggiani, L., Camporeale, R., Dimitrijević, B., Vidović, M., 2020a. An approach to modeling bike-sharing systems based on spatial equity concept. Transp. Res. Procedia 45, 185–192. https://doi.org/10.1016/j.trpro.2020.03.006.

Caggiani, L., Colovic, A., Ottomanelli, M., 2020b. An equality-based model for bike-sharing stations location in bicycle-public transport multimodal mobility. Transp. Res. A Policy Pract. 140, 251–265. https://doi.org/10.1016/j.tra.2020.08.015.

Calvert, S., Minderhoud, M., Taale, H., Wilmink, I., & Knoop, V. (2016). *Traffic Assignment and Simulation Models*. 10.13140/RG.2.1.3784.4560.

Carlier, K., Inro, T., Fiorenzo-Catalano, S., Lindveld, C., & Bovy, P. (2002). A supernetwork approach towards multimodal travel modeling.

CBS. (2022). *Dutch National Travel survey*. https://www.cbs.nl/en-gb/our-services/methods/surveys/brief-survey-description/dutch-national-travel-survey.

Chou, M. C., Liu, Q., Teo, C.-P., Yeo, D., Chou, M. C., Liu, Q., . . . Yeo, D. (2019). Models for Effective Deployment and Redistribution of Shared Bicycles with Location Choices. 409-434. 10.1007/978-3-030-01863-4_17.

Correia, G. H. d. A., & Antunes, A. P. (2012). Optimization approach to depot location and trip selection in one-way carsharing systems. Transport. Res. Part E: Logist. Transport. Rev., 48(1), 233-247. 10.1016/J.TRE.2011.06.003.

de Dios Ortúzar, J., Willumsen, L.G., 2011. Modelling Transport. Wiley. https://books.google.nl/books?id=qWa5MyS4CiwC.

CE Delft. (2021). *Effect of shared electric mopeds on CO2 emissions*. https://cedelft.eu/wp-content/uploads/sites/2/2022/02/CE_Delft_210383_Effect-of-shared-electric-mopeds-on-CO2-emissions_FINAL.pdf.

Dixit, M., Cats, O., Brands, T., van Oort, N., Hoogendoorn, S., 2021. Perception of overlap in multi-modal urban transit route choice. Transportmetrica a: Transport Science 1–23. https://doi.org/10.1080/23249935.2021.2005180.

Duran-Rodas, D., Wright, B., Pereira, F.C., Wulfhorst, G., 2021. Demand And/oR Equity (DARE) method for planning bike-sharing. Transp. Res. Part D: Transp. Environ. 97, 102914. https://doi.org/10.1016/j.trd.2021.102914.

Fan, Z., Harper, C.D., 2022. Congestion and environmental impacts of short car trip replacement with micromobility modes. Transp. Res. Part D: Transp. Environ. 103, 103173 https://doi.org/10.1016/j.trd.2022.103173.

Fazio, M., Giuffrida, N., Le Pira, M., Inturri, G., Ignaccolo, M., 2021. Bike oriented development: Selecting locations for cycle stations through a spatial approach. Res. Transp. Bus. Manag. 40, 100576. https://doi.org/10.1016/J.RTBM.2020.100576.

Frade, I., Ribeiro, A., 2015. Bike-sharing stations: A maximal covering location approach. Transp. Res. A Policy Pract. 82, 216–227. https://doi.org/10.1016/j.tra.2015.09.014.

Frank, L., Dirks, N., Walther, G., 2021. Improving rural accessibility by locating multimodal mobility hubs. J. Transp. Geogr. 94, 103111. https://doi.org/10.1016/j.jtrangeo.2021.103111.

García-Palomares, J.C., Gutiérrez, J., Latorre, M., 2012. Optimizing the location of stations in bike-sharing programs: A GIS approach. Appl. Geogr. 35 (1–2), 235–246. https://doi.org/10.1016/j.apgeog.2012.07.002.

Gemeente Amsterdam. (2013). *MobiliteitsAanpak Amsterdam 2030* https://www.amsterdam.nl/en/policy/policy-traffic/.

Gemeente Amsterdam. (2021). *Amsterdamse Thermometer van de Bereikbaarheid 2021*.

Guler, D., & Yomralioglu, T. (2021). Bicycle Station and Lane Location Selection Using Open Source GIS Technology. 9-36. 10.1007/978-3-030-58232-6_2.

Hoogendoorn-Lanser, S., Bovy, P., 2007. Modeling Overlap in Multimodal Route Choice by Including Trip Part-Specific Path Size Factors. Transp. Res. Rec. 2003 (1), 74–83. https://doi.org/10.3141/2003-10.
Huang, K., Correia, G. H. d. A., & An, K. (2018). Solving the station-based one-way carsharing network planning problem with relocations and non-linear demand. Transport. Res. Part C: Emerg. Technol. 90, 1-17. 10.1016/J.TRC.2018.02.020.
Jorge, D., Correia, G.H.A., Barnhart, C., 2014. Comparing Optimal Relocation Operations With Simulated Relocation Policies in One-Way Carsharing Systems. IEEE Trans. Intell. Transp. Syst. 15 (4), 1667–1675. https://doi.org/10.1109/TITS.2014.2304358.
Kabak, M., Erbaş, M., Çetinkaya, C., Özceylan, E., 2018. A GIS-based MCDM approach for the evaluation of bike-share stations. J. Clean. Prod. 201, 49–60. https://doi.org/10.1016/J.JCLEPRO.2018.08.033.
Kanjanakorn, T., & Piantanakulchai, M. (2013, 2013/6//). Prioritizing Suitable Locations of Bike Sharing Station by Using the Analytic Hierarchy Process (AHP). undefined.
Krajzewicz, D., Heinrichs, M., Beige, S., 2018. Embedding intermodal mobility behavior in an agent-based demand model. Procedia Comput. Sci. 130, 865–871. https://doi.org/10.1016/j.procs.2018.04.082.
Kurniadhini, F., Roychansyah, M.S., 2020. The suitability level of bike-sharing station in Yogyakarta using SMCA technique. IOP Conference Series: Earth and Environmental Science 451 (1), 012033. https://doi.org/10.1088/1755-1315/451/1/012033.
Larsen, J., Patterson, Z., & El-Geneidy, A. (2012). Build It. But Where? The Use of Geographic Information Systems in Identifying Locations for New Cycling Infrastructure. *https://doi.org.tudelft.idm.oclc.org/10.1080/15568318.2011.631098*, *7*(4), 299-317. 10.1080/15568318.2011.631098.
Li, W., Kamargianni, M., 2019. An Integrated Choice and Latent Variable Model to Explore the Influence of Attitudinal and Perceptual Factors on Shared Mobility Choices and Their Value of Time Estimation. Transp. Sci. 54 (1), 62–83. https://doi.org/10.1287/trsc.2019.0933.
Li, W., Kamargianni, M., 2020. Steering short-term demand for car-sharing: a mode choice and policy impact analysis by trip distance. Transportation 47 (5), 2233–2265. https://doi.org/10.1007/s11116-019-10010-0.
Li, X., Ma, J., Cui, J., Ghiasi, A., Zhou, F., 2016. Design framework of large-scale one-way electric vehicle sharing systems: A continuum approximation model. Transp. Res. B Methodol. 88, 21–45. https://doi.org/10.1016/J.TRB.2016.01.014.
Liao, F., Correia, G., 2022. Electric carsharing and micromobility: A literature review on their usage pattern, demand, and potential impacts. Int. J. Sustain. Transp. 16 (3), 269–286. https://doi.org/10.1080/15568318.2020.1861394.
Lin, J.-R., Yang, T.-H., Chang, Y.-C., 2013. A hub location inventory model for bicycle sharing system design: Formulation and solution. Comput. Ind. Eng. 65 (1), 77–86. https://doi.org/10.1016/j.cie.2011.12.006.
Liu, J., Li, Q., Qu, M., Chen, W., Yang, J., Xiong, H., Fu, Y., 2015. Station Site Optimization in Bike Sharing Systems. https://doi.org/10.1109/ICDM.2015.99.
Luo, H., Zhang, Z., Gkritza, K., Cai, H., 2021. Are shared electric scooters competing with buses? a case study in Indianapolis. Transp. Res. Part D: Transp. Environ. 97, 102877 https://doi.org/10.1016/j.trd.2021.102877.
Mirjalili, S., 2019. Genetic Algorithm. In: Mirjalili, S. (Ed.), Evolutionary Algorithms and Neural Networks: Theory and Applications. Springer International Publishing, pp. 43–55. https://doi.org/10.1007/978-3-319-93025-1_4.
Mounce, R., Nelson, J.D., 2019. On the potential for one-way electric vehicle car-sharing in future mobility systems. Transp. Res. A Policy Pract. 120, 17–30. https://doi.org/10.1016/j.tra.2018.12.003.
Nair, R., Miller-Hooks, E., 2014. Equilibrium network design of shared-vehicle systems. Eur. J. Oper. Res. 235 (1), 47–61. https://doi.org/10.1016/J.EJOR.2013.09.019.
Nair, R., Miller-Hooks, E., 2016. Equilibrium design of bicycle sharing systems: the case of Washington D.C. EURO J. Transport. Logist. 5 (3), 321–344. https://doi.org/10.1007/s13676-014-0055-3.
Nawaro, Ł., 2021. E-scooters: competition with shared bicycles and relationship to public transport. Int. J. Urban Sustain. Developm. 13 (3), 614–630. https://doi.org/10.1080/19463138.2021.1981336.
Nikiforiadis, A., Aifadopoulou, G., Grau, J.M.S., Boufidis, N., 2021. Determining the optimal locations for bike-sharing stations: methodological approach and application in the city of Thessaloniki, Greece. Transp. Res. Procedia 52, 557–564. https://doi.org/10.1016/J.TRPRO.2021.01.066.
OECD/ITF. (2020). *Good to Go? Assessing the Environmental Performance of New Mobility*. https://www.itf-oecd.org/good-to-go-environmental-performance-new-mobility.
Papu Carrone, A., Hoening, V.M., Jensen, A.F., Mabit, S.E., Rich, J., 2020. Understanding car sharing preferences and mode substitution patterns: A stated preference experiment. Transp. Policy 98, 139–147. https://doi.org/10.1016/j.tranpol.2020.03.010.
Petrović, M., Mlinarić, T.J., Šemanjski, I., 2019. Location Planning Approach for Intermodal Terminals in Urban and Suburban Rail Transport. Promet – Traffic Transport. 31 (1), 101–111. https://doi.org/10.7307/PTT.V31I1.3034.
Reck, D.J., Haitao, H., Guidon, S., Axhausen, K.W., 2021. Explaining shared micromobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland. Transport. Res. Part c: Emerg. Technol. 124, 102947 https://doi.org/10.1016/j.trc.2020.102947.
Rijkswaterstaat. (2021). *Landelijk Model Systeem verkeer en vervoer - Begrippen en Definities*.
Romero, J.P., Ibeas, A., Moura, J.L., Benavente, J., Alonso, B., 2012. A Simulation-optimization Approach to Design Efficient Systems of Bike-sharing. Procedia. Soc. Behav. Sci. 54, 646–655. https://doi.org/10.1016/j.sbspro.2012.09.782.
Santos, G.G.D., de Almeida Correia, G.H., 2019. Finding the relevance of staff-based vehicle relocations in one-way carsharing systems through the use of a simulation-based optimization tool. J. Intell. Transp. Syst. 23 (6), 583–604. https://doi.org/10.1080/15472450.2019.1578108.
Shelat, S., Huisman, R., van Oort, N., 2018. Analysing the trip and user characteristics of the combined bicycle and transit mode. Res. Transp. Econ. 69, 68–76. https://doi.org/10.1016/j.retrec.2018.07.017.
Stam, B., van Oort, N., van Strijp-Harms, H.J., van der Spek, S.C., Hoogendoorn, S.P., 2021. Travellers' preferences towards existing and emerging means of first/last mile transport: a case study for the Almere centrum railway station in the Netherlands. Eur. Transp. Res. Rev. 13 (1), 56. https://doi.org/10.1186/s12544-021-00514-1.
Steiner, K., & Irnich, S. (2020). Strategic Planning for Integrated Mobility-on-Demand and Urban Public Bus Networks. https://doi-org.tudelft.idm.oclc.org/10.1287/trsc.2020.0987, 54(6), 1616-1639. 10.1287/TRSC.2020.0987.
TNO. (2022). *The healthy city: accessible, safe and vital*. https://www.tno.nl/en/digital/smart-traffic-transport/societal-impact/healthy-city-accessible-safe-vital/#:~:text=Urban%20Strategy%20helps%20with%20spatial,where%20they're%20not%20required.
van Eck, G., Brands, T., Wismans, L., Nes, R., 2014. Model Complexities and Requirements for Multimodal Transport Network Design. Transport. Res. Record J. Transport. Res. Board 2429, 178–187. https://doi.org/10.3141/2429-19.
van Kuijk, R.J., de Almeida Correia, G.H., van Oort, N., van Arem, B., 2022. Preferences for first and last mile shared mobility between stops and activity locations: A case study of local public transport users in Utrecht, the Netherlands. Transp. Res. A Policy Pract. 166, 285–306. https://doi.org/10.1016/j.tra.2022.10.008.
van Marsbergen, A., Ton, D., Nijënstein, S., Annema, J.A., van Oort, N., 2022. Exploring the role of bicycle sharing programs in relation to urban transit. Case Stud. Transport Policy 10 (1), 529–538. https://doi.org/10.1016/j.cstp.2022.01.013.
van Mil, J.F.P., Leferink, T.S., Annema, J.A., van Oort, N., 2021. Insights into factors affecting the combined bicycle-transit mode. Public Transport 13 (3), 649–673. https://doi.org/10.1007/s12469-020-00240-2.
Weustenenk, A.G., Mingardo, G., 2023. Towards a typology of mobility hubs. J. Transp. Geogr. 106, 103514 https://doi.org/10.1016/j.jtrangeo.2022.103514.
Wortmann, C., Syré, A.M., Grahle, A., Göhlich, D., 2021. Analysis of Electric Moped Scooter Sharing in Berlin: A Technical Economic and Environmental Perspective. World Electric Vehicle Journal 12 (3). https://doi.org/10.3390/wevj12030096.
Wuerzer, T., Mason, S., Youngerman, R., 2012. Boise Bike Share Location Analysis. Community and Regional Planning. https://scholarworks.boisestate.edu/planning_facpubs/8.