



# Sustainable mobility strategies and their impact: a case study using a multimodal activity based model

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## ABSTRACT

Nowadays, many cities are intending to reduce the use of private vehicles. Governments are incorporating new mobility services and are adapting their parking policies to promote a more sustainable mobility, as both strategies are believed to have the potential to reduce private vehicle use. To understand the effects of these strategies, one needs to be able to model complex travel behaviour up to a very high level of detail. Owing to their flexibility, robustness and ability to model travel activity behaviour on an individual level, activity based travel demand models (ABM) offer a highly suitable methodology for this purpose.

In this paper, we employ this methodology to perform a case study in a metropolitan region in the Netherlands which surrounds and includes the cities of Rotterdam and The Hague. This region is of vital economic importance and has a very developed and dense road network. The population of this region is growing, which motivates the ambition to improve its accessibility and move towards sustainable mobility. Therefore, the findings of this study are important to similar regions seeking to do this as well. After setting up a suitable, calibrated ABM able to perform a comprehensive study on the effects of new mobility services and parking policy adaptations in the above-mentioned region, we design seven scenarios to give quantitative answers to policy-related questions on how altering features can reduce the extent to which private vehicles are used for travelling. These features include the availability of mobility hubs (hubs on neighbourhood level where sustainable travel modes are linked), the availability of car/bike sharing services, the availability of 'Mobility as a Service' (MaaS) subscriptions, the amount of parking capacity in the region and the parking costs. We also study what the impact would be of an improved public transport service with lowered public transport travel times to and from the city centers, and the impact of an improved cycling network infrastructure with significantly lowered travel times for bike and e-bike travellers.

Based on the case study, we find that the introduction of mobility hubs alone has limited impact. However, combining this with making sharing services available to the public through MaaS subscriptions, there is a potential to reduce the number of car trips significantly, while the number of trips undertaken by a more sustainable (shared) e-bike increases as well as the number of so-called multi-modal mode trips (trips undertaken by a combination of various modes). Furthermore, improving the public transport service and micromobility network further increases the potential of mobility hubs in terms of making mobility more sustainable. The case study also shows that limiting parking capacity and increasing parking costs in the city centers is especially helpful for the reduction of vehicle use, leading to an improved car flow.

## 1. Introduction

Globally, many cities, spurred by e.g. the effects of a growing population on the mobility system, are intending to reduce the use of private vehicles to promote more sustainable mobility and create a more livable

environment. One strategy to achieve this purpose, the study of which recently gained momentum, is the introduction of new mobility services (NMS) as defined in Storme et al. (2021). As further explained and studied in that paper, these services refer to private or public transportation services that are mostly available on-demand and are

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supported by mobile technology as well as real-time location data. They form an alternative to privately-owned travel modes; NMS for example include ‘Mobility as a Service’ (MaaS). MaaS can be thought of as an integration of various modes (even within a single trip) into a single service, accessible on demand within a single payment application. Via seamless digital planning, this makes combining multiple modes within a single trip attractive for the traveller; see e.g. [Giesecke et al. \(2016\)](#) and [Jittrapirom et al. \(2017\)](#) and references therein for a precise definition and detailed study of MaaS. As MaaS provides users the option of choosing multimodal mode alternatives, it is believed that it offers a good alternative to private car use as for example mentioned in [Hesselgren et al. \(2020\)](#). Another promising example of NMS is given by the promoted use of mobility hubs. Mobility hubs are hubs at a neighbourhood level where at least two sustainable travel modes are connected to one another, such as bus stops and train stations. Here, travellers use one mode to travel from the origin to the mobility hub and then switch to another travel mode to continue their journey towards their destination. The third and final category of NMS that we mention is that of shared mobility services, including the sharing of (e-) bikes and cars. Due to the increased level of automation and electrification of vehicles, bringing the advent of the e-scooter, e-bike, micro-car, etc., shared mobility services have generated a great deal of interest worldwide; cf. [Fulton, 2018](#); [Oh et al., 2021](#)) and references therein for studies on the impact of shared mobility services. With these services, travellers have access to transportation modes on an as-needed basis, which helps to reduce road congestion. Next to the introduction of NMS, another strategy to obtain sustainable mobility may be to adapt parking policies in densely populated areas. For example, increasing parking costs or reducing parking capacity may relieve the use of private cars in city centers, since travellers may choose different travel modes or choose not to travel to these areas at all, as witnessed by [Yan et al. \(2018\)](#).

Before the actual adoption of NMS and/or adapted parking policies, governments would like to know their impact. For instance, the Dutch Ministry of Infrastructure and Water management recently sought to know whether stimulating the use of light electrical vehicles can have positive effects on sustainability, safety, accessibility and congestion of the Dutch infrastructure, which resulted in the work of [Knoope and Kansen \(2021\)](#). However, obtaining a comprehensive understanding of how such measures affect our transportation system is not a trivial task, for a multitude of reasons. First, each travelling individual may react differently to these policies. As a result, one needs to be able to model complex travel behaviour down to the level of the individual activities of each traveller. Second, since NMS include novel travel modes which, because of MaaS, may also be used as part of a multimodal trip, one requires a model that is capable of integrating all these modes and combinations. Third, even when a model incorporates all the required features, efforts required to do computations based on this model may be infeasibly high. Fortunately, activity-based demand models (ABMs) offer a highly suitable methodology for this purpose. With their ability to model a fine level of detail, ABMs allow individual travellers’ characteristics to be taken into account, so that they are capable of capturing the heterogeneity of travellers. Furthermore, they are flexible enough to incorporate new modes, and allow for implementations that are fast enough so that results can be obtained within a reasonable amount of time, especially with the help of speed-enhancing techniques such as parallel computing ([Zhou et al., 2019](#)), the technique of common random numbers ([Zhou et al., 2022](#)) as well as appropriate bundling of travel modes ([Zhou et al., 2020](#)). In this paper, we therefore apply an ABM to investigate the effects of NMS and several parking policies. For more information on ABMs, see [Castiglione et al. \(2015\)](#) and references therein.

There have been multiple studies in the literature on several policies aimed at increasing sustainability of the mobility system. For example, ABMs have been used to analyse the impact of different policies, such as car access restriction, bus frequency and dynamic fare, on traffic congestion and air quality, as was for example done in [Azevedo et al.](#)

(2016), [Snelder et al. \(2019\)](#), [Becker et al. \(2020\)](#). Those studies, however, incorporated only a small number of new modes. Moreover, access and egress modes are not explicitly modeled, so that multimodal mode trips as a result of MaaS are not considered. In the study of [Knapen et al. \(2021\)](#), the access and egress modes have been considered but only for public transport as a main mode. Other models explicitly considering multimodal modes (that is, trip modes which actually incorporate a multitude of modes, including access and egress modes) can be found in e.g. the studies of [Liao et al. \(2010\)](#) and [Vovsha et al. \(2017\)](#). These studies, however, still only consider a limited number of new mobility modes or combinations thereof. In contrast, the current study considers the entirety of NMS as sketched above. To incorporate NMS in an ABM, we build on previous work ([Zhou et al., 2020](#)), in which ActivitySim, an open platform for activity-based travel modelling (see [Gali et al. \(2008\)](#) for a description of ActivitySim), was extended to include multimodal modes as mode choices at a complete tour level. As a result, with this implementation, travellers can change modes at a mobility hub within a single trip. The travellers can also use sharing services, such as shared cars, shared bikes or shared e-bikes. To keep the computational burden brought by these extensions limited, this setup brings, through ActivitySim, the capability of using multiprocessing of the computer to split up the computations on multiple processing cores. To this end, we draw on the above-mentioned parallel computing techniques by [Zhou et al. \(2019\)](#) to accelerate the computational speeds of the ABM using a computer’s graphical processing unit (GPU).

In the remainder of this paper, we first set up an ABM and calibrate it using survey data. This ABM is then used to conduct a case study to understand to what extent the introduction of NMS (including MaaS and mobility hubs) as well as adaptation of parking policies on capacity, searching time and costs can make the mobility system more sustainable. It is worth mentioning that in this paper, the modal split is mainly used as a first-order-indicator for the level of sustainability. Other commonly used indicators such as emission levels or air quality would require additional modelling. We also regard what the impact would be of an improved public transport service resulting in lowered public transport travel times to and from the city centers, and the impact of an improved cycling network infrastructure resulting in lowered travel times for bike and e-bike travellers. For this purpose, we set up seven scenarios for the Metropolitan Rotterdam and Den Haag region (MRDH) of The Netherlands, which is our case study area. This region is of economic importance for the Netherlands (it represents 15% of gross national product in The Netherlands) and its traffic network is very dense, as witnessed by the fact that the motorway between Rotterdam and Den Haag is the busiest Dutch motorway. Furthermore, the population in this area is growing, and the region aims to improve the accessibility and strengthen the public transport network towards a more sustainable mobility as witnessed by the website of the MRDH region ([Metropoolregio Rotterdam Den Haag, 2021](#)). Since these features are typical for regions e.g. seeking to reduce private vehicle use, we expect results for this region to be of interest for other regions as well. The questions that the case study seeks to answer are the following:

- To which extent do the mobility hubs help to reduce the number of car trips?
- When half of the total population would own a MaaS subscription, to which extent do the mobility hubs in combination with sharing services contribute to more sustainable mobility in the MRDH region?
- To which extent can an improved cycling infrastructure and public transport service stimulate the utilisation rate of mobility hubs?
- To which extent would the parking capacity and parking cost affect the car flow in the city centers of the MRDH region (i.e., the centers of Delft, Rotterdam and The Hague)?

While these questions are answered fully and in detail at a later stage of this paper, we already mention that it will turn out that mobility hubs

**Table 1**  
List of modes considered in this study.

Type	Mode names
Unimodal modes	WALK WALK-BIKE-WALK WALK-EBIKE-WALK WALK-CAR-WALK WALK-CP-WALK WALK-DRT-WALK WALK-PT-WALK
Multimodal modes (CAR as main mode)	WALK-CAR-BIKE, BIKE-CAR-WALK WALK-CAR-EBIKE, EBIKE-CAR-WALK WALK-CAR-PT, PT-CAR-WALK WALK-CAR-DRT, DRT-CAR-WALK
Multimodal modes (CP as main mode)	WALK-CP-BIKE, BIKE-CP-WALK WALK-CP-EBIKE, EBIKE-CP-WALK WALK-CP-PT, PT-CP-WALK WALK-CP-DRT, DRT-CP-WALK
Multimodal modes (DRT as main mode)	WALK-DRT-BIKE, BIKE-DRT-WALK WALK-DRT-EBIKE, EBIKE-DRT-WALK WALK-DRT-PT, PT-DRT-WALK
Multimodal modes (PT as main mode)	WALK-PT-BIKE, BIKE-PT-WALK, BIKE-PT-BIKE

alone do not alter car use that much. This changes, however, when MaaS subscriptions become available. That is, car use then decreases because parking costs at destinations can be avoided. For example, the car can be parked for free at a mobility hub and less expensive shared services are used to reach the destination. Indeed, the case study later in this paper for the MRDH region will show that the share of trips undertaken solely by car may reduce by roughly 4%. At the same time, especially the use of e-bikes increases, while the introduction of MaaS also increases the number of multimodal trips. Next, the results of the case study will also show that improving the infrastructure in favour of public transport and micromobility (i.e., bikes and e-bikes) significantly increases the potential of mobility hubs further, while introducing more stringent parking policies may reduce car flow to a considerable extent.

The rest of this paper is organised as follows. Section 2 describes the ABM that we use for the case study in more detail and explains the procedure used to calibrate the model. In Section 3, we give a description of each of the scenarios that we consider to answer the research questions mentioned above, and we provide model results for each of these. Finally, Section 4 presents detailed answers to these questions and provides avenues for further research.

## 2. Modelling approach

This section describes the activity-based modelling approach that we adopt in this paper. In particular, Section 2.1 provides a detailed description of the ABM as well as its several components. Then, Section 2.2 describes the choice models and their utility functions underlying the components, after which we discuss the suitable estimation of coefficients of these utility functions in Section 2.3.

### 2.1. Model description

The goal of the ABM is to predict a complete activity schedule including travel modes used for every travelling individual on any given day and any given scenario. This leads to travel demand forecasts specified per travel mode, which can be used to measure the impact of NMS and parking policies in any scenario. To create these schedules, our ABM consists of a series of choice components. Each of these components makes a decision for every member in a synthesised population of the MRDH-region as obtained in Snelder et al. (2021). We describe these choice components in Section 2.1.1, after which separate attention to a choice component customly coded for this study is given in Section 2.1.2.

#### 2.1.1. Components of the ABM

The first component of the ABM makes long-term decisions for each individual traveller. One can for example think of the selection of school/work locations, which are choices that do not vary on a daily basis. Once all long-term decisions have been made, the main activity purpose of the day is determined for each traveller (e.g. attend school, go to work) as part of the second component of the ABM, taking into account the interaction with other household members. Having

generated the main activity purposes, the next choice component of the ABM decides for each person the number of mandatory tours, i.e., tours resulting from having to go to school and work, as well as the number of non-mandatory tours, i.e., tours with the purpose of e.g. shopping, visiting an acquaintance or eating in a restaurant. This decision includes the start time, duration, destination as well as the preferred travel mode of each of these tours. The choice components hereafter make decisions concerning each tour. More precisely, the number of trips per tour is determined, as well as the starting times of these trips, the durations, the destinations and the trip modes.

The implementation used in this paper for the components is based on ActivitySim, but we adopt a separately coded component for the trip mode choice, which we created in previous work; cf. Zhou et al. (2020). This component is embedded within the ActivitySim framework and allows for the modelling of multimodal trips alongside the possible unimodal trips that ActivitySim is already capable of processing. This capability is essential for the modelling of NMS. The customly coded mode choice component also makes sure that all modes within a trip make up a consistent combination within a tour. For instance, a private car cannot be used for an inbound trip if it was not used for the outbound trip, and the multimodal mode choice component takes this into account.

#### 2.1.2. The trip mode choice component

The main advantage of the trip mode choice component is its capability to incorporate a wide variety of unimodal and multimodal modes, which will be described now. First, we include in the model seven mode categories that represent the seven most commonly used unimodal modes in the Netherlands: walking (WALK), cycling (BIKE), using an e-bike (EBIKE), driving a car (CAR), being a passenger in a car (CP), demand-responsive transport (DRT) and public transport (PT). Each of these modes, which are also displayed in Table 1, represents a different combination of mode speed, vehicle weight, vehicle space per person and passenger capacity, so that the modes form seven categories that together represent more or less the complete spectrum. For example, while the walking mode represents very slow travel modes, the bike mode represents travel modes with a speed between 5 and 20 km/h, so that it covers (non-motorised) scooters as well. At the same time, the e-bike mode is representative for modes with speeds between 20 and 30 km/h, so that it also covers e-scooters. The bike and e-bike modes together represent all micromobility vehicles. The car mode represents other transportation modes with speeds over 30 km/h (which can be electric or even autonomous). Meanwhile, car passengers (CP) can ride a private car with someone else from their household, or use a shared car (such as a taxi). It is worth noting that the bike, e-bike and car modes represent both private and shared vehicles. The demand-responsive transport category includes minibuses, shared taxis and shuttles with a small passenger capacity. It should be noted that, in the MRDH region, which we will focus on later in the paper, the demand-responsive transport category is mostly represented by taxis. In particular, the use of minibuses is currently limited. Municipalities are exploring the potential impact of minibuses in the future, especially as they become automated. The final category represents conventional public transport, including bus, tram, metro, and train. This is a rather broad category. Specifically for the MRDH region, it does not only capture the Dutch train network in this region, but also the so-called Randstad Rail, which is the LRT network between the cities of The Hague, Rotterdam and Zoetermeer.

The vast majority of new travel modes brought by NMS falls in one of these categories. It should also be noted that when any of the categories mentioned in this section except for WALK is used as a unimodal mode, it is implicitly assumed that WALK is used as both the access and egress mode. This is a result of the fact that it is always necessary to walk a short distance to and from, e.g., your bike, car, or public transport stop before and after using these modes. Therefore, WALK is presented as an access or egress mode in Table 1 for all unimodal modes, except for WALK

itself. Although one could argue that these should then be considered multimodal modes, we still regard these as unimodal modes for the purposes of this paper.

Apart from representing all unimodal modes, the choice component can form a wide variety of multimodal modes within a single trip by combining them. That is, while all unimodal modes assume walking to be the access as well as the egress mode as mentioned, multimodal modes depart from this assumption in that for example a mode from the (e) bike category can also form an access and/or egress mode for a mode in the car category. While it is tempting to include all  $7(\text{access mode}) \times 7(\text{main mode}) \times 7(\text{egress mode}) = 343$  combinations as multimodal modes in the ABM, this comes with a huge strain on computational requirements. It also unnecessary, since for example the car will hardly ever serve as an access or egress mode for a main mode from the bike category. The 25 out of 343 combinations that are most likely to be used are included in the model; cf. Zhou et al. (2020) for an explanation of how these likely combinations are selected. Table 1 provides a complete list of these 25 multimodal modes, along with the 7 unimodal modes, each of which corresponds to the mode categories mentioned above.

Connecting from one travel mode to another within a trip is done through a mobility hub, which can accommodate several combinations of preceding and succeeding mode: CAR and PT, CAR and BIKE as well as CAR and EBIKE. The mobility hubs enable an easy transfer between said modes. Thus, for instance, in the morning, after walking to their car, travellers drive to a mobility hub, park their cars there and then continue their trip by PT to their final destinations, leading to WALK-CAR-PT as the used multimodal mode. It is worth mentioning that a mobility hub does not take the order of modes into account: in the afternoon, the travellers go back to the same mobility hub by PT and then drive their car back home, leading to PT-CAR-WALK as the used multimodal mode. While planning the trips, the ABM selects mobility hubs in the following manner. It first selects feasible mobility hubs, meaning that within each origin–destination zone pair, the mobility hub accommodates the transfer between the two modes and is not farther than 3 km away from the intended destination if it is to be reached by the BIKE-mode, while this number reads 10 km and 20 km in case of the PT and CAR mode, respectively. Afterwards, the best mobility hubs are selected by checking which ones lead to the shortest travel distance to (or from) the point of interest. This is typically the destination of a trip to the city center, or, the origin of the succeeding trip away from the city center. One could argue that travellers may pick the mobility hub incurring the shortest travel time rather than the shortest travel distance. These two conditions are however very similar, since the mode used for the leg between the mobility hub and the point of interest (or vice versa) is typically undertaken by a mode that does not suffer much from congestion, such as e-bike or PT.

## 2.2. Utility functions and their structure

All of the components of the ABM mentioned in Section 2.1 make their subsequent choices based on a discrete choice model. This choice model assigns utilities to all possible alternatives between which a choice needs to be made according to a utility function. The alternative which happens to have the highest utility is then chosen. All components are based on multinomial logit or probit models. In the present section, we zoom in on the structure of the utility functions used in the various components. This leaves the question of how to estimate the coefficients that appear in the utility functions, which will be addressed in Section 2.3.

### 2.2.1. Multinomial logit model

The components mentioned in Section 2.1.1, except for the customly

coded trip mode choice component, are based on a multinomial logit model. In such a model, the utility  $U_{ij}$  assigned to any alternative  $i$  and traveller  $j$  has the following form:

$$U_{ij} = \alpha_i + \sum_{k=1}^N \beta_{i,k,alt} C_{i,k}^{alt} + \sum_{k=1}^M \beta_{i,j,k,trav} C_{j,k}^{trav} + \varepsilon_{ij}. \quad (1)$$

Next to an alternative-specific constant  $\alpha_i$ , this expression includes two sums, each representing the utility contribution of several attribute values. In particular, the first sum

$$\sum_{k=1}^N \beta_{i,k,alt} C_{i,k}^{alt}$$

forms a linear combination of the attribute values  $C_{i,1}^{alt}, \dots, C_{i,N}^{alt}$  that represent  $N$  attributes specific to alternative  $i$ , such as travel time and travel cost. Likewise, the second sum

$$\sum_{k=1}^M \beta_{i,j,k,trav} C_{j,k}^{trav}$$

forms a linear combination of the attribute values  $C_{j,1}^{trav}, \dots, C_{j,M}^{trav}$  that represent  $M$  attributes specific to traveller  $j$ , such as age and income. The quality of the model typically depends on the selection of the right attributes as well as the usage of carefully chosen accompanying coefficients  $\beta_{i,1,alt}, \dots, \beta_{i,N,alt}$  and  $\beta_{i,j,1,trav}, \dots, \beta_{i,j,M,trav}$ . Finally, the utility function includes an error term  $\varepsilon_{ij}$ . For the multinomial logit model, these error terms are assumed to be independent and Gumbel distributed. This has the advantage that the error terms do not actually need to be sampled, since under these assumptions a closed-form expression exists for the probability that an alternative  $i$  has the highest utility. For further explanation on this topic, cf. Chapter 2 of Castiglione et al. (2015).

### 2.2.2. Multinomial probit model

Not all components of our ABM implementation, however, follow a multinomial logit model. In the multinomial probit choice model, the utility function of an alternative  $i$  retains the form of (1). However, the error term  $\varepsilon_{ij}$  is no longer assumed to be Gumbel distributed, but is assumed to be normally distributed with zero mean and appropriate variance. This makes for the fact that multiple separate error terms can be incorporated in the model easily, because a sum of normally distributed random variables is again normally distributed. The Gumbel distribution in the multinomial logit choice model does not have this characteristic. The customly coded trip mode choice component described in Section 2.1.2 for instance incorporates a multinomial probit choice model, so that multiple error terms can be combined in the utility function on a trip level. Furthermore, the normal distribution comes in useful when combining the utilities of trip mode choices to form the total utility of a tour mode choice combination. Since this again requires the combination of multiple error terms, the ‘addition properties’ of the normal distribution make that this is facilitated by the multinomial probit choice model, unlike the multinomial logit choice model.

The utility function of the multimodal mode alternatives of the trip mode choice component deserves additional explanation. The reason for this is that multimodal mode alternatives consist of an access, a main and an egress mode, rather than just a single mode. In particular, let us denote a multimodal mode alternative  $i$  as a vector  $(i_{acc}, i_{main}, i_{egr})$ , where  $i_{acc}$  refers to the access mode,  $i_{main}$  to the main mode, and  $i_{egr}$  to the egress mode of alternative. Then, the utility  $U_{ij}$  of multimodal mode alternative  $i$  and traveller  $j$  can be expressed as follows:

$$\begin{aligned}
U_{ij} = & \alpha_{i_{\text{main}}} + \sum_{k=1}^M \beta_{i,j,k,\text{trav}} C_{j,k}^{\text{trav}} + \sum_{k \in \{\text{acc}, \text{main}, \text{egr}\}} \beta_{i_k, \text{time}} \left( \text{ST}_{i_k} + \text{TT}_{i_k} \right) \\
& + \sum_{k \in \{\text{acc}, \text{main}, \text{egr}\}} \beta_{i_k, \text{cost}} \left( O_{i_k} + \text{SU}_{i_k} \right) + \sum_{k \in \{\text{acc}, \text{main}, \text{egr}\}} \beta_{i_k, \text{p-cost}} P_{i_k} \quad (2) \\
& + \sum_{l \in \{(i_{\text{acc}}, i_{\text{main}}), (i_{\text{main}}, i_{\text{egr}})\}} \beta_{\text{walk, time}} T_{l, \text{transfer}} + \beta_{\text{parking}} \ln \left( \text{PC}_{i_{\text{main}}} \right) + \mu_{ij} + \eta_{ij}.
\end{aligned}$$

In the remainder of the current section, this utility function is explained in detail.

**Alternative-specific constant and socio-demographic attributes.** The first two terms on the right-hand side of this equation also appear in (1) and serve similar purposes. That is,  $\alpha_{i_{\text{main}}}$  is a constant specific to the main mode of the multimodal mode alternative  $i$ , while the second term represents the utility contribution of  $M$  socio-demographic attributes specific to the traveller, such as age, the number of cars present in the household, income and composition of the household, et cetera. Note that  $\alpha_{i_{\text{main}}}$  is assumed to depend only on the main mode of alternative  $i$ . This assumption keeps the number of coefficients that require estimation limited. Incorporation of access and egress modes here requires a study of how to do this efficiently and how to estimate the resulting new coefficients accurately, both of which are outside the scope of this paper. It is also worth noting that the attributes which are only specific to the mode choice (and not to the traveller) are presently not grouped in a single term  $\sum_{k=1}^N \beta_{i,k,\text{alt}} C_{i,k}^{\text{alt}}$  as in (1), but are instead represented in the remaining, more detailed terms of (2), which are discussed below.

**Attributes dependent on access and egress modes.** The next few terms of (2) pertain to attributes that are very dependent not only on the main mode, but also on the access and egress modes. For example, the term

$$\sum_{k \in \{\text{acc}, \text{main}, \text{egr}\}} \beta_{i_k, \text{time}} \left( \text{ST}_{i_k} + \text{TT}_{i_k} \right)$$

represents the utility contribution of the searching time (e.g. the time to look up and access an available shared e-bike) and the travel time undertaken for the access, main and egress modes. The actual searching time and travel time are given by the attributes  $\text{ST}_{i_k}$  and  $\text{TT}_{i_k}$ , which are weighed through the coefficient  $\beta_{i_k, \text{time}}$ .

In a similar vein, the terms

$$\sum_{k \in \{\text{acc}, \text{main}, \text{egr}\}} \beta_{i_k, \text{cost}} \left( O_{i_k} + \text{SU}_{i_k} \right) + \sum_{k \in \{\text{acc}, \text{main}, \text{egr}\}} \beta_{i_k, \text{p-cost}} P_{i_k}$$

represent the utility contribution of the costs of the underlying modes. In particular, this term describes the operational costs ( $O_{i_k}$ ), start-up costs ( $\text{SU}_{i_k}$ ) and parking costs ( $P_{i_k}$ ) of the access, main and egress mode. It is worth noting that the start-up costs only entail the fixed cost component of using the specific alternative for the corresponding trip. It does not include the costs of e.g. possibly required car ownership and/or a possibly required MaaS subscription. Whether or not travellers own a car or possess a MaaS subscription will be part of the scenario input, and are as a result not part of the choice model.

It is worth noting that when any of the aforementioned properties are not applicable, the corresponding value is set to zero. For example,  $P_{\text{walk}}$  evidently equals zero, as there is no such thing as parking costs when walking. Similarly, if the traveller cannot use a shared vehicle (because of no MaaS subscription), the operational or start-up cost is zero. An exception to this is the value of  $P_{\text{PT}}$ , which is assumed to be non-zero for reasons specified at the end of this section. Also, since parking costs are valued differently than the operational and start-up costs, they are weighed through a separate coefficient  $\beta_{i_k, \text{p-cost}}$ . Furthermore, we mention that the travel times  $\text{TT}$  and costs  $O$  differ between private and shared vehicles. The answer to the question which of the two sets of values should be used in any given situation depends on three personal

properties of the traveller. These are possession of a driving license, ownership of a car and possession of a MaaS subscription. For example, in the case of the car mode, if a traveller does not own a car, inevitably the attributes pertaining to a shared car are used. Hence, if shared modes can be used, they will be used, even if a person owns a car and has a driver's license. In all other cases, the attributes of private cars are used. For the bike and e-bike modes, a similar mechanism is in place except for the fact that a driver's license is not required.

**Effects of mode switching.** The utility function (2) also contains a term that incorporates the utility effect of the transfer times as a result of switching from the access mode  $i_{\text{acc}}$  to the main mode  $i_{\text{main}}$ , and as a result from switching from the main mode  $i_{\text{main}}$  to the egress mode  $i_{\text{egr}}$ . The first of these transfers is denoted by  $(i_{\text{acc}}, i_{\text{main}})$ , while the second is denoted as  $(i_{\text{main}}, i_{\text{egr}})$ . Given this notation, the term  $\sum_{l \in \{(i_{\text{acc}}, i_{\text{main}}), (i_{\text{main}}, i_{\text{egr}})\}} \beta_{\text{walk, tt}} T_{l, \text{transfer}}$  includes these effects in the utility function, where  $T_{l, \text{transfer}}$  is the transfer time of the specific transfer  $l$ .

It is important to mention that another distinction between possible transfers can be made. All transfers within the multimodal modes listed in Table 1 take place at a mobility hub as a CAR-PT, CAR-BIKE OR CAR-EBIKE connection, except for the multimodal modes with public transport as a main mode, which we describe separately at the end of the section. While many transfers (not involving public transport as a main mode) implied by the multimodal modes in Table 1 can be trivially assigned to any of the three connection types mentioned above (CAR-PT, CAR-BIKE and CAR-EBIKE), note that transfers involving the car and demand-responsive transport (DRT) are all recorded as a CAR-PT transfer. At the same time, transfers between demand-responsive transport and the bike (e-bike) is deemed to be a CAR-BIKE (CAR-EBIKE) transfer.

The above distinction is not only made to specify which types of connections a mobility hub is geared toward, but it also comes in handy for the purpose of determining the actual transfer time. That is, transfers that qualify as CAR-PT connections are assumed to take eight minutes, based on Schakenbos and Nijenstein (2014), while, based on empirical evidence, the transfer times of other connections are set to five minutes. It is also worth remarking that all transfers are assumed to be done by walking, which is why  $\beta_{\text{walk, time}}$  is used as a coefficient for the transfer time. Although one might argue that the value of time for transfers and waiting is higher than that of walking, there are no data available on this to the best of our knowledge.

**Parking capacity.** The term  $\beta_{\text{parking}} \ln(\text{PC}_{i_{\text{main}}})$  in (2) models the utility contribution of the parking capacity ( $\text{PC}_{i_{\text{main}}}$ ) at the destination. Since the difference between say 50 and 100 parking places is much more profound than between 150 and 200 parking places, the parking capacity is included on a (naturally) logarithmic scale. It should be noted that the parking capacity is mode-dependent. Since parking capacity is only an issue when using the car mode, in the case study  $\text{PC}_{\text{car}}$  is set equal to the number of available car parking spaces. For all other main modes, we set  $\text{PC}_{i_{\text{main}}} = 1$ , so that the amount of parking capacity does not influence the associated utility.

**Error terms.** What remains in the utility functions are the terms  $\mu_{ij}$  and  $\eta_{ij}$ , which represent the errors made in computing the utility of the multimodal mode. In this regard, we implement the error structure introduced in the tour-based travel mode choice model of Miller et al. (2005). That is, the first term  $\mu_{ij}$  is specific to the mode and traveller. It models the personal preference with respect to a multimodal mode, and is not resampled whenever the same mode/traveller combination is regarded for a different trip (both within a tour or across multiple tours), so as to enforce consistency. The second term  $\eta_{ij}$  is not only specific to the mode and traveller, but also to the actual trip. This term models random effects not covered by  $\mu_{ij}$ , and is resampled also when the same mode/traveller combination is considered for a different trip. As mentioned before, both of these errors are assumed to follow a normal distribution with zero mean and appropriately chosen standard deviation. We choose for a zero mean so as not to interfere with the alternative-specific constant in the utility function. The standard deviations of the two error terms are

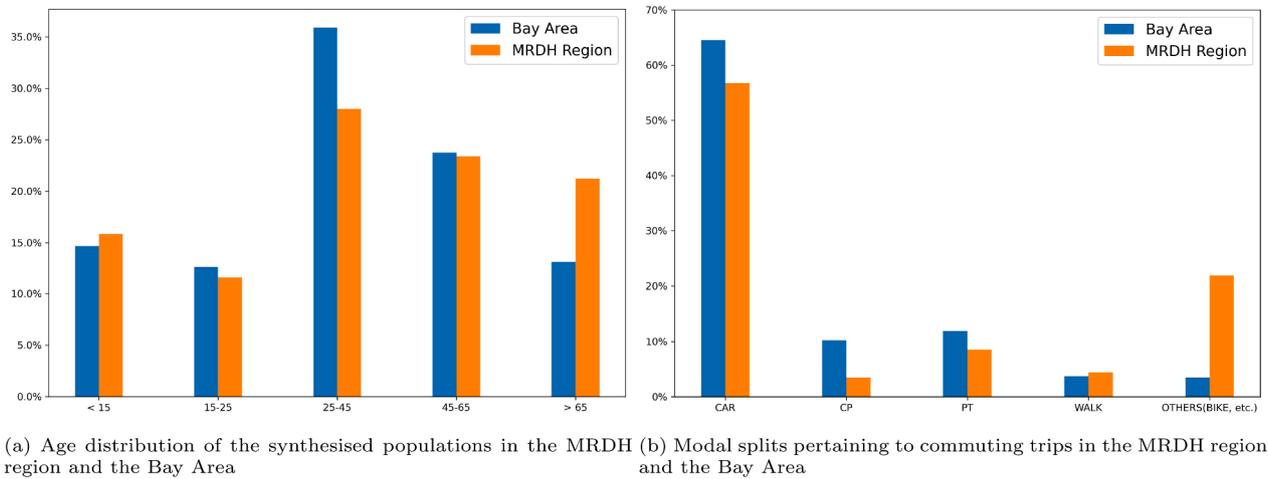


Fig. 1. Comparison between the Bay Area and the MRDH region.

chosen equally in such a way that the standard deviation of the sum of the two terms equals 10% of the average absolute utility. As mentioned above, the benefit of the errors being normally distributed is that the sum of such errors will again be normally distributed. This comes in handy when adding the utilities of several trips together to obtain the utility of a complete tour. Then, the error terms corresponding to the complete tour will again have a normal distribution. The multinomial logit model lacks this characteristic, which is why the trip mode choice component follows a multinomial probit model.

*Utility for multimodal modes with PT as main mode.* The discussion above deferred the treatment of the utility of multimodal modes with public transport as the main mode. These multimodal modes are different from other multimodal modes, because the transfer from an access mode to public transport and that from public transport to the egress mode does not necessarily occur at a mobility hub. In fact, they may occur at any access point to public transport. Multimodal trips involving transfers between public transport and the bike are especially complicated, because from the input data (which will be discussed in Section 3.1), we can only extract information on the entire time and cost of the complete multimodal trips, but not separately per leg of the trip. As a result, the terms in the utility function (2) which describe the contribution of travel time and cost for these multimodal trips cannot be computed by summing the contributions of the access, main and egress modes separately, but rather, the utility function is now defined as follows:

$$U_{i,j} = \alpha_{PT} + \sum_{k=1}^M \beta_{i,j,k, trav} C_{j,k}^{trav} + \beta_{PT,time} TT_i + \beta_{PT,cost} O_i + \beta_{PT,p-cost} P_i + \mu_{i,j} + \eta_{i,j} \quad (3)$$

Note that (3) has many terms in common with (2), which are already explained above. That is, just like (2), the utility function has an alternative-specific constant  $\alpha_{PT}$  as well as a sum

$$\sum_{k=1}^M \beta_{i,j,k, trav} C_{j,k}^{trav}$$

describing the contribution of all the socio-demographic features, and two error terms  $\mu_{i,j}$  and  $\eta_{i,j}$ . As implicated earlier, the terms  $\beta_{PT,time} TT_i$ ,  $\beta_{PT,cost} O_i$  and  $\beta_{PT,p-cost} P_i$  detailing the time and cost components do not have separate contributions for the access and egress modes anymore. Also, these terms do not involve e.g. searching time and start-up costs, since these are not applicable to the main mode of public transport, as well as its usual access and egress modes, namely WALK or BIKE. It should be noted, however, that (3) does include a contribution for parking costs. In particular, we assume in this model that  $P_{PT} = P_{car}$ . While this

may strike as odd since public transport induces no actual parking costs for travellers, high parking costs in the neighbourhood may make public transport an attractive alternative for the traveller. Hence, the associated coefficient  $\beta_{PT,p-cost}$  is positive, unlike  $\beta_{car,p-cost}$  in (2).

### 2.3. Coefficients of the utility functions

Now that the structure of the utility function has been explained, we have to estimate suitable values of the coefficients involved, namely the alternative-specific constant  $\alpha$  as well as the  $\beta$ -coefficients that appear in (1) and (2). This process is detailed in this section. More particularly, in Section 2.3.1 we explain how to select an initial set of values, after which these values are made subject to further calibration and validation in Section 2.3.2.

#### 2.3.1. Estimating coefficients using other regions

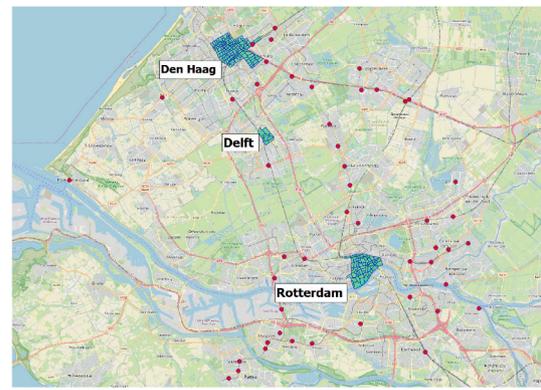
Estimating suitable values for the coefficients in the utility function is not a trivial task. Although many of these parameters can be estimated based on the Dutch survey data OViN/ODiN (Centraal Bureau voor de Statistiek, 2018), a lack of information on e.g. household level remains, such as joined tours of multiple persons within a household. Furthermore, the number of registered multimodal trips is also too low to estimate the parameters. It has been suggested in the literature that in such case coefficients can be transferred based on their counterparts from other regions, which are not too dissimilar from the region studied, cf. the work of Gliebe et al. (2014) on transferability of parameters. For example, in Ziemke et al. (2015) coefficients are transferred from an ABM study pertaining to the Los Angeles area, California, USA to one pertaining to the region of Berlin, Germany.

Spurred by this approach and inspired by the particular region used, we set out to discover whether it is possible to transfer parameters found in the study of MTC (2018) to our setting. This study includes an ABM studying a representative part of the Bay Area, which is the area surrounding San Francisco in northern California in the USA. The ABM simulates travelling activity on a weekday to assist policy makers in this region in planning activities. From this point on, when we refer to the Bay Area, we actually refer to this representative part of it, which covers the cities of San Francisco and San Mateo.

To see whether the Bay Area is representative enough for the MRDH region, following the suggestions made in Gliebe et al. (2014), the demographic information of San Francisco and San Mateo in the Bay Area is first compared to that of the cities of The Hague and Rotterdam in the MRDH region. In doing so, we found that the average number of persons in a household in the Bay Area, namely 2.4, is comparable to its counterpart 2.1 in the MRDH region. Next, we regard the age distributions of the populations in both areas, which are displayed in Fig. 1a. The age



(a) The Netherlands consists of 7011 TAZs, 5924 of which represent the MRDH region.



(b) The Hague, Delft and Rotterdam centers (cyan-blue blocks) and mobility hubs (red points)

**Fig. 2.** MRDH region in the Netherlands and main city centers.

distributions of both areas are quite similar, except perhaps for the fact that the Bay Area consists of a higher percentage of individuals aged between 25 and 45 years, while the MRDH region consists of more elderly people. Furthermore, the average number of private cars per household is 1.4 in the Bay Area, while with 1.7 it is only slightly higher in the MRDH area. As such, one can conclude that from a demographic point of view, the two regions are similar.

While the demographic similarity between the regions is encouraging, also the travel modes used by travellers in both areas should be compared. Regarding the mode choice of commuting trips, it turns out that the modal splits of both areas differ significantly. That is, results in [Centraal Bureau voor de Statistiek \(2018\)](#) and [MTC \(2021\)](#), depicted in [Fig. 2](#), show that in the Bay Area travellers mainly use the car and public transport, while cycling is far more popular in the MRDH region. In line with conclusions from [Gliebe et al. \(2014\)](#), it is therefore not justified to simply copy all coefficient values used in [MTC \(2018\)](#) for use in the utility functions of our model. Rather, these coefficients can be used as a basis for further calibration and subsequent validation. These steps are discussed in the next section.

### 2.3.2. Calibration and validation of coefficients

In this section, we describe the procedure that we used to further calibrate and subsequently validate the coefficients transferred from [MTC \(2018\)](#). The starting point of the calibration is a suitably synthesised population as obtained in [Snelder et al. \(2021\)](#), which is representative for the MRDH region. These population data are further described in [Section 3.1](#), as they will serve as input data for the ABM model. For the purpose of calibration, we select a fraction of 10% of this population, while making sure that this selection remains representative for the complete population in terms of e.g. the age distribution. The calibration process is performed with this fraction rather than the complete population, since it relieves the otherwise infeasible computational burden. Next to these data, the process of calibration and validation also requires a benchmark, and this role is fulfilled by the Dutch survey data OViN/ODiN ([Centraal Bureau voor de Statistiek, 2018](#)) pertaining to the population of the MRDH region. A description of these survey data, as well as an overview of how these data were processed to act as a benchmark, is given in [Appendix A.1](#).

The calibration procedure that is used in this paper is the one described in [Bowman et al. \(2014\)](#). In this procedure, the alternative-specific constant  $\alpha_i$  as well as the coefficients pertaining to the travel time ( $\beta_{car,tt}$  and  $\beta_{PT,tt}$ ) and the travel cost ( $\beta_{car,cost}$  and  $\beta_{PT,cost}$ ) of the car and public transport modes are tweaked. This is done in such a way that the output of the model using the new coefficient values reflects the situation as sketched by the benchmark data well. While in principle all coefficients of (2) could have been made subject to alteration, we opted to tweak only specifically these parameters, since these parameters are

known to cause the biggest issues with transferability, as concluded in the work of [Bowman and Bradley \(2017\)](#) on this topic. The procedure is iterative: in each iteration, the ABM model is run with the (10%-fraction of the) synthesised population data under a current-day scenario, and the output of the model is compared to the survey data in terms of measures such as modal split, purposes of tours undertaken and departure times of the trips. Based on this comparison, the above-mentioned coefficients are altered slightly. This process repeats until the coefficients hardly change anymore.

After undertaking this procedure, as can be seen in [Appendix A.2](#), the model output of the ABM based on (the fraction of) the synthesised population match sufficiently well with the survey data under the current-day scenario. As a result, the model is now ready for use in a case study under possible future scenarios.

## 3. Case study

Now that we have explained the model, regarded the underlying utility functions and calibrated their parameters, we proceed with the case study in an effort to answer the questions mentioned in [Section 1](#). Broadly speaking, we explore whether NMS and parking policies lead to a more sustainable mobility. This is done by running the ABM model for the MRDH region for the year 2030. We focus on this particular year, since forecasted data on different aspects of the population in this year is available, as detailed below. [Section 3.1](#) first explains the input data of the MRDH region on which the case study is based in more detail. After this, [Section 3.2](#) defines seven scenarios that we will use in order to address the questions raised in [Section 1](#) and reach conclusions. Each of these scenarios includes a significant change geared to improve the sustainability of the mobility. Then, [Section 3.3](#) presents the results obtained by running the ABM model in these scenarios. Finally, [Section 3.4](#) performs a sensitivity analysis on some parameter models on the model in an effort to make sure that possibly unreliable estimations do not impact the observations of the earlier sections.

### 3.1. Input data

As mentioned before, the region which this case study focuses on is the Metropolitan Region Rotterdam and The Hague in the Netherlands, which has an area of about 1130 km<sup>2</sup>. The Dutch name for The Hague is Den Haag, which leads to the commonly used abbreviated term MRDH region.

The first category of data that is relevant for the case study concerns data on the population of the MRDH region. For this purpose, we use the population data of [Snelder et al. \(2021\)](#) pertaining to the year 2030 that was synthesised through a population generator based on data of the Dutch governmental institution Statistics Netherlands (CBS) ([Centraal](#)

**Table 2**  
List of parameters to determine level of service.

Name	Value	Source
Average time to search shared bike	1 min	
Price for shared bike	€0.00/min	
Start-up cost of shared bike	€1.925	OV-fiets
Area where shared bikes are allowed	Everywhere	
Price shared e-bike	€0.30/min	Felyx scooter
Searching time for car sharing	5 min	
Price car sharing	€0.10/min	Greenwheels
Start-up cost car sharing	0	Greenwheels
The area allowed for car sharing	Everywhere	
Avg waiting time car passenger for shared vehicle (e.g. taxi)	5 min	
Price car passenger in shared vehicle	€0.35/min	
Start-up cost of car passenger in shared vehicle	€3.00	Uber
Area where car passengers in shared vehicle are allowed	Everywhere	
Price DRT per min	€0.00/min	
Start-up cost DRT	€3.00	
PCU value for DRT	0.2	Assumed 5 passengers

Bureau voor de Statistiek, 2020) pertaining to the year 2016. In particular, this synthesised population consists of 2.564.603 individuals spread over a total of 1.223.275 households. The synthesised population data contains many characteristics of the population on an individual level such as age, possession of private vehicles, etc. Concerning the age individuals, the data distinguish between five categories. That is, in 2030, 16% of the synthesised population is younger than 15 years old, while 12% is at least 15 years old, but still younger than 25 years old. A fraction of 28% of the population is between 25 and 45 years old, and a 23% large fraction has an age between 45 and 65 years old. The remaining 21% of the population is older than 65 years old.

The second type of data that this paper relies on originates from the V-MRDH 2.6 model in Schoorlemmer (2020), which concerns the land use of 7.011 pre-specified traffic analysis zones (TAZ) in the entire Netherlands. The number of TAZs in the MRDH region is relatively high: the region is comprised of 5.924 TAZs. Many of these TAZs cover a relatively small area, so that the TAZs form a very granular picture of the MRDH region; see Fig. 2a. The land use data report for every TAZ information on the number of employment places (offices, shops, etc.), number of education places (i.e., schools), the actual area of the TAZ and its urbanisation level (i.e., the population density), the number of paid and non-paid parking spaces and the average hourly parking costs. Another relevant piece of input data, which could also in a way be interpreted as land use data, concerns the locations of the mobility hubs. In this study, these locations are also taken from Schoorlemmer (2020). In short, this means that current P + R locations (i.e., park & ride locations) will be considered as mobility hub locations. In addition, train stations are also considered mobility hub locations in the remainder of this paper. Since transit opportunities to public transport are typically already available at a train station, the investment of turning it into a fully-fledged mobility hub is minor. The mobility hub locations are

**Table 3**  
Overview of the scenarios considered in the case study.

#	Scenario Title	Mobility hubs	Rate of MaaS subscription possession	Travel time PT to/ from city Center	(E-) bike travel time to/ from city centers	Parking capacity	Extra parking searching time	Extra parking cost
1	Reference 2030	No	0%					
2	Mobility hubs	Yes	0%					
3	MaaS	Yes	50%					
4	PT travel time	Yes	50%	-7.5%				
5	Micromobility travel time	Yes	50%	-7.5%	-20%			
6	Center parking capacity	Yes	50%	-7.5%	-20%	-30%	+14 min	
7	Center parking cost	Yes	50%	-7.5%	-20%	-30%	+14 min	+32%

depicted in Fig. 2b. Each of these mobility hubs may accommodate one or more of the transfer types mentioned in Section 2.2.2: CAR-PT, CAR-BIKE and CAR-EBIKE. The answer to the question which of these transfer types are actually available for a particular trip depends on the origin and the destination of this trip: the CAR-PT type can only be used whenever the distance undertaken by car would be at least 20 km, and the distance undertaken by public transport would not exceed 10 km. For the CAR-BIKE and CAR-EBIKE transfer type, the former restriction also applies, but there the latter restriction concerns the distance undertaken by bike or e-bike, and these numbers should not exceed 5 km or 8 km, respectively, rather than 10 km.

The final category of relevant input data concerns level-of-service data for each possible pair of origin TAZ and destination TAZ (or simply origin-destination pair). That is, for each possible pair and each of the seven unimodal travel modes that are considered, we generate travel time, cost and distance for three different periods over the day (morning peak, evening peaking and off-peak). These characteristics have been derived using both results in Snelder et al. (2021) and the values presented in Table 2 on new modes from various sources which are not specific to the day period. When no sources are mentioned in this table, the values are based on expert judgement. It should be noted that travel times and travel costs are considered static in this study. One may argue that it is plausible these are in fact highly dynamic as a result of the network assignment. Incorporation of these dynamics would entail considerable extension of the model, which is discussed in Section 4.2.

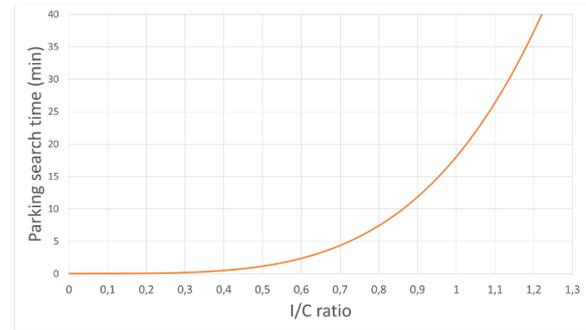
### 3.2. Scenario description

We proceed by giving an overview of the scenarios that are considered in the case study. These scenarios are summarised in Table 3 and are cumulative in nature. That is, each consecutive scenario introduces an additional feature, which we now describe one by one.

1. The first scenario, titled 'Reference 2030', is the scenario which acts as a reference. We base this reference on the study in Manders and Kook (2015) on the future year 2030. In particular, the scenario is based on the forecast of the population made in this study, while the transport system is similar to today's one. In particular, the parking policies assumed are the ones that are in place in the MRDH region of 2016, and without any shared services or any other form of NMS. Since the forecast anticipates a relatively strong population and economy growth, this reference scenario will entail a heavily loaded traffic infrastructure, highly likely leading to many traffic jams. In the next scenarios, several new features (i.e., new mobility services and parking policies) are added to this base scenario to measure the individual impact of each of them on the mobility system, and in particular its sustainability.
2. The second scenario 'Mobility hubs' introduces mobility hubs in the MRDH region that allow travellers to park their cars just outside of the city center, and travel onwards using public transport or private (e-)bike. As mentioned before, the locations of the mobility hubs are



(a) The city center of Rotterdam, together with the neighbourhoods of Kralingen and Feijenoord as well as the three mobility hubs.



(b) The BPR function of the parking search time

Fig. 3. Scenarios 5 and 6.

- depicted in Fig. 2b and parking at these hubs is assumed to be completely free of charge in this and all following scenarios.
- The third scenario 'MaaS' adds new mobility concepts to the previous scenario. That is, shared modes are now available as well as MaaS. The scenario assumes that 50% of the population in each age category mentioned in Section 3.1 owns a MaaS subscription. Within each age category, the population generator decides, before the ABM is executed, which travellers obtain this MaaS subscription. This is done through random sampling independent of any traveller characteristics, other than age. As a result, half of the population has access to MaaS. When a traveller owns a MaaS subscription, this person has access to shared cars and shared (e-) bikes, which can be picked up and be dropped off at any public parking spot. Furthermore, the subscription enables the use of a shared taxi, minibus or other shared modes which are not included in conventional public transport (such as the bus, tram, metro and train). Travellers possessing a MaaS subscription are assumed to be fully willing to use these shared services, even when they own a private vehicle. This may be a strong assumption, which is why we will revisit this assumption in Section 3.4. Many travellers in this scenario now have access to a multitude of shared modes, which encourages these travellers to use multimodal modes to travel from origin to destination.
  - The fourth scenario 'PT travel time' improves connections with and within the city centers. That is, the travel time of public transport to and from the centers of the cities is assumed to be 7.5% faster. We believe such a decrease may be in reach by optimising schedules and implementing technological advances. Obtaining such an improvement, however, also requires investments in e.g. increase of the fleet size and the number of employees (bus drivers, LRT operators, etc.). It is worth mentioning that the change of utility that this assumption brings was also applied in an addendum to the V-MRDH model (de Vries et al., 2021), albeit due to a different reason. In this addendum, it was observed that travellers are less sensitive to travel time brought by public transport as initially believed, leading to a reduction in the utility contribution of public transport travel time. It should be noted that the transfer time between different PT modes is implicitly assumed to be part of the travel time. It however does not include the transfer time required between PT-modes and non-PT modes. These transfer times are explicitly modelled as described in Section 2.2.1.
  - In addition to the improved public transport service to and within the city centers, policy makers may also consider plans to improve other forms of mobility. To this end, the fifth scenario, which we call 'Micromobility travel time', considers other mobility improvements specifically in the city of Rotterdam. In particular, in this scenario, the travel times of the bike and e-bike from the three mobility hubs in

and around Rotterdam, which can be used for (e-) bike transfers, to the city center and vice versa are reduced by 20% compared to the reference scenario. Such improvements may be achieved by placing strategically located tunnels and bridges. The placement of new bridges and/or tunnels by the local government is currently being considered; see e.g. the current so-called 'Oeververbinding project' (Werkgroep et al., 2021). To obtain an idea of the placement of the Rotterdam mobility hubs with respect to the city center of Rotterdam, we refer to Fig. 3a).

- Next, to observe the effect of reducing parking facilities, the scenario 'Center parking capacity' reduces the total parking capacity by 30% in the city centers of The Hague, Delft and Rotterdam (see Fig. 2b). As a result of the reduced parking capacity, the scenario will also take into account the extra searching time required to find a parking spot in the city centers. This extra parking searching time is determined by a BPR function; cf. Fig. 3b. This function specifies for each I/C ratio (i.e., the intensity/capacity ratio) the expected searching time. Note that both the intensity and capacity are measured in the number of vehicles per minute, so that the I/C ratio itself is unitless. The parameters used to derive this BPR function are taken from Snelder et al. (2021). In the previous scenarios on average 70% of the total parking places is occupied in the city centers over time, leading to an I/C ratio of 0.7 and thus an average parking searching time of close to five minutes. Due to the 30% reduction in parking capacity from this scenario on, however, the I/C ratio equals one, which according to the BPR curve leads to a parking searching time that averages around a duration as long as 18 minutes, which is an increase of 14 minutes when compared to the reference scenario.
- In the final scenario 'Center parking cost', the hourly parking cost in the city centers is increased by 32%. This number is based on the study of Hiderink and Kieft (2012), which considers the Amsterdam region. In this study a 25% increase in hourly parking cost from 2020 to 2030 is considered in accordance with the guideline of the Dutch Ministry of Infrastructure and the Environment, which is tantamount to a yearly increase of roughly 2.25% ( $1.25^{10} \approx 1.0225$ ). We expect the yearly increase of the parking costs in the MRDH region to be a little lower based on historical numbers, which is why we assume a yearly increase of parking costs of 2% in the MRDH region. As the parking costs in the reference scenario are based on those which were in place in the year 2016, the assumed parking costs in this scenario are thus 32% higher with respect to the reference scenario, since  $1.02^{2030-2016} \approx 1.32$ .

Now that the input data is specified and all scenarios are defined, the results of our case study can be presented.

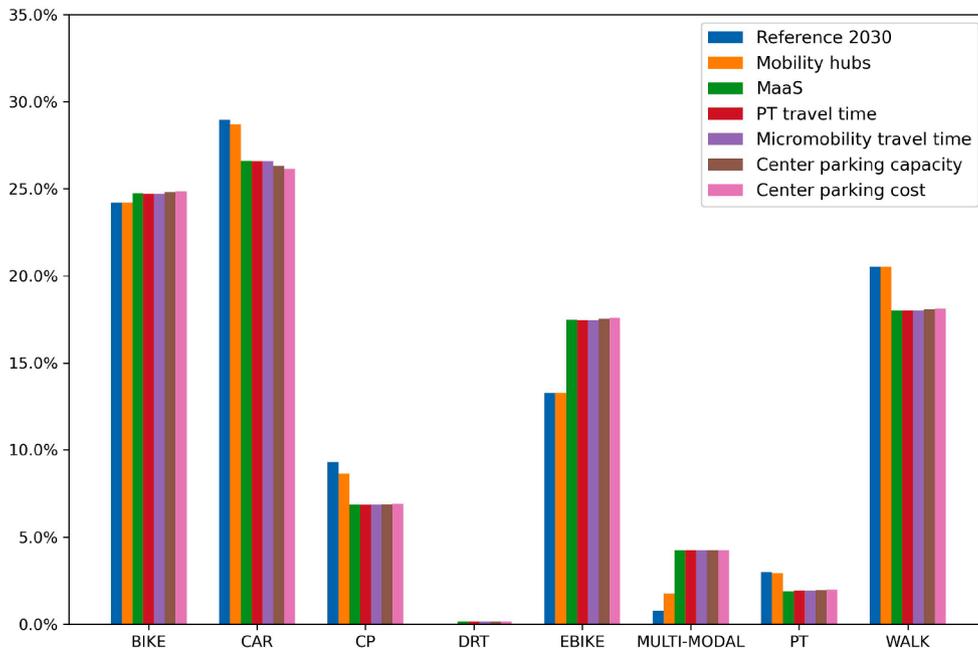
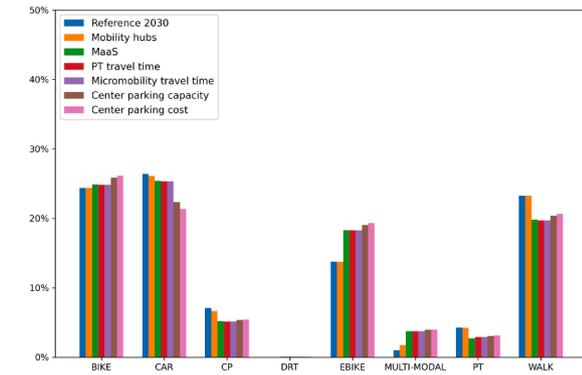
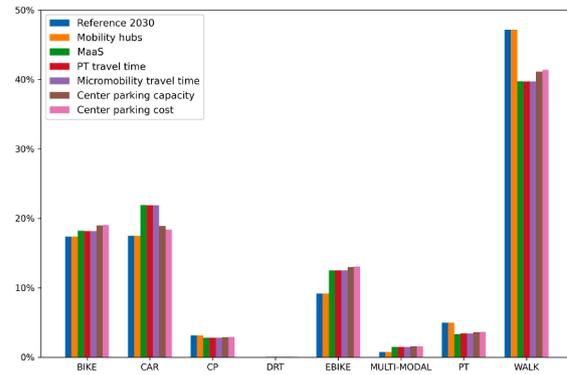


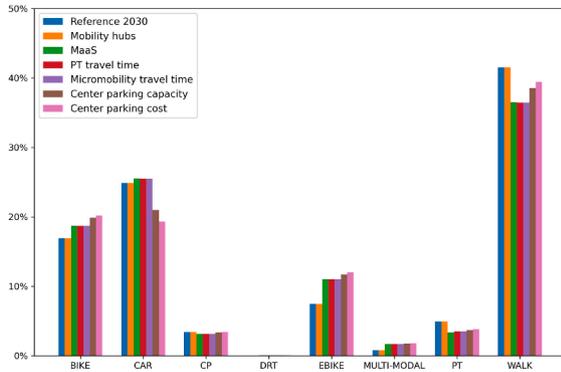
Fig. 4. Bar chart representing the modal split of all simulated trips in the MRDH region under the various scenarios.



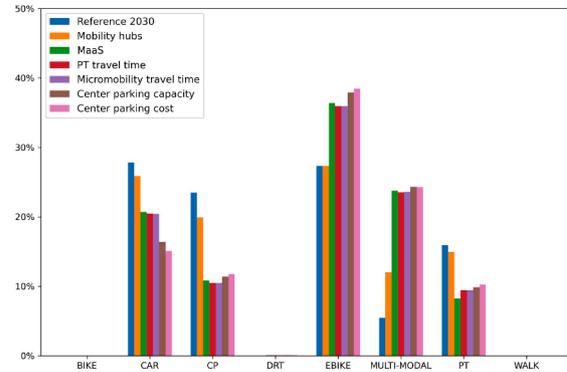
(a) Trips originating from a city center with a destination outside of a city center and vice versa



(b) Trips taking place within the center of Rotterdam



(c) Trips taking place within the center of The Hague



(d) Trips originating from the city center of The Hague with a destination in the center of Rotterdam and vice versa

Fig. 5. Bar charts representing the modal split for several subsets of the simulated trips.

### 3.3. Results

Using the ABM implementation as detailed in Section 2, we have simulated the seven scenarios described in the previous section. A single run, covering the complete MRDH region for a complete week day in one

of the seven scenarios, took about 3.5 hours to run on a server with 128 GB RAM and an Intel Xeon(R) Gold 5115 2.4 GHz CPU. Each scenario has been simulated eight times using the common random numbers methodology that was explained in Zhou et al. (2022), and the results in this section are based on averages of these eight runs. The common

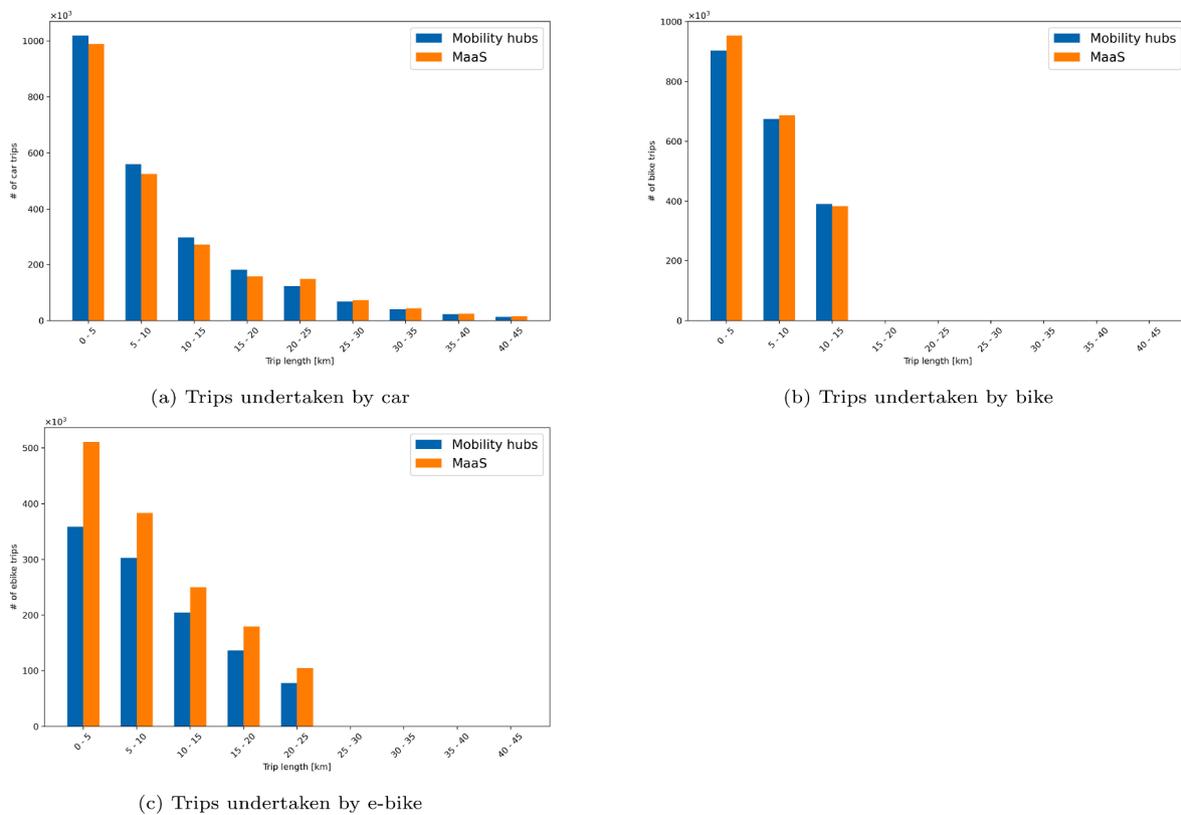


Fig. 6. Numbers of trips undertaken by car, bike and e-bike (as a unimodal trip or as part of a multimodal trip) for several distance ranges in scenario 3.

random methodology ensures that the effect of simulation error on the model output is mitigated and the results are statistically significant. We further comment on this in Remark 1.

We proceed by discussing the numerical observations concerning the modal split pertaining to the various scenarios, so as to draw conclusions about the consequences of NMS and parking policies. Figs. 4 and 5 graphically summarise the modal splits of the scenarios in several bar charts, where all multimodal modes are grouped into a single category named ‘multi-modal’. Not only the modal split based on all simulated trips (Fig. 4) is presented, but for reasons that will become clear later, we also plot the modal splits of several subsets of these trips (Fig. 5). For example, Fig. 5a represents trips that either originate or have their destination in a city center (i.e., the city center of Delft, The Hague or Rotterdam), but not both. Furthermore, Figs. 5b and 5c show the modal split of trip movements within the city centers of Rotterdam and The Hague, respectively. Finally, Fig. 5d shows the modal split of trips from the center of The Hague to the center of Rotterdam and vice versa.

*Scenario 1: Reference 2030.* Before the differences between the scenarios are treated, we note that the leftmost bars in Figs. 4 and 5, representing the reference scenario in the year 2030 if no NMS or additional parking policies were to be introduced, already paint a different picture than that of the current-day infrastructure. For example, Fig. 4 shows that in the reference scenario, 13.2% of the trips are made using the e-bike. This is much higher than the share of e-bike trips undertaken in the MRDH region in 2016, which is 4.3% as per the OViN/ODiN survey data. This difference can be attributed to the fact that in 2030, expected e-bike ownership is much higher; cf. Snelder et al. (2021). Furthermore, we observe that Figs. 5b and 5c show a very low use of multimodal modes in the reference scenario. While this can be explained by the fact that the reference scenario contains no mobility hubs, eliminating most multimodal modes, it is worth noting that even when these mobility hubs would be present (as is the case in the other scenarios), these multimodal modes will still hardly be used. The reason for this is that these mobility hubs would not be located in the city centers, rendering their usefulness

negligible for internal city trips. As mentioned in Section 2.2, multimodal modes involving PT as a main mode do not require mobility hubs, and these are the multimodal modes that show up in Figs. 5b and 5c. In a similar vein, Fig. 5d reveals that no trips are undertaken solely walking or cycling between the two city centers of Rotterdam and The Hague: the distance is simply too large. The bike can be used as an access or egress mode, however, in which case the trip is recorded in the category ‘multi-modal’.

Since we are interested in the impact of NMS and parking policies, we now focus on the difference in modal splits in between the scenarios.

*Scenario 2: Mobility hubs.* The orange bars in Fig. 4 reveal that if mobility hubs were to be introduced, a number of car and car passenger trips (equivalent to 0.9% of the total number of trips) become multimodal mode trips: car users can now park their cars at mobility hubs, so that onward journeys can be made using another mode. While Fig. 5d suggests that, as expected, this shift is largest for trips with large distances, it should be noted that this shift is rather small in a general sense. Plausible reasons for this could be the fact that extra travel time needs to be incurred to reach the mobility hubs, while the actual transfer between modes at the hubs also requires time. Furthermore, the fact that this scenario does not include shared modes yet also plays a role: to transfer to e.g. a bike mode, travellers have to arrange a private bike at the mobility hub beforehand or e.g. bring a folding bike the whole trip.

*Scenario 3: MaaS.* In the third scenario, shared modes such as shared bike services become available, and 50% of the travelling population now has a MaaS subscription. Judging by Fig. 4, compared to the previous scenario introducing mobility hubs, the car and car passenger mode shares combined lose another 3.9% of the total number of trips. At the same time, the share of the e-bike mode increases from 13.3% to 17.5%, while the multimodal share also grows to 4.2%. Side effects are that there is also a modal shift from walking (from 20.5% of the total number of trips to 18%) and public transport (from 2.9% of the total number of trips to 1.9%) to shared modes, which can be negative for the business case of public transport and can have negative health effects.

These shifts can be explained as follows. In this scenario, shared services are enabled by the presence of MaaS subscriptions, which makes that a traveller does not require a private vehicle anymore to use the CAR, BIKE or EBIKE mode. This explains the increased use of EBIKE, and also the lesser increased use of BIKE: travellers can now use (e-)bikes without having them at their disposal at the origin of the trip. The increased use of e-bikes occurs at the expense of the walking mode: e-bikes can now be used for short distances. Another attractive feature of this scenario is that shared services offer a wider accessibility to mobility hubs, which usually allow for parking at reduced or even no cost. This explains why the share of the multimodal mode increases, while those of CAR and CP decrease.

Fig. 5a shows that the modal split of trips which either originate or have their destination in a city center shows similar effects. While the shift from the WALK to EBIKE mode is again easily identified, the shift of CAR and CP to the use of multimodal modes however seems less profound. This could be explained by the fact that again the use of mobility hubs may induce longer travel times (see e.g. Fig. 2b), which are unattractive. The next two scenarios address these long travel times.

For trips within the city centers, illustrated by Figs. 5b and 5c, multimodal mode trips are necessarily trips with public transport as the main mode since they do not require mobility hubs as earlier mentioned. As a result, the share of CP remains largely unaffected by the introduction of MaaS, while the share of CAR only increases in this scenario. The reason behind this is that this scenario allows travellers without a private car to use shared vehicles. Note that the figures could give a slightly exaggerated idea of this increase, because of the assumption in our model that enough shared vehicles are available for anyone requiring one, which may not be the case everywhere. Nevertheless, this effect seems to be substantial, especially in the Rotterdam area. The increase is less generous in The Hague, presumably because it is known that the average number of cars per household is larger there. Furthermore, generally speaking, The Hague imposes lower parking fees than Rotterdam, so that the benefit of free parking for shared cars is less.

When considering the trips between the two city centers (cf. Fig. 5d), we also see a significant increase of the use of the e-bike and multimodal modes. As the increase of the e-bike mode cannot occur at the expense of the walking mode since they are not used for trips between the city center to begin with, the use of the CAR and CP drops more significantly with the introduction of MaaS.

Finally, it should be noted that in this scenario, compared to the previous scenario introducing the use of mobility hubs, the total distance covered by cars increases by 0.9%. Based on Fig. 6a, which shows for both the current and the previous scenario the simulated numbers of trips in several distance ranges undertaken by car (either for a unimodal trip or as part of a multimodal trip), it seems that this is because under the MaaS scenario, cars are now used more frequently for trips with longer distances, although the overall number of trips undertaken by car has decreased. Instead, especially for shorter distances, the bike and e-bike have largely gained in popularity (cf. Figs. 6b and 6c), due to the availability of shared bikes and e-bikes at the mobility hubs. We conclude that offering shared services decreases overall car popularity, while the bike and e-bikes modes become more attractive.

**Scenario 4: PT travel time.** As mentioned above, when travelling by a multimodal mode through a mobility hub, the travel times may become much longer than when travelling directly using a unimodal mode. There are multiple reasons behind this; the alternative routing associated with the transfer at the mobility hub, the actual transfer time and potentially lower travel speeds than that of the car need to be taken into account. The effect of this is not to be underestimated, which is illustrated by the fact that in the third scenario, the average duration of the trips was about 22 min longer than the average duration in case all trips were undertaken by the unimodal CAR mode.

In an effort to remedy this effect, the fourth scenario assumes public transport services from and to city centers to be faster. It can be seen in Fig. 5a that, as a result of this, the share of the PT mode only increases

from 2.7% to 2.9%. That is, the share of PT trips either originating or having a destination in a city center (or both) only increases slightly. The effect of the reduced PT travel time in Fig. 5d is more pronounced; the number of trips undertaken by PT between the centers of The Hague and Rotterdam increases from 8.2% to 9.5%. This difference is in line with other findings in the literature, e.g. Willigers et al. (2021). Yet, also in this case, the increase seems limited. At the same time, however, although the total number of trips from and to city centers using mobility hubs connecting the CAR and PT modes remain limited (a few thousand), this number has remarkably increased by 9%. It is hence fitting to conclude that a more efficient public transport system may stimulate the use of mobility hubs.

**Scenario 5: Micromobility travel time.** As mentioned in Section 3.2, the fifth scenario improves the connection between the Rotterdam city center and the three surrounding mobility hubs, also in an effort to reduce the longer travel times induced by the multimodal modes. Figs. 4 and 5 hardly show any impact on the modal split of this scenario. This, however, is not at all surprising, given the fact that this scenario mainly impacts trips that are only going to or from the Rotterdam city center (but not both). Indeed, the output of the model shows that, compared to the previous scenario, the total number of simulated daily trips between Rotterdam city center and the three mobility hubs increases from 7177 to 7313, which is an increase of 1.9%. For these trips, the usage of both a car and an (e-)bike becomes more attractive, as witnessed by an increase of transfers between the CAR and BIKE modes as well as the CAR and EBIKE modes at the mobility hubs by 8.1% and 1.5%, respectively. At the same time the transfer rate between CAR and PT at the mobility hubs is slightly reduced by 1.4%. This is expected since a traveller requires less travel time when using the bike or the e-bike from or to the three mobility hubs in Rotterdam. Overall, we can conclude that, also in line with the conclusions of the previous scenario, infrastructure improvements help to stimulate the use of mobility hubs.

**Scenario 6: Center parking capacity.** In the next two scenarios the effects of possible parking policies are studied. As mentioned before, in Scenario 6, the parking capacity in the city centers of Rotterdam and The Hague has been reduced by 30%. As can be seen in Fig. 4, this does not seem to have a very large overall effect. This is not surprising, since the reduction brought by this scenario only pertains to the city centers.

However, the bar charts of Fig. 5 paint a different picture, as all of these pertain to trips at least partially undertaken in city centers. Indeed, in each of these bar charts, a drop in the use of the car mode can be observed. More generally, when regarding trips which have an origin or destination (or both) in the city center, use of the car mode dropped from 25.3% to 22.4%. This reduction implies a parking capacity elasticity of  $-0.1$ , which is consistent with the parking capacity elasticity of the city of Amsterdam, which is  $-0.08$  as observed in the 'Traffic model Amsterdam' (VMA) model introduced and explained in Gemeente Amsterdam Verkeer en Openbare Ruimte (2019). As a result of the decline in using the car mode, the share of the bike, e-bike and walk modes increases. One can thus conclude that the city centers will be less attractive for car users and that travellers are more willing to use more sustainable modes. However, there seems to be no real increase in the use of multimodal modes, perhaps still as a result of the higher travel time incurred by the use of mobility hubs.

**Scenario 7: Center parking cost.** Next to the reduction of parking capacity, another obvious measure to discourage car use in city centers would be to increase parking cost. The seventh scenario therefore increases parking costs in the city centers by 32%.

While Fig. 4 again does not reveal a big impact, Fig. 5 shows that this measure reduces the popularity of the car mode in the city centers even further, but not as much as was the case in the previous scenario. Compared to the previous scenario, the modest decrease of the share of car trips (partly) in the city centers from 22.4% to 21.3% implies a parking cost elasticity of  $(21.3 - 22.4)/32 = -0.03$ . This is smaller than the parking cost elasticity of the Amsterdam city center as reported by the earlier-mentioned VMA model. The difference in these parking cost

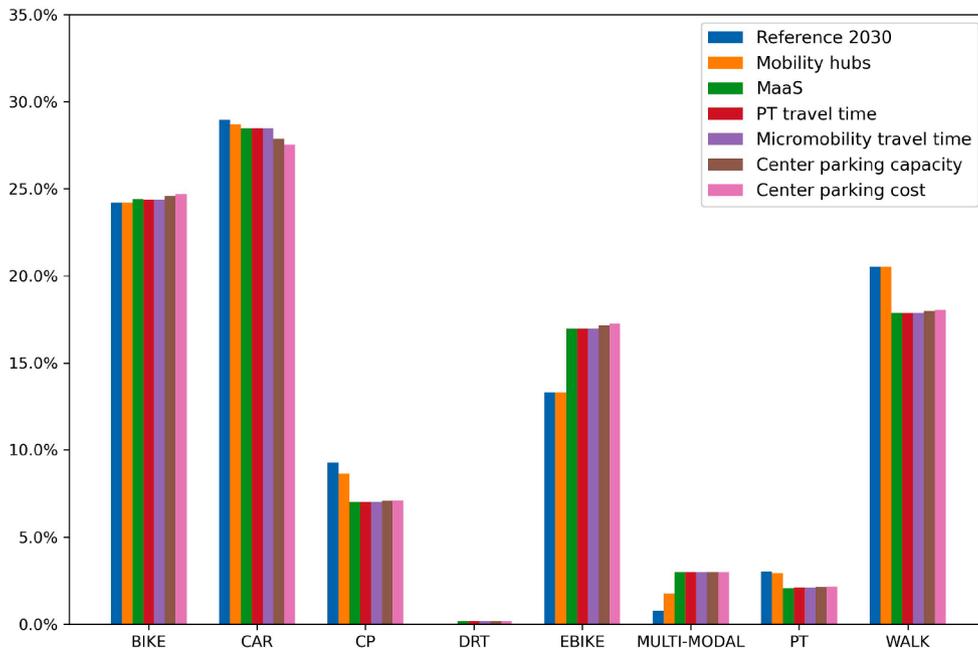


Fig. 7. Equivalent of Fig. 4 when a decision between a private and shared car is always made in favour of the private car.

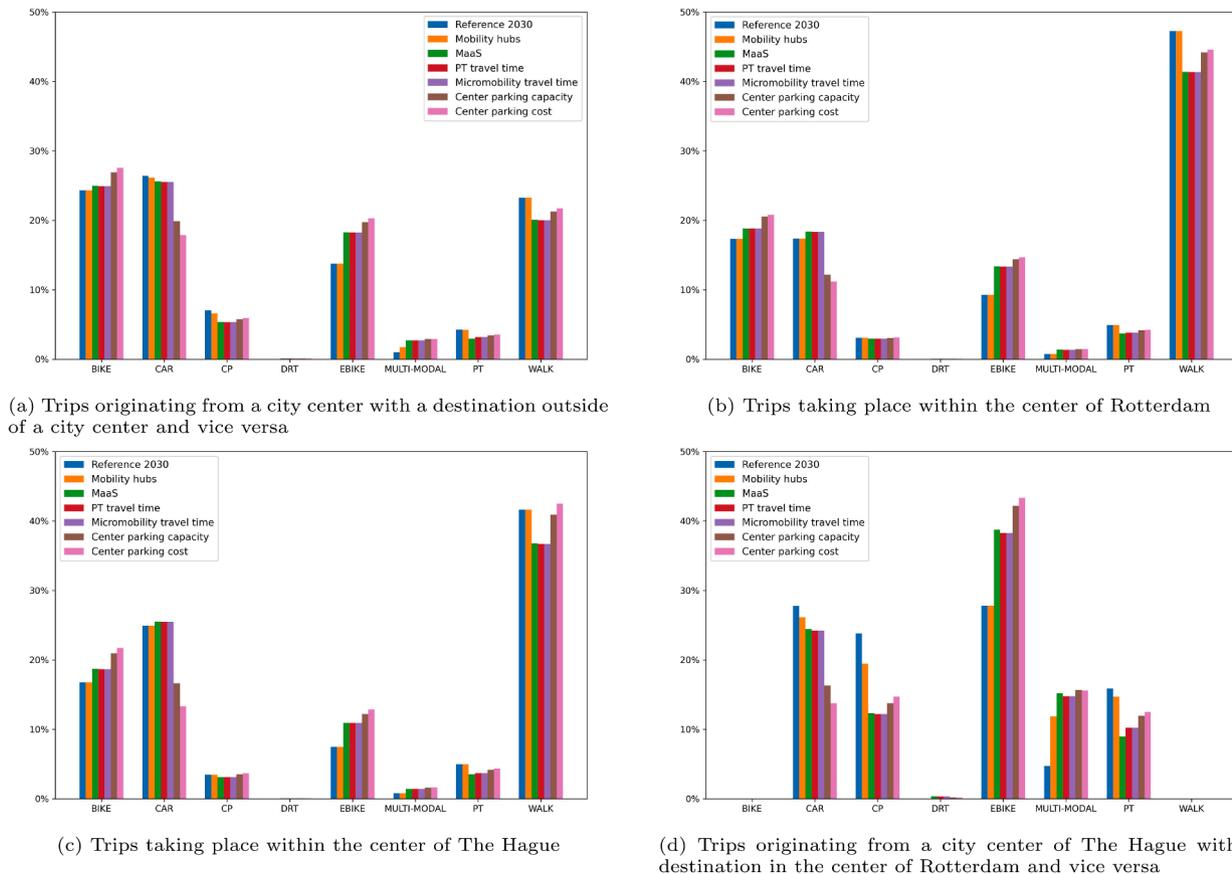


Fig. 8. Equivalent of Fig. 5 when a decision between a private and shared car is always made in favour of the private car.

elasticities may be explained by the fact that the hourly parking cost in Amsterdam is generally much higher than in the city centers of Rotterdam and The Hague. Furthermore, the limited reduction of car trips in the city centers may occur because the reduction in the previous scenario was already significant. Yet another reason could be that many

working places are situated in the city centers of Rotterdam and The Hague, so that any increase in parking costs may be compensated by the employer, leaving the commuting travellers indifferent. One can however see that, just like the previous scenario, the decrease in car use does again lead to an increase of use of the bike, e-bike and walking modes,

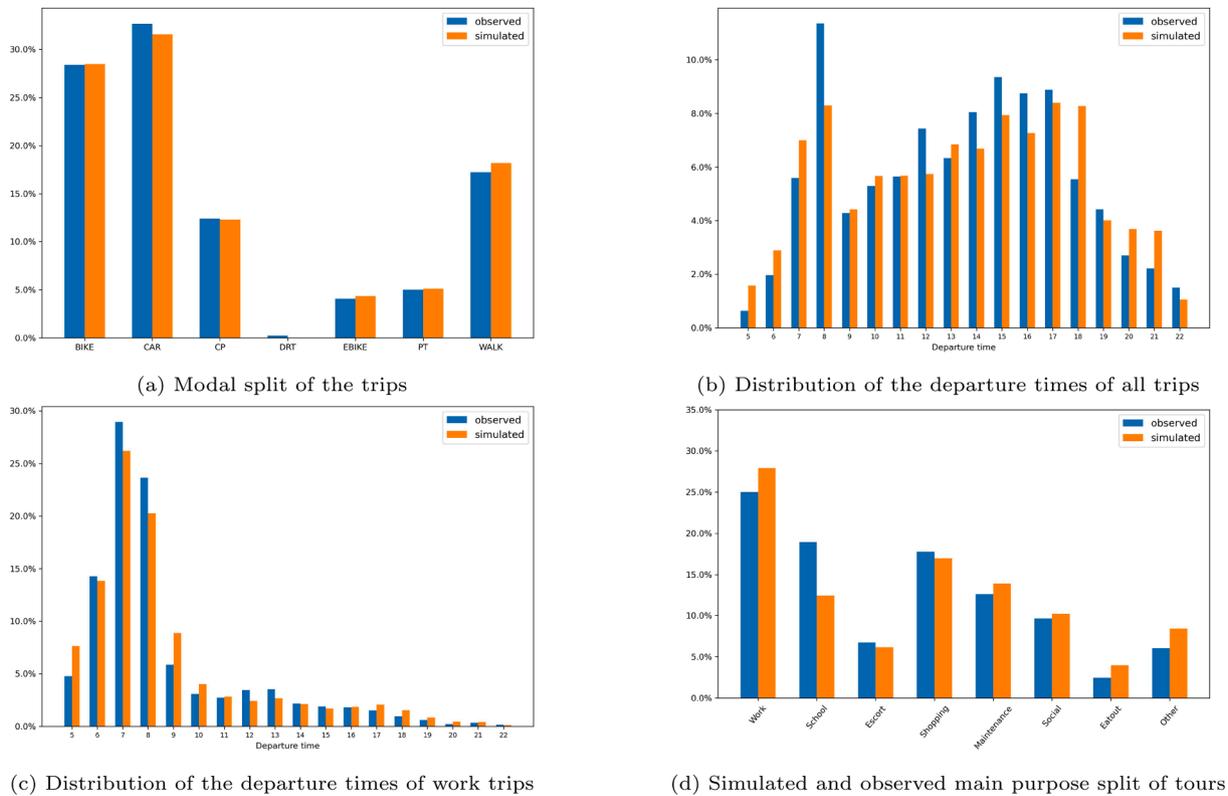


Fig. 9. Validation Results.

Table 4

Access and egress modes used in multimodal trips with public transport as the main mode for different periods of the day.

	ABM division			V-MRDH division		
	Morning Peak	Off-Peak	Evening Peak	Morning Peak	Off-Peak	Evening Peak
WALK-PT-WALK	48%	46%	61%	51%	42%	58%
WALK-PT-BIKE	12%	24%	21%	7%	23%	26%
BIKE-PT-WALK	31%	24%	10%	35%	31%	9%
BIKE-PT-BIKE	9%	6%	8%	7%	4%	6%

but not necessarily of the multimodal modes.

Furthermore, it should be mentioned that the overall distance undertaken by car, as part of a unimodal car trip or a multimodal mode trip involving a leg undertaken by car, in this scenario has reduced by 0.4% compared to the previous scenario. Therefore, we conclude that also the parking cost policy may have a decreasing impact on car use.

**Remark 1.** It remains to explain that eight runs in this study is enough to obtain reliable results. To argue why this is the case, we computed the confidence interval for every performance indicator computed in this section. To this end, for the eight estimates of each performance indicator, say  $X_1, X_2, \dots, X_8$ , we computed the sample mean  $\bar{X}$  and the sample standard deviation  $S_X$ . Then, the 95%-confidence interval corresponding to each performance indicator was calculated according to its formula

$$\left[ \bar{X} - q_{0.975} \frac{S_X}{\sqrt{8}}, \bar{X} + q_{0.975} \frac{S_X}{\sqrt{8}} \right],$$

where  $q_{0.975}$  is the 97.5% quantile of the standard normal distribution, having a numerical value close to 1.96.

For almost all of the confidence intervals computed, the width of the confidence interval (CI) was smaller than 5% of the actual estimated value  $\bar{X}$ , and often even much smaller than that (e.g. in the order of 0.1%). The exceptions were formed by some of the DRT shares computed in this section, as well as some of the shares of trips between the city centers of The Hague and Rotterdam (i.e., Fig. 5d). The first exception can be explained by the fact that the estimates themselves are incredibly small in this case: none of them exceed 0.1%. Random deviations will then still be small in terms of absolute numbers, and will not harm the conclusions of the paper. The second exception can be explained in a similar way. Namely, the absolute number of trips undertaken between the city centers of The Hague and Rotterdam are generally small. Therefore, in cases where the bars in Fig. 5d are low, some of the confidence interval widths exceed 5% of the actual estimated value. As this only really plays a role in determining the value of the multimodal share in the first scenario, this does not harm the general picture painted by Fig. 5d either.

As a result, for this case study, eight runs can be deemed enough to obtain reliable results. Of course, performing more than eight runs would increase the reliability further. However, it should be noted that basing experiments on more runs immediately implies a significantly larger required computation time. As mentioned before, in our setup a single run constituted a computation time around 3.5 hours.

### 3.4. Sensitivity analysis

In the current study, several parameters, such as the coefficients in the utility functions, have been estimated on the basis of e.g. survey data. For some of these parameters, however, relevant data have been

lacking, leaving the values of the parameters used possibly unreliable. In this subsection, we perform a sensitivity analysis on these parameters to see what effect estimation errors this unreliability may have on the results obtained. Based on the findings, one can conclude that these effects will not significantly alter the observations of Section 3.3.

#### 3.4.1. Demand-responsive transport

The first parameters to be investigated concern the demand-responsive transport mode. Due to lack of data on DRT modes in [Centraal Bureau voor de Statistiek \(2018\)](#), the alternative-specific constant  $\alpha_{DRT}$  as well as the time and cost coefficients  $\beta_{DRT,time}$  and  $\beta_{DRT,cost}$  in (2) may be unreliable. To assess the sensitivity of the model results to these parameters, we rerun the model for Scenario 3 with different values for these parameters. In particular, we first rerun the model where  $\alpha_{DRT}$  is now taken to be equal to  $\alpha_{PT}$ , the alternative-specific constant of public transport, while keeping all other parameters the same as before (i.e., *ceteris paribus*). It should be noted that  $\alpha_{PT}$  is significantly higher than the originally estimated alternative-specific constant for DRT, so that this change effectively makes DRT more attractive. Afterwards, we repeat these experiments with the time and cost coefficients. That is, we run two experiments with  $\beta_{DRT,time}$  reduced by 10% and 20% (with the original alternative-specific constant and cost coefficients), respectively, and two more experiments with  $\beta_{DRT,cost}$  reduced by 20% and 50%, respectively (with the original alternative-specific constant and time coefficients).

The simulation results show that of the parameters mentioned above, the change of the alternative-specific constant has the largest impact. In making DRT more attractive than assumed before, the mode share of the DRT mode as a unimodal mode increases from 0.16% to 0.89%. Next to this, while before DRT appeared as part of a multimodal mode in 1.15% of the total number of trips simulated, this is now 1.4%. While these are relatively large increases, it should be noted that the absolute increases in modal share are modest, which suggests that large estimation errors in the alternative-specific constant of the DRT mode would probably not affect the effects and trends observed in Section 3.3.

We also find that these observed effects and trends should remain intact in case the time and cost coefficients would change considerably. That is, we find that if travel time is decreased by 10% or 20%, the modal share of DRT even remains unaffected at 0.16%, while the percentage of the number of multimodal mode trips including demand-responsive transport only increases by a hundredth of a percentage point in case of a 10% reduction, and two hundredths in case of a 20% reduction. Likewise, if the travel cost is decreased by 20% or 50%, the modal share of DRT again remains unaffected at 0.16%. Only in case of the 50% reduction, there is an ever so slight change in the multimodal setting; in that case, the share of the multimodal mode trips including DRT increases by three hundredths of a percentage point.

#### 3.4.2. Parking searching time

The second sensitivity analysis that we perform pertains to Scenario 6, where the parking capacity of the city centers of The Hague, Delft and Rotterdam are reduced by 30%. The extra searching time this induces for travellers wishing to park their cars is unpredictable. In the results, the searching time is assumed to increase by 14 minutes, but this assumption was chosen purely on what we deem plausible. As a result, we have rerun the model on Scenario 6, where we have taken the extra searching time for travellers, instead of the original 14 minutes, to be equal to 2.5, 5, 10 and 20 minutes, respectively.

These experiments show that changing the parking searching time may have some effect on the modal split. That is, when rerunning Scenario 6 with the mentioned parking searching times, the simulations report a share of the car mode in trips from and to the city centers of 24.5%, 24%, 23% and 21.4% respectively. While mutually these numbers seem quite different, especially since these differences are of the same order as those encountered between scenarios in Section 3.3, it

should be kept in mind that an extra searching time lower than 10 minutes as a result of capacity reduction is not very plausible. Therefore, the impact on the findings of Section 3.3 as a result of estimation errors in the extra parking searching time is expected to be limited.

#### 3.4.3. Ownership of private car and MaaS subscription

In the absence of relevant data, from the third scenario onwards, it is assumed that travellers who are confronted with the choice between a shared car through their MaaS subscription or using their private vehicle, will always choose for the shared car. Due to the heterogeneity of travellers, however, it is very conceivable that not all travellers will make this choice, so that one could question this assumption.

It turns out that, for our purposes, the impact of this assumption also appears limited. To show this, we have rerun the model with the other extreme as an assumption: a choice between a shared car and a private car is always made in favour of the private car by the traveller. [Figs. 7 and 8](#) present the equivalents of [Figs. 4 and 5](#) under the new assumption. As the change of assumption does not play a role in the first two scenarios, the bars pertaining to these scenarios are unaffected. For Scenarios 3 to 7, the overall share of the multimodal modes can generally be seen to be a little lower than before, while the share of the car mode increases. While this is to be expected, the effects observed in Section 3.3 remain intact in these figures. For example, we observe in [Fig. 8a](#) that the share of car trips from or to the city centers is still greatly diminished by the introduction of the parking policies in Scenarios 6 and 7, even though the private car should be used more often due to the change of assumption. As mentioned above, [Figs. 4 and 5](#) on one hand and [Figs. 7 and 8](#) on the other hand represent two extremes while exhibiting the same effects. Therefore, any assumption regarding the mode choice of travellers having access to both private and shared cars is likely to show the effects observed earlier, making the earlier-made assumption irrelevant. As a result, the lack of data on this topic is not an issue.

## 4. Conclusions and further research

In this section, we round off this paper with a conclusion, explicitly answering the research questions posed in Section 1, and a discussion on further avenues of research on this topic.

### 4.1. Conclusion

In this paper, we have conducted a case study situated in the MRDH region in the Netherlands, with the aim of investigating the impact of strategies that are believed to lead to more sustainable mobility. The MRDH region is of economic importance to the Netherlands, has a dense road network as witnessed by the fact that it includes the busiest motorway in the Netherlands and has a growing popularity. Below, concluding answers to the questions raised in Section 1 are provided for this region. We believe that these answers are also representative for other regions when considering e.g. the introduction of NMS and parking policies.

The first of these questions concerned the extent up to which mobility hubs reduce the number of car trips. To this end, we regarded the modal split of the trips in a reference scenario where mobility hubs are not used, and compared it to the modal split in a scenario where the use of mobility hubs by travellers is allowed, *ceteris paribus*. The simulation results following these experiments suggest that especially for large-distance trips, there is a modest shift from car trips to multimodal trips. The overall impact of the introduction of mobility hubs on their own however appears quite limited, which is because of the fact that the use of mobility hubs induces a longer travel time. This longer travel time mainly occurs since travellers do have to stop and transfer at the mobility hub, rather than travelling directly. Another plausible reason can be found in the fact that when shared modes and MaaS are not available to the population (yet), privately-owned modes would have to be available at the mobility hubs for the travellers, decreasing

the appeal of the use of mobility hubs. This raises the natural question of what the impact of mobility hubs is when shared services are actually available, which relates intimately to the next research question.

That is, the second question in Section 1 considered the extent at which mobility hubs in combination with sharing services contribute to a more sustainable mobility in the MRDH region in case half of the population has access to MaaS. The corresponding scenario in the case study reveals that this extent is rather large: after introduction of MaaS, the share of total trips undertaken as a car driver or car passenger decreases by an amount which is equivalent to 3.9% of the total number of trips, while the share of trips undertaken by e-bike or by a multimodal mode increases by about 4.2% and 2.5%, respectively. As these shifts are considerable, one may deduce that the introduction of MaaS would considerably contribute to more sustainable mobility, in part because it also allows mobility hubs to reach their full potential. It is however worth noting that especially in city centers, the trips made by walking and public transport will be less numerous, as MaaS makes it more attractive to use shared (e-) bikes for short distances.

To answer the third question on the extent to which an improved cycling infrastructure and public transport service can stimulate the utilisation rate of mobility hubs, two more scenarios have been considered in this case study. In the first of these scenarios, the travel time of public transport is reduced by about 7.5% in the city centers, while in the second scenario, the travel time of micromobility (i.e. BIKE and EBIKE) in the city centers is reduced by 20%. It turns out that in case only the travel time required by public transport is reduced, the modal split of trips appears to be hardly affected. Nevertheless, the number of connections made through a mobility hub from the car to public transport (or the other way around) increases by about 10%. A similar observation can be made when the micromobility travel time is decreased by 20%. That is, although this hardly affects the modal split, the number of connections between the car and (e-) bike at mobility hubs increases, partly at the expense of the number of connections between car and public transport. Taking the latter into account, the reduced micromobility travel time leads to another net increase of 1.9% of the total number of trips using mobility hubs.

The final question posed in Section 1 concerns the extent to which parking capacity and parking cost rates affect the car flow in the city centers of the MRDH region. To this end, the case study includes two scenarios reducing parking capacity by 20% and increasing cost rates by 32% in the city centers. It turns out that reducing the parking capacity reduces the number of trips undertaken by car from and/or to the city centers by about 3% (from 25.3% to 22.4%), while increasing the use of more sustainable modes. Especially when the infrastructure is utilised at a close to critical level, such a small-seeming decrease can improve and smoothen the car flow to a considerable extent. Furthermore, when increasing parking costs, the percentage share of car-based modes in the city centers faces another decrease of 1% (from 22.4% to 21.3%) in our results, improving car flow even further.

Now that these conclusions for the MRDH region have been reached, one may wonder to what extent they also apply to other regions. We expect that the conclusions for the MRDH region paint a representative picture of the potential of the strategies in other regions in the Netherlands as well, such as the metropolitan region Amsterdam (MRA), which is not far away from the MRDH region. This is mostly due to the similar urban density (711 dwellings/km<sup>2</sup> in the MRA region versus 796 in the MRDH region) of the two regions, the similar population size (2.5 million versus 2.4 million), a similar population age distribution as well as a similar annual income; cf. [Metropoolregio Rotterdam Den Haag \(2021\)](#) for the MRDH region and [Gemeente Amsterdam \(2018\)](#) for the MRA region. However, there are differences between the these two regions too. For example, the MRA region includes the busy airport Schiphol, while the Rotterdam-The Hague Airport in the MRDH region is much smaller. Furthermore, there are two major cities in the MRDH area, whereas in the MRA many trips are concentrated in and around Amsterdam. Therefore, a specific case study for the MRA region may still

have an added benefit. Similar observations may be made for other regions in the Netherlands. For example, the North-Brabant region, which contains the cities of Tilburg, Eindhoven and Den Bosch also houses the second largest airport in the Netherlands (after Schiphol) near Eindhoven. Furthermore, the areas of study may be widened to capture the entire Randstad region, which also contains the city of Utrecht. For other regions outside of the Netherlands, although it is conceivable that similar effects occur, the order of magnitude might differ substantially. Application in other regions requires estimation of the relevant coefficients in the utility functions and subsequent calibration of those should be performed based on local survey data, in order to make sure that the difference in region characteristics do not lead to different conclusions.

#### 4.2. Avenues for further research

We conclude this study by suggesting a number of avenues for further research. One category of such avenues is based on the notion that the current model allows for variation of model parameters in all kinds of dimensions. For example, the current paper has studied the impact of the measures in an incremental fashion. It could however also be interesting to see the effects of e.g. decreasing parking costs without the introduction of MaaS. Similarly, one could also be interested in studying more MaaS penetration rates than the 0% (Scenarios 1 and 2) and the 50% (Scenarios 3 to 7) studied in this paper. The model used in this study could also be applied to study the impact of social changes. For instance, due to the covid-19 pandemic, travellers may now be much more inclined to work at home, heavily altering their daily activity pattern. In turn, this may lead to different travel behaviour and could thus have implications for the mobility system. It is for example conceivable that the use of public transport may not reach pre-pandemic levels anymore. Due to its flexibility, ABM is geared to take these social changes into consideration, and further research may thus chart the implications of hybrid working for the infrastructure, including effects on public transport ridership. Furthermore, the model may also be used to study other topics, such as the optimisation of the location of mobility hubs to make mobility as sustainable as possible. Sharing service providers might also benefit from the model, e.g. to see which vehicle relocation strategies work in their favour and to study their optimal fleet sizes. Another topic concerns pricing and reward schemes of subscriptions (such as MaaS). That is, the model could be extended to take reward schemes and subscription packages with reduced fee rates into account, in order to assess their impact in detail.

Next, also from a modelling point of view a number of suggestions may be made. For example, it may be worthwhile to see whether the utility functions underlying the model can be improved. Currently, the utility function (2) of a multimodal mode does not take the access and egress mode into account in terms of the alternative-specific constant and the socio-demographic attributes. By including only the attributes of the main mode, already known estimations based on unimodal modes can be used, and we expect them to model the utility reasonably well. Nevertheless, this could be improved upon by also involving the access and egress modes in these terms of the utility function. Inclusion of the access and egress modes would entail a comprehensive estimation of the associated coefficients, because no data exist on how the traveller values the convenience of the access and egress modes in comparison to the main mode. Research in this direction would be helpful, so that this can be included in future models. We also mention the destination choice component, where the set of available travel modes is already taken into account (although the actual mode choice is taken later). The current model only considers the aggregated impact of all available unimodal modes, whereas the model may be amenable to further refinement by also considering the impact of available multimodal modes. To this end, one would need to consider the actual impact of the availability of multimodal modes, data on which is currently lacking. Another suggestion entailing the utility function may be the incorporation of the

departure time. This way, time-related features could be captured. For example, a departure during rush hours may make public transport less attractive due to crowdedness. This incorporation would introduce considerable complexity to the choice behaviour modelling, and is thus best left to a separate study. We conclude our discussion of possible improvements to the utility function by noting on the effects of available parking space. Currently, these effects are represented by the inclusion of (the logarithm the) parking capacity in the utility function. This however does not take into account the decrease in parking availability as a result of an increase in the number of parked cars. To accommodate this effect into the utility function, a more detailed micro-simulation model such as the one developed in [Vuurstaek et al. \(2018\)](#) could be developed to track the occupancy of parking spaces.

Another direction of further research concerns certain assumptions made throughout this paper. For example, in this paper we assumed that every traveller owning a MaaS subscription is willing to use shared services in all circumstances. However, this may not always be the case. Despite the fact that we have concluded in Section 3.4 that a deviation from this assumption, e.g. private cars always being chosen over shared cars when being presented a choice, does not exceedingly alter the conclusions of the case study, it may be good to include a more realistic assumption. To this end, research would have to be done on the willingness of travellers to use shared services offered by MaaS and the impact of MaaS and shared services on car ownership. Another assumption to be studied concerns the fleet sizes of shared vehicles. Currently, limiting fleet sizes of vehicles are not taken into account, while doing this would perhaps paint a slightly more realistic picture. This however requires inclusion of an optimised model for shared services. In this direction of research, it may also be worthwhile to incorporate shared car services like SnappCar, which is also available in the Netherlands. With this service, car owners can share their privately-owned car with other travellers, while the car is not in possession of e.g. a car-rental company.

Finally, it is worth mentioning the fact that we have not incorporated feedback from a network assignment model into the current travel demand model. More particularly, the current case study only predicts the travel demand in the MRDH region in future scenarios, without taking results from a network assignment model into account. As a

consequence, the current paper observes solely first-order effects, and these observations may be amenable to improvement. As an example, one might argue that the car use in city centers may currently be slightly overestimated since the effect of vehicle congestion as a result of high car travel demand does not have a dampening feedback effect on this demand. At the same time, one might also argue that MaaS and other shared mobility services induce a lesser traffic congestion, causing travellers to opt for car travel more easily, thus leading to underestimation. To overcome the issues brought by these feedback effects, they may be incorporated in the future by connecting the current model to a travel assignment model, which is still in development for inclusion of multimodal modes and shared vehicle dispatching. A next step would then be to compute the impact on air quality, noise and spatial usage to get more accurate insights in livability effects.

#### CRediT authorship contribution statement

**H. Zhou:** Data-curation, Methodology, Software, Writing – original draft. **J.L. Dorsman:** Writing – review & editing, Supervision. **M. Mandjes:** Writing – review & editing, Supervision. **M. Snelder:** Writing – review & editing, Supervision.

#### 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.

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## Appendix A. Model calibration and assessment

### A.1. OViN/ODiN survey data and its processing

The OViN/ODiN survey data ([Centraal Bureau voor de Statistiek, 2018](#)) contains data based on a survey conducted among the Dutch population of 6 years and older over the period of one year. In total, about 45 thousand respondents registered the trips that they made during a pre-selected day in that year. Per surveyed individual, the data set contains data on e.g. the main modes of the trips (so that a picture of modal split can be obtained), the departure times of these trips and the main purpose of each trips.

For the purpose of calibration and validation, we use the data of the OViN/ODiN survey that pertain to inhabitants of the MRDH region. These data first however need to be processed. For example, as the ABM considers a daily simulation of all traffic between 5AM and 11PM, we have taken out trips that, in part or completely, are undertaken outside of this time frame. Furthermore, the data includes trips that do not make up a complete tour with other trips in the data. For the purposes of data integrity, these trips have therefore been filtered out as well. This leaves us with a data set which consists of complete daytime tours with data on a trip level. Another point of attention is that the survey data includes information on the origin and destination of the trips on the level of postal code in the Netherlands. However, the ABM model works at a different granular level, namely on the level of traffic analysis zones (TAZs). In case the postal code area consists of a single TAZ, the translation of postal code area of TAZ is easily made. However, especially in the MRDH region, a postal code area may consist of more than one TAZ. In these cases, we assign the most probable TAZ to the applicable origin or destination. For instance, if the trip purpose is work, the TAZ of the postal code area having the highest employment number is selected. As for the recorded modes of the trips, we categorise them in the seven unimodal modes as described in Section 2.1.2.

Next to shaping up the dataset, each tour in the data set needs to be labelled with a main purpose, so that these can be compared with the output of the ABM model. However, since survey data is collected on individual trips, it is not trivial to infer the primary purpose of the complete tour. To remedy this, we have defined a hierarchy to categorise them. These categories, in an order from high in the hierarchy to low in the hierarchy, are given by work, school, dropping off or picking up passengers, shopping, maintenance (e.g. medical visits, bringing car to garage, etc.), social, eat-out and a remainder category called 'other'. Now, if a tour consists of a trip that has a work purpose, work is also considered to be the main purpose of the complete tour. Otherwise, if the tour involves a school trip, then the tour has school as its main purpose, and so on.

## A.2. Validation

After the calibration has been performed, we compare different measures of interest to see if the ABM model has been sufficiently calibrated. This is done by comparing the output of the ABM model, based on the 10%-fraction of the synthesised population in Snelder et al. (2021) (simulation) to the OViN/ODiN survey data as processed in the previous section (observation).

First, the simulated average trips per person, namely 3.2, is very close to the observed average of 3.3. Also the simulated modal split of the trips is quite close to that of the observed modal split, as is graphically illustrated in Fig. 9a. The correlation coefficient between the simulated numbers of trips undertaken per mode and their observed counterparts is 0.9995, which indeed supports the observation that the simulated and observed modal split are comparable. Next, we regard the simulated and observed departure times of all trips in general, and those of all work trips in particular. We do this, because the work trips form the most important category of trips. Figs. 9b and 9c illustrate these simulated and observed departure times. In particular, the per-hour share of departure times is depicted, where the value represents the start of the hour. With a correlation coefficient of 0.8963 for all trips and 0.9859 for work trips, the simulation and observation is again quite nicely aligned, even when observing some differences in the figure. The difference observed in the hour starting at 5AM can be explained by the fact that observed trips with departure times just before 5AM are not considered, while the ABM model might schedule such trips right after 5AM.

Finally, a comparison is performed based on the simulated and the observed main purpose split of the tours, cf. Fig. 9d. The correlation coefficient in this case is 0.9238, again indicating a large similarity. Judging by the figure, the observed share of school tours is a bit larger than the simulated share. However, according to the CBS report (Centraal Bureau voor de Statistiek, 2018), school trips are over-represented in the OViN/ODiN survey data. As a result, we conclude that the ABM is reliable in this respect.

The OViN/ODiN survey data is however not the only source of data which we can compare our calibrated model against. In the reference scenario, not including mobility hubs or any form of MaaS, the ABM that considered in this paper does in principle not consider multimodal modes. The public transport mode forms an exception to this, however. Whenever a traveller uses public transport, the ABM does predict whether (s)he uses walking or cycling as an access and egress mode. Since the OViN/ODiN survey data is known to have an underrepresented number of trips undertaken by bike (cf. Knäpen et al. (2021)), we have compared the output of the ABM with results from the study V-MRDH (Van de Werken, 2018), which does include information on this. Table 4 shows for different periods of the day the access and egress trips undertaken when using public transport as predicted by our ABM and as concluded by the V-MRDH study. As can be observed from the table, the numbers match rather well, adding to the reliability of the calibrated ABM.

As a final check, we consider the travel time elasticity and the travel cost elasticity of both the car and public transport modes, as well as the values of time corresponding to these two modes. The time (cost) elasticity is defined as the relative increase in percentage of travelled kilometers if the travel time (cost) is increased by 1%. We compute these numbers for the current-day scenario with our calibrated ABM, and compare them to values deemed plausible in Willigers et al. (2021) and references therein. Also this comparison checks out. The simulated travel time and travel cost elasticities of the private car, being  $-0.4$  and  $-1.2$  respectively, are within the plausible domains of values ( $-0.9$ ,  $-0.2$ ) and ( $-1.3$ ,  $-0.3$ ), respectively. Similarly, for public transport, these elasticities are  $-0.18$  and  $-0.35$ , respectively, which again fall in the domains of values deemed possible for public transport, namely ( $-0.5$ ,  $0.15$ ) and ( $-1.2$ ,  $-0.3$ ), respectively. As recommended by Willigers et al. (2021), we also check the values of time of the car mode and the public transport as observed by this model. A value of time represents the opportunity costs of the traveller spent per time unit on his or her journey undertaken. We note that the value of time may differ between car and the public transport, because time spent driving may be deemed completely lost, while in public transport it may still be possible to e.g. do some work. For the two modes, the values of time assumed by our model can be computed by calculating  $\beta_{\text{car,time}}/\beta_{\text{car,cost}}$  and  $\beta_{\text{PT,time}}/\beta_{\text{PT,cost}}$  respectively. This results in a car value of time of 9 euro's per hour, whereas for public transport this number reads 6.1 euro's per hour. Again, these values are well within the plausible ranges reported by Willigers et al. (2021) and references therein.

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