Impact assessment of new mobility services using accelerated activity-based demand modeling

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Publication date
2023

Document Version
Final published version

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The research for/publication of this doctoral thesis received financial assistance from TNO and the NWO Gravitation Project NETWORKS, Grant Number 024.002.003.

ISBN: 978-94-6469-146-7

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ACADEMISCH PROEFSCHRIFT

ter verkrijging van de graad van doctor
aan de Universiteit van Amsterdam
op gezag van de Rector Magnificus
prof. dr. ir. P.P.C.C. Verbeek
ten overstaan van een door het College voor Promoties ingestelde commissie,
in het openbaar te verdedigen in de Agnietenkapel
op maandag 30 januari 2023, te 14.00 uur

door Han Zhou
geboren te Chengdu

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ACKNOWLEDGEMENTS

After twelve years working at TNO, mainly as an urban environmental modelling engineer, I was thinking of pursuing another knowledge in addition to geo-information science (my master's degree). It would be necessary for my future career. Thanks to Erik. de Romph, your presentation brought the concept of "Activity-based traffic demand modelling" to me. This advanced modelling has high computational needs. I started to consider whether my experience in accelerating the computational speed of environment models could meet this high computational requirement. The combination of traffic demand modelling and high-speed computing could be a very intriguing study. Fortunately, my supervisors, Michel Mandjes and Maaike Snelder offered me a great opportunity to work on this subject as a part-time PhD student at the University of Amsterdam. Michel and Maaike, please accept my deepest gratitude. Also, many thanks to Jeroen Dezaire, Jeroen Borst, and Fieke Beemster from TNO. Without your support, my PhD studies could not go through smoothly at the same time as my TNO work.

Traffic modelling was new to me in my first study year. It took me quite some time to understand this new topic. I am so grateful to my supervisor Jan-Pieter Dorsman. You shared your PhD experience with me, helped me understand the model's principles and carefully revised my first paper. And I also want to appreciate all my supervisors for your valuable reviews and feedback. A conference accepted my first paper, and it was my first time presenting my study to a conference audience. I couldn't do it without your help.

The second year of my studies started a bit difficult. Maaike, Michel, Jan-Pieter and Erik, you were always there to show me how to navigate the academic world and help me escape the stress. Another conference accepted my second paper. This success encouraged me a lot to continue my study. Hartstikke bedankt voor jullie hulp!

The COVID-19 pandemic from the beginning of my third study year forced us to work as much as possible at home. Therefore, most of the meetings had to be held online. And it's a pity that we missed face-to-face contact. Even in this difficult time, Maaike, Michel and Jan-Pieter, you guided me a lot in improving the model. Thanks to my TNO colleagues, Bachtijar, Dawn, Eleni, Erwin, Gerdien, Marieke, Reinier and Yashar, you helped me to provide the data and have many brainstorming sessions. Thanks to all my other colleagues, I enjoyed the wonderful atmosphere of our online meetings. I also thank Kimberly, an internship student at TNO, for taking the time to work on the parameters.

The fourth year went quite well. Maaike, please accept my sincere appreciation for your guidance on the research direction. Michel and Jan-Pieter, you taught me to understand the equations from statistics via online lessons. I learned a lot and like them!

At the last phase of the journey, Michel, thank you again for connecting all the developed knowledge to a great storyline in this thesis. Meanwhile, I would like to thank all my PhD committee for being on my committee, reading my thesis and presenting at my defence.

Finally, I feel deeply indebted to my wife. A combination of work and study sounds good, but the burden can not be solved without you. Your encouragement always helps me to get rid of negative thinking. "You raise me up"! My PhD journey cannot go to an end without your support.

Han Zhou
Zoetermeer, November 27 late at night, 2022

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1

Introduction

1.1 Background

We are living in a fast-evolving world. One of the reasons for this is that the digital world has gotten closer to us since the first real smartphone came out in 2007. Increasingly convenient smartphone apps have greatly simplified our daily lives, by enabling e.g. online shopping, travelling, and social networking. Digitalisation also affects the mobility world. For instance, sharing services, by which one can share vehicles via a smartphone without any paperwork, are very convenient for service providers and customers. Ride-sharing and ride-hailing also benefit significantly from such technology. Mobility as a Service (MaaS) combines all these technologies and services, thus offering a tailored mobility package for individual travellers (Kamargianni et al., 2016; Jittrapirom et al., 2017; Hesselgren et al., 2020). MaaS complements new mobility services and offers more alternatives to private car-oriented transportation systems. It is highly related to mobility hubs, where at least two travel modes are connected, such as P+R locations, bus stops and train stations. At these locations, travellers use one mode to travel from an origin to the mobility hub, and then switch to another travel mode to continue their journey towards their destination (Bell, 2019; Storme et al., 2021). These hubs could also provide functionalities such as (shared) vehicle parks, charging locations or other social functions (e.g. meeting locations). In the field of automotive technology, the development of electric and self-driving cars has also received the attention of governments, which may lead to more sustainable modes of travel. All these innovations have the potential to redefine the travellers' behaviour (Delbosc and Currie, 2015). However, this behaviour is also impacted by other evolving factors. For example, in light of evolving demographics, the preferences, lifestyles and connectedness of travellers may change the landscape of mobility. These personal attributes are recognised as part of the paradigm shift taking place in the transportation systems of cities (Puignau Arrigain et al., 2020).

Next to this, economic and land-use changes affect the transportation system's performance, while there is also a general desire to move towards a more sustainable mobility.

In the face of the above societal changes, policy makers want to know how the transportation system will perform in the future and what kind of policies and interventions should be proposed to achieve the desired output. They are confronted with many questions. Would shared services lead to better accessibility and livability? Will Mobility as a Service (MaaS) reduce car ownership? Would investment in a new transit line alleviate traffic jams? Would mobility hubs stimulate car users to use public transport more often? Does restricted parking capacity limit private car use while still keeping the economy health? Given a set of desired outcomes, the decision makers wish to identify capital investments and policies that will achieve these objectives (Castiglione et al., 2015). To assess the impacts of investment in new mobility services (share service, mobility hubs, MaaS) and policies, travel demand models are required that convert travellers' needs to perform activities into travel demand, providing quantitative information on travel demand and performance of the transportation system. Decision makers can then use this information to make informed decisions.

There exists a wide variety of travel demand models. Sketch-planning models are designed to produce rough estimates of travel demand when the order of magnitude information is required. Strategic-planning models incorporate significant detail in the specific study area. They can test a wide range of large-scale policy and investment alternatives but are less appropriate for analysing detailed project alternatives. Another category of models is formed by so-called trip-based models, also referred to as four-step trip models, which are widely used in practice to support transportation analysis and decision making. These models, however, are not suitable for the purposes of the present context, since many large-scale and detailed experiments need to be run in a feasible amount of computation time. Therefore, we now focus on a modelling framework, namely activity based modelling, which is considered appropriate for this type of computation tasks.

Sharing some similarities to the traditional trip-based models, activity-based travel demand models (ABMs) are more advanced models that are used to describe the individual's daily travel schedule. They aim at closely replicating actual travelling decisions in that it is based on behavioural theories on how people make decisions to participate in activities in the presence of constraints (Castiglione et al., 2015). For each individual, they predict travellers' decisions on what activities to do, where and when to do them, and how to go there. They often provide better forecasts of future travel patterns than traditional trip-based travel models because: (*a*) they explicitly keep the time and space consistency, (*b*) they link individuals with other household members, (*c*) they are sensitive to investment and policy changes by operating on individual or household levels and (*d*) they have advanced explanatory power.

The advantages of ABM allow the painting of a representative picture of the travel behaviour emerging from socio-economic changes, environmental changes (Shiftan and Ben-Akiva, 2010), land use planning and interventions as well as innovative policies (Dianat et al., 2020). As the new mobility services aim to provide tailored transport services to satisfy individual travellers' needs, and as an ABM has many advantages and incorporates a high level of detail, it is natural to choose the ABM framework to model new mobility services and evaluate their impact on the transportation system. Although ABM has the potential to model them, there are various challenges. It requires the capability to model traditional as well as new mobility modes as well as simulate a plethora of scenarios fast and generate stable output. In the next section, we review the literature dealing with these aspects.

1.2 Literature review

This section reviews the literature on: (*a*) the use of ABM to assess the impact of new mobility services, (*b*) technologies to reduce the computation time of ABM and the variance of results generated by ABM.

The rapid development of new mobility services, such as shared mobility services, automated vehicles and Mobility as a Service (MaaS), is making the mobility system more complex than ever. Different studies have explored the impact of those innovations. For example, (Snelder et al., 2019) has studied the impact of automated driving and sharing in the province of North Holland, The Netherlands, using an explorative iterative model. They showed that both positive and negative effects can be expected on mobility patterns and traffic performance. The impact of automated vehicles was also studied by (Rodier et al., 2018) by increasing the road capacity or reducing the operational cost. (Ciari et al., 2015) studied the impact of different pricing schemes for free-floating car sharing in Zurich. Another study illustrates the high efficiency of automated mobility-on-demand (Basu et al., 2018), but also concludes that traditional public transport is still irreplaceable. The study by (Oh et al., 2021) showed that vehicle kilometres and delays increase when introducing an automated mobility-on-demand service. Finally, the study of (Balac and Horl, 2021) showed that shared bikes as a first/last mile solution for public transport can potentially reduce travel times.

The study of (Becker et al., 2020) included car/bike-sharing and ride-hailing to a city-scale transport system using MATSim (Michael et al., 2009). It concludes that a MaaS scheme with shared mobility may slightly increase efficiency on the supply side by providing accessibility to low travel demand areas. The study of (MaaS Alliance, 2017) also suggests that MaaS might improve transportation system accessibility and create new economic growth opportunities. In (Fioreze et al., 2019), they found that MaaS is less attractive for daily car users but more attractive for public transport users and people concerned with the environment and with a healthy commuting lifestyle. The study of (Lopez-Carreiro et al., 2021) has a similar conclusion after comparing the willingness to adopt MaaS in Madrid, Spain and Randstad in The Netherlands. Their conclusion is based on survey data using a generalised ordered logit model. In terms of the role of MaaS in the economy, (Hörcher and Graham, 2020) shows that by modelling MaaS in a simple network with only two regions, differentiated pricing more effectively achieves the goals of MaaS.

The capability of ABM models to tackle this challenge is still limited. In the study of (Azevedo et al., 2016), they use the SimMobility framework to study the on-demand autonomous mobility in Singapore. Integrated with MATSim CEMDAP (Ziemke et al., 2015) and TASHA (Hao et al., 2010) analysed the impact of different policies, such as car access restriction, bus frequency and dynamic fare, on congestion and air quality. However, those studies use limited new mobility modes in the trip. The access and egress mode is not explicitly modelled. The work of (Knapen et al., 2021) has studied the impact of parking, hubs and new mobility services using FEATHERS (Adnan et al., 2020). However, it only took the mobility hubs as interchange places for public transport with bicycles. The rising MaaS concept integrates many new transport options for the travelling public. It offers more mobility combinations within a single journey than ever. Multimodality is essential for MaaS within a trip and between trips. Since transport mode choices are becoming more flexible, handling this flexibility in the model is important. However, those studies mainly focus on one or a few new mobility modes. A comprehensive study including all travel modes is still a challenge. An ABM model that can comprehensively tackle the new mobility services (sharing service, MaaS, hubs) using random utility maximisation is still missing.

ABM models mainly use Monte Carlo simulation to obtain discrete samples from the probability distribution of the alternatives. Different from the deterministic approaches using fixed trip generation rates and applying mode shared to aggregated estimates of demand (Rasouli and Timmermans, 2012), even the same probability distribution may result in a different choice. The reason for this is that in most cases, these models adopt a simulation approach that makes choices based on (pseudo-)random numbers. Therefore, the variability caused by the generation of these random numbers triggers random fluctuations in the output of the ABM (Vovsha et al., 2008). Consequently, the ABM models have to be rerun many times to get reliable results. Different studies have been conducted to investigate the effect of variability on model output. The studies of (Veldhuisen et al., 2000; Castiglione et al., 2003) concluded that the simulation error is neglectable when the aggregated level of output is high. But it is a problem if the number of alternatives is large or some alternatives are very rare. The finding of (Horni et al., 2011) also supports their conclusion because the variability in daily volumes on the road links is little but significant in hourly volumes. The result of (Bao et al.,

2015) gives a quantitative result showing the minimum required simulations run to obtain enough confidence in the output. However, quantifying the difference in multiple traffic scenarios within ABM may require more simulation runs, which means more computation time. The latin hypercube sampling is a sampling technique to generate near-random numbers representative of the real variability, so that the number of simulations need to achieve accurate results can reduce. Another technique is the common random numbers (CRN). It is a technique that attempts to induce a positive correlation between the outputs of different scenarios. The impact of CRN in terms of the required number of simulation runs, resulting in less computation time, is not fully studied.

As ABM models work on the individual level, they incorporate significantly more detailed input information. Their run time is dependent primarily on the population size, number of traffic analysis zones and time periods, complexity of model design, number of alternatives included, and the level of convergence required. The requirement of computational power is one of the reasons that ABM models are still not widely used (Tajaddini et al., 2020). The ABM model used by (Heinrichs et al., 2018) took 4 hours for a single run on 16 cores and 64 GB RAM computer. Besides using CRN, which reduces the number of simulation runs in multiple scenarios, there are also other types of approaches to reduce the computation time. The first type is to reduce the size of the input, e.g. with a fraction of population (Kwak et al., 2012) or fewer activity locations (Saleem et al., 2018). The second type is to use the multiple CPU processors, each of which processes a part of the whole population. An example of this approach is ActivitySim (Gali et al., 2008). The third type is to use a computer's graphics processing unit (GPU). For instance, a GPU-based queue algorithm has been implemented within MATSim to move vehicles (Strippgen and Nagel, 2009). They reported a speed-up of up to 60 times compared with the optimised java implementation. However, the potential speed-up by GPU parallel computing for ABM models has not yet been explored. ABM models predict the activity schedules of individuals. These schedules could be generated in parallel by GPU, resulting in less computation time.

A fast activity-based demand modelling framework that can handle many new transportation modes and model multimodal transportation patterns even within a single trip using random utility maximisation appears to be lacking in the academic literature. Fast in this context does not only mean a shorter running time but also a smaller number of simulation runs, which effectively also reduces the computation time required. Therefore, the main scientific gap to be dealt with in this thesis is a methodology for modelling the new mobility services in the traveller's daily activities (activity type, destinations, mode choice, departure time and duration), using variance reduction methods and state-of-the-art computer technology to accelerate the calculation speed.

1.3 Research objective and research questions

New mobility services introduce new travel modes, such as car-sharing, ride-sharing, ride-hailing, and e-steps. It is necessary to include these new travel modes in the ABM. However, this is not at all the only challenge brought by new mobility services. For example, MaaS stimulates the use of several travel modes in a single trip, leading to so-called multimodal modes. As such, when considering MaaS, the ABM needs to take these multimodal modes into account too.

In order to provide information to decision makers, one should be able to simulate different scenarios many times to obtain accurate and reliable results. Despite the above-mentioned challenges, a fast and reliable ABM is thus required with a greatly reduced computation time compared to the current state-of-art. Therefore, the main objective of this thesis is to develop fast activity-based travel demand models to evaluate the impact of new mobility services and policy alternatives. This model should be able to handle different transportation modes and simulate different scenarios efficiently and accurately. In order to reach this objective, this thesis addresses the following key research questions.

1. As mentioned above, due to the advent of MaaS, travellers may use different travel modes throughout a trip, leading to multimodal trip modes. That is, a multimodal mode does not constitute a single mode like a classical unimodal modes does, but rather, combines an access mode, a main mode and an egress mode. For example, during a trip from home to work, a traveller may first walk to a bus stop, leading to walking as an access mode. Then, the traveller takes the bus (or any other form of public transport) to the stop nearest to the destination, making public transport the main mode of the trip. Finally, the traveller may take a shared bicycle to go from the bus stop to the trip destination, so that the bicycle is used as an egress mode. Walk-public transport-bike thus constitutes the multimodal trip mode used in this example.

   Due to the many mode combinations possible, many multimodal mode alternatives exist, leading to computational challenges if each of these alternatives are evaluated for each trip of a complete tour. That is, a tour consists of two or more trips, where the origin of the first trip is the destination of the last trip. It should be noted, though, that in reality the number of multimodal mode alternatives may be limited. To mention an example, we regard a home-work-home tour, where commuters may use the multimodal mode walk-car-bike in the morning to get from home to work. In that case, a traveller walks from home to their car in the morning, drives to a specific location to park the car there, from which the traveller goes to their work location by bike. Suppose, however, that the traveller uses a private car and a private bicycle for this purpose. Then, when going back home in the evening, only a single reasonable alternative exists: cycling back to the parking location to drive the private car back home. As a result, all other multimodal modes can be written off as alternative options. However, this constraint is less restrictive when using free-floating shared cars or bicycles since travellers can drop off these vehicles anywhere. In that case, more combinations of multimodal mode alternatives for the complete tour, also called multimodal mode chains, may exist in that case. This example shows that, depending on required vehicle ownership and vehicle locations, not every multimodal mode chain may be feasible.

When constraints as those mentioned above are not taken into account, a phenomenal number of different modal mode chains has to be considered by the model, creating an immense computational burden. In order to take away this burden, it is important to only take feasible multimodal mode chains into account. This immediately leads to the first research question: *how to identify all feasible multimodal mode chains in a tour?*

2. As mentioned before, in addition to the traditional travel modes, such as car-driving, cycling, walking or public transport, new mobility services bring many additional, new travel modes and services, such as e-step, car-sharing and ride-sharing, as described in Section 1.1. However, this again brings a potential computational burden for the ABM, as many new modes need to be evaluated, also as part of the multimodal mode chains defined above. This brings the next research question: *how to efficiently model different new mobility services in the ABM?*

3. While the previous two research questions are based on the suggestion of reducing the computational work required for the ABM, another way to improve computational efficiency is to simply increase the computational power. Since an ABM in principle performs a multitude of similar calculations that can be performed in parallel, one can thus also explore the use of state-of-the-art computer techniques that accelerate the computation of the ABM. One may for example think of using a graphical processing unit (GPU) of a computer, which is designed for the parallel execution of the same function on different data elements. Using NVIDIA's Compute Unified Device Architecture (CUDA) (cf. (NVIDIA, 2007)), this may enable the ability to analyse many scenarios within a reasonable amount of time. These thoughts are at the core of the third research question: *how to reduce the computation time of an ABM using a computer's GPU?*

4. Other than reducing the number of choice alternatives, and the exploitation of parallel computing techniques, another direction to be pursued to speed up computations is based on reducing the stochastic simulation errors involved in the model. Indeed, ABMs provide a high level of detail

when modelling complex travel behaviour. Since these models are based on stochastic simulation, this high level may induce large random fluctuations in the output. Due to the randomness, in different simulation runs of the model, different choices may be made even if the likelihood of each alternative is exactly the same. This may lead to unrepresentative outliers, which necessitates many model reruns so as to not give too much weight to these outliers. This may especially become a computational burden when comparing travel behaviour between multiple scenarios, in which case each scenario requires its own simulation. For this purpose, it may thus be helpful if one can reduce the variance of the observed travel behaviour differences between scenarios. The fourth research question addresses this: *how to reduce the number of simulation runs while keeping the difference between scenarios stable?*

5. When all the previous research questions are addressed and its solutions are implemented in an ABM, one should have a powerful tool to analyse many scenarios. When selecting these scenarios carefully, this helps us understand the impact of new mobility services and additional parking policies, which can aid policymakers and governments to implement smart policies leading to more sustainable transport and mobility. The final research question can therefore be formulated as follows: *what is the impact of new mobility services and restricting parking policies on sustainable mobility?*

1.4 Approach and contributions

In order to address the research questions mentioned in the previous section, we follow an incremental approach to develop a comprehensive ABM. This approach consists of four main steps, each of which addresses one of the first four research questions and corresponds to a chapter of this thesis. We start with an ABM model, which we develop while undertaking each of these steps. This finally results in a model that achieves the research objective at a desirable level. Each of the steps is illustrated via a numerical study. When this ABM has been developed, we provide a case study to answer the final research question in a separate chapter. We now provide an overview of the four steps.

The first step determines all feasible multimodal mode chains in a tour. That is, to effectively handle the many choices of mobility combinations inside an ABM, we construct a travel mode structure which integrates new travel modes as well as conventional ones. This mode structure explicitly models the access and egress modes for each trip next to the main mode, forming multimodal modes. After this, a procedure is developed that efficiently generates all possible combinations of modes for the trips within a tour. This procedure is integrated into the mode choice component of the ABM. This step, addressing the first research question, is represented by **Chapter 2**.

The second step develops a multimodal tour-based mode choice model as part of the ABM, which makes mode chain choices for each tour undertaken by any traveller. In doing so, it uses the procedure from the first step to create the feasible mode chains on a tour level. These tour-level mode chain choices thus incorporate all applicable restrictions e.g. concerning personal vehicle ownership, MaaS subscription ownership and vehicle states. To incorporate new mobility services into this component, we introduce the concept of mode categorisation to reduce the large number of possible mode chain alternatives. We propose seven mode categories that include both private and shared mobility concepts, while still representing the modes, both new and already existing, well. This categorisation ensures that modes are mutually sufficiently different in nature so reasonably unbiased mode chain choices can be made. We illustrate the potential of the resulting component by simulating travel demand in the metropolitan region surrounding and including the cities of Rotterdam and The Hague in the Netherlands. This step addresses the second research question and is represented by **Chapter 3**.

The third step, addressing the third research question, includes the implementation of state-of-the-art technology on parallel computing using a computer's graphics processing unit (GPU) to speed up calculations. Since ABMs incorporate a much higher level of detail than traditional travel demand models, they have high computational requirements, making them challenging to use for analysis and optimisation purposes. We therefore conduct a pilot study illustrating the potential of the GPU in speeding up an ABM's computations. We compare the observed computation time of an ABM GPU implementation that we built using NVIDIA's CUDA framework with similar, non-parallel implementations. We conclude that speed-ups up to a factor of 50 can be realised. This paves the way for use of an ABM for analysis of scenarios and optimisation purposes without excessive computation times. **Chapter 4** represents this step.

The fourth step introduces the so-called technique of *common random numbers* in the developed model to mitigate random fluctuations in the output. Common random numbers is a technique that reuses the same random numbers for choices made by travellers between scenarios. This ensures that any observed difference in output across scenarios cannot be attributed to mutual differences in drawn random numbers, eliminating an important source of random fluctuation. We demonstrate by a numerical study that the technique of common random numbers can greatly reduce the number of runs needed, and thus again has a reducing effect on the required computation time of an ABM to obtain a reliable output. This step addresses the fourth research question and is represented by **Chapter 5**.

When all four steps are taken, all the underlying developments have been included in the ABM. This leaves us with an ABM which, while including a rich level of detail, is computationally efficient enough so that it can be used for large-scale experiments. In this thesis, we therefore also conduct a comprehensive case study using this developed ABM. This case study evaluates the impact of new mobility services and policy alternatives on sustainable mobility. In particular, new mobility services and parking policies are studied, since both are believed to have the potential to reduce private vehicle use, and therefore also to promote more sustainable mobility. The case study evaluates these mobility services and parking policies in the future year 2030 in the metropolitan region of the Netherlands that surrounds and includes the cities of Rotterdam and The Hague. This region is of vital economic importance and has one of the most developed infrastructures in the world. The population of this region is growing, which motivates the ambition to improve accessibility and move towards sustainable mobility. Therefore, the findings of this study are important to similar regions seeking to do this as well. Seven scenarios are designed 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 the neighbourhood level where sustainable travel modes are linked), the availability of 'Mobility as a Service' subscriptions and car/bike-sharing services. We also study the impact of 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. Moreover, the impact of less parking capacity in the region and higher parking costs are also studied. **Chapter 6** presents this case study.

1.5 Thesis organization

As mentioned in the previous section, each of the following four chapters is devoted to a main step of the ABM development. That is, Chapter 2 explains the process of determining all feasible multimodal mode chains in a tour, while Chapter 3 includes new mobility services in a multimodal tour-based mode choice model. Consequently, Chapter 4 introduces parallel computing by means of the GPU to the ABM, after which Chapter 5 studies how to use the technique of common random numbers in an ABM. After these development steps are taken, the fully developed ABM enables us to perform a detailed case study into the impact of new mobility services and policy alternatives. Chapter 6 is devoted to this case study. Finally, Chapter 7 provides overall conclusions, with special attention to the research questions raised in Section 1.3, and gives recommendations for future research.

In an effort to enable the reader to read the chapters of this thesis in a standalone fashion, we opted to make these chapters self-contained. Therefore, the introductions of the chapters hereafter may contain overlap with the current chapter, and some notation differences between the different chapters may be present.

2

Effective determination of MaaS trip modes in activity-based demand modelling

The rising Mobility as a Service (MaaS) concept integrates many new transport options for the travelling public, such as the use of public bikes and car-sharing services. As such, it offers more mobility combinations within a single journey than ever. To effectively handle the choice for such a mobility combination inside an activity-based travel demand model, we propose a travel mode structure which integrates all these new travel modes next to the conventional ones. This mode structure explicitly models the access and egress modes for each trip, since the impact of the access and egress modes can be significant. We also propose a procedure that efficiently generates all possible combinations of modes for the trips within a tour, while ignoring all infeasible ones. In doing so, we present the tools for the effective determination of MaaS trip modes in the choice component of an activity-based travel demand model.

2.1 Introduction

In recent years, the rising number of innovative mobility services (e.g. Uber and Mobike), the introduction of autonomous vehicles and the growing opportunities offered by smartphone technology has led to an increasing interest in the Mobility as a Service (MaaS) concept. While this mobility concept has been defined in multiple ways in the literature (cf. (Kamargianni et al., 2016; Jittrapirom et al., 2017)), MaaS can be thought of as a novel service that allows users to get from their origin to their destination by combining several available mobility options (such as public transport, shared bike, etc.) and presents those in a single online interface, while the user is not required to e.g. own a car or bike her/himself.

Due to the popularity of MaaS and its enormous impact that it is expected to have on the daily travel patterns of travellers in the future, it is crucial to gain an in-depth understanding of this impact through traffic modelling. For instance, the influence of MaaS on the travel behaviour of individuals and/or complete households needs to be assessed. To do so, one requires a travel demand model that can capture all travelling activities of each individual traveller and handle the sheer number of combinations of travel modes that MaaS will offer. Due to their high level of detail, Activity-Based travel demand Models (ABMs) are most suitable for this purpose.

Only few studies have been aimed at using ABMs for the assessment of the MaaS concept. For example, (Iqbal et al., 2019) reports ongoing process on an ABM-framework that studies the effect of MaaS on the individual car ownership of travellers. Likewise, the studies of (Hörcher and Graham, 2020; Zarwi et al., 2017) investigate the impact of MaaS on the transport system by focusing on a single choice component within an ABM. Nevertheless, several hurdles still need to be overcome to apply ABMs effectively (cf. (Jittrapirom et al., 2017; Miller, 2019)). For example, the many available travel modes brought by MaaS lead to a much higher uncertainty in the travellers' decision making compared to traditional traffic models. Next to this, while travel demand models often assume the traffic behaviour of different households to be completely independent, this would not be the case anymore with the introduction of MaaS because of its facilitation of e.g. ride-sharing between households (Miller, 2017). In fact, to the best of the authors' knowledge, no study in the literature has concentrated on the question how to include all novel travel modes in a flexible mode structure that MaaS facilitates, such as ride-sharing and bike-sharing, in an ABM.

In this chapter, we specifically address this question. More particularly, we propose a travel mode structure that allows for the effective implementation of MaaS modes in an ABM. Unique for this structure is that it not only includes unimodal modes such as 'car' and 'public transport'. It also includes multimodal modes, which, apart from the main mode, also contain information on the access and egress mode used to undertake a trip. In many studies so far, the travel modes for access and egress are assumed fixed (e.g. travellers always walk to/from their own car or the bus station) (Krajzewicz et al., 2018; Creemers et al., 2015), so that a unimodal mode suffices. However, MaaS facilitates the combination of many possible new travel modes within a single trip, so that this assumption is not valid anymore (Creemers et al., 2015) and multi-modal modes are required. For example, as alluded to in (Hensher, 2017), travellers may now opt to use a point-to-point service such as Uber (access mode) to reach the bus station, while a shared bike takes the traveller to the final destination (egress mode). Another advantage of this structure is that it is flexible: additional unimodal or multimodal modes can be added without any additional effort. Therefore, the structure can keep up with the increasing number of mode alternatives MaaS will offer.

Other than the travel mode structure, we also introduce a procedure that explores all the chain mode sets (sets containing the modes of all trips making up a tour), and discards all infeasible ones. More particularly, inspired by (Miller et al., 2005), we propose the use of four different consistency checks between the modes within a chain mode set to filter out the infeasible chain mode sets. These checks reduce the number of alternatives in the choice set with several hundreds or even millions depending on the number of trips in a tour and the number of modes considered. Because of this reduction, the introduction of new travel modes will not lead to an explosive increase of choices. Yet, if the introduction of new modes still implies a significant computational burden in the future, GPU parallelisation (Zhou et al., 2019) can be used to tackle this problem.

The remainder of this chapter is organised as follows. Section 2.2 explains our travel mode structure and the above-mentioned procedure in detail, after which Section 2.3 provides numerical illustrations. Finally, Section 2.4 concludes the chapter and describes future work.

2.2 Method

In this section, we explain our travel mode structure and consistency check procedure in detail. In particular, Section 2.2.1 discusses how the travel mode structure can integrate all the various MaaS modes. Then, Section 2.2.2 categorises the traveller's trips, after which Section 2.2.3 explains how our procedure discards infeasible travel mode combinations.

2.2.1 MaaS modes

In Figure 2.1, we display an example of a set of conventional travel modes which could be considered for modelling in a non-MaaS setting. There are unimodal modes, such as 'car', which means the traveller uses only the car to get from origin to destination. It also lists multimodal modes that can be encountered in a non-MaaS setting, such as 'Car-PT-Walk' (Park & Ride), which means that the traveller drives as an access mode to the bus stop or train station (PT=public transport). After the bus or train ride, the traveller walks to the destination of the trip. In this figure, all mobility options together lead to 12 mode choices (both unimodal modes and multimodal modes). MaaS, however, will introduce more travel modes. For example, MaaS creates a platform for car-sharing, i.e. short-term car rental. MaaS will also provide the opportunity to carpool, so that travellers will also have the opportunity to ride-share on a wide scale. We also mention bike-sharing, increasingly popular in cities, where subscribed travellers can make ad-hoc use of public bicycles to go from one bike station to the other.

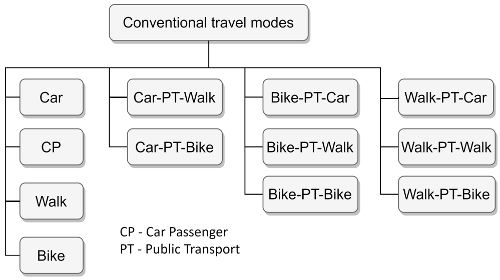


FIGURE 2.1: Possible mode choices in a non-MaaS setting (12 choices).

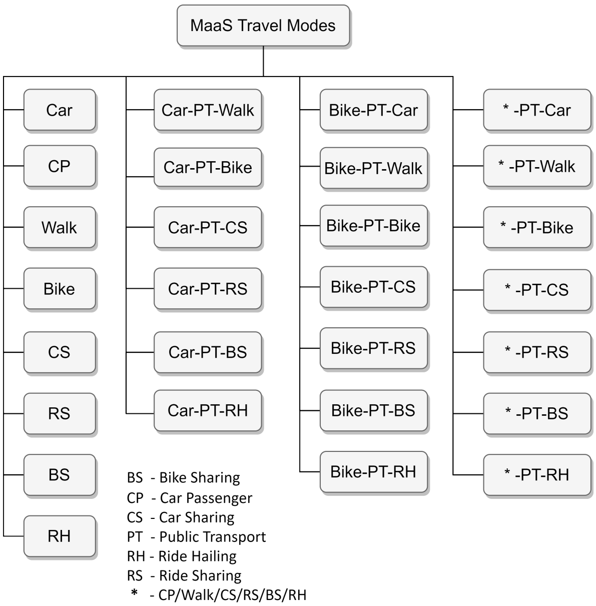


FIGURE 2.2: Possible mode choices in a MaaS setting (63 choices).

As Figure 2.2 shows, adding such mobility options could lead to a total of 63 mode choices, rather than just the 12 of Figure 2.1. This supports the claim that MaaS integrates many more modes, especially considering the fact that MaaS may lead to more novel mobility options than the ones we mentioned above. Figure 2.2 also show why this structure is flexible: new unimodal (such as 'e-scooter') or multimodal modes can be easily added. In an ABM, whether or not the traveller uses MaaS could be one of the traveller's long-term decisions. This serves as input for the mode-selection step of an ABM: in case the traveller has a MaaS subscription, Figure 2.2 lists all the modes, otherwise only the choices in Figure 2.1 are valid.

2.2.2 Classification of trips

Now that we have discussed the modes that can be used within a trip, we classify the trips themselves. It is important to note that trips make up a daily tour, as we will explain in more detail in Section 2.2.3. We distinguish between the following classes of trips.

- A trip is called an *outbound trip* if its origin coincides with a destination of another trip which takes place later in the tour. The origin of an outbound trip is an *anchor point* (Miller et al., 2005; Castiglione et al., 2015). A tour always starts with an outbound trip.
- An *inbound trip* is a trip of which the destination is an anchor point. A tour always ends with an inbound trip.
- All trips which are neither outbound or inbound trips are *intermediate trips*. These trips do not originate or end at an anchor point.

This classification allows us to check whether a certain mode can be used for a certain trip within the tour. For example, if the traveller does not take her/his own car for an outbound trip, then it is not possible to use the car for the inbound trip either. Likewise, if a tour for example consists of the outbound trip 'home to work' and the inbound trip 'work to home', the multimodal mode 'walk-PT-car' will be unfeasible for the outbound trip, since the traveller's car will still be at home rather than at the bus/train station. This multimodal mode would however be feasible for the inbound trip if the traveller chose 'car-PT-walk' as the mode for the outbound trip.

2.2.3 Generation of all feasible chain mode sets

Now that the trips of a tour are categorised, we introduce our procedure that generates all the feasible chain mode sets. Recall that a feasible chain mode set of a tour amounts to a feasible combination of modes chosen for each trip of a tour. This procedure is suitable for different kinds of tours, for example simple tours such as Figure 2.3a, tours which have multiple destinations in sequence such as Figure 2.3b or tours which have sub-tours in them such as Figure 2.3c.

To generate the feasible chain mode sets of a tour, the procedure recursively considers each of its trips, and iteratively checks whether each of the modes shown in Figure 2.1 or Figure 2.2 is consistent both with the trip itself and the previous trips. If a candidate mode for some trip does not satisfy the consistency check, chain mode sets containing that candidate mode for that trip will be discarded. In the end, all possible chain mode sets which have not been discarded will form all feasible chain mode sets.

The consistency check contains the following parts.

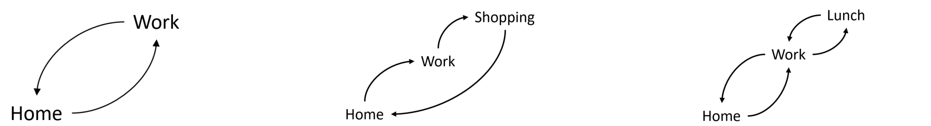
- *Mode ownership/subscription*: for candidate modes such as 'car', 'bike' and 'bike-PT-walk', the procedure checks whether the traveller owns the required car or bike or has the right subscription to use a shared mode (which is a long-term choice made in an earlier stage of the ABM-model). If this is not the case, the candidate mode is discarded.

- *Mode availability*: the procedure checks whether the required mode is available at the origin of the trip. For example, if the traveller's owned bike is not at the origin of the trip for instance because walking is used in the previous trip, 'bike-PT-walk' must be discarded.

- *Final location*: The procedure checks whether the traveller's own vehicles (car/bike) are back at the anchor point at the end of a (sub)tour.

- *Mode allowance/presence*: check if the mode is allowed at the origin or destination of the trip. For instance, congested zones in cities may not allow cars. Also, some shared services might not be available for certain trips.

Note that for the multimodal modes, these checks mainly concern the access and egress modes. We explain this using the tour of Figure 2.3b, which consists of three trips: from home to work, from work to the shopping mall, and back home again. According to the trip classification of Section 2.2.2, the 'shopping mall-home' trip is inbound. When considering the multimodal mode 'bike-PT-walk' as a candidate mode (i.e., the bike forms the access mode, while the egress mode is simply walking), the mode ownership check first verifies whether the agent has a bike. If not, the complete multimodal mode is discarded. Otherwise, the mode availability subsequently checks whether the traveller's bike is available as a result of the mode choice for the trip 'work-shopping mall'. If not, this check fails. If this would not fail, however, the final location check would still fail, as at the end of the tour, the traveller's bike will not have returned home. Since the final location check already disqualifies this particular multimodal mode, the mode allowance check is not performed any more.



(A) A tour with two trips (B) A tour with three trips (C) A tour with a sub-tour (four trips)

FIGURE 2.3: Tours with different trips

By recursive construction of the chain mode sets and repetitively applying these consistency checks, all feasible chain mode sets are generated, while all infeasible ones are discarded. In the choice model for the mode selection part of the ABM, the utility of each chain mode set can be computed by simply summing the utilities of all mode choices for each of the trips within the tour. The strength of the travel mode structure and this checking procedure is that, provided that the mode choices are sufficiently different in nature, no nested choice model will have to be used. More particularly, a simple multinomial logit model now suffices for simulation purposes. Moreover, no utilities will have to be calculated for infeasible chain mode sets, increasing numerical efficiency. Given the still potential large number of feasible chain mode sets, the computation of utilities and the subsequent can be made even more efficient by using parallelisation techniques (Zhou et al., 2019).

2.3 Numerical illustration based on the Rotterdam-The Hague area

In this section, we provide numerical evidence why discarding infeasible chain mode sets is important. We do this based on a recent study called V-MRDH (Verkeersmodel Metropoolregio Rotterdam Den Haag) (Van de Werken, 2018), that models the traffic network of the Rotterdam-The Hague area in the Netherlands. This study considers the following eight travel modes: 'car', 'car passenger', 'bike', 'walk-PT-walk' (wptw), 'walk-PT-bike' (wptb), 'bike-PT-walk' (bptw), 'bike-PT-bike' (bptb) and 'walk'. We also consider the utility functions as derived in (de Romph et al., 2019), which are based on this traffic network. These functions incorporate a total of 13 attributes including personal and household properties. In this network, we consider a home-work-shop-home tour of a traveller as shown in Figure 2.3b. The distances of the home-work and shop-home trips are more than 25 kilometres, while the work-shop distance is about 7.5 kilometres, which can be traversed by bike. The traveller we consider owns a bike, but not a car.

TABLE 2.1: Mode probabilities of each trip in the home-work-shop-home tour.

Trip	P_{car}	P_{cp}	P_{bike}	P_{wptw}	P_{wptb}	P_{bptw}	P_{bptb}	P_{walk}
home-work	0.00%	14.61%	12.00%	71.95%	0.06%	1.15%	0.24%	0,00%
work-shop	0.00%	4.36%	68.88%	24.35%	0.02%	0.29%	0.05%	2.04%
shop-home	0.00%	17.81%	8.77%	71.49%	0.08%	1.51%	0.34%	0.00%

The mode choice probabilities for these trips corresponding with the utility functions of (de Romph et al., 2019) are shown in Table 2.1. In a trip-based approach, it is highly likely that 'wptw', 'bike' and 'wptw' would be chosen as modes for each of the respective trips. The probability of having this chain set would be 35.5%. However, this mode combinations is not a valid combination:

the traveller cannot use the bike during the second trip since it was not used during the first trip either.

Under our approach, with 51% probability, 'wptw' would be chosen for each trip, which is feasible. Particularly, our procedure only flags 37 chain mode sets out of all 512 possible combinations as feasible and discards the rest. This reduction would be even more pronounced when more mode alternatives would be considered. If one would for example consider all 63 mode choices of Figure 2.2, only 48825 out of $63^3 = 250047$ chain mode sets would be deemed feasible.

2.4 Conclusions and future work

In this chapter, we proposed a MaaS-oriented travel mode structure for use within a travel mode choice component in an ABM. We made effective use of unimodal modes and multimodal modes so that the trip choice model remains non-nested, as long as mode options differ significantly from one another. When similar modes such as shared bikes and shared e-scooters are regarded, a nested choice model should be considered so that the joint probabilities of similar modes are not overestimated. We also described a consistency check procedure that prevents the evaluation of infeasible mode combinations, improving numerical efficiency.

Several other hurdles still need to be overcome to model MaaS inside an ABM. One of the remaining challenges is to acquire information such as the typical travel time of models, cost, etcetera. Only with this information can utility functions be constructed and reliable utilities be computed. When these hurdles are overcome, however, the presumably significant impact of MaaS on the traffic system and the population of travellers can be assessed.

3

A TOUR-BASED MULTIMODAL MODE CHOICE MODEL FOR IMPACT ASSESSMENT OF NEW MOBILITY CONCEPTS AND MOBILITY AS A SERVICE

Mobility as a Service (MaaS) and new mobility concepts mutually inspire each other, provide alternatives for the private car-oriented transport system as we know it, and will offer more mobility choices in a single journey than ever. This multitude of mobility choices however poses challenges in modeling the travelers' mode choices in travel demand prediction models. To address these challenges, this chapter develops a multimodal tour-based mode choice model as part of an activity-based demand model. By explicitly modeling access and egress modes, this choice model creates multimodal mode chain sets on a tour level based on restrictions with respect to personal vehicle ownership, MaaS subscription ownership and vehicle states, and subsequently makes mode choices for every traveler.

For the creation of these mode chain sets, we introduce the concept of mode categorization. We propose seven mode categories that include both private and shared mobility concepts. This categorization makes sure that modes are mutually sufficiently different in nature, so that reasonably unbiased mode chain choices can be made. Furthermore, the reduction to seven categories enables the study of large scenarios, while the introduced categories still represent new and already existing modes well.

We illustrate the potential of the model by simulating travel demand in the Metropolitan region Rotterdam-The Hague. The results show that our model is capable of making plausible mode choices in the presence of MaaS and new mobility concepts, and can be used to assess the impact of mobility hubs where access and egress mode choice is important.

3.1 Introduction

We are witnessing the development of new transport technologies, such as connected vehicles using 5G, level 3, 4 or 5 automatic vehicles, and mobile app-based car-sharing or ride-sharing services. *Mobility as a Service* (MaaS) combines all these technologies and services, thus offering a tailored mobility package for individual travelers (Jittrapirom et al., 2017; Hesselgren et al., 2020). In the context of this chapter, we assume that MaaS offers travelers full freedom to choose any traffic mode at any time.

On the one hand, MaaS promotes including multiple modes in a single trip (called *multimodal mode*) by the use of mobility hubs and the use of multiple (multimodal) modes in a tour (called multimodal mode chain). On the other hand new mobility concepts (such as the electrical vehicle, autonomous car, shared bike, Uber) also stimulate the development of MaaS (Milakis et al., 2017; Snelder et al., 2019; Wright et al., 2020). This chapter develops a methodology to study multimodal mode choice, explicitly including the modes brought forth by MaaS and new mobility concepts, in the context of activities and related trips that people make during a day. Throughout this chapter, we refer to a series of trips starting and ending at home as a *tour*.

Owing to its flexibility, robustness and efficiency to model complex travel behavior (Miller, 2019), *Activity-based modeling* (ABM) offers a highly suitable methodology for quantifying the impact of MaaS and new mobility concepts. There is a growing body of literature on this approach: for example (Narayan et al., 2019) have investigated ride-sourcing for car and public transport in Amsterdam, while (Hörcher and Graham, 2020) did a study on car ownership with subscriptions to alternative modes. Furthermore, (Matyas, 2020) studied the opportunities and barriers for a modal shift via interviews about people's attitudes towards MaaS. In (Snelder et al., 2019), an explorative iterative model has been developed to study the impact of automated driving and shared mobility using a network fundamental diagram. In (Ciari et al., 2012), car-sharing demand has been modeled in MATSim, an open-source multi-agent transport simulation framework (Horni et al., 2016). We also note that (Franco et al., 2020) have modeled the demand of ride-sharing services, which is also fundamental for the implementation of MaaS, in MATSim. The above-mentioned studies in the first place show that there is ample potential for MaaS and new mobility concepts. Importantly, however, their focus has predominantly been on unimodal trips, thus ignoring the pivotal role multimodal modes play in MaaS. Another omission of the existing literature is that one typically does not align the trips that people make during a day, leading to possibly inconsistent mode choices within a tour.

MaaS and new mobility concepts stimulate the use of multimodal modes. Several studies have stated that mass public transport (PT) is essential for MaaS and suggest to shape complementary services to it (Basu et al., 2018; Matyas and Kamargianni, 2018), such as taxis (Wang and Ross, 2017), a car-sharing system (Mounce and Nelson, 2019), or on-demand mobility (Salazar et al., 2018). Furthermore, (Creemers et al., 2015; Olvera et al., 2015; Himmel et al., 2016) have analyzed access and egress mode choice based on surveys in the context of PT-based multimodal mode choice. We also mention (Krajzewicz et al., 2018), where an agent-based demand model is used to study multimodal mobility behavior, considering multimodal modes on a trip level, but only with PT as a main mode. On the operational side, (Zgraggen et al., 2019) have developed a routing algorithm to optimize coordination between new mobility concepts and public transit, while (Wright et al., 2020) has presented a journey planning app where carpooling and public transport are connected. Although these studies do foster the use of multimodal modes within a trip by considering multimodal mode choice, they still do not check the consistency of mode choices within a tour. Moreover, many of these studies focus on single new mobility concepts, while MaaS typically requires the incorporation of a wide range or mixture of concepts.

A relatively low number of studies explicitly checks the consistency of modes within a tour. For instance, one model approach which actively does this is the supernetwork approach. In this regard, we mention the works of (Arentze and Timmermans, 2004; Liao et al., 2010; Fu and Lam, 2014; Liao, 2016), where multi-state supernetworks have been developed to model activity location, time, duration, (multimodal) mode and route choice simultaneously, based on least-cost path choices. The supernetwork approach can also consider household joint activity choices simultaneously (Vo et al., 2020). This approach is very powerful, as witnessed by the fact that it is amenable to extension, see e.g. the study of (Li et al., 2018), which incorporates free-floating car sharing as an alternative mode. Next to the supernetwork approach, another useful approach in the literature is that of discrete choice models (DCM) for mode choice. For example, the stand-alone tour-based mode choice model developed by (Vovsha et al., 2017) also explicitly checks for consistency of modes within a tour. The supernetwork and the DCM approaches are mutually different in nature, both having their advantages. On one hand, the supernetwork approach is much more flexible in that it can incorporate all kinds of new modes simultaneously based on a 'unified path choice' approach. On the other hand, the DCM approach offers more flexibility to include mode specific advantages via alternative specific constants and non-observable utility via error terms in the underlying utility functions of the choice models. Furthermore, its parameters can be estimated based on stated and/or revealed preference data. In the present chapter, we focus on the second of these two approaches. To the best of our knowledge, the models known in literature following the DCM approach only consider single new modes or a limited combination of new modes. With the advent of MaaS, however, it is important to include all new modes and mode combinations within a single model, motivating why in our chapter we strive to do this.

We proceed by detailing the contributions of our work. In the first place, we develop a multimodal tour-based mode choice model, as part of an activity-based demand model called ActivitySim (Gali et al., 2008), where on the trip level multimodal modes are considered. The underlying model creates multimodal mode chain sets on a tour level, based on restrictions with respect to personal vehicle ownership, MaaS subscription ownership, vehicle availability and vehicle locations. By imposing these restrictions, it enforces mode consistency throughout the whole tour. Subsequently, for each tour, inspired by the mechanisms presented in (Miller et al., 2005; Vovsha et al., 2017), the multimodal mode chain having the highest utility is chosen. As a second contribution, this chapter introduces the concept of mode categorization: modes with similar properties are placed in a single mode category and afterwards considered as the same mode. This alleviates selection bias as a result of modes being similar in nature (i.e., it reduces the problem of similar modes having higher likelihood to be chosen). In our specific case, we introduce seven categories that cover many new mobility concepts such as micro-modalities (e.g., bike, scooter) and on-demand PT. Both private and shared mobility concepts are considered, and all the multimodal mode alternatives are based on combinations of those seven modes/mode categories. As an additional benefit, this mode categorization reduces the computational complexity due to the smaller number of mode alternatives, and as a result the smaller total number of multimodal mode combinations. It renders our model numerically efficient: it can handle cases with large-scale multimodal mobility corresponding to up to millions of travelers. To substantiate this claim, we present, as a last contribution, a study for a large-scale instance that focuses on the Rotterdam-The Hague area in the Netherlands. It demonstrates the potential of our methodology, explicitly including multimodal modes and mode consistency within tours, for assessing the impact of MaaS, mobility hubs and new mobility concepts.

The remainder of this chapter is organized as follows. Section 3.2 explains the details of the compartments our methodology consists of. In Section 3.3, we provide a large-scale numerical experiment that illustrates the potential of our approach. Finally, Section 3.4 presents the conclusions, discussion, and recommendations for future research.

3.2 Methodology

Because our model can be interpreted as a component of an activity-based model (ABM), we start by explaining how our model interacts with ActivitySim. First, a population is synthesized as pointed out in (Snelder et al., 2021). ActivitySim then makes long-term decisions, taking into account the number of cars each household owns, parking availability, work/school locations, etc. Next, the daily main activity purpose of each person is determined considering the interaction with other household members. After this, each individual makes decisions on the number of tours to be undertaken that day, and the number of stops in each tour including the start time, duration, the destinations and modes of each trip in the tour. The trip mode chosen at this stage is not final, but it will be considered by our model as the main mode of the uni- or multimodal mode to be chosen. In particular, our new tour-based mode chain choice model subsequently determines access and egress modes to generate a feasible trip mode combination for the tour.

In the next subsection, we detail the mode categorization of seven main modes as will be applied in the numerical experiment of Section 3.3. We argue that this categorization covers most of the traditional as well as new mobility modes. Afterwards, we derive multimodal mode alternatives from these seven main modes, which enables us to explain how our multimodal mode choice model works.

3.2.1 Mode categorization

We now describe the unimodal mode alternatives included in our ABM. In doing so, we introduce the notion of mode categorization, meaning that modes from different categories should be seen as different in nature. The main goal of this categorization is the reduction of selection bias at the mode choice selection stage of the model, as we will explain in greater detail later in this section. The underlying categories can be chosen in many ways, in line with the analysis that needs to be performed. To illustrate, we have identified seven different modes categories depending on the speed, weight, vehicle space per person, and passenger capacities, where it is noted that most of the traditional travel modes as well as new mobility modes fit into these categories. An advantage of using mode categories instead of single modes is that new modes can easily be added to the model as long as they fit within one of the seven categories. Per aspect, we distinguish between the following elements:

- Speed (km/h): $\text{S} \in \{\leq 5, 5-20, 20-30, > 30\}$;
- Weight: $\text{W} \in \{\text{MM}, \geq \text{car}\}$;
- Vehicle space per person: $\text{VS} \in \{\leq 0.25, 0.25-0.5, > 0.5\}$;
- Passenger capacity: $\text{PC} \in \{< 1, 1-8, > 8\}$.

The vehicle space per person is defined as the space a person occupies compared to a passenger car unit (PCU). Pedestrians and people in public transport fit for instance in the first class ($\leq$ 0.25 PCU), cyclists in the second class (0.25 – 0.5 PCU), and car drivers in the third category ($>$ 0.5 PCU). As a result, there are $4 \times 2 \times 3 \times 3 = 72$ combinations. However, not all the combinations are valid. Below we list all *infeasible* combinations, with an argumentation:

- {W $\geq$ car} & {S $\leq$ 30}: a vehicle that weighs at least as much as a car should drive faster than 30 km/h.
- {W $\geq$ car} & {PC $<$ 1}: a vehicle that weighs at least as much as a car should have capacity for one or more passengers.
- {W $\geq$ car} & {PC $>$ 8} & {VS $>$ 0.25}: the passenger capacity exceeding 8 implies that the vehicle space should be in the category '$\leq$ 0.25'.
- {W = MM} & {PC $\geq$ 1}: micro-modalities do not have space for passengers.
- {W = MM} & {S $>$ 30}: micro-modalities will not move faster than 30 km/h.
- {W = MM} & {VS $>$ 0.5}: micro-modalities do not take that much space.
- {W = MM} & {S $>$ 5} & {VS $\leq$ 0.25}: assuming that the speed of anyone with a means of micro-modality transport is higher than 5 km/h, the vehicle space per person is higher than a quarter of a PCU.
- {W = MM} & {S $\leq$ 5 } & {VS $>$ 0.25}: micro-modalities moving at such low speeds typically take less space than the quarter of a passenger car unit.

Category	S (in km/h)	W	VS (in PCU)	PC	Example
Micro5	$\leq$ 5	MM	$\leq$ 0.25	$<$ 1	walk (WA)
Micro15	5 – 20	MM	0.25 – 0.5	$<$ 1	bike (B)
Micro25	20 – 30	MM	0.25 – 0.5	$<$ 1	e-bike (EB)
Private	$>$ 30	$\geq$ car	$>$ 0.5	1 – 8	car (C)
Shared private	$>$ 30	$\geq$ car	0.25 – 0.5	1 – 8	CP
Shared on demand	$>$ 30	$\geq$ car	$\leq$ 0.25	1 – 8	DRT
Shared traditional	$>$ 30	$\geq$ car	$\leq$ 0.25	$>$ 8	PT

TABLE 3.1: Overview feasible mode categories

Eliminating the invalid combinations, seven mode categories remain; see Table 3.1. The last column provides, for each category, a representative example, which we will now comment on. We will use the abbreviations presented in this table in the remainder of this chapter. The walk mode (WA) has a speed less than 5 km/h. The bike (B) mode corresponds with a travel mode with a speed between 5 and 20 km/h, thus covering (non-motorized) scooters as well. For the e-bike (EB) mode the speed is between 20 and 30 km/h, so that it also covers e-scooters. The car mode (C) effectively represents a transportation mode with speeds over 30 km/h (which can be electric or even autonomous). Here, both private and shared (e-)bikes and cars are considered. Car passengers (CP) can ride a private car with someone else from their household, or use a shared car (such as a taxi). Demand responsive transport (DRT) includes minibuses, shared taxis or shuttles of which the passenger capacity is smaller than the capacity of traditional public transport. Conventional public transport (PT) includes bus, tram, metro, and train.

The categorization example that we show in this chapter was chosen based on expert judgement so as to distinguish between modes as much as possible. It could happen, however, that mode categorization, although it reduces selection bias significantly and enables efficient, tractable computation, may lead to heterogeneity issues. That is, travellers may still have different personal preferences regarding two modes which are placed in the same category. The categorization may therefore be further optimized to diminish these issues as much as possible, while retaining the positive effects of selection bias reduction and computational efficiency; cf. Section 3.4.

3.2.2 Multimodal mode alternatives

We continue by explaining the multimodal mode alternatives that we consider. Each multimodal mode contains an access mode, a main mode and an egress mode, so that there are $7 \times 7 \times 7 = 343$ multimodal mode alternatives. To model multimodal modes, we have introduced two types of hub locations. A hub is a place where travelers change their travel mode within a trip, i.e., travelers use a unimodal mode to travel from an origin to a hub location and then switch to another travel mode to continue their journey. The two hub types are C-PT and C-B hubs. For each origin-destination zone pair, hubs are first selected where the maximum cycle distance to/from the hubs is 3 km, the maximum distance for PT is 10 km, and the minimum car distance is 20 km. Then, the best hub is selected based on shortest travel distance. However, not all multimodal modes are valid. We use the following rules to select the valid multimodal modes:

1. Each of the seven unimodal modes are valid access, main or egress modes.
2. For all unimodal modes, walk is implicitly used as access and egress mode, because it is always necessary to walk a short distance to, e.g., your bike, car, or PT stop.
3. When WA, B or EB is used as main mode, the access and egress mode can only be WA.
4. If a traveler owns a MaaS subscription and he/she chooses to use B, EB or C, we let this traveler use a shared bike, shared e-bike or shared-car, even in case he/she owns these vehicles privately as well.
5. Transfers within public transport are possible, but not considered as a mode switch.
6. In scenarios without MaaS, cars should return home at the end of a tour.

7. In scenarios without MaaS, bike or e-bike should return home or can stay at hubs/stations at the end of a tour.

8. In scenarios without MaaS, when the car is the main mode, the access or egress mode should be WA. This simplification ensures that only one hub is used.

9. In scenarios without MaaS, B and EB cannot be used as egress mode in a sub-tour.

10. At a C-PT hub, C/CP can switch to PT or DRT mode, while PT or DRT can switch to C/CP mode.

11. At a C-PT hub, DRT can switch to PT, while PT can switch to DRT mode.

12. At a C-B hub, C/CP/DRT can switch to B/EB mode, while B/EB can switch to C/CP/DRT.

13. travelers can change their travel mode only once within a trip (walking excluded). To ensure that a multimodal mode always has one access mode, one main mode and one egress mode, either the access or egress mode is WA. B-PT-B is an exception. (Due to lack of service data we have not included EB-PT-EB; conceptually it is no problem to add this option once this data is available.)

14. C is only considered as main mode. This is because in The Netherlands, Park+Ride facilities are located at the edges of cities, so people typically prefer to use PT or B for the last part of their trip (CROW-KpVV, 2008). Hence, C is not used as an access and/or egress mode in this chapter.

The non-MaaS related rules are based on the large-scale travel survey OViN/ODiN (see (Centraal Bureau voor de Statistiek (CBS), 2018b)), while the MaaS-related rules are based on the judgement of stakeholders. Based on the considerations provided above, we end up with just 32 multimodal modes (out of the possible 343). They are provided in Figure 3.1.

It is worth stressing that our modeling framework is highly flexible. In principle, it can also include various other multimodal modes, thus also multimodal modes using C as access/egress mode, or multimodal modes that do not include WA. In the next section, we explain how to calculate the utility of multimodal modes.

3.2.3 Multimodal mode utility calculation

We now discuss the calculation of utilities of the multimodal mode alternatives. In particular, the utility function of multimodal modes is derived from the utility

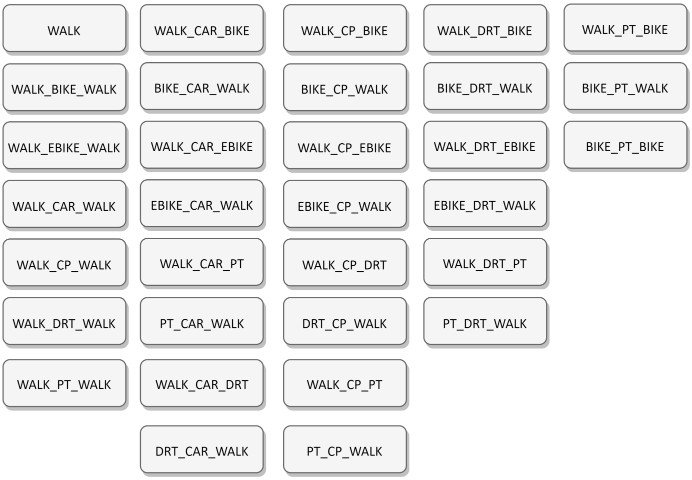


FIGURE 3.1: Selected multimodal modes

functions of unimodal modes. It covers socio-demographic attributes, travel times and costs.

The socio-demographic attributes include age, gender, driving license, household number of cars, household income, household composition, education level and activity type; there are N attributes, with C_j denoting the value of the j-th attribute. The parameters for these attributes and the mode alternative specific constant (ASC) are set equal to the parameters of the main mode of the trip. Intuitively, it would feel natural to also include the socio-demographic attributes and ASC of the access and egress mode in the utility function. This would however entail a comprehensive estimation of the associated coefficients, because these are not known in the literature. By including only the attributes of the main mode, we can use already known estimations based on unimodal modes, while we expect them to model the utility reasonably well.

The utility contributions of the search time (ST), travel time (TT), operational cost (O), start-up cost (SU), parking cost (P) are summed over the access, main and egress mode. Furthermore, a multimodal mode will consist of two transfers, from access mode to main mode and from main mode to egress mode. Hence, the utility contribution of the hub transfer time (T_{transfer}) is summed over these two transfers. In addition we include terms $\mu_{\text{multimodal}}$ and $\eta_{\text{multimodal}}$ that represent the errors made in computing the utility of the multimodal mode of the trip. In line with (Miller et al., 2005), the first term $\mu_{\text{multimodal}}$ is specific to the mode and traveler. It models the personal preference with respect to a mode, and is not resampled whenever the same mode/traveler combination is regarded for a different trip (both within a tour or across multiple tours), so as to enforce consistency. The second term $\eta_{\text{multimodal}}$ is not only specific to the model and traveler, but also to the actual trip. This term models any other random effects, and is resampled also when the same mode/traveler combination is considered for a different trip. We assume both of these terms to follow a normal distribution, each with mean zero and appropriately chosen variance. In summary, the utility function of the multimodal mode thus becomes:

$$\begin{aligned}U_{\text{multimodal}} = \text{ASC}_{\text{main}} + \sum_{j=1}^{N} \beta_{j,\text{main}} \text{C}_j &+ \sum_{i \in \{\text{acc,main,egr}\}} \beta_{\text{tt},i} (\text{ST}_i + \text{TT}_i) \\ &+ \sum_{i \in \{\text{acc,main,egr}\}} \beta_{\text{cost},i} (\text{O}_i + \text{SU}_i + \text{P}_i) \\ &+ \sum_{i \in \{\text{acc}-\text{main,main}-\text{egr}\}} \beta_{\text{tt,walk}} \text{T}_{\text{transfer},i} \\ &+ \mu_{\text{multimodal}} + \eta_{\text{multimodal}} \end{aligned} \tag{3.1}$$

Here, $\beta_{\text{tt},i}$ is the coefficient corresponding to travel time of the access, main and egress mode respectively (indexed by $i \in \{\text{acc}, \text{main}, \text{egr}\}$); the coefficients $\beta_{\text{cost},i}$ and $\beta_{\text{tt,walk}}$ are defined analogously. The transfer time at hubs is a constant: for C-B hubs it is set to 5 minutes, and for C-PT hubs to 8 minutes based on the public transport transfer times reported in (Schakenbos and Nijenstein, 2014). The transfer mode is assumed to be WA.

The travel time and travel cost differ for private and shared vehicles. It depends on the combined value of three personal attributes which one should be used: driving license, car ownership and MaaS subscription. If a person owns a MaaS subscription and has a driving license the utility of a car is computed using the attributes for shared vehicles even if she/he also owns a private vehicle. Otherwise the attributes of private vehicles are used. For bike or e-bike, it works similarly except for the fact that a driving license is not required.

It is worth noting that the utility function of a multimodal mode is based on that of a traditional unimodal mode. In fact, the utility function of a non-shared unimodal mode is given by

$$\begin{aligned}U_{\text{unimodal}} = \text{ASC}_{\text{main}} &+ \sum_{j=1}^{N} \beta_{j,\text{main}} \text{C}_j \\ &+ \beta_{\text{tt,main}} \text{TT}_{\text{main}} + \beta_{\text{cost,main}} (\text{O}_{\text{main}} + \text{SU}_{\text{main}} + \text{P}_{\text{main}}) \\ &+ \mu_{\text{unimodal}} + \eta_{\text{unimodal}} \end{aligned} \tag{3.2}$$

The differences that can be observed between (3.1) and (3.2) stem from the difference in nature between multimodal and traditional unimodal modes. For example, (3.2) does not include terms for the access and egress modes, as a unimodal mode only consists of a single (main) mode. Next to this, traditional unimodal modes do not include search times and transfer times, which is why they are not represented in (3.2) either.

3.2.4 Choice model

After the utility calculation, a multimodal mode choice is generated through the following two steps.

⋆ Step 1: *generate multimodal mode chain sets.* Using the 32 multimodal modes, we generate valid multimodal mode chain sets for each tour type by taking into account the long-term decisions made in an earlier stage of the ABM. In particular, we consider vehicle ownership and availability restrictions of the travelers. We also factor in mode consistency on a tour level. Vehicle ownership here should be interpreted as a combination of car, bike and e-bike ownership: there are 8 combinations ranging from not owning a vehicle to full ownership of all three vehicles. For each ownership combination, we calculate all valid multimodal mode chains of different tour types consisting of 2 trips, 3 trips, 4 trips without sub-tour, 4 trips including a sub-tour or 5 trips. In the settings we considered, these tour types typically cover the vast majority (more than 98% according to OViN data (Centraal Bureau voor de Statistiek (CBS), 2018b) between 2013 and 2015) of all tours. For other tour types the model chooses one of the seven unimodal modes. We apply the rules with respect to mode ownership, mode availability in the tour, locations where vehicles should be returned and mode allowance as explained in (Zhou et al., 2020b) in combination with the following rules for the situation without MaaS:

1. C is a valid main mode in an inbound trip when the egress mode is walk;
2. C is a valid main mode in an outbound trip when the access mode is walk;
3. B/EB is a valid access mode or egress mode in inbound and outbound trips (where it is recalled that (e-)bikes can be left at hubs/stations).

For instance, in a scenario without MaaS, if a tour consists of a trip from home to work and a trip from work back to home, the combination WA-C-B from home to work and B-C-WA from work to home is valid, whereas WA-C-B combined with B-PT-WA is not valid because the privately owned car has not returned home.

The description above is based on the condition that the travelling person does not have a MaaS subscription. If he/she does, then we relax all constraints on the mode choice per trip. This means that the traveler can pick up shared cars or bikes on all locations where they are available. Hence, the number of possible multimodal mode chains is simply the full combination of all 32 modes for each tour type.

⋆ Step 2: *select a multimodal mode chain from the set of valid multimodal mode chains.* To make a multimodal mode chain choice, we regard the set of valid mode chains as generated by step 1 corresponding to the individual's vehicle ownership, tour type and the main modes of the trips within the tour. Subsequently, we calculate the total utility of each multimodal mode chain in this set for the complete tour, by adding together the utilities of the (unimodal or multimodal) modes corresponding to each trip within the tour; cf. Equation (3.1). The multimodal mode chain having the highest utility will then be the selected multimodal mode chain. It is worth emphasizing that in this approach, we do not compute probabilities of which mode chain set should be selected. Due to the normally distributed error terms in (3.1) and (3.2), these probabilities would not allow for a manageable closed-form expression in this case. Rather, we select mode chain sets directly by checking which one corresponds to the highest utility. Due to the presence of the normally distributed error terms in the utility functions, stochasticity is however involved, so that this approach should not be mistaken with a deterministic approach. In fact, since the uncertainty in the utility functions is represented by a normally distributed component, the current approach is reminiscent of the multinomial probit choice model.

3.3 Illustrational example

In this section, we demonstrate how the ABM, that includes our tour-based multimodal mode choice model, can be used to simulate the travel demand. This we do by means of a large-scale numerical experiment, corresponding to the metropolitan region Rotterdam–The Hague (MRDH) in the Netherlands. In our setup we explicitly include, in the way discussed in the previous section, the scenario that MaaS and new mobility concepts are available. The type of results that we obtain illustrates the added value of our approach for assessing the impact of MaaS and new mobility concepts, and is as such an indispensable tool facilitating future policy evaluation.

As mentioned, first a population synthesizer (Snelder et al., 2021) has been used to generate a population. It contains, per individual, the home location, household situation, gender, driving license, education level, student public transport card, income level, roots of the individuals, bike type, vehicle type and urbanization level. For this illustrational case, we focus on the population of the cities of Delft, Pijnacker, Nootdorp and Zoetermeer, being located between the two major cities in the MRDH area (Figure 3.2). There are 278698 people (131466 households) living in this area in the year of 2016. 16% of the population is younger than 15, 15% is between 15 and 25, 26% is between 25 and 45, 27% is between 45 and 65 and 16% is older than 65.

The MRDH road network includes access roads besides the main roads, while outside MRDH only the main roads have been included. The network also contains hubs (depicted by the blue points in Figure 3.2), where travelers can transfer from car to (e-)bike or from car to PT and vice versa.

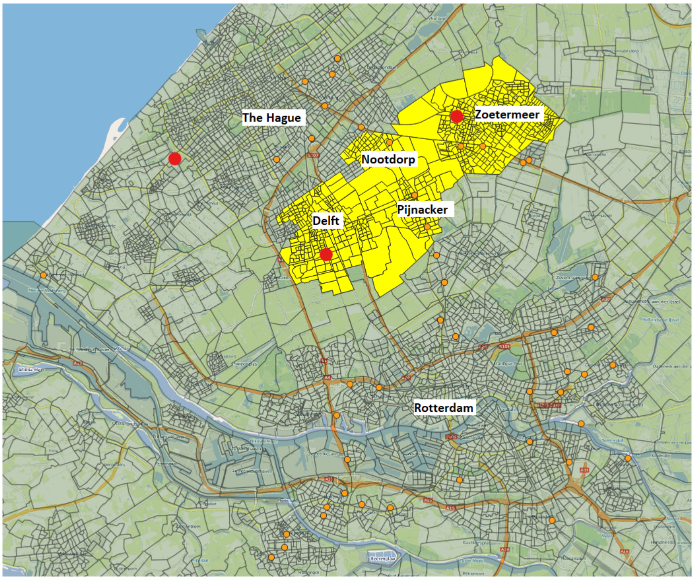


FIGURE 3.2: Population living area (in yellow) between The Haag and Rotterdam, the orange and red points are hubs

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 bike is allowed	Everywhere	
Factor speed (shared) e-bike	1.5	25 km/h: 15 km/h
Price shared e-bike	0.3 € /min	Felyx scooter
Search time for car sharing	5 min	
Price car sharing	0.1 € /min	Greenwheels
Start-up cost car sharing	0	Greenwheels
The area allowed for car sharing	Everywhere	
Factor speed car-sharing car	1	
Waiting time car passenger in 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
PCU value car passenger in shared-vehicle	1	
Area allowed for car passenger in shared-vehicle	Everywhere	
Factor speed DRT	1	
Waiting time constant DRT	0	
Price DRT per min	0	
Start-up cost DRT	€ 3.00	
PCU value for shared on demand	0.2	Assumed 5 passengers

TABLE 3.2: List of input parameters used in level of service

For each origin-destination pair, the level of service data (including distance, travel time and cost for the seven main modes directly) has been derived using the values presented in Table 3.2. Where applicable, the source of these numbers are mentioned in the table. If no source is mentioned, these numbers are assumption-based. If a shared mode happens not to be available at the origin or not allowed at the destination, then a very high impedance is imposed to ensure that the mode will not be selected (i.e., the model will assign a very low utility to this mode).

Parking rates per zone have been obtained in (RDW, 2015). While in practice parking rates tend to vary between days and over time, we have used a simplified approach in which parking rates are fixed (i.e., the rates of Tuesday afternoon 15.00h). The hourly parking rates in a zone are calculated as weighted averages of all parking places in the corresponding zone. We assume in our study that parking at hubs is free (but evidently the experiments can also be performed for situations with parking fees).

3.3.1 Model parameters

Since some unimodal and multimodal modes are at the moment hardly ever used, it is not possible to estimate all model parameters. In our case, we therefore decided to restrict the estimation to all unimodal modes for which sufficient data is available; here we rely on the large-scale travel survey OViN/ODiN (Centraal Bureau voor de Statistiek (CBS), 2018b) in the Netherlands for the years 2013–2017. The model parameters for DRT are inherited from the car passenger mode. The model parameters for the EB mode are based on those of the B mode. The utilities for the multimodal modes are computed using the parameters of the unimodal modes as explained by Equation (3.1). While we deem these numbers to be representative, setting up a detailed estimation of model parameters pertaining to MaaS and/or new mobility concepts is outside of the of this chapter. In this respect, it should be kept in mind that our primary objective here is to demonstrate the kind of scenario evaluation that can be performed with our approach.

3.3.2 Scenario description

Table 3.3 gives an overview of all scenarios that we considered in our illustration case. The reference scenario, scenario 1, disables the DRT mode (demand-responsive transport), so there are six unimodal modes. There are also no shared services, so people cannot rent a shared car or shared (e-)bike or use the DRT services. In all other scenarios the DRT mode is enabled.

In the scenarios having '16.5% MaaS' in their names, we assume that 10% of the people younger than 15 or older than 65 have a MaaS subscription, while 20% of the people between 15 and 65 have a MaaS subscription. As a result, on average 16.5% of the population has a MaaS subscription. In any of the MaaS scenarios, having a MaaS subscription implies that a person can use a shared car/bike/e-bike, or use a shared taxi, minibus or other shared mode, which does

#	Scenario name	MaaS subscription%	Run multimodal mode chain model	Parking cost w.r.t. normal	Operation Cost w.r.t. normal
1	Reference	0%	No	1.0	1.0
2	16.5% MaaS	16.5%	No	1.0	1.0
3	100% MaaS	100%	No	1.0	1.0
4	16.5% MaaS + MM	16.5%	Yes	1.0	1.0
5	100% MaaS + MM	100%	Yes	1.0	1.0
6	16.5% MaaS + MM + Parking 200%	16.5%	Yes	2.0	1.0
7	100% MaaS + MM + Cost 50%	100%	Yes	1.0	0.5
8	100% MaaS + MM + Cost 20%	100%	Yes	1.0	0.2
9	100% MaaS + MM + Cost 20% (excepts cars)	100%	Yes	1.0	0.2

TABLE 3.3: Scenario overview; 'MM' stands for multimodal.

not belong to the traditional public transport modes (bus, tram, metro, train). In the scenarios having '100% MaaS' in their names, 100% of the population has a MaaS subscription. In scenarios 2 and 3 multimodal trips are excluded. These scenarios show how MaaS and new mobility concepts can be included as main modes in a mode choice model, the numerical results providing an indication of the potential of shared mobility concepts and DRT. Scenarios 4 and 5 do include multimodal modes, so as to assess the added value of modeling access and egress modes and show the potential of hubs. In scenario 6 the parking costs have been increased, to study whether hubs in these circumstances are used more intensively to avoid higher parking costs. In scenarios 7 and 8 the operational cost of all modes have been reduced in order to study its effect on the mode choice. In scenario 9 this has also been done, except for the shared car mode. This way, one can quantify the possible impact of a flexible cost mechanism to further reduce car usage.

3.3.3 Scenario results

Using an ActivitySim implementation, which includes the model described in this chapter as the multimodal mode choice component, we have simulated the aforementioned nine scenarios. Each of these scenarios took about 5 hours to run on a server (CPU: Intel Xeon(R) 2.4GHz, Memory: 128 GB). We now proceed by discussing the numerical findings pertaining to the various scenarios. The modal split effects are shown in Figure 3.3. In scenarios 1 and 2, WA and B are the dominant modes because the main destinations are in the city centers. In scenario 2 the share of DRT trips is 7%, which is relatively high given the fact that the DRT mode is available for only 16.5% of the population; compared to scenario 1, these DRT trips mainly stem from WA and CP. There is also a modest (order of 1%) increase in e-bike trips. When everybody owns a MaaS subscription, in scenario 3, the total share of C trips decreases from 22.4% to 18% while the share of EB trips increases from 4% to 8%. So MaaS prompts people to choose the EB mode (instead of C). This also results in a significant decrease in the total number of car kilometres: this number goes down by as much as 7%.

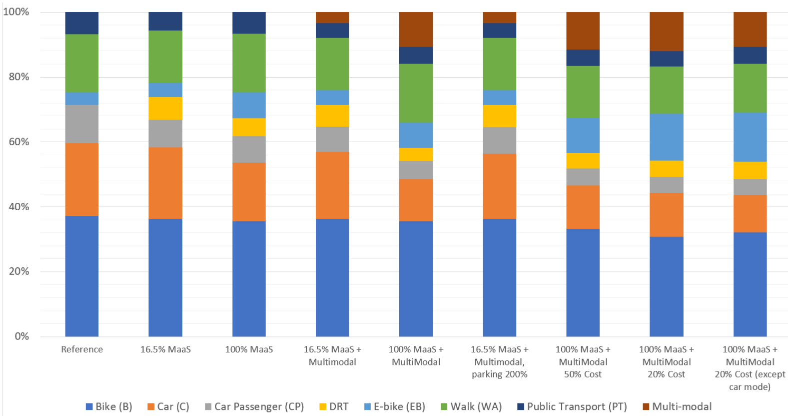


FIGURE 3.3: Modal split in different scenarios. Sharing and non-sharing trips are aggregated, and multimodal mode trips are aggregated.

In scenario 4, 3.3% of all trips use multimodal modes (such as combinations of C, PT and B/EB). Among those trips, 89% uses the C-PT hubs and 11% uses the C-B hubs. In particular, the share of trips using C-B hubs with private car and bike is only 0.05%. This low percentage is in line with our expectation because currently, the share of park and ride is also very low: in the OViN 2016 data, just 0.02% of all trips in the Netherlands uses a C-B hub.

In the extreme scenario 5, the total share of C trips reduces from 22.4% to 13%. Those C trips are mainly shifted to e-bikes and multimodal modes. This results in an increase by a factor of 2 of e-bike trips (to 7.9%), and an increase of multimodal mode use (to 10.7%). This shift can be explained by the fact that shared mobility concepts make it easier to use multimodal modes and do not impose any restrictions with respect to mode availability. The higher travel time via a hub is compensated by a reduced cost, recalling that car parking at hubs is free (as was assumed in Section 3.3.2) and that the cost for a shared e-bike is also relatively low (as can be seen in Table 3.2).

In scenario 6 the parking cost has been increased by 100%, relative to scenario 4. The total number of trips using a car has decreased from 20.8% to 20.1%. This small change can be explained by the fact that the daily parking costs are on average low for private car travelers. However, the number of trips using a private car, whose destinations are the three most visited paid parking zones, has reduced by 10.6% (from 2590 to 2316), which is again in line with what could be expected. Based on the modal splits observed for scenarios 5 and 6, we can claim that the mode choice is sensitive to MaaS subscription ownership and parking cost.

In scenario 7 and 8 the operational cost has been decreased to 50% and 20%, respectively, with respect to scenario 5. Compared to 7.9% of e-bike trips in scenario 5, the percentage of e-bike trips increases: it becomes 10.9% in scenario 7 and 14.5% in scenario 8. These trips have primarily shifted from bike trips and walk trips. The multimodal trips have also slightly increased to 11.6% and 12%, respectively, compared to 10.7% in scenario 5 due to the overall lower cost.trave

In scenario 9, again all operational costs have been decreased to 20%, but this time except for the private and shared car modes. The total car trips percentage decreases to 11.5% compared to 13.5% in scenario 8. Those car trips have mainly shifted to other unimodal modes.

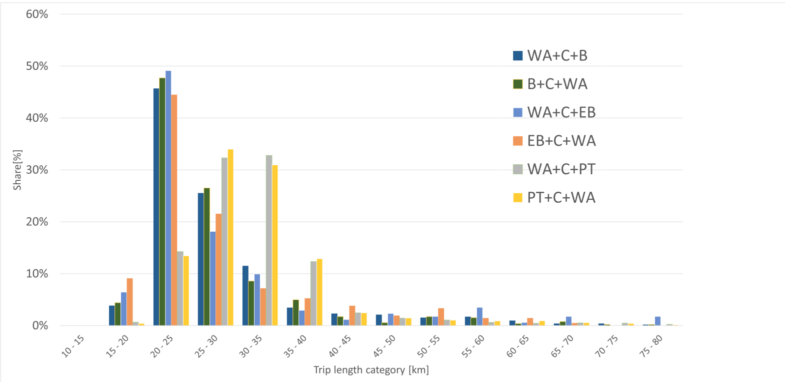


FIGURE 3.4: Trip length distribution for WA+C+B/EB, WA+C+PT

We continue, in Figure 3.4, by analyzing the resulting trip length distribution of a few multimodal modes of scenario 4, normalized by the total number of trips per mode. Clearly, C-PT hubs are used for longer trips than the trips C-B hubs are used for. The top 3 most visited hubs are the hubs located on the boundaries of the cities Delft, Zoetermeer and The Hague (the three red circles in Figure 3.2). This makes sense, as travelers prefer to switch from C to B/EB or PT to enter the cities and switch back to C when leaving the cities.

As a further sanity check, we zoom in on one specific hub ('Kralingse Zoom', located near the highway pass through Rotterdam), particularly focusing on the W-C-B mode. Figure 3.5 shows the origins and destinations of travelers using this hub. When considering scenario 4 instead of the reference scenario 1, on average the traveled distance increases by 2.1 km and the travel time by 10 minutes. This may be surprising, as there seems to be no incentive for a shift to a mode having

FIGURE 3.5: Trip origins (yellow blocks) and destinations (light red blocks) using the same hub (red point) by the WA+C+B mode.

higher travel distance or travel time. However, there are no parking costs involved when transferring at a hub. As a result, the utilities of the W-C-B mode and the car mode are in general close to each other. Because of traveler heterogeneity, modeled by the error terms, multimodal modes such as the W-C-B mode will be chosen in scenario 4, as compared to the reference scenario. The average extra 2.1 km travel distance can be covered by bike: when a bike is used as access/egress mode for PT the average cycle distance is between 1-3 kilometers (Jonkeren et al., 2018), thus confirming the plausibility of our results.

3.3.4 Sensitivity analysis

There are two normally distributed error terms incorporated into the utility function, so as to represent the unobserved utility; see Equation (3.1). For both normal distributions, we choose 0 as mean without loss of generality, and an adjustable σ as standard deviation. In our calculations, we picked σ such that the standard deviation of the sum of the two error terms equals 50% of the average absolute utility of all modes.

We have in addition run experiments where σ was set so that the standard deviation of the combined error terms was equal to only 10% of the average absolute utility. In this case, in scenario 4, the percentage of multimodal trips reduced from 3.3% to 1.5%. Hence, with a small standard deviation, the multimodal modes are unattractive compared to the unimodal modes. This can be explained by the fact that the mode having the highest utility is selected, and generally the utilities of unimodal modes are higher than that of multimodal modes. This experiment quantifies the impact of σ on the modal split; in general, an appropriate value of σ can be identified e.g. by using survey data.

3.4 Conclusion and discussion

In this chapter, we presented a novel tour-based multimodal mode choice model for the impact assessment of new mobility concepts and Mobility as a Service. It includes mode consistency restrictions with respect to personal vehicle ownership, MaaS subscription ownership and vehicle states. We also introduced the concept of mode categorization. More specifically, we showed that a categorization into seven main modes includes most of the traditional modes and new mobility concepts like micro-modalities and on-demand public transport. Other new modalities can be added to the framework as well, and the model can deal with both shared and non-shared modalities. The categorization helps to reduce selection bias, while it induces numerical efficiency: our model is able to handle large scenarios up to millions of inhabitants. A possible drawback of categorization, however, could be that it introduces heterogeneity issues. That is, travellers could still have different personal preferences regarding two modes in a single category, leading to anomalous choice behavior. Solving these heterogeneity issues is a topic for further research. That is, by selecting different aspect elements than those chosen in Section 3.2.1, or even choosing different aspects, this issue may be reduced to a minimum. With this model, insight in the expected impact of new mobility concepts and Mobility as a Service on mode choice can be obtained. Moreover, it can be used to analyze the accessibility of hub locations in the future.

Since the multimodal mode choice model has been integrated in an ABM, the impact of new mobility concepts and MaaS on trip activities and destination choice can also be explored. However, this requires a connection with a multimodal traffic assignment. Such a connection would also make it possible to assess the impact of changes in mode choice on travel times which in turn can affect activity, destination and mode choice. Since this chapter does not integrate our model in a multimodal assignment model, only first-order impacts have been presented, which implies that some effects might have been slightly overestimated, especially in congested areas. Therefore, we recommend to integrate our model within a multimodal traffic assignment model.

Concerning the multimodal mode alternatives, we have assumed them in this study to include just a single main mode. However, one may reason that there may be more than one main mode used within a single trip. For example, think of a park and ride service, which uses both a car and a public transport mode. Although inclusion of multiple main modes in a multimodal mode alternative is no problem from a modeling point of view, this will aggravate the computational complexity because of the exponential increase in the number of mode combinations. This is a point for further research.

Next, in the current study, in the utility calculation of the multimodal mode alternatives only the ASC and the socio-demographic attributes of the underlying main mode are considered. The reason behind this is that in this way, previously estimated coefficients of these attributes in a unimodal setting could be used. This however leads to the possibly undesirable effect that personal preferences on the various access or egress modes are not taken into account. To include these modes, a comprehensive estimation of coefficients in a multimodal setting is required. A possible approach could be that of dynamic discrete choice modelling studied by (Hasnine and Habib, 2018).

Finally, when making multimodal mode choices, the model either requires the traveler to fully use their private vehicles or shared vehicles, without allowing a mixed use of private and shared vehicles. This can be improved by adjusting the mode consistency check in such a way that mixed use is also possible or by introducing a rule-based approach: e.g. when a private vehicle is available in the tour, the private vehicle is included in the choice set and otherwise the shared vehicle is included in the choice set. Moreover, mobility packages (Esztergár-Kiss and Kerényi, 2020) and the type of sharing services such as free-floating or station-based sharing also affects the multimodal mode choice patterns (Kopp et al., 2015). Since we have assumed free-floating services in a situation with MaaS, the model can be improved by including station-based sharing.

4

GPU-BASED PARALLEL COMPUTING FOR ACTIVITY-BASED TRAVEL DEMAND MODELS

Activity-based travel demand models (ABMs) are gaining popularity in the field of traffic modeling because of their high level of detail compared to traditional travel demand models. Due to this, however, ABMs have high computational requirements, making ABMs hard to use for analysis and optimization purposes. We address this problem by relying on the concept of parallel computing using a computer's graphics processing unit (GPU). To illustrate the potential of GPU computing for ABM, we present a pilot study in which we compare the observed computation time of an ABM GPU implementation that we built using NVIDIA's CUDA framework with similar, non-parallel implementations. We conclude that speed-ups up to a factor 50 can be realized, enabling the use of ABMs both for fast analysis of scenarios and for optimization purposes.

4.1 Introduction

With the advent of new mobility services such as Mobility as a Service (MaaS), travel demand models are indispensable as they forecast travel demands of the population under alternative circumstances. These forecasts allow traffic supply models to assess the future performance of traffic networks. Activity-based travel demand models (ABMs) view travel demand as a result of people's desires to participate in activities. Based on behavioral theories, they predict the activities which individuals will undertake, which then translate to travel demand forecasts. ABMs stand out as compared to traditional travel demand models due to their high level of detail. This is partly due to the fact that ABMs model activity behavior on an individual level, rather than on an aggregated level. They do this by keeping track of individual agents separately. More particularly, for this purpose, ABMs may include probabilistic choice models to allow individuals to have mutually different behavior, although they might have the same behavior characteristics. As a result, ABMs tend to make more reliable travel demand forecasts. As mentioned in (Zhang and Levinson, 2004), ABMs and agent-based modeling are intimately related. For more background, see (Bhat and Koppelman, 1999; Castiglione et al., 2015; Arentze and Timmermans, 2004).

The high accuracy level of ABMs, though, does come at the price of high computational requirements. An ABM studied in (Heinrichs et al., 2018) involving a scenario with a population size of three million is reported to take 4 hours to run a single iteration on an Intel Xeon processor with 16 cores, 32 threads at 3.4GHz and 64GB of RAM. Due to the stochastic nature of the model, however, many runs are required to produce reliable forecasts. On top of this, the use of ABMs for optimization purposes requires the analysis of many scenarios. In such cases, it is clear that the computation time of ABMs becomes unacceptably high. In this chapter, we address this problem by presenting a method to reduce the computation time of ABMs.

In the literature, several attempts to reduce computation times have already been made (Bradley et al., 1999). Most aim to do this by reducing the level of detail, for example by running the ABM only with a fraction of the population (Kwak et al., 2012) or by reducing the number of possible activity locations (Saleem et al., 2018). However, this detail reduction is not desired, as this reduces the accuracy of the forecasts. Therefore, another strategy for computation time reduction is required. For a related model based on genetic algorithms, such a strategy can be found in (Wang and Shen, 2012), which is based on the use of a computer's graphics processing unit (GPU). GPUs can also be used to reduce computation times in MATSim, which is an open-source framework implementing large-scale agent-based transport simulations (Strippgen and Nagel, 2009).

Inspired by this, we propose in this chapter the use of GPU-based parallel computing in ABMs. We contribute to the existing literature by explaining how to implement parallel computing using the fact that an ABM is comprised of a large number of independent computations, which can be done in parallel. This independence stems from the fact that activity schedules of individual persons are mostly uncorrelated, so that these schedules can be generated concurrently. ABMs do acknowledge the fact that dependence may arise between persons within a particular household. In these cases, however, parallel computing can still be incorporated on a household level. We propose the use of a computer's GPU instead of its CPU, as GPUs are designed for parallel computation purposes. To our knowledge, the use of parallel computing using a computer's GPU, has not been considered before in an ABM context in combination with discrete choice models.

Next to explaining how GPU-based parallel computing can be done in ABMs, we explore the speed-up in computation time that can be realized. To this end, we implemented GPU-based parallel computing in one of ABM's computational components using NVIDIA's Compute Unified Device Architecture (CUDA) (NVIDIA, 2007). By using the CUDA framework, a function can be executed on many data elements in parallel. Hence, by exploiting the independence properties mentioned above, households and/or persons can be processed in parallel by many different CUDA threads. We performed a pilot study, from which we conclude that for realistic scenario sizes, speed-ups of up to 50 in terms of computation time can be realized compared to a similar non-parallel implementation based on the open-source ABM-package ActivitySim (Gali et al., 2008). This speed-up relieves the above-sketched problem, and paves the way for the extensive use of ABM in the analysis and optimization of any given model scenario.

The remainder of this chapter is organized as follows. Section 4.2 provides an explanation of how ABMs work. Then, we explain in Section 4.3 how GPU-based parallel computing can be implemented into the framework of ABM. Subsequently, Section 4.4 presents the pilot study, after which conclusions are presented in Section 4.5.

4.2 The activity-based travel demand model

In this section, we consider ABMs in more detail. The goal of an ABM is to predict a complete activity schedule for every member of the population on a given day, which in turn leads to travel demand forecasts. After a preliminary phase where the scenario along with its population is built using input data (surveys, etc), ABM essentially consists of four components making subsequent choices for each person which fulfill the goal. The first component makes several long-term choices for each person (e.g. concerning ownership of a car, the location of school or work, etc.), based on which the second component chooses for every individual on a daily level what the main activity purpose will be (work, leisure, etc). Given this purpose, the third component subsequently generates and schedules the tours each person that day undertakes (e.g. home-work-home), along with the preferred travel mode (e.g. car, train, etc). The final component then decides on the individual trips that make up this tour, and schedules the trips during the day and the travel mode of each trip.

While all components make decisions for each person on different levels of detail, they are typically made using the same discrete choice model such as the multinomial logit model. In this model, each alternative i from an alternative set $\mathscr{I}$ is associated with a utility value V_i that is computed by

$$V_i = \alpha_i + \sum_{j=1}^{N} \beta_{i,j} C_j. \tag{4.1}$$

Next to an alternative-specific constant α_i, the utility V_i is driven by a linear combination of the attributes $C_1, \ldots, C_N$ of the chooser (think of a person's age, size of household, etc.) and the $\beta_{i,j}$ represent their coefficients for alternative i. The determination of the constant and the coefficients in (4.1) comprises an area of research that is beyond the scope of this chapter. It is worth emphasizing, however, that fitting a utility function to reality is never done perfectly, and thus an error term ϵ_i should be included to represent the non-observable utility of an alternative. The multinomial logit model assumes that a traveler will choose the alternative i with the highest utility $U_i = V_i + \epsilon_i$. Furthermore, it is assumed that the error terms are mutually independent and Gumbel distributed. From these assumptions, it follows that the choice for alternative i is made with probability

$$P_i = \frac{e^{V_i}}{\sum_{j \in \mathscr{I}} e^{V_j}}. \tag{4.2}$$

Through simulation, the choices in each of the components can now be sampled. This leads to scheduled activities for each person in the population, which translates directly to travel demand forecasts. Because of the stochastic nature of this approach, multiple model iterations are required to obtain reliable forecasts. For more background on the components of ABM and its underlying discrete choice models, see Chapter 3 in (Castiglione et al., 2015).

For illustrative purposes, we now focus on the second mentioned component, the daily main activity purpose (DAP) component, in more detail. This is the component in which we will implement GPU-based parallel computing for our pilot study in Section 4.4. Below, we describe the setup of the DAP-component as implemented in ActivitySim. Recall that the goal of the DAP-component is to make choices concerning the main activity purposes of persons. For each person, there are three alternatives, namely staying home (H), a mandatory activity such as school or work (M), or a non-mandatory activity such as shopping (N). Since there is dependence between persons within households, the component incorporates the following steps per household.

1. First, the importance rank of each person in the household is determined based on the persons' attributes. This is done to determine the exact dependence between persons of a household, as will become clear in step 3.

2. Then, the utility of all alternatives (H, M, or N) for each person in the household is determined using (4.1). The attributes of this function include age, income, etc.

3. Subsequently, the utility for all alternatives within a complete household is determined, where importance ranks are taken into account. For a three-person household, one of these alternatives for example is 'HMN', where the most important person stays home, the next important person has a mandatory activity purpose, etc. The utility function on a household level again has the form of (4.1), where the utilities computed in the previous step act as attributes.

4. Sample daily activity purpose choices for all of the households, using random number generation in combination with (4.2).

4.3 GPU-based parallel computation of an ABM's components

Based on the ideas of the previous section, we explain now in more detail how GPU-based parallel computing can be utilized and implemented for the DAP component. It is worth to note, however, that computations of the three other components consist of similar steps to those of the DAP component, and hence all of them are amenable to parallel computing, increasing its potential of reducing computation times.

It is clear that the above-mentioned steps of the DAP involve computations which are mutually independent between households. Therefore, these steps can be performed simultaneously for different households. Figure 4.1 shows the computational stages that are involved in the DAP-component. The left block shows the stages which are not parallelized and thus run on the CPU. This includes reading data needed for the computation, such as the attributes of every household and its members corresponding to the C_j in (4.1), as well as the alternative-specific constants (α_i) and the coefficients ($\beta_{i,j}$). Note that part of the attributes C_j incorporate output of the long-term choice component preceding the DAP-component. This data is then copied from the computer's RAM to the GPU's memory.

The right block, in contrast with the left block, involves stages that are run by the GPU and thus contain the parallel computations. The first of the DAP-component's steps mentioned in Section 4.2 requires sorting of importance levels. The second and the third steps entail the calculation of each alternative's utilities using (4.1), and the fourth step involves random number generation in combination with the calculation of (4.2). We now elaborate on how each of these computational tasks can be handled in parallel fashion using the CUDA framework. The sorting can be done efficiently since CUDA exploits the shared memory in the GPU. Then, the utility function in (4.1) is calculated by multiplying attribute values (the C_j) with their corresponding coefficients (the $\beta_{i,j}$) and adding a constant (α_i). As (4.1) needs to be calculated for every alternative and every chooser, the required computations brought by (4.2) can be interpreted as a matrix-matrix multiplication. Such matrix operations can be done efficiently in parallel using the CUDA library cuBLAS (NVIDIA, 2017b). Likewise, random numbers can be generated efficiently by use of the cuRAND library (NVIDIA, 2017a). Finally, for each chooser, the alternative choice is made by computing (4.2) for every alternative and subsequent sampling using a generated random number. These computations can be done in parallel quite naturally (and hence need no specific library) in case the alternative choices of the choosers are uncorrelated. When a household is the

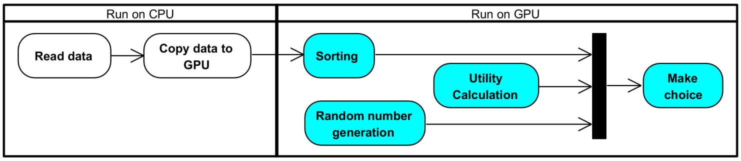


FIGURE 4.1: The non-parallel (left block) and parallel stages (right block) of a component's computations.

chooser, this is always the case in the DAP-component.

As mentioned, all parallel computations mentioned above are implemented using the CUDA architecture. This architecture facilitates efficient parallel computation by using the structure of arrays/vectors to store data.

As the most time-consuming computations are now done parallelly, we anticipate significant speed-ups in computation time. In the next section, we investigate how large these speed-ups can be.

4.4 Pilot study and resulting speed-ups

We now perform a pilot study, which compares the computation times of a DAP-component implementation using GPU-based parallel computing by way of the CUDA architecture as explained in Section 4.3, with those of a similar implementation using the CPU (which is optimized for the CPU) and the implementation of ActivitySim. Both of the latter two components do not incorporate parallel computing. These comparisons are done for different numbers of population sizes, attributes and alternatives in Sections 4.4.1, 4.4.2 and 4.4.3, respectively, to get a feel of their impact on the computation time. The computation time of the GPU implementation includes the time of data transfer between the RAM and the GPU memory, but excludes the time of reading data into the host memory since this time is the same for both the GPU and the CPU implementation.

The computation times of each of the implementations are based on two different datasets, which can be downloaded from (Metropolitan Transportation Commission, 2016). Dataset 1 contains 369845 households with 797674 persons and thus has an average household size of 2.15. We also consider a larger dataset; dataset 2 contains 2732722 households with 7053334 persons and an average household size of 2.58. For each dataset, we use ActivitySim to export partial test sets containing different numbers of households, so that we can report computation times for differently sized scenarios. For each of these scenarios, we present the speed-ups in computation time of the GPU-based implementation as compared to the CPU-based implementation and the ActivitySim-implementation. All computation times and speed-ups presented in this section are based on computations run on a Windows desktop PC with an Intel Core i9-7900X 3.30GHz CPU, 32 GB

RAM, and a NVIDIA GeForce GTX 1080Ti GPU with 3584 CUDA cores and 11 GB memory. In particular, for each computation time or speed-up presented, we ran the underlying actual scenario four times, and took the average of the four computation times.

We have chosen to compare our GPU-based implementation not only with a similarly-coded CPU-based (non-parallel) implementation, but also with the implementation of ActivitySim. We have done this for reference purposes. It is worth emphasizing, however, that the ActivitySim package is written in Python, whereas our GPU and CPU-based implementations are written in C/C++. Python is a programming language that is interpreted, while C/C++ is compiled. This creates additional speed-up effects which cannot be attributed to the introduction of parallel computing. The speed-up of the GPU-based implementation with respect to the CPU-based implementation, however, can be fully attributed to parallel computing.

4.4.1 Speed-ups for different population sizes

We first present the sensitivity of the speed-up to the actual population size of a scenario, which is highly correlated with the number of households. As we can see in Tables 4.1 and 4.2 for each dataset respectively, the speed-up of the GPU-based implementation as compared to the CPU based implementation is sensitive to the population size. For small populations, the speed-up is not very high as the overhead of the left block in Figure 4.1 is then significant. For larger populations, though, the parallelisation capabilities of the GPU can be used to its full potential, as more computations can be done in parallel. We reach speed-up values up to 35 for the DAP-component, from which we conclude that GPU-based parallel computing has a profound potential in ABM. It is interesting to note that the speed-up with respect to the ActivitySim implementation is also increasing. The difference in computation time between the ActivitySim implementation (up to 2.5 minutes) and the study referred to in Section 4.1 (about 4 hours) is due to the fact that we only consider the DAP-component in this section rather than a complete ABM implementation.

4.4.2 Speed-ups for different numbers of attributes

We now consider the speed-ups when varying the number of attributes (N in Equation (4.1)) considered in the utility functions underlying the DAP component, based on dataset 2 with 2732722 households. Table 4.3 shows results for this dataset using utility functions with the original number of attributes (1x), as well as twice and thrice this number of attributes (2x and 3x). When the number of attributes becomes higher, the speed-up of the GPU-implementation over the CPU-implementation hardly increases. This is because parallel computing allows for

TABLE 4.1: Computation time comparisons for dataset 1 when varying the number of households. Asim, CPU and GPU refer to the computation times of ActivitySim's DAP-implementation, our CPU-based DAP-implementation and our GPU-based DAP-implementation, respectively.

Number of households	Population size	Asim [*seconds*]	CPU [*seconds*]	GPU [*seconds*]	Speed-up GPU w.r.t Asim	Speed-up GPU w.r.t. CPU
150000	323911	14.29	2.64	0.48	29.7	5.5
300000	646920	19.33	5.07	0.56	34.7	9.1
369845	797674	21.69	6.12	0.59	36.4	10.3

TABLE 4.2: Computation time comparisons for dataset 2 when varying the number of households.

Number of households	Population size	Asim [*seconds*]	CPU [*seconds*]	GPU [*seconds*]	Speed-up GPU w.r.t. Asim	Speed-up GPU w.r.t. CPU
150000	387268	15.81	3.44	0.52	30.5	6.6
300000	774027	22.38	6.79	0.59	37.8	11.5
369845	953841	25.53	8.27	0.63	40.8	13.2
1000000	2578064	55.70	22.52	0.98	56.6	22.9
2000000	5162014	110.57	45.20	1.50	73.7	30.1
2732722	7053334	150.43	61.79	1.77	85.2	35.0

the concurrent evaluation of different utilities (cf. Equation (4.1)), but the evaluation of a single utility itself cannot be parallelized efficiently. The increasingness of the speed-up factor with respect to the ActivitySim implementation is an effect that cannot be attributed to the incorporation of parallel computing.

TABLE 4.3: Computation time comparisons for different numbers of attributes.

Number of households	Population size	Number of attributes	Asim [*seconds*]	CPU [*seconds*]	GPU [*seconds*]	Speed-up GPU w.r.t. Asim	Speed-up GPU w.r.t. CPU
2732722	7053334	1x	150.43	61.79	1.77	85.2	35.0
2732722	7053334	2x	171.50	63.29	1.83	94.0	34.7
2732722	7053334	3x	189.85	65.45	1.87	101.7	35.1

4.4.3 Speed-ups for different numbers of alternatives

Table 4.4 shows the speed-up factors that we obtain when varying the number of alternatives. The computation times reported are based on the same dataset 2 used in Section 4.4.2. We vary the number of alternatives in the second step of the DAP-component (cf. Section 4.2) between 3 and 5. This means that for a household with e.g. five members, the number of different alternatives on a household level (i.e. the third step of the DAP-component) varies between $3^5 = 243$ and $5^5 = 3125$. We deduce that also when increasing the number of alternatives, the speed-up of the GPU-based implementation with respect to the CPU-based implementation increases significantly, up to a factor of 50, again marking the potential of GPU-based parallel computing. This is explained by the fact that increasing the number of alternatives also increases the number of utilities that need to be calculated, which can be done in parallel. It is interesting to note that the speed-up with respect to the ActivitySim implementation increases significantly when the number of alternatives become larger.

TABLE 4.4: Computation time comparisons for different numbers of alternatives.

Number of households	Population size	Number of alternatives	Asim [*seconds*]	CPU [*seconds*]	GPU [*seconds*]	Speed-up GPU w.r.t. Asim	Speed-up GPU w.r.t. CPU
2732722	7053334	3	150.43	61.79	1.77	85.2	35.0
2732722	7053334	4	185.09	77.60	2.04	90.8	38.1
2732722	7053334	5	319.59	109.82	2.28	140.3	48.2

4.5 Conclusion and future research opportunities

In this chapter, we introduced parallel computing using a computer's GPU to reduce the computation time of ABMs. We implemented GPU-based parallel computing into the DAP-component, and compared its computation time to those of other implementations that do not perform parallel computations. We observed that speed-up factors of up to 50 can be obtained, and that they are highly sensitive to the number of households and the number of alternatives contained in the scenario. We conclude that GPU-based parallel computation addresses the problem of high computations times to a large extent.

The observed speed-up enables the use of ABMs for optimization purposes as well as extensive scenario analysis, which opens up an area of further research. For example, we plan to explore the impact of new smart mobility concepts such as autonomous vehicles and mobility as a service (MaaS) in future work. These concepts introduce more interaction between individuals, which brings the challenge of sharing information among threads in a parallel implementation. Another option is to include additional information in a scenario, such as the weather condition.

5

On the use of common random numbers in activity-based travel demand modeling for scenario comparison

Activity-based travel demand models provide a high level of detail when modeling complex travel behavior. Since stochastic simulation is used, however, this high level may induce large random fluctuations in the output, necessitating many model reruns to produce reliable output. This may become prohibitive in terms of computation time when comparing travel behavior between multiple scenarios, in which case each scenario requires its own simulation.

To alleviate this issue, we study the use of common random numbers, which is a technique that reuses the same random numbers for choices made by travelers between scenarios. This ensures that any observed difference in output across scenarios cannot be attributed to mutual differences in drawn random numbers, eliminating an important source of random fluctuation. We demonstrate by a numerical study that common random numbers can greatly reduce the number of runs needed, and thus also the required computation time, to obtain reliable output.

5.1 Introduction

In this chapter, we study an efficient simulation method to compare the travel demand behaviour under different traffic scenarios by means of activity-based travel demand modeling (ABM). Owing to its flexibility, robustness and high level of detail, ABM offers a highly suitable methodology to model complex travel behaviour. In travel demand simulation, for each individual, ABM predicts what, where (destination), when (time) and for how long (duration) travel activities are conducted as well as which mode chain of transport is involved (Rasouli and Timmermans, 2012). To achieve this high level of detail, ABM consists of different discrete choice models which successively make choices on e.g. destinations, time, duration, and mode. In most cases, these models adopt a simulation approach that makes choices based on (pseudo-)random numbers. The variability caused by the generation of these random numbers however trigger random fluctuations in the output of the ABM (Vovsha et al., 2008), also referred to as simulation error. This may cause the activity-based model to have to be rerun many times in order to get reliable results, which may not be feasible due to the excessive simulation effort required.

As mentioned above, ABM models travel behaviour at a high level of detail, and thus provides output at a very low level of aggregation. In the literature, multiple studies have shown that the lower the level of aggregation of a model's output is, the more profound the issue of variability/simulation error becomes, underlining the fact that this is especially a complication for ABM. Indeed, while (Veldhuisen et al., 2000) concluded that in the context of their RAMBLAS framework the simulation error is negligible when studying the output at a highly aggregated level, (Castiglione et al., 2003) confirmed this finding based on a case study on the travel demand in San Francisco but with the remark that simulation error becomes problematic when there are many choice alternatives or when some of these alternatives are very rare. To quantify these effects, (Bao et al., 2015) used FEATHERS to determine the minimum number of runs required to obtain enough 'confidence' at different aggregation levels, i.e., the minimum number of runs required so that the output is sufficiently reliable. The results of this work indicate that the lower the aggregation level is of the desired output, the more model runs are required. We also mention (Horni et al., 2011), where the random variability over multiple runs of MATSim is studied by analyzing travel demand on specific road links in a traffic network. The authors concluded that there is relatively little variability when regarding daily volumes, but that variability is significant when considering hourly volumes. This is in line with the fact that the lower the aggregation level of the results is, the more variability becomes an issue. It is worth noting that in traffic modeling, travel demand models and travel assignment models are often used in an alternating way, so that unreliable results in travel demand have direct ramifications for travel assignment. These ramifications have been studied in e.g. (Vovsha et al., 2008; Horni et al., 2011; Bekhor et al., 2014).

While the studies mentioned above are mainly focusing on the model output of a single traffic scenario, the issue of simulation error is even more profound when comparing multiple traffic scenarios for the purpose of quantifying the difference between them. Especially when the actual difference between scenarios is not very large, much computation time may have to be spent to produce a reliable output for each of the scenarios, before any conclusion can be drawn regarding the difference. In this context it should be noted that when differences between scenarios are small, this does not necessarily mean that such differences are by definition irrelevant. For example, even when a certain scenario leads to only a 2% increase in the number of trips undertaken, in the regime of a highly loaded network this may have a significant impact on the level of congestion.

In this chapter, we discuss techniques to control the simulation-error issue in this multi-scenario context. More particularly, we study the use of the technique of *common random numbers* (CRN) to overcome the problem of requiring too many simulation runs to reliably estimate the simulation error. CRN is a celebrated technique stemming from the stochastic simulation community that attempts to induce a positive correlation between the outputs of different scenarios. It does so by using the same generated pseudo-random numbers for the same purposes across the simulation of different scenarios. When doing this, the observed difference in the model output for the different scenarios can then not be attributed to the fact that random numbers across scenarios differ, which is one of the sources of simulation error. This increases the likelihood that any difference in observed model output is a result of the intrinsically different features of the scenarios. This means that the number of required simulation runs will decrease, and as a result it induces less required computation time. For a more detailed explanation on CRN, see (Glasserman and Yao, 1992) and Section 9.7 of (Ross, 2013). In the context of activity-based travel demand modeling, the use of CRN in has been suggested before in e.g. (Vovsha et al., 2008) and has been implemented in CEMDAP (Pinjari et al., 2008). However, to the best of our knowledge, there has been no quantitative study on the added value of CRN in terms of required number of runs and computation time savings. This chapter seeks to fill that gap. More particularly, in the sequel of this chapter, we aim to show how computation times can be shortened drastically by using CRN.

The contributions of this work can be summarized as follows. First, we demonstrate how to implement CRN in an activity-based travel demand model to compare multiple scenarios. We do this based on an extension of an activity-based travel demand model, which was recently developed by the authors (Zhou et al., 2020a). This extension integrates a tour-based multimodal mode choice component in the activity-based model, which makes travel mode choices on a tour level using a multinomial probit choice model. We however stress that the technique of CRN can also be applied to all other components of an ABM, also those based on a multinomial logit choice model, which we will also cover. Secondly, based on this extension, we demonstrate the potential of CRN when assessing multiple scenarios, in particular with regard to the question which scenario is more favorable (according to a given criterion). We do so by analyzing the variability of the difference between the model output of these scenarios, with and without the implementation of CRN, and we will conclude that the implementation of CRN greatly reduces this variability (measured in terms of the sample variance of the differences). As a result, to obtain reliable output, only a fraction of the earlier required simulation runs is still needed. For example, we show that, to keep the width of the confidence intervals of simulated indicators under a certain level, a reduction of the number of required simulation runs by a factor 100 is not an exception, which evidently has a drastic effect on the computation time needed. It turns out that CRN is especially worthwhile when the order of magnitude of the differences between the scenario outputs is either not too large, in which case traditional methods are already able to reliably indicate which scenario is favorable in an acceptable amount of time, or not too small, in which case the scenarios hardly differ in terms of the indicator studied anyway. We back all the aforementioned claims by studying numerical results of our extended model based on data of the metropolitan region Rotterdam-The Hague in The Netherlands stemming from various sources, such as (Snelder et al., 2021; Van de Werken, 2018).

The remainder of this chapter is organized as follows. Section 5.2 explains how CRN can be incorporated in an activity-based travel demand model. It furthermore introduces several ways of assessing the impact of CRN, such as by computation of the minimum required number of runs in order to keep confidence interval widths limited. In Section 5.3, we present the numerical study investigating the potential of CRN, which leads to the findings mentioned above. Finally, Section 5.4 presents conclusions and a brief discussion.

5.2 Method

An activity-based travel demand model makes, based on generated random numbers, choices at several levels. That is, from the perspective of a traveler, subsequent choices are made on long-term decisions, number of tours to be undertaken during a day, number of trips to be undertaken in each tour and finally the start time, duration, destination and mode of each trip. Since stochasticity is introduced on each of these choice levels, the final model output may be prone to large random fluctuations, which may lead to having to rerun the model many times and average the results to obtain reliable output. To address this issue, the use of CRN may be introduced at any of these levels. In Section 5.2.1, we demonstrate how to do this for activity-based travel demand models. Then, in Section 5.2.2, we describe several ways to assess the impact of CRN.

5.2.1 CRN generation in ABM

To explain the implementation of CRN into an ABM, we take previous work (Zhou et al., 2020a) as an example, which concerned an extension of ActivitySim (Gali et al., 2008) based on a multinomial probit choice model. We also explain how to apply CRN to a multinomial logit choice model.

5.2.1.1 Multinomial probit choice model

As an activity-based travel behavior model, ActivitySim produces random numbers to make choices on the level of individuals, households, tours and trips. For instance, at an individual level, random numbers are used to select the individual's choice on the location of work or school, while at a trip level, they are used to make choices for trip duration and destination. To apply CRN, one needs to make sure that across different scenarios, the same random numbers are used for the same choices, even when the scenario input is different. While ActivitySim incorporates an option to do this on all levels, implementation of CRN is perhaps best explained based on the extension we performed in (Zhou et al., 2020a), which we will introduce now.

Our previous work (Zhou et al., 2020a) has extended ActivitySim so that it also includes a tour-based multimodal mode choice component. This component makes multimodal mode choices at a trip level by combining the access, main and egress modes, while making sure that the combination of these multimodal modes within a complete tour is feasible. For example, when dealing with a tour that consists of a home-work trip and work-home trip, and when the mode used for the outbound trip is the multimodal mode walk-car-bike (access-main-egress), the component will ensure that not just the bike as a unimodal mode is used for the inbound trip, since the car needs to be at home at the end of a tour. The model considers in total 32 feasible multimodal modes (consisting of access, main and egress modes) based on the following seven modes of transport: walk, bike, e-bike, car, car-passenger, demand-responsive-transport and public transport. To make choices in this component, a multinomial probit choice model is used. That is, a utility function is evaluated for each multimodal mode choice for every trip in the tour. This utility function incorporates two normally distributed error samples: one error sample is specific to every traveler/mode combination and models the traveler's personal mode preference (and is thus considered equal across trips), while the other error sample is specific to every traveler/mode/trip combination and models other random effects. Ultimately, the choice for all trip modes in the tour corresponds to the feasible mode combination with the highest aggregated utility. For the numerical study in this chapter, we adopt the error parameters used in (Zhou et al., 2020a).

To apply CRN in this additional ABM component, one needs to make sure that across scenarios the same error samples are used for every traveler/mode combination and every traveler/mode/trip combination respectively. To make this happen, we use the notion of initial seeds. Every time the same initial seed is set in a random number generator (RNG), it will generate the same sequence of random numbers. Therefore, incorporating CRN for traveler/mode combinations errors can be done by associating with each traveler a seed. Then, every time a different scenario is considered, the RNG will still generate the same traveler/mode errors, independent of the actual scenario. For the traveler/mode/trip errors, this can be done at a trip level: we associate with each trip a seed, so that each time the trip is considered, the same traveler/model/trip errors are computed. This way, the errors between scenarios are maximally synchronized. Furthermore, this strategy has the additional computational advantage that, when a trip is not undertaken in a certain scenario, the required traveler/mode/trip errors will not be generated either, saving computation time.

5.2.1.2 Multinomial logit choice model

The multimodal mode choice component treated above incorporates a multinomial probit choice model. In travel demand modeling, however, multinomial logit choice models are also omnipresent. Unlike probit choice models, which assume error terms to be normally distributed, logit choice models assume error terms to be Gumbel distributed. By doing this, these models are able to directly assign a probability to each alternative without having to sample the error terms. A final choice is then made using a single uniformly distributed random number. We explain how this works through an example. Suppose there are three alternatives: A, B and C. Furthermore, let us suppose the multinomial logit choice model assigns probabilities 0.5, 0.3 and 0.2 to these alternatives, respectively. Then, when the single uniform random number happens to be smaller than 0.5, the choice for alternative A is made, if it is between 0.5 and 0.8, alternative B is chosen, and otherwise, alternative C will be the choice made.

In travel demand modeling, many choices for a traveling individual may be made this way within a single simulation experiment. To apply CRN in a multinomial logit choice model, one cannot reuse error samples between scenarios as before, since there are no error terms to be sampled anymore. Instead, the variability of results now stems from the uniformly distributed random numbers. Therefore, in multinomial logit choice models, when contemplating the same choice between scenarios, CRN will now be reusing the same uniform random number. For the sole choice mentioned in the previous paragraph, suppose that the uniform number sample would be 0.663, so that alternative B is chosen. Furthermore, suppose that as a result of a change in scenario, the probability of choosing alternative A would increase by 0.1, while the probability of choosing any of the other two alternatives lowers by 0.05 each. In this new scenario, the 'probability boundaries' move from 0.5 and 0.8 to 0.6 and 0.85. CRN would however again use the number 0.663, so that again scenario B would be chosen. By using this principle for every choice generated by a multinomial logit choice model between scenarios, different choices would only be made as a result of the probability boundaries shifting, making sure that different output is caused by the a difference in the nature of the scenario.

5.2.2 Assessing the impact of CRN

We now detail how we will assess the impact of CRN in the sequel. In particular, we will regard two scenarios, which we will describe in more detail in Section 5.3.2, in the metropolitan region Rotterdam-The Hague (MRDH) in The Netherlands. For this pair of scenarios, we record the differences of several indicators in each of the following two experiments, adopting the model parameters from (Zhou et al., 2020a) (unless specified otherwise):

1. Base experiment: we run the model 30 times for both scenarios, and we do not apply CRN.

2. Inclusion of CRN: we run the model 30 times for both scenarios while using the same initial seeds, and thus applying CRN.

Note that in our model, each run covers one day of activities. In both experiments, we opted to observe 30 simulation runs, as this number enables graphical presentation of all outcomes, while at the same time it allows us to make conclusions regarding the effectiveness of CRN. For any considered indicator, each of these experiments thus leads to 30 differences $X_1, \ldots, X_{30}$. These differences are obtained by subtracting the simulated indicator values found under the second scenario from those found under the first scenario. To assess the impact of CRN, in the sequel we use the following measures.

Sample variance S_X^2. We consider the sample variance of the differences

$$S_X^2 = \frac{1}{29} \sum_{i=1}^{30} (X_i - \bar{X})^2,$$

where $\bar{X}$ represents the sample mean of the 30 differences. The sample variance, which equals the square of the sample standard deviation S_X of the differences, is a proxy for the reliability of the results. From a mathematical perspective, it is to be expected that CRN leads to a smaller sample variance, since the indicators under both scenarios are now positively correlated. At the same time, the lower the variance of the differences are compared to the sample mean, the more reliable and representative the results are. To make the notion of reliability more precise, we build upon the sample variance to obtain the next two performance measures, in line with e.g. (Wunderlich et al., 2019).

Width of the confidence interval. Using basic statistics, assuming for the moment that modeling assumptions are correct, the real expected difference between the indicators corresponding to the two scenarios lies with 95% probability between the numbers $\bar{X} - t_{29,0.975}\, S_X / \sqrt{30}$ and $\bar{X} + t_{29,0.975}\, S_X / \sqrt{30}$, with $t_{29,0.975} \approx 2.045$

representing the 97.5% quantile of the student t-distribution with 29 degrees of freedom. The resulting interval

$$\left[\bar{X} - t_{29,0.975}\frac{S_X}{\sqrt{30}}, \bar{X} + t_{29,0.975}\frac{S_X}{\sqrt{30}}\right]$$

is therefore called the 95% confidence interval (CI). One ideally would like the CI to be as narrow as possible, which is why the width of the 95%-CI, being $2 \times t_{29,0.975}\, S_X/\sqrt{30}$, is a good proxy for the reliability of the results after 30 simulation runs. We expect CRN to result in higher reliability, and thus a smaller confidence interval.

Required number of simulation runs. Another approach to assess reliability would be to pose the question of how many models runs would be minimally required so that the width of the 95%-CI is smaller than a fraction β of the actual expected difference μ. In case the actual variance of the difference between the indicators is given by σ^2, the width of the 95%-CI based on N runs is given by $2 \times q_{0.975}\, \sigma/\sqrt{N}$, where $q_{0.975} \approx 1.96$ is the 97.5% quantile of the normal distribution. We are thus looking for the smallest number N for which $2q_{0.975}\, \sigma/\sqrt{N} \leq \beta\mu$, which is given by

$$N_{\min} = \left\lceil \frac{4q_{0.975}^2\sigma^2}{\beta^2\mu^2} \right\rceil.$$

Since both μ and σ^2 are unknown parameters, we use $\bar{X}$ and S_X^2 to estimate these, yielding the formula

$$N_{\min} = \left\lceil \frac{4q_{0.975}^2 S_X^2}{\beta^2\bar{X}^2} \right\rceil. \tag{5.1}$$

It is easily argued that the lower $N_{\min}$, the lower the computation time that is required to obtain reliable output. In line with earlier statements, we generally anticipate the second experiment with CRN to have a much lower $N_{\min}$ than the first experiment without CRN. In the next section, we choose $\beta = 0.2$ for reporting the number of $N_{\min}$. Thus, the number reported is the minimum number of simulation runs required so that the width of the confidence interval does not exceed 20% of the average of the indicator values found. It is worth noting, however, that, although the value of β will affect the the values of $N_{\min}$ themselves, the percentual reduction of $N_{\min}$ as a result of implementing CRN is insensitive to the actual value of β considered. This is due to the fact that the numbers for both the base experiment and the experiment including CRN are calculated using the same value of β (cf. the denominator of the fraction in (5.1)).

It should be noted that the three measures discussed above are related. Therefore, in the sequel, we may not compute every of these measures for every indicator that we consider. For example, when CRN decreases the required number of runs significantly, one can already conclude that the width of the confidence interval for a fixed number of runs will also be considerably smaller. Next to these measures, we will at times also perform a standard double-sided t-test on the differences. More particularly, for several indicators in the second experiment, we may test the null hypothesis that the expectation of the differences between scenarios equals zero. Should the t-test not reject this hypothesis with a confidence level of 95%, we induce that there is not an observed significant difference between the indicators under both scenarios. We will see in the sequel that even though the implementation of CRN in those cases reduces the width of the 95%-CI and $N_{\min}$ significantly, the computation times remain infeasibly long.

5.3 Experimental results

In this section, we describe the results obtained from doing the two experiments described in the previous section. As mentioned before, to perform these experiments, we apply the model of (Zhou et al., 2020a) to data for the metropolitan region Rotterdam-The Hague (MRDH) in The Netherlands taken from various sources, which are also described in (Zhou et al., 2020a). We describe this data in more detail in Section 5.3.1, and we describe the scenarios considered in Section 5.3.2. Then, we perform the first two experiments presented in Section 5.2.2 using several indicators, namely for the average daily number of trips per day (Section 5.3.3), average travel distance per traveler per part of the day (Section 5.3.4) and modal split (Section 5.3.5). Note that the output presented in these sections is the result of a series of subsequent choice components, involving both multinomial probit models and multinomial logit choice models. We implemented CRN in each of these components as explained in Section 5.2.1.

5.3.1 Input data

The input data, on which the numerical experiments are based, include information on the population and land use as well as level-of-service data on travel times, distances and travel costs for each conceivable origin-destination trip pair in the MRDH area. This area covers the cities of Delft, Pijnacker, Nootdorp and Zoetermeer, being located between the two major cities of Rotterdam and The Hague. These data origin from various sources, which can be found in (Zhou et al., 2020a).

The population data that we use for this area have been synthesized in (Snelder et al., 2021). The dataset consists of 278 698 individuals, making up 131 466 households. For our simulation, we randomly selected 10% of these households. Within the selected households, 18% of the population is younger than 15 years old, 14% is between 15 and 25 years old, 26% is between 25 and 45, 27% is between 45 and 65 and finally, 15% of the population is older than 65 years old.

For each individual, the synthesized data contains information on the home location, household composition, gender, whether the individual possesses a driving license and/or a student subscription for free public transport, level of education, income, migration background, types of owned bikes and/or vehicles, as well as urbanization level (which specifies the address density in the direct area of the individual's residence).

Concerning land use, the input data contains per traffic analysis zone information on the number of places of employment (offices, shops, etc.), number of education places, area (in m^2) and the average parking costs per hour.

5.3.2 Scenario descriptions

For the numerical study, we focus on the impact of *Mobility as a Service* on travel demand. To explain this concept, it is worth noting that we are witnessing the development of new transport technologies, such as connected vehicles using 5G, level 3, 4 or 5 automatic vehicles, and mobile app-based car-sharing or ride-sharing services. Mobility as a Service (MaaS) combines all these technologies and services, thus offering a tailored mobility package for individual travelers (see e.g. (Jittrapirom et al., 2017) for more background). Therefore, when a traveler owns a MaaS subscription, this person has access to a shared car, a shared bike and a shared e-bike. Furthermore, the subscription enables the use of a shared taxi, minibus or other shared modes which are not used in conventional public transport (such as the bus, tram, metro and train).

To assess the impact of MaaS, in the sequel we consider the following two scenarios, differing in terms of the adoption level of MaaS:

1. In the first scenario, to be referred to as 'partial MaaS', 10% of the people younger than 15 or older than 65 have a MaaS subscription, while 20% of the remaining population also has a MaaS subscription. As a result, 16.5% of the overall population has a MaaS subscription.

2. In the second scenario, 'full MaaS', 100% of the population has a MaaS subscription.

The main goal is to quantitatively assess the difference between both scenarios in terms of several indicators.

5.3.3 Average daily number of trips

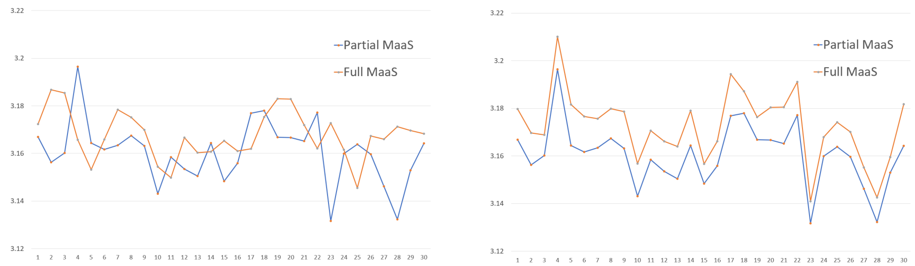
The first indicator that we study is the average number of trips undertaken by a traveler during a day, which illustrates the impact of CRN particularly well. We first consider the number of daily trips for all age classes mentioned in Section 5.3.1 together. We then also regard results at a more detailed level, which distinguishes between the different age classes of the population.

5.3.3.1 Daily number of trips for all age classes combined

The study of the average number of trips undertaken by a traveler during a day turns out to illustrate the beneficial effects of CRN remarkably well. Figure 5.1a presents the average numbers of daily trips undertaken by a traveler in 30 different simulation runs for each of the two scenarios independently, using the base experiment where no CRN is applied. Although the mean value of the blue plot (i.e., partial MaaS) appears to be smaller than that of the orange plot (full MaaS), basing firm conclusions on this figure would be hard. Indeed, the sample variance of the difference of the left-hand figure, having value 0.00027, is still significant compared to the average of these differences, bearing the value of 0.007. In Figure 5.1b, we plot the same quantities based on the same number of runs, but this time we *do* apply CRN, and thus introduce positive correlation. We consider the same simulation output as before for partial MaaS (and hence obtain the same blue plot), but unlike before, we use the exact same error samples for the simulation of the average number of daily trips for full MaaS, leading to a different orange plot. The effect is clear: the level of variability observed in both plots is similar to that of the base experiment, but the plots move almost parallel and do not intersect anymore as a result of the synchronization. Specifically, the figure shows that the differences between the simulated number of trips are roughly constant. This is also illustrated by the fact that, although the average difference in the right-hand picture is 0.012 (which is similar to the average in the left-hand picture as expected), the sample variance of the differences in the right-hand picture now is only around the order of 8×10^{-6}, confirming the fact that CRN offers a lot more reliability.

Figure 5.1 confirms that by applying CRN the variability of simulated indicator value differences reduces dramatically, as these differences can now solely arise as a result of different scenarios. Therefore, one can now much more comfortably draw the conclusion that MaaS will probably lead to more trips per day per traveler. Indeed, if we deploy a t-test as explained in Section 5.2.2 on the 30 differences of the values plotted on Figure 5.1b, it rejects the null hypothesis that the expected number of trips per traveler per day are equal under both scenarios. This supports such a conclusion, which can be explained by the fact that a MaaS subscription makes traveling more accessible and flexible, and therefore more attractive. If we were to deploy a t-test on the 30 differences of Figure 5.1a, however, the t-test would not reject, which is in line with the fact that Figure 5.1b sketches a more reliable picture.

To quantify the impact of CRN in practical terms, computation of $N_{\min}$ as provided in Section 5.2.2 leads to 2042 runs for the base experiment, while the inclusion of CRN brings this number down to 23. This means that, to obtain a confidence interval for the indicator difference that has a width less than 20% of the actual expected difference, the minimally required number of runs (and thus



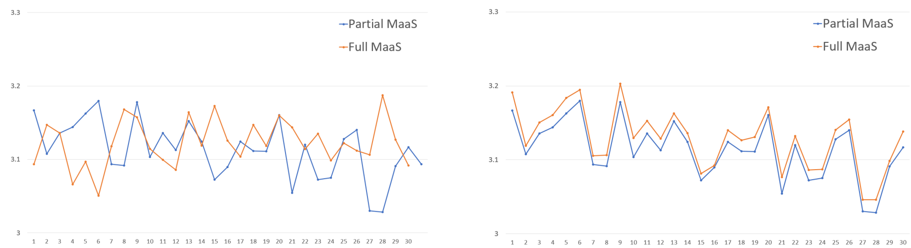
(A) Base experiment (B) Inclusion of CRN

FIGURE 5.1: Average daily numbers of trips per traveler in 30 simulation runs.

the minimally required computation time) is reduced by almost 99% when using CRN. Again, this shows the beneficial impact of CRN on numerical experiments.

5.3.3.2 Daily number of trips per age class

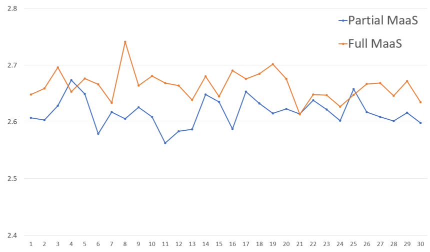
We now regard the daily number of traveler trips for all different age classes separately. The age class covering travelers between 15 and 25 years old sketches a similar picture as that of the aggregated level combining all age classes. That is, in the absence of CRN, it is hard to identify the influence of the varying natures of the scenarios on the difference of the average number of trips undertaken by a traveler based on 30 simulation runs, as shown in Figure 5.2a.



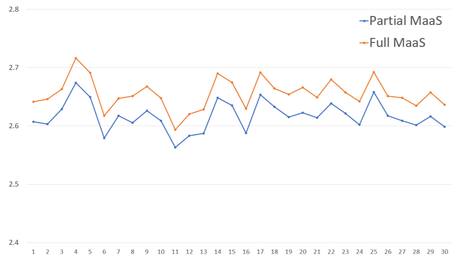
(A) Base experiment (B) Inclusion of CRN

FIGURE 5.2: Average daily numbers of trips per traveler between 15 and 25 years old in 30 simulation runs.

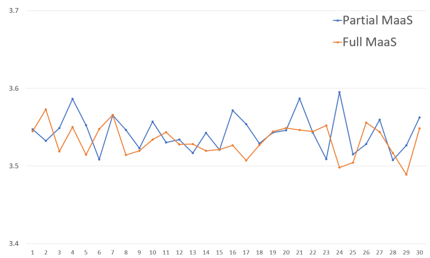
In contrast, Figure 5.2b, which includes CRN, again clearly shows that the possession of a MaaS subscription increases the traveling activity of young travelers. We obtain similar findings when regarding the age classes representing travelers younger than 15 years old, travelers between 25 and 45 years old, and travelers older than 65 years old, see Figure 5.3. For each of these age classes, the double-sided t-test applied on the 30 observed differences rejects the null hypothesis that the expected difference in the number of trips undertaken by a traveler equals zero, and N_{min} in all of these four age classes is reduced by over 94% due to the use of CRN.



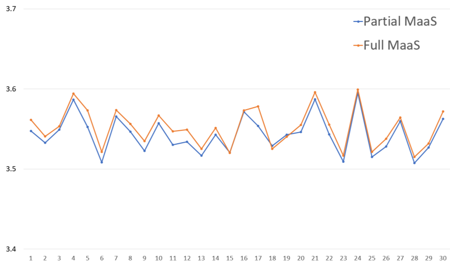
(A) Base experiment



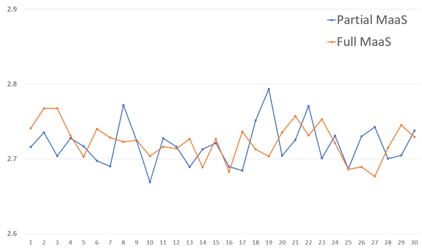
(B) Inclusion of CRN



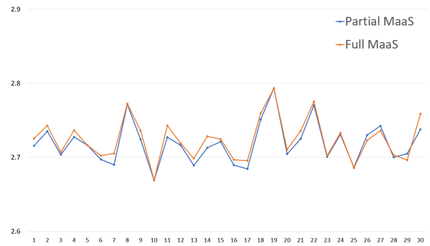
(C) Base experiment



(D) Inclusion of CRN



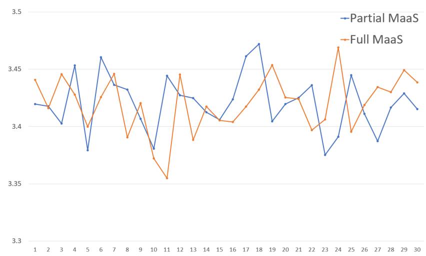
(E) Base experiment



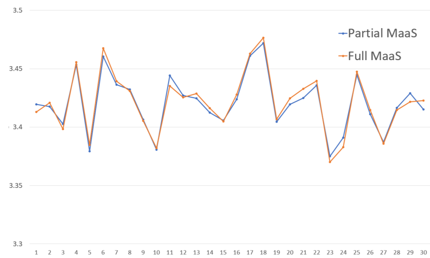
(F) Inclusion of CRN

FIGURE 5.3: Average daily numbers of trips per traveler younger than 15 years old ((a) and (b)), between 25 and 45 years old ((c) and (d)) and older than 65 years old ((e) and (f)) in 30 simulation runs.

The age class concerning the population between 45 and 65 years old, however, shows an additional effect. For this case, Figure 5.4a again shows much more variability in the differences than 5.4b, in which the two plots are rather parallel to one another. However, even in the latter figure, the plots intersect a lot, so that no reliable conclusions can be drawn on which of the two scenarios leads to more trips in this age class. Indeed, the sample variance of the observed differences equals 0.000022, while the average of these differences only equals 0.00086. As a result, the variability of the differences based on these 30 runs is still too large to produce a reliable conclusion. These findings are confirmed by performing a t-test, which does not at all reject the null hypothesis that there is no difference in indicator value between the two scenarios.



(A) Base experiment



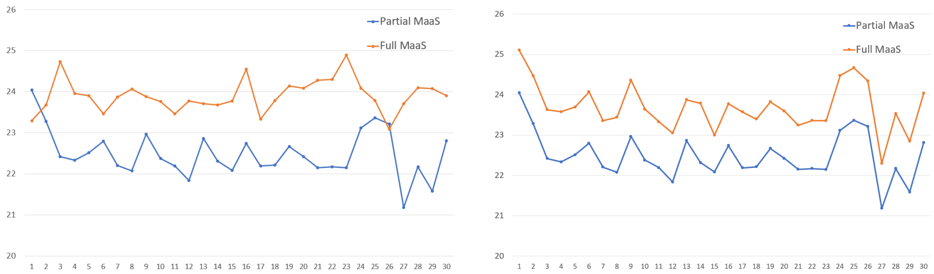
(B) Inclusion of CRN

FIGURE 5.4: Average daily numbers of trips per traveler between 45 and 65 years old in 30 simulation runs

This is not to say that CRN in this case bears no effect. Indeed, the width of the 95%-CI based on the 30 runs reduces from 0.026 to 0.0035. While the latter number is still very large (relative to the quantity we wish to estimate, that is), the reduction is significant. Similarly, we find that by implementation of CRN, N_{min} is reduced from 698 551 to 11 487, yielding a decrease of required runs of about 98%. Yet, performing 11 487 simulation runs is prohibitive in terms of computation time. The conclusion to be drawn here is that CRN still is very effective, but that, at the same time, the actual difference between scenarios in this case is so small, that the effect of using CRN is too small to allow for a feasible computation time. This being said, one may wonder how important this unfeasible simulation would be, as the conclusion could be drawn that the difference between the two scenarios for this age class is negligible anyway. Intuitively, this is not surprising when considering the fact that most activities undertaken by these individuals are mandatory. In other words, having a MaaS subscription may alter the travel mode used, but in the absence of such a subscription, no trips will be dropped in this age class.

5.3.4 Average travel distance per traveler

The next indicator that we consider is the average travel distance covered by a traveler within a day in kilometers. We focus on the age class of travelers between 15 and 25 years old, while noting that the study of all other age classes would lead to similar findings. When performing the base experiment and the experiment



(A) Base experiment (B) Inclusion of CRN

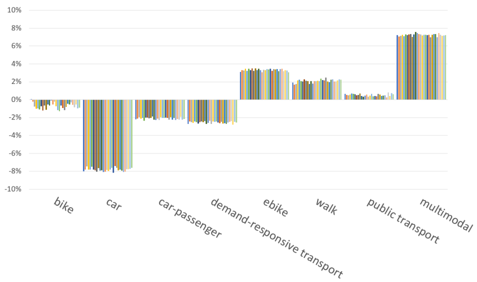
FIGURE 5.5: Average daily travel distance of young travelers (15-25 years old) in kilometers in 30 simulation runs

including CRN for this ages class, we obtain Figure 5.5. Again, the effect of CRN is clear as the differences in the right-hand picture are much more constant than in the left-hand picture, and thus more firm conclusions can be drawn. However, one may argue that also based on the left-hand picture, although the blue and orange plot intersect three times there, one can comfortably conclude that the more MaaS is available to young travelers, the more they will travel in terms of distance covered.

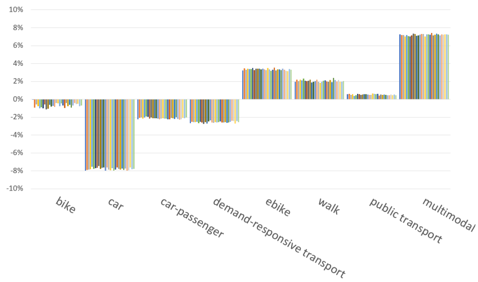
The fact that the left-hand picture already is rather informative is due to the fact that the difference between the two scenarios is relatively large. In fact, it is so large, that the variability of the differences in the left-hand picture (the sample variance of the differences is 0.488) does not outweigh the actual difference (the sample mean of the differences is 1.423). Still, CRN has a substantial effect on computational complexity in this case. The widths of the 95%-CIs of the differences observed for the 30 runs of Figures 5.5a and 5.5b are 0.52 and 0.093, respectively, the latter thus offering a much higher level of reliability. Similarly, the value N_{min} for the base experiment would be 93, while this number equals 4 for the experiment which incorporates CRN. Therefore, although one may argue that CRN is not needed for this indicator, still a substantial amount of computation time can be saved when doing batch experiments.

5.3.5 Modal split

Finally, we inspect the so-called 'modal split' for travelers used. That is, we regard the (differences in) the percentage of trips that are undertaken by each mode (between scenarios). As mentioned in Section 5.2.1, next to the seven unimodal modes (walk, bike, e-bike, car, car-passenger, demand-responsive transport and public transport), we also consider 25 multimodal mode alternatives made up of a combination of single modes. In Figure 5.6 differences in mode use between the partial MaaS scenario and the full MaaS scenario are plotted. Each bar corresponds to one of the 30 simulation runs and represents the difference observed in the percentage of trips undertaken with the corresponding mode ('full MaaS minus partial MaaS'). For the purposes of this section, we have combined all 25 multimodal modes in a single category 'multimodal'. Figure 5.6a shows the results observed in the base experiment, while Figure 5.6b shows them for the experiment including CRN.



(A) Base experiment



(B) Inclusion of CRN

FIGURE 5.6: The difference in modal split between two scenarios: a positive value means that mode use is higher for the full Maas scenario than for the partial MaaS scenario. Each bar corresponds to one of the 30 simulation runs and represents the difference observed in the percentage of trips using the corresponding mode.

As expected, the figures show that when moving from a partial MaaS to a full MaaS scenario, the e-bike and multimodal modes gain in popularity at the cost of the car modes and demand-responsive transport. In particular, in Figure 5.6b, the share of the car mode dropped by 7.8% on average, while the e-bike was used in an additional 3.4% of the trips. Moreover, in an additional 7.3% of the trips on average, multimodal modes were chosen. Also the bike mode became less popular, which can be explained as follows. When travelers for example choose to use a personal bike for an outbound trip of a tour, typically it also needs to be chosen for an inbound trip. However, with access to MaaS, many more mode options are considered for use in each of the trips. As a result, if one of those modes is much more favourable than the bike for an inbound trip, then this also has automatic ramifications for the mode choice of the outbound trip, making the choice for the bike less obvious. The modes of walking and public transport do not have this issue, making them slightly more popular at the expense of the bike. The astute reader, however, will note that the effects impacting the bike mode should also impact the e-bike mode. However, for the e-bike mode, these effects are offset by the fact that a MaaS subscription makes the e-bike more popular.

What is intriguing is that Figures 5.6a and 5.6b hardly present mutually differing pictures, like in the previous sections. Indeed, in both the base experiment and the experiment including CRN, $N_{\min}$ is very small, almost never exceeding ten simulation runs for any mode. The only exception to this is the bike mode in the base experiment, for which $N_{\min} = 121$, which is indeed confirmed by the fact that the 'bike bars' in Figure 5.6a show a lot of variability.

The reason for this is that in this case variability of results is not so much an issue as it was in Sections 5.3.3 and 5.3.4. As mentioned in Section 5.2.1, mode choice is dictated by a multinomial probit choice model, and in many of these modes, the error terms only have a small impact on the ultimate mode choice. That is, the variability caused by the error terms in general is a lot smaller than the actual difference in 'observed utility' between the modes. As a result, the variability of the error terms do not have a lot of impact on e.g. whether or not the car is chosen. Since a similar effect also plays for the full MaaS scenario, the variability of the random number generation cannot trigger large fluctuations in terms of which modes are chosen. As a result, one cannot hope for a large impact of CRN in terms of $N_{\min}$ either. An exception to this is the bike mode, where the variability of the errors actually does impact the utilities of the bike modes enough to cause changes in the ultimate mode choice. Since variability is thus more of an issue here, CRN indeed has a larger impact.

In summary, these findings show that when variability of pseudo-random number generation is not a problem, there is not much to solve for CRN either. As a result, the use of CRN overall does not have as much a dramatic impact as it had in the previous sections. That said, this does not mean that CRN does not have any merit at all. For example, the width of the computed 95%-CI in the percentage difference of trips that are taken with the car is reduced by 33.9% after implementation of CRN, which adds to the reliability of simulation results. As a final remark considering the modal split, it is reasonable that one would argue that, for the purposes of correct modeling, the variance parameters of the normal distributions underlying the error terms should have been estimated differently (i.e., taken to be a bit larger), so that error terms will have a larger influence on the mode choice. In that case, the variability of the errors will increase, and as a result, we expect the impact of CRN to be larger as well.

5.4 Conclusions and discussion

In this chapter, we have considered the use of CRN in the context of activity-based travel demand modeling. More particularly, in this chapter we showed how this technique can be applied to effectively simulate the impact of scenario changes to any indicator. By making sure that between scenarios the exact same pseudo-random numbers are used for the same purposes, any difference in output can in all likelihood be attributed to the change in scenarios. As a result, the variability of the simulated differences is much smaller, and therefore less simulation runs and less computation time is required to perform a simulation study with a meaningful output.

After we explained how CRN can be implemented in an activity-based travel demand model, we set out to demonstrate the potential of CRN in practice by studying the impact of MaaS on travel demand in the MRDH region. In particular, we studied the question of whether a scenario in which the complete population has a MaaS subscription yields different indicators than the scenario in which only a small part of the population has such a subscription. We found that the implementation of CRN yields a computationally very efficient tool to answer this question in the affirmative: when everybody has a MaaS subscription, travelers will travel more, and use different (possibly multimodal) modes. We found that with CRN, such conclusions can be reliably drawn using up to 99% less simulation runs than the conventional setting without CRN. In a similar vein, when we compute the 95%-CI of a certain indicator difference based on a fixed number of runs, a simulation setting with CRN typically comes with a much smaller interval than a setting without. This shows that CRN can shorten the computation times required drastically, especially when considering the complete sequence of choice models/components in an ABM.

By comparing various indicators, we also found that CRN is especially worthy of implementation when the differences between scenarios are moderate. In case they are very large, CRN still reduces computational complexity, but conventional simulation methods already can provide conclusions in reasonable time. In contrast, when differences are very small so that they are hardly observable, even though CRN reduces computational complexity also in this case, the setting with CRN still requires too many runs in order to decide which of the scenarios scores better. In such a setting, however, one can say that the difference in the nature of the scenarios hardly has an impact on the indicators.

Finally, we showed that the impact of CRN is related to the degree at which the variability of generated random numbers can cause random fluctuations in the model output. We saw that when this cannot occur to a large extent, CRN cannot be expected to yield up to 99% less required simulation runs as reported above. Nevertheless, the implementation of CRN still yields smaller confidence intervals, adding to the reliability of the results.

In further research, it would be worthwhile to study the robustness of CRN. That is, we conjecture that the implementation of CRN makes the model output more robust against (i.e., less sensitive to) inaccurate modeling assumptions, such as inaccurately estimated coefficients of the utility functions used by the discrete choice models. Since CRN makes sure that any inaccuracy would be consistently applied to both scenarios, we believe that such inaccuracies have a lesser impact on the output, increasing the reliability of the model output even further.

Furthermore, it would be worth studying the potential of other variance reduction techniques developed in the stochastic simulation literature in the context of travel modeling. For example, we believe that the results in this chapter may be further improved by implementing advanced sampling techniques such as hypercube sampling.

Finally, another venue of further research would be in the direction of travel assignment models. Since this study only focused on the travel demand, any change of level-of-service output such as travel time of trips is not considered. This would require a connection of the current travel demand model with a travel assignment model. When this connection would be made, the impact of CRN on the whole model chain could be considered. Given the results in this chapter, we would expect that CRN also has great potential when considering the complete model chain.

6

SUSTAINABLE MOBILITY STRATEGIES AND THEIR IMPACT: A CASE STUDY USING A MULTIMODAL ACTIVITY BASED MODEL

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 chapter, 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 multimodal 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. We also find 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.

6.1 Introduction

Globally, we see that 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 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), which can be thought of as an integration of various modes (even within a single trip) into a single service, accessible on demand and with a single payment application, obtained via seamless digital planning across all modes available; see e.g. (Giesecke et al., 2016; Jittrapirom et al., 2017; Muller et al., 2021) and references therein. As MaaS provides users with multimodal mode alternatives, it is believed that it offers a good alternative to private car use (Sochor et al., 2018; Lyons et al., 2019; Hesselgren et al., 2020). Another promising example of NMS is formed 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, cf. (Bell, 2019; Knapen et al., 2021). 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. With shared mobility services, travellers have access to transportation mode 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; cf. (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 (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., 2022a) as well as appropriate bundling of travel modes (Zhou et al., 2020a). In this chapter, 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 (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) (Liao et al., 2010; Vovsha et al., 2017) do exist, but even then only limited new mobility modes or limited combinations of new modes are considered. In this study, we explicitly consider the entirety of NMS as sketched above. To incorporate NMS in an ABM, we build on previous work (Zhou et al., 2020a), where we have extended ActivitySim (Gali et al., 2008), an open platform for activity-based travel modeling, to include multimodal modes as mode choices (Zhou et al., 2020a) 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 of (Zhou et al., 2019) accelerate the computational speeds of the ABM.

In the remainder of this chapter, 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 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 chapter, we mainly use modal split 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 we have selected as 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 (Wikipedia, 2022). 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 (Metropoolregio Rotterdam Den Haag, 2021a). 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 we wish to answer in the case study 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 we answer these questions fully and in detail at a later stage of this chapter, we already mention that mobility hubs 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. At the same time, especially the use of e-bikes increases, while the introduction of MaaS also increases the number of multimodal trips. Next, we will find 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 chapter is organised as follows. Section 6.2 describes the ABM that we use for the case study in more detail and explains the procedure used to calibrate the model. In Section 6.3, 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 6.4 presents detailed answers to these questions and provides venues for further research.

6.2 Modelling approach

In this section, we describe the activity-based modelling approach that we adopt in this chapter. In particular, Section 6.2.1 provides a detailed description of the ABM as well as its several components. Then, Section 6.2.2 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 6.2.3.

6.2.1 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 given any 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 which makes a decision for every member in a synthesized population of the MRDH-region as obtained in (Snelder et al., 2021). We describe these choice components in Section 6.2.1.1, after which we give separate attention to a choice component customly coded for this study in Section 6.2.1.2.

6.2.1.1 Components of the ABM

The first component of the ABM makes long-term decisions on things such as the selection of school/work locations for each individual traveller. 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 we use for the components is based on ActivitySim (Gali et al., 2008), but we adopt a separately coded component for the trip mode choice, which was introduced in (Zhou et al., 2020a). We do this mainly so as to be able to model multimodal trips alongside the possible unimodal trips that ActivitySim is capable of processing. This is essential for the modelling of NMS. While doing so, this 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 mode choice component takes this into account.

6.2.1.2 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 we will proceed to describe 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 6.1, 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 remaining two categories are demand-responsive transport, which includes minibuses, shared taxis and shuttles with a small passenger capacity. The final category represents conventional public transport, including bus, tram, metro, and train. The vast majority of new travel modes brought by NMS falls in one of these categories. We also note 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 6.1 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 chapter.

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 (access mode) × 7 (main mode) × 7 (egress mode) = 343 combinations as multimodal modes in the ABM, this comes with a huge strain on computational requirements. It 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., 2020a) for an explanation of how these likely combinations are selected. Table 6.1 provides a complete list of the unimodal and feasible multimodal modes

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

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

TABLE 6.1: List of modes considered in this study.

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.

6.2.2 Utility functions and their structure

All of the components of the ABM mentioned in Section 6.2.1 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. The components in the ABM that we use are all 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. We will leave this question for Section 6.2.3.

6.2.2.1 Multinomial logit model

The components mentioned in Section 6.2.1.1, except for the customly coded trip mode choice component, are based on a multinomial logit model. In such a model, the utility $U_{i,j}$ assigned to any alternative i and traveller j has the following form:

$$U_{i,j} = \alpha_i + \sum_{k=1}^{N} \beta_{i,k,\mathrm{alt}} C_{i,k}^{\mathrm{alt}} + \sum_{k=1}^{M} \beta_{i,j,k,\mathrm{trav}} C_{j,k}^{\mathrm{trav}} + \epsilon_{i,j}. \tag{6.1}$$

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

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

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

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

forms a linear combination of the attribute values $C_{j,1}^{\mathrm{trav}}, \ldots, C_{j,M}^{\mathrm{trav}}$ 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

$$\beta_{i,1,\mathrm{alt}}, \ldots, \beta_{i,N,\mathrm{alt}} \ \text{ and } \ \beta_{i,j,1,\mathrm{trav}}, \ldots, \beta_{i,j,M,\mathrm{trav}}.$$

Finally, the utility function includes an error term $\epsilon_{i,j}$. 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; cf. (Castiglione et al., 2015, Chapter 2).

6.2.2.2 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 (6.1). However, the error term $\epsilon_{i,j}$ 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. Because of this, we opt for the customly coded trip mode choice component in Section 6.2.1.2 to incorporate a multinomial probit choice model. We do this, because of the fact that multiple error terms are included in the utility function on a trip level as we see below, but also because one needs to be able to combine the utilities of trip mode choices in a total utility of a tour mode choice combination. Since this requires combining multiple error terms too, 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 $(i_{\text{acc}}, i_{\text{main}}, i_{\text{egr}})$, 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 $U_{i,j}$ of multimodal mode alternative i and traveller j can be expressed as follows:

$$\begin{aligned}U_{i,j} =& \alpha_{i_{\text{main}}} + \sum_{k=1}^{M} \beta_{i,j,k,\text{trav}} C_{j,k}^{\text{trav}} + \sum_{k \in \{\text{acc,main,egr}\}} \beta_{i_k,\text{time}} (\text{ST}_{i_k} + \text{TT}_{i_k}) \\ &+ \sum_{k \in \{\text{acc,main,egr}\}} \beta_{i_k,\text{cost}} (\text{O}_{i_k} + \text{SU}_{i_k}) + \sum_{k \in \{\text{acc,main,egr}\}} \beta_{i_k,\text{p-cost}} \text{P}_{i_k} \\ &+ \sum_{l \in \{(i_{\text{acc}}, i_{\text{main}}), (i_{\text{main}}, i_{\text{egr}})\}} \beta_{\text{walk,time}} \text{T}_{l,\text{transfer}} + \beta_{\text{parking}} \ln(\text{PC}_{i_{\text{main}}}) + \mu_{i,j} + \eta_{i,j}.\end{aligned} \tag{6.2}$$

In the remainder of the current section, we give an explanation of this utility function.

Alternative-specific constant and socio-demographic attributes The first two terms on the right-hand side of this equation also appear in (6.1) 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. We make this assumption to keep 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 chapter. 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 $\sum_{k=1}^{N} \beta_{i,k,\mathrm{alt}} C_{i,k}^{\mathrm{alt}}$ as in (6.1), but are instead represented in the remaining, more detailed terms of (6.2), which are also discussed below.

Attributes dependent on access and egress modes The next few terms of (6.2) pertain to attributes that are very much dependent not only on the main mode, but also the access and egress modes. For example, the term

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

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 ST_{i_k} and TT_{i_k}, which are weighed through the coefficient $\beta_{i_k,\mathrm{time}}$.

In a similar vein, the terms

$$\sum_{k \in \{\mathrm{acc},\mathrm{main},\mathrm{egr}\}} \beta_{i_k,\,\mathrm{cost}}(\mathrm{O}_{i_k} + \mathrm{SU}_{i_k}) + \sum_{k \in \{\mathrm{acc},\mathrm{main},\mathrm{egr}\}} \beta_{i_k,\mathrm{p\text{-}cost}} \mathrm{P}_{i_k}$$

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 (SU_{i_k}) and parking costs (P_{i_k}) of the access, main and egress mode. It is worth noting that when any of the aforementioned properties are not applicable, the corresponding value is set to zero. For example, we evidently have that $\mathrm{P}_{\mathrm{walk}}$ equals zero, as there is no such thing as parking costs when walking. An exception to this is the value of P_{PT}, which we assume 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 $\beta_{i_k,\mathrm{p\text{-}cost}}$. Furthermore, we mention that the travel times 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, namely 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 (6.2) also contains a term that incorporates the utility effect of the transfer times as a result of switching from the access mode i_{acc} to the main mode i_{main}, and as a result from switching from the main mode i_{main} to the egress mode i_{egr}. The first of these transfers we denote by $(i_{\text{acc}}, i_{\text{main}})$, while the second is denoted as $(i_{\text{main}}, i_{\text{egr}})$. Given this notation, the term $\sum_{l\in\{(i_{\text{acc}},i_{\text{main}}),(i_{\text{main}},i_{\text{egr}})\}} \beta_{\text{walk,tt}}\mathrm{T}_{l,\text{transfer}}$ includes these effects in the utility function, where $\mathrm{T}_{l,\text{transfer}}$ 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 6.1 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 6.1 can be trivially assigned to any of the three connection types mentioned above (CAR-PT, CAR-BIKE and CAR-EBIKE), we 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, we set the transfer times of other connections at five minutes. It is also worth remarking that all transfers are assumed to be done by walking, which is why we use $\beta_{walk,\text{time}}$ 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 $\beta_{\text{parking}}\ln(\mathrm{PC}_{i_{\text{main}}})$ in (6.2) models the utility contribution of the parking capacity ($\mathrm{PC}_{i_{\text{main}}}$) 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 we set PC_{car} equal to the number of available car parking spaces. For all other main modes, we set $\mathrm{PC}_{i_{\text{main}}} = 1$, so that the amount of parking capacity does not influence the associated utility.

Error terms What remains in the utility functions are the terms $\mu_{i,j}$ and $\eta_{i,j}$, which represent the errors made in computing the utility of the multimodal mode.

In line with (Miller et al., 2005), the first term $\mu_{i,j}$ 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 $\eta_{i,j}$ is not only specific to the mode and traveller, but also to the actual trip. This term models random effects not covered by $\mu_{i,j}$, 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 chosen equally so 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 by normally distributed. This among other things comes 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 In the discussion above, we 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 we will discuss in Section 6.3.1), 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 (6.2) 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:

$$\begin{aligned} U_{i,j} = &\alpha_{\mathrm{PT}} + \sum_{k=1}^{M} \beta_{i,j,k,\mathrm{trav}} C_{j,k}^{\mathrm{trav}} + \beta_{\mathrm{PT,time}} \mathrm{TT}_i \\ &+ \beta_{\mathrm{PT,\,cost}} \mathrm{O}_i + \beta_{\mathrm{PT,p\text{-}cost}} \mathrm{P}_i + \mu_{i,j} + \eta_{i,j}. \end{aligned} \tag{6.3}$$

Note that (6.3) has many terms in common with (6.2), which are already explained above. That is, just like (6.2), the utility function has an alternative-specific constant α_{PT} as well as the sum

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

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 $\beta_{\mathrm{PT,time}}\mathrm{TT}_i$, $\beta_{\mathrm{PT,cost}}\mathrm{O}_i$ and $\beta_{\mathrm{PT,p\text{-}cost}}\mathrm{P}_i$ 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 (6.3) does include a contribution for parking costs. In particular, we assume in this model that $P_{\mathrm{PT}} = P_{\mathrm{car}}$. 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 $\beta_{\mathrm{PT,p\text{-}cost}}$ is positive, unlike $\beta_{\mathrm{car,p\text{-}cost}}$ in (6.2).

6.2.3 Coefficients of the utility functions

Now that we have explained the structure of the utility function, we have to estimate suitable values of the coefficients involved, namely the alternative-specific constant α as well as the β-coefficients that appear in (6.1) and (6.2). We detail this process in this section. More particularly, in Section 6.2.3.1 we explain how we select an initial set of values, after which these values are made subject to further calibration and validation in Section 6.2.3.2.

6.2.3.1 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 (CBS), 2018b), 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. (Gliebe et al., 2014). For example, in (Ziemke et al., 2015) coefficients are transferred from an ABM study pertaining to a region, called the Bay Area, surrounding Los Angeles, 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

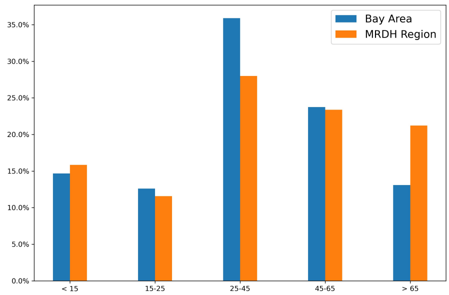
(MTC, 2018) to our setting. This study includes an ABM studying a representative part of the above-mentioned Bay Area. The ABM simulates travelling activity on a weekday to assist policy makers in this region in planning activities. From this point on, when we refer to the Bay Area, we actually refer 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), we first compare the demographic information of San Francisco and San Mateo in the Bay Area, to 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 Figure 6.1a. The age 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.

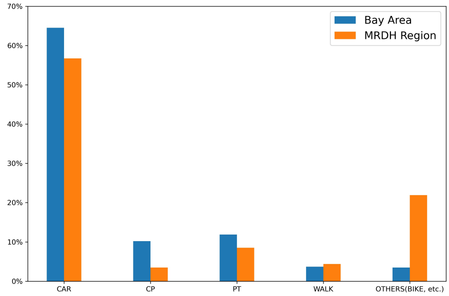
While the demographic similarity between the regions is encouraging, we also compare the travel modes used by travellers in both areas. Regarding the mode choice of commuting trips, it turns out that the modal splits of both areas differ significantly. That is, results in (Centraal Bureau voor de Statistiek (CBS), 2018b) and (MTC, 2021), depicted in Figure 6.1b, 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; Bowman et al., 2014), it is therefore not justified to simply copy all coefficient values used in (MTC, 2021) for use in the utility functions of our model. Rather, these coefficients can be used as a basis for further calibration and subsequent validation. We discuss these steps in the next section.

6.2.3.2 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, 2021). The starting point of the calibration is a suitably synthesized population as obtained in (Snelder et al., 2021), which is representative for the MRDH region. These population data are further described in Section 6.3.1, 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. We perform the calibration process with this fraction rather than the complete population, since it relieves the otherwise unfeasible computational burden. Next to these data, the



(A) Age distribution of the synthesized populations in the MRDH region and the Bay Area



(B) Modal splits pertaining to commuting trips in the MRDH region and the Bay Area

FIGURE 6.1: Comparison between the Bay Area and the MRDH region

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 (CBS), 2018b) 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 6.A.1.

The calibration procedure that we use is the one described in (Bowman et al., 2014). In this procedure, the alternative-specific constant α_i as well as the coefficients pertaining to the travel time ($\beta_{\text{car,tt}}$ and $\beta_{\text{PT,tt}}$) and the travel cost ($\beta_{\text{car,cost}}$ and $\beta_{\text{PT,cost}}$) of the car and public transport modes are tweaked so that the output of the model using the new coefficient values reflects the situation as sketched by the benchmark data well. While in principle we could have made all coefficients of (6.2) subject to alteration, we opted to tweak only specifically these parameters, since these parameters are known to cause the biggest issues with transferability; cf. (Bowman and Bradley, 2017). The procedure is iterative: in each iteration, the ABM-model is run with the (10%-fraction of the) synthesized 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 using damping factors (cf. (Brinckerhoff, 2015)). This process repeats until the coefficients hardly change anymore.

After undertaking this procedure, as can be seen in Appendix 6.A.2, the model output of the ABM based on (the fraction of) the synthesized 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.

6.3 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 6.1. Broadly speaking, we explore whether NMS and parking policies lead to a more sustainable mobility. We do this by running the ABM model for the MRDH region for the year 2030. We focus on this particular year, since we will see below that forecasted data on different aspects of the population in this year exists. In Section 6.3.1, we first explain the input data of the MRDH region on which the case study is based in more detail. After this, Section 6.3.2 defines seven scenarios that we will use in order to address the questions raised in Section 6.1 and reach conclusions. Each of these scenarios includes a significant change geared to improve the sustainability of the mobility, for example the introduction of stricter parking policies, broader use of MaaS by travellers or the introduction of an improved public transport service. Furthermore, Section 6.3.3 presents the results obtained by running the ABM model in these scenarios. Finally, Section 6.3.4 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.

6.3.1 Input data

As mentioned before, the region which the case study focuses on is the Metropolitan Region Rotterdam and The Hague in the Netherlands, which has an area of about 1130 km^2. 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 Bureau voor de Statistiek (CBS), 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 synthesized 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 we rely on is from the V-MRDH 2.6 model in (Schoor-

(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)

FIGURE 6.2: MRDH region in the Netherlands and main city centers

lemmer, 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 Figure 6.2a. 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, we use P+R locations (park&ride) currently already in place in the traffic infrastructure as well as current train stations as locations of the mobility hubs; cf. (Schoorlemmer, 2020). These are depicted in Figure 6.2b. Each of these mobility hubs may accommodate one or more of the transfer types mentioned in Section 6.2.2.2: CAR-PT, CAR-BIKE and CAR-EBIKE. 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 e-bike, 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 we consider, we generate travel time, cost and distance for three different periods over the day (morning peak, evening peaking and off-peak). These characteristics

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

TABLE 6.2: List of parameters to determine level of service (Zhou et al., 2020b)

have been derived using both results in (Snelder et al., 2021) and the values presented in Table 6.2 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.

6.3.2 Scenario description

We proceed by giving an overview of the scenarios that we consider in the case study, which are summarised in Table 6.3. As can be seen in the table, the scenarios 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. This scenario is based on the forecast of the population made in (Manders and Kook, 2015), 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, we will add several new features (i.e., new mobility services and parking policies) to this base scenario to measure the individual impact of each of them to 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,

#	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%

TABLE 6.3: Overview of the scenarios considered in the case study

and travel onwards using public transport or private (e-)bike. As mentioned before, the locations of the mobility hubs are depicted in Figure 6.2b and parking at these hubs is assumed to be free.

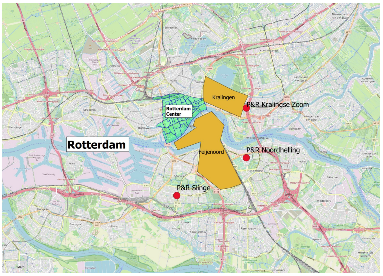
3. The third scenario 'MaaS' adds new mobility services to the previous scenario. That is, shared modes are now available as well as MaaS. The scenario assumes that 50% of the population in each age category mentioned in Section 6.3.1 owns a MaaS subscription. As a result, half of the population has 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 it in Section 6.3.4. 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.

4. 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, which can be realised by optimising schedules and implementing technological advances as indicated by (de Vries et al., 2021).

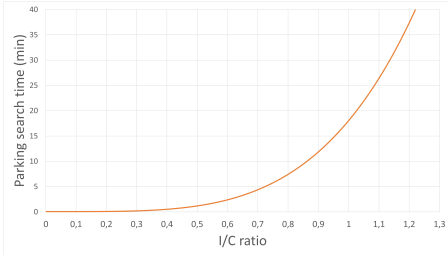
5. In addition to the improved public transport service to and within the city centers, policy makers may also consider plans to improve other forms of mobility. To this end, the fifth scenario, which we call ‘Micromobility travel time’, considers other mobility improvements specifically in the city 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 nautiek MIRT-verkenning Oeververbindingen regio Rotterdam, 2021). To obtain an idea of the placement of the Rotterdam mobility hubs with respect to the city center of Rotterdam, we refer to Figure 6.3a).

6. 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 Figure 6.2b). 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 volume-delay function based on a study of (Lam et al., 1999), which is called the BPR-curve; cf. Figure 6.3b. That is, the BPR-curve 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. 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.

7. 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% ($1.25^{\frac{1}{10}} \approx 1.0225$). We expect the yearly increase of the parking costs in the MRDH region to be a little lower based on historical numbers, which



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



(B) The BPR curve

FIGURE 6.3: Scenarios 5 and 6

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 we have specified the input data and defined all scenarios, we are ready to present the results of our case study.

6.3.3 Results

Using the ABM implementation as detailed in Section 6.2, 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 2.4GHz CPU. Each scenario has been simulated eight times using the common random number technology that was explained in (Zhou et al., 2022a). This methodology ensures that the effect of simulation error on the model output is mitigated and eight runs is sufficient for aggregated indicators as shown in (Zhou et al., 2022a). That is, each of the results in this section is based on an average of eight simulated values, of which the corresponding confidence interval is small enough to deduce that the average is not significantly influenced by outlying samples.

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. Figures 6.4 and 6.5 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'. We not only

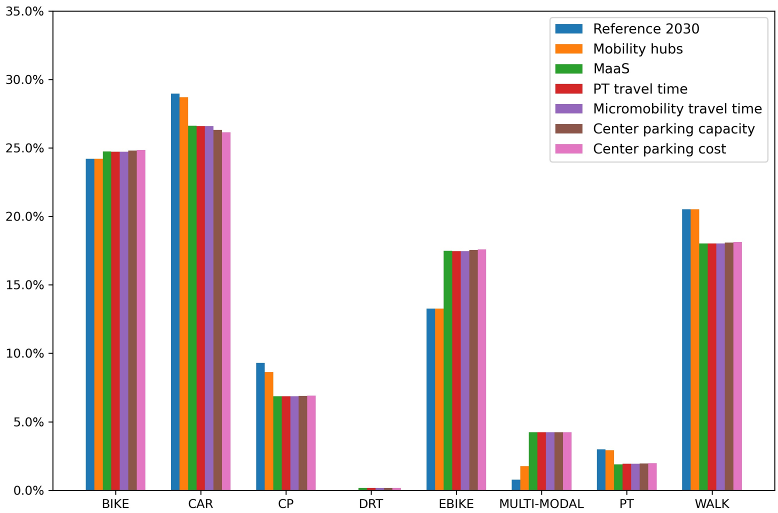
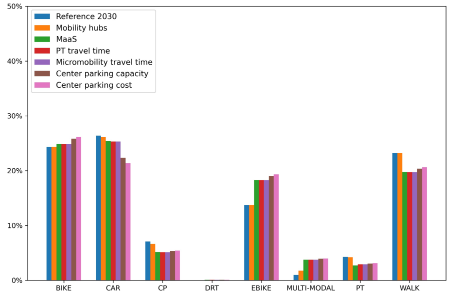


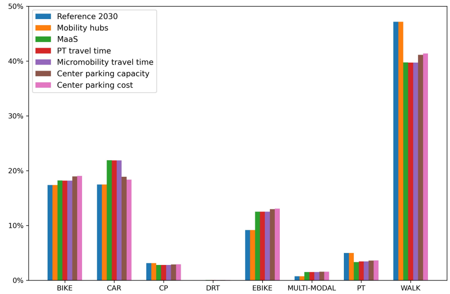
FIGURE 6.4: Bar chart representing the modal split of all simulated trips in the MRDH region under the various scenarios

present the modal split based on all simulated trips (Figure 6.4), but for reasons that will become clear later, we also plot the modal splits of several subsets of these trips (Figure 6.5). For example, Figure 6.5a 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, Figures 6.5b and 6.5c show the modal split of trip movements within the city centers of Rotterdam and The Hague, respectively. Finally, Figure 6.5d shows the modal split of trips from the center of The Hague to the center of Rotterdam and vice versa.

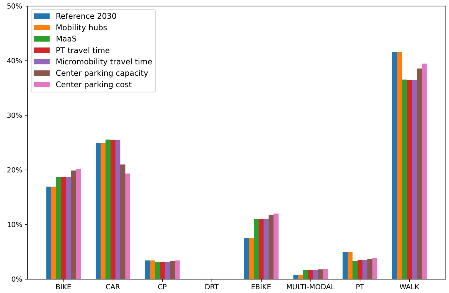
Scenario 1: Reference 2030 Before we treat the differences between the scenarios, we note that the leftmost bars in Figures 6.4 and 6.5, representing the reference scenario in the year 2030 if no NMS or additional parking policies were to be introduced, already paint a different picture than that of the current-day infrastructure. For example, Figure 6.4 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 Figures 6.5b and 6.5c shows 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.



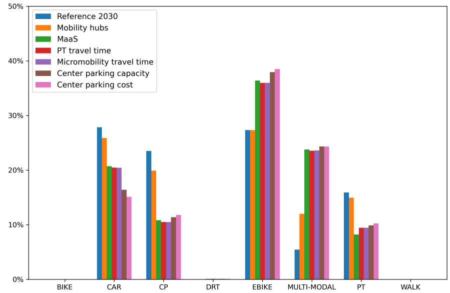
(A) Trips originating from a city center with a destination outside of a city center and vice versa



(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

FIGURE 6.5: Bar charts representing the modal split for several subsets of the simulated trips

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 6.2.2, multimodal modes involving PT as a main mode do not require mobility hubs, and these are the multimodal modes that show up in Figures 6.5b and 6.5c. In a similar vein, Figure 6.5d 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. 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 Figure 6.4 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 Figure 6.5d 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 Figure 6.4, 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 necessarily need to own 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.

Figure 6.5a 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. Figure 6.2b), which are unattractive. The next two scenarios address these long travel times.

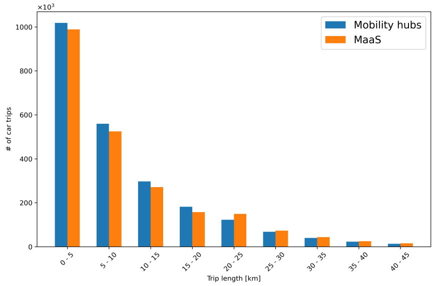
For trips within the city centers, illustrated by Figures 6.5b and 6.5c, multimodal mode trips are necessarily trips with public transport as the main mode since they do not require mobility hubs as earlier mentioned. As a result, the share of CP remains largely unaffected by the introduction of MaaS, 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. Figure 6.5d), 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 trips between the city center was not used to begin with, the use of the CAR and CP drops more significantly with the introduction of MaaS.

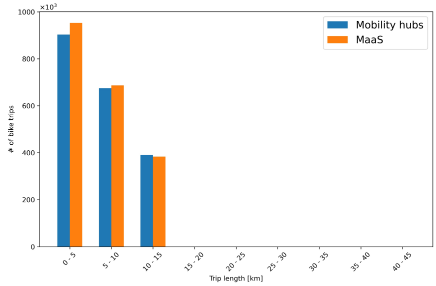
Finally, we note that in this scenario, compared to the previous scenario introducing the use of mobility hubs, the total distance covered by cars increases by 0.9%. Based on Figure 6.6a, which shows for both the current and the previous scenario the simulated numbers of trips in several distance ranges 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. Figures 6.6b and 6.6c), 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 minutes longer than the average duration in case all trips were undertaken by the unimodal CAR mode.

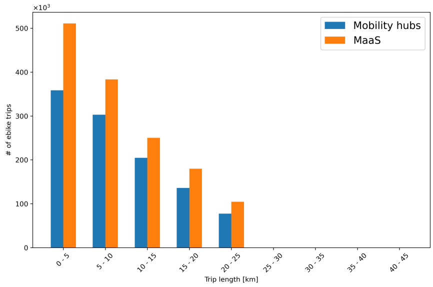
In an effort to remedy this effect, the fourth scenario assumes public transport services from and to city centers to be faster. It can be seen in Figure 6.5a that, as a result of this, the share of the PT mode only increases from 2.7% to 2.9%. That is, the share of PT trips either originating or having a destination in a city center (or both) only increases slightly. The effect of the reduced PT travel time in Figure 6.5d is more pronounced; the number of trips undertaken by PT between the centers



(A) Trips undertaken by car



(B) Trips undertaken by bike



(C) Trips undertaken by e-bike

FIGURE 6.6: 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.

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%. We thus conclude that a more efficient public transport system may stimulate the use of mobility hubs.

Scenario 5: Micromobility travel time As mentioned in Section 6.3.2, 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. Figures 6.4 and 6.5 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 Figure 6.4, 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 Figure 6.5 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 VMA model (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. As a result, it can be concluded 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 Figure 6.4 again does not reveal a big impact, Figure 6.5 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 VMA model (Gemeente Amsterdam Verkeer en Openbare Ruimte, 2019), which is -0.12. The difference in these parking cost 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. We do 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, but not necessarily of the multimodal modes.

Furthermore, we mention that the 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.

6.3.4 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, we will conclude that these effects will not significantly alter the observations of Section 6.3.3.

6.3.4.1 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 (CBS), 2018a), the alternative-specific constant α_{DRT} as well as the time and cost coefficients $\beta_{\text{DRT,time}}$ and $\beta_{\text{DRT,cost}}$ in (6.2) may be unreliable. To assess the sensitivity of the model results to these parameters, we have rerun the model for Scenario 3 with different values for these parameters. In particular, we have first rerun the model where α_{DRT} is now taken to be equal to α_{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 α_{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 $\beta_{\text{DRT,time}}$ reduced by 10% and 20% (with the original alternative-specific constant and cost coefficients), respectively, and two more experiments with $\beta_{\text{DRT,cost}}$ reduced by

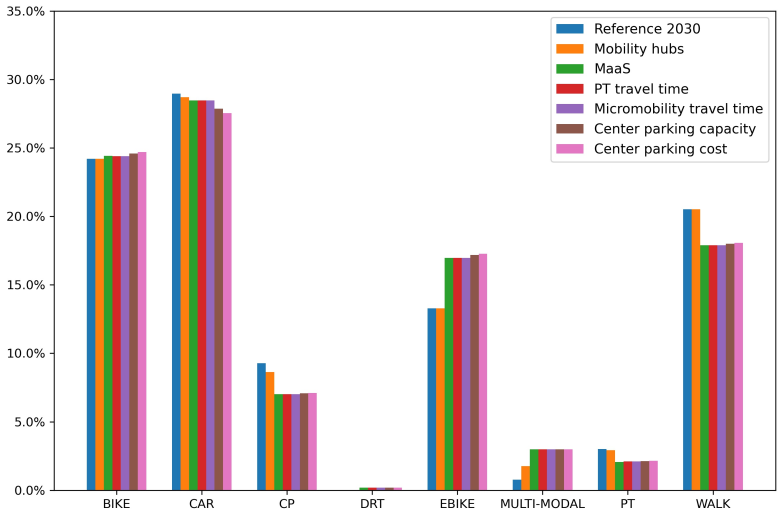


FIGURE 6.7: Equivalent of Figure 4 when a decision between a private and shared car is always made in favour of the private car.

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 we 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 6.3.3.

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, we see 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.

6.3.4.2 Parking searching time

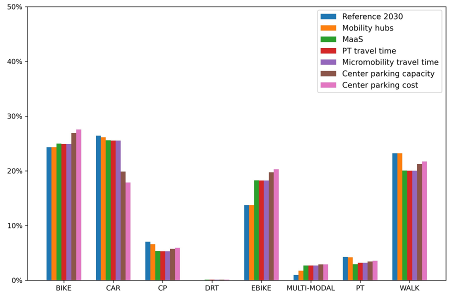
The second sensitivity analysis that we perform pertains to Scenario 6, where the parking capacity of the city centers of The Hague, Delft and Rotterdam are reduced by 30%. The extra searching time this induces for travellers wishing to park their cars is unpredictable. In the results, we have assumed searching time 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 6.3.3, 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, we expect the impact on the findings of Section 6.3.3 as a result of estimation errors in the extra parking searching time to be limited.

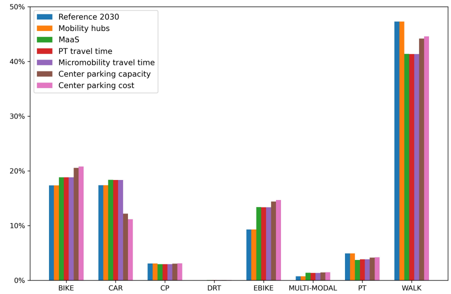
6.3.4.3 Ownership of private car and MaaS subscription

In the absence of relevant data, we have assumed from the third scenario onwards 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.

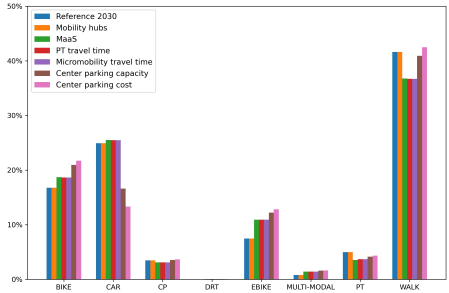
It turns out that, for our purposes, the impact of this assumption also appears limited. To show this, we have rerun the model with the other extreme as an assumption: a choice between a shared car and a private car is always made in favour of the private car by the traveller. Figures 6.7 and 6.8 present the equivalents of Figures 6.4 and 6.5 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, we see generally that the overall share of the multimodal modes is a little lower than before, while the share of the car mode increases. While this is to be expected, the effects observed in Section 6.3.3 remain intact in these figures. For example, we observe in Figure 6.8a 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



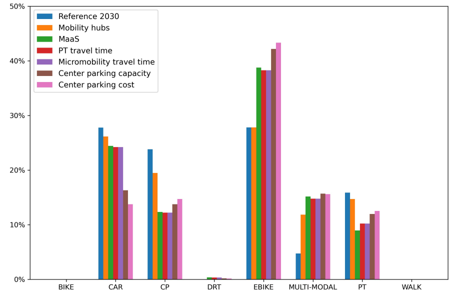
(A) Trips originating from a city center with a destination outside of a city center and vice versa



(B) Trips taking place within the center of Rotterdam



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



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

FIGURE 6.8: Equivalent of Figure 5 when a decision between a private and shared car is always made in favour of the private car.

above, Figures 6.4 and 6.5 on one hand and Figures 6.7 and 6.8 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.

6.4 Conclusions and further research

In this section, we round off this chapter with a conclusion, explicitly answering the research questions posed in Section 6.1, and a discussion on further avenues of research on this topic.

6.4.1 Conclusion

In this chapter, 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, we provide concluding answers to the questions raised in Section 6.1 for this region, which we believe 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 is mainly a result of the fact that 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 6.1 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, we have considered two more scenarios in this case study. In the first of these scenarios, the travel time of public transport is decreased 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 6.1 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 percentual 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 have been reached, one may wonder to what extent the conclusions reached in these chapter for the MRDH region 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^2 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, 2021b) 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, in line with (Linh et al., 2019), a specific case study for the MRA region may still have an added benefit. 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.

6.4.2 Avenues for further research

We conclude this study by suggesting a number of avenues for further research. First, the model used in this study may 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. Due to its flexibility, ABM is however geared to take these social changes into considerations, and further research may thus chart the implications of hybrid working for the infrastructure. Furthermore, the model may also be used to study other topics, such as the optimisation of the location of mobility hubs for an as sustainable as possible mobility. 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.

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 (6.2) 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, we can use already known estimations based on unimodal modes, while 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 direction of further research concerns certain assumptions we made throughout this chapter. For example, in this chapter 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 6.3.4 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.

Finally, we mention 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 chapter observes solely first-order effects, and these observations may be amenable to improvement. As an example, 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. This feedback effect 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.

Appendix 6.A Model calibration and assessment

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

The OViN/ODiN survey data (Centraal Bureau voor de Statistiek (CBS), 2018b) 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.

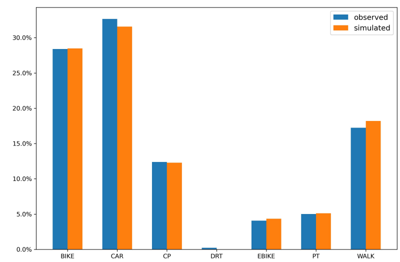
For the purpose of calibration and validation, we use the data of the OViN/ODiN survey that pertain to inhabitants of the MRDH region. We first however process these data. For example, as the ABM considers a daily simulation of all traffic between 5AM and 11PM, we have taken out trips that, in part or 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, we have therefore filtered out these trips 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 6.2.1.2.

Next to shaping up the dataset, we also need to label each tour in the data set 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 categorize 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 which we call ‘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.

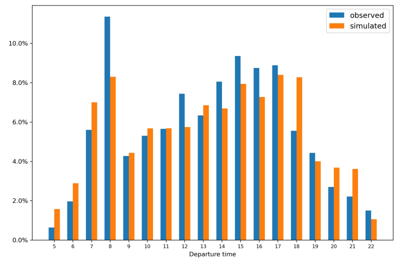
6.A.2 Validation

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

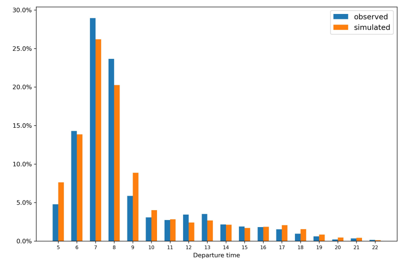
First, the simulated average trips per person, namely 3.2, is very close to the observed average of 3.3. Also the simulated modal split of the trips is quite close to that of the observed modal split, as is graphically illustrated in Figure 6.A.1a. The correlation coefficient between the simulated numbers 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,



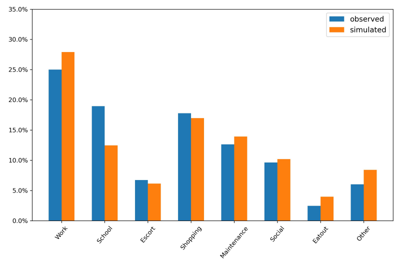
(A) Modal split of the trips



(B) Distribution of the departure times of all trips



(C) Distribution of the departure times of work trips



(D) Simulated and observed main purpose split of tours

FIGURE 6.A.1: Validation Results

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. Figures 6.A.1b and 6.A.1c 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, we perform a comparison based on the simulated and the observed main purpose split of the tours, cf. Figure 6.A.1d. 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 (CBS), 2018a), 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 we consider in this chapter 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. (Knapen 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 6.A.1 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.

	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%

TABLE 6.A.1: Access and egress modes used in multimodal trips with public transport as the main mode for different periods of the day.

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.

7

Conclusions and Recommendations

The main objective of this thesis is to develop fast activity-based travel demand models to evaluate the impact of new mobility services and policy alternatives. To achieve this objective, a few methodological hurdles have been cleared. For example, the model can now include many new travel modes without sacrificing numerical efficiency. Furthermore, the mode choice model constructs feasible mode chains within trips and tours and implements parallel computing to speed up computations. Moreover, techniques have been implemented that reduce the number of required reruns while the output of the model remains reliable. With the thus obtained improved model, we performed a large-scale case study to demonstrate the potential of the developed methodology.

Each of the above-described hurdles corresponds to a research question. In Section 7.1, we describe the answers to the questions which summarise this thesis's main findings and scientific contributions. This section is then followed by practical implications in Section 7.2 and future research directions in Section 7.3.

7.1 Main findings and scientific contributions

This section summarises the main findings of this thesis. It answers all research questions raised in **Chapter 1**.

1. How to identify all feasible multimodal mode chains in a tour? (**Chapter 2**)

We proposed a MaaS-oriented travel mode structure to be used within a travel mode choice component of our ABM. The unimodal and multimodal modes are different, so all the trip mode alternatives remain non-nested. As MaaS could offer more and more travel mode alternatives, this flexible mode structure allows adding new unimodal or multimodal modes. Next, since not all the mode combinations are feasible from the tour's perspective, we developed a consistency check procedure to prevent the evaluation of infeasible mode combinations, improving numerical efficiency. The numerical illustration shows that filtering only feasible mode chain choices effectively reduces the number of mode chain alternatives.

2. How to efficiently model different new mobility services in the ABM framework? (**Chapter 3**)

We introduced a mode categorisation into seven categories, in which traditional modes as well as modes introduced by new mobility services can be placed. While modes in the same category are understood to be similar, we aimed at maximising the heterogeneity between different categories. Future travel modes can also be added in these categories. The categorisation helps to reduce selection bias while it induces numerical efficiency.

Next to this, we also developed a novel tour-based multimodal mode choice model to model new mobility services. As multimodality is an essential feature in this context, we explicitly modelled the multimodal mode in a single trip. We included checks in the model that ensures that the mode chain used for the complete tour is feasible in terms of personal vehicle ownership, ownership of a driving licence, MaaS subscription ownership and vehicle states. We found that the penetration rate of MaaS subscriptions highly affects the rate at which multimodal modes are used.

3. How to reduce the computation time of an ABM using a computer's GPU? (**Chapter 4**)

Due to the high level of detail that is modelled by an ABM, the evaluation of the ABM can become prohibitively slow. However, the activity schedules of individual persons are mostly uncorrelated. Therefore, the schedules can be generated concurrently using a computer's GPU, because it is designed for parallel computation. The persons/households are processed in parallel by the GPU's many cores. By moving the data into a GPU's memory, accessing its memory efficiently and doing the intensive computation in parallel by many GPU processors, the implemented GPU-based daily activity pattern led to speedup factors in the order of 50. These factors are sensitive to the number of households and the number of alternatives in the scenario. The result shows that GPU-based parallel computation addresses the problem of high computation time to a large extent.

4. How to reduce the number of simulation runs while keeping the difference between scenarios stable? (**Chapter 5**)

We studied the use of common random numbers (CRN), which reuses the same random numbers for travellers' choices. This technique ensures that the difference in the output of multiple scenarios is attributed to changes in the scenarios but not to the drawn random numbers. The results of our experiments have shown three important findings. First, CRN typically greatly reduces the required number of simulation runs, thus less computation time to obtain reliable results. Second, CRN is especially worthy of implementation when the differences between scenarios are moderate. Third, the impact of CRN is also related to the degree to which the variability of generated random numbers can cause random fluctuations in the model output. If the random numbers cannot trigger large fluctuations, CRN will not greatly impact the required number of simulation runs. Nevertheless, the implementation of CRN still yields smaller confidence intervals, adding to the reliability of the results.

5. What is the impact of new mobility services and restricting parking policies on sustainable mobility? (**Chapter 6**)

The case study of the MRDH region in the Netherlands, which implements the above-mentioned ABM improvements, provides answers to this question. First, the introduction of shared services makes the use of mobility hubs more appealing to car users. Furthermore, the share of trips undertaken as a car driver or passenger decreases, while the share of trips undertaken by e-bike or multimodal mode increases. However, people may walk less for short distances because shared services are available. Second, improving the performance of services and better infrastructure could also stimulate the use of public transport and multimodal modes via mobility hubs. Third, reducing the parking capacity and increasing the parking cost in the city centers makes the car mode less popular in the city centers.

While this case study was aimed at the region including and surrounding the cities of Rotterdam and The Hague, its conclusions paint a representative picture of the potential of the several strategies in other regions in the Netherlands. However, due to the differences between these regions, a specific case study for the different regions may still have an added benefit. For other regions outside of the Netherlands, at least an estimation of the relevant coefficients in the utility functions and subsequent calibration of those should be performed based on local survey data to ensure that the difference in region characteristics does not lead to different conclusions.

7.2 Implication for practice

In this thesis, we have developed methodologies (i) to model new mobility services efficiently and (ii) to evaluate the impact of policies relatively quickly and reliably. Furthermore, the methods developed in the thesis are general and flexible, so we could use our methodologies to assess the effect of different policies as well.

The model presented in the thesis can be applied in studies of the penetration of MaaS subscriptions. The impact of different penetration rates on MaaS subscriptions can be explored to help policymakers and MaaS providers optimise the MaaS package. The model can also help to evaluate the effect of people's willingness to use MaaS.

The case study in Chapter 6 has indicated that when shared services are available at the mobility hubs, they could be much more attractive than the situation without them. This is mostly due to the fact that in the latter case, travellers would need to make sure that privately-owned vehicles are available at the mobility hub. While the primary purpose of mobility hubs is indeed to allow travellers to change to more sustainable modes, however, these hubs may offer additional social services (such as shops and restaurants) so that they become multi-functional hubs. Our model allows for the inclusion of these features, so that comprehensive results can be used to analyse the accessibility of hub locations. With these results, hub designers can optimise the locations of the mobility hubs and improve their usability.

The case study results have also shown that reducing the parking capacity and increasing the parking cost inside the city centers can improve the car flow and increase the use of more sustainable modes. Therefore, the policymakers could adapt their parking policies to improve the urban living environment and safety. Furthermore, more flexible parking cost policies may also be explored to improve the relationship between traffic flow and city parking income.

7.3 Future research directions

This section presents a number of opportunities for future research from the perspective of methodology as well as the perspective of the model's applicability.

7.3.1 Methodology

From a methodological point of view, we remark that the multimodal modes that we considered in the ABM contains an access mode, a main mode and an egress mode. Although it does not happen often, more complex mode combinations could occur in practice, involving more than three modes in a combination. Enumerating all these combinations and chains is a complicated task. A dynamic discrete choice mode combination or super-network approach can be taken into consideration to sequentially make access, main and egress mode choices.

Next, we mention that the categorisation implemented in this thesis may still be further optimised to avoid heterogeneity issues as much as possible. That is, currently, travellers could still have different personal preferences regarding two modes in a single category. Solving these heterogeneity issues is a topic for further research. That is, by selecting different aspect elements than those chosen in

Section 3.2.1, or even choosing different aspects, this issue may be reduced to a minimum.

Furthermore, it is worth noting that the utility function of a multimodal mode mainly relies on the main mode's socio-demographic attributes. This approach may ignore the heterogeneity in travellers' preferences concerning access and egress modes. It may be useful to include these in the utility functions of the multimodal modes, which requires careful parameter estimations.

Finally, we remark on the possibility of integrating our ABM within micro-simulation traffic assignment models. While an ABM is necessary to predict travelling behaviour considering the typical operational level of several services and the individual nature of the behaviour of travellers, micro-simulation traffic assignment models typically employ microscopic and time-dynamic simulation of this behaviour based on the constraints of the transport network (Anderson et al., 2017). Therefore, when attempting to understand completely new future services, such as MaaS, it may be worthwhile to integrate the ABM within an agent-based microscopic traffic assignment model. In such a system, the micro-simulation can assign the travel demand directly to the transportation network, while taking fleet sizes and dynamic traffic performance into account. By doing this, the ABM can then adjust the travel demands by getting feedback from the transportation network. However, this may require additional non-trivial modelling developments.

7.3.2 Applicability

We now mention two possibilities for further research from the point of view of the applicability of the model. As for the first of these two possibilities, we note that we have applied the methods and models developed in this thesis in a case study in the metropolitan region which includes and surrounds the Dutch cities Rotterdam and The Hague. The conclusions from this case study could be representative for other regions in the Netherlands with similar urban density, population distribution and income. For regions outside of the Netherlands, although it is conceivable that the same conclusions essentially apply there as well, at least an 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 inadequate conclusions.

Furthermore, we mention that the case study in Chapter 6 has studied the impact of sharing services and urban parking policies on city accessibility but has not yet considered the impact on economy, traffic safety, noise and air pollution, which are of interest too to policy makers and designers. For these kinds of analyses, other models need to be included.

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Summary

Impact assessment of new mobility services using accelerated activity-based demand modeling

We are living in a fast-evolving world. One of the reasons for this is that the digital world has gotten closer to us since the first real smartphone came out in 2007. Increasingly convenient smartphone apps have greatly simplified our daily lives by enabling e.g. online shopping, travelling and social networking. Due to this kind of digital developments, new mobility services such as mobility as a service (MaaS) and mode-sharing services may affect the behaviour of individual travellers significantly. Next to this, evolving factors concerning the travelling population (e.g. demographics, preferences and lifestyle) may also change the mobility landscape. Moreover, there are changes in the economy and land use that affect the transportation system's performance. In the face of all the above-mentioned societal changes, policymakers want to know how the transportation system will perform in the future and what kind of policies and interventions should be proposed to achieve the desired output.

For this purpose, accurate estimations of future travel demand are needed. As new mobility services aim to provide tailored transport services to satisfy individual travellers' needs, demand models are required that incorporate a high level of detail. As an example of such models, activity-based travel demand models (ABMs) are advanced models that are used to describe the individual's daily travel schedule. They aim at closely replicating actual travelling decisions based on behavioural theories on how people make decisions to participate in activities in the presence of constraints. For each individual, these models predict their decisions on what activities to do, where and when to do them, and how to go there. It is natural to choose the ABM framework to model new mobility services and evaluate their impact on the transportation system.

However, while the ABM framework in principle has the potential to estimate actual travel demand models accurately, various challenges arise, mostly due to the high level of detail that ABMs bring. That is, the framework requires the capability to model traditional and new mobility modes, simulate a plethora of scenarios fast and generate stable output. These challenges are at the heart of this

thesis. Put differently, the main objective of this thesis is to develop fast activity-based travel demand models to evaluate the impact of new mobility services and policy alternatives. To achieve this objective, the model should be able to handle different transportation modes and simulate different scenarios efficiently and accurately. In order to reach this objective, a number of methodologies are developed that overcome the above-mentioned challenges. After that, a large-scale case study is performed, demonstrating the potential of the ABM framework together with the developed methodologies. We now proceed to describe the methodologies that are developed and the case study that is conducted in the several chapters of this thesis.

The first challenge concerns the required capability to efficiently model both traditional and new mobility modes. To overcome this challenge, Chapter 2 introduces a MaaS-oriented travel mode structure within a travel mode choice component of the ABM. This flexible mode structure allows adding new unimodal or multimodal modes. The unimodal and multimodal modes are modelled separately, so that all trip mode alternatives remain non-nested, which helps the ABM to remain as numerically efficient as possible. The chapter also describes a consistency check procedure to prevent the evaluation of infeasible mode combinations, further improving numerical efficiency. A numerical illustration shows that filtering only feasible mode chain choices effectively reduces the number of mode chain alternatives. Also in an effort to address the first challenge, Chapter 3 introduces a mode categorisation into seven mode categories, in which both traditional and new modes can be placed. This categorisation again limits the number of mode choice alternatives, benefitting numerical efficiency, while maximising the heterogeneity between different categories. As an added advantage, this categorisation reduces possible selection bias.

As mentioned above, the high level of detail is a desirable feature of the ABM framework. However, this level of detail also brings a large computational burden. This leads to the fact that evaluating scenarios is computationally a very intensive endeavour, while for the purposes of policy making, one needs to be able to evaluate a plethora of scenarios in a timely manner. To overcome this challenge, in Chapter 4 we exploit the use of a computer's GPU to accelerate the computational speed of ABM. Since the activity schedules of individual travellers, which lead to travel demand, are mostly uncorrelated, generation of these scheduled can be done in parallel. This makes the schedule generation extremely suitable for a GPU, which is designed to perform parallel computations. Analysis in this chapter shows that speedup factors up to 50 can be obtained this way, solving the problem of an ABM's high computational time to a large extent.

The previous chapters leave the third challenge, which entails the stable output of an ABM. That is, as the ABM employs simulation, output is prone to stochastic error. To make sure that this error does not make the output unreliable, a common strategy is to increase the number of simulation runs. However, this strategy is flawed in that it may increase the computation time significantly, possibly up to an infeasible extent. As an alternative strategy, Chapter 5 proposes the use of common random numbers (CRN) in the ABM framework. With this strategy, when evaluating multiple scenarios, the same drawn random numbers are used for common features in both scenarios. This way, the difference in the output between scenarios can mostly be attributed to scenario differences, rather than varying random numbers. The experiments performed in this chapter show that CRN may significantly reduce the computation time required to obtain stable output.

Once all challenges are addressed, a large-scale case study is performed in Chapter 6, which concerns the metropolitan region including and surrounding the cities of Rotterdam and The Hague in the Netherlands. Not only does this case study demonstrate the potential of the ABM framework, but it also provides insight into the possible impact of new mobility services. The case study shows for example that, when shared services are introduced, mobility hubs may be appealing to car users. At the same time, the overall share of trips undertaken as a car user (both driver and passenger) decreases, while the share of trips undertaken by e-bike or multimodal mode increases. However, the ease of use of shared services may also discourage travellers to simply walk short distances. Furthermore, the case study suggests that improving the infrastructure and performance of services may stimulate the use of public transport and multimodal modes via mobility hubs, and that reducing parking capacity and/or increasing parking cost in the city centers also makes the car mode less popular in the city centers.

SAMENVATTING

Evaluatie van de impact van nieuwe mobiliteitsdiensten met behulp van activiteit-gebaseerde modellering van de vervoervraag

We leven in een snel evoluerende wereld. Een van de redenen hiervoor is dat de consument toegang heeft tot een steeds groter wordende digitale wereld sinds de eerste echte smartphone in het jaar 2007 uitkwam. De ontwikkeling van allerlei smartphone-apps hebben ons dagelijks leven enorm vereenvoudigd door bijvoorbeeld online winkelen, reizen boeken en netwerken via social media mogelijk te maken. Door dit soort digitale ontwikkelingen kunnen nieuwe mobiliteitsdiensten zoals Mobility as a Service (MaaS) en deelmobiliteit het gedrag van individuele reizigers aanzienlijk beïnvloeden. Daarnaast kunnen veranderende reizigersvoorkeuren (bijv. demografie, voorkeuren en levensstijl) ook het mobiliteitslandschap beïnvloeden. Ook zijn er veranderingen in de economie en het landgebruik die de prestaties van het transportsysteem beïnvloeden. Door alle bovengenoemde maatschappelijke veranderingen rijst bij beleidsmakers de vraag hoe het vervoerssysteem in de toekomst zal presteren en welk soort beleid en interventies moeten worden voorgesteld.

Teneinde deze vraag te beantwoorden, zijn nauwkeurige schattingen van de toekomstige vervoervraag nodig. Aangezien nieuwe mobiliteitsdiensten gericht zijn op het aanbieden van vervoersdiensten op maat om aan de behoeften van individuele reizigers te voldoen, zijn vraagmodellen nodig met een hoog detailniveau. Een voorbeeld van zulke modellen zijn activiteit-gebaseerde modellen (ABM's). Deze geavanceerde modellen worden gebruikt om het dagelijkse, individuele reisschema van reizigers te beschrijven. Ze zijn gericht op het in detail repliceren van beslissingen op basis van gedragstheorieën over hoe mensen beslissingen nemen omtrent deelname aan activiteiten gegeven bepaalde restricties. Voor elke reiziger voorspellen deze modellen welke activiteiten ondernomen worden, waar en wanneer ze ondernomen worden en welk vervoermiddel gebruikt wordt. In dit proefschrift bestuderen we hoe nieuwe mobiliteitsdiensten met een ABM kunnen worden gemodelleerd en wat de impact van deze diensten is op het transportsysteem.

Hoewel een ABM de potentie heeft om de vervoervraag nauwkeurig te modelleren, doen zich verschillende uitdagingen voor voornamelijk als gevolg van het hoge detailniveau dat door ABM's geboden. Zo moet het beoogde ABM-raamwerk zowel traditionele als nieuwe vervoerwijzen kunnen modelleren, een groot aantal scenario's snel kunnen doorrekenen en stabiele output kunnen genereren. Deze uitdagingen staan centraal in dit proefschrift. Anders gezegd, het hoofddoel van dit proefschrift is de ontwikkeling van snelle, activiteit-gebaseerde modellen om de impact van nieuwe mobiliteitsdiensten en beleidsalternatieven te evalueren. Om dit doel te bereiken, moet het model met verschillende vervoerwijzen kunnen omgaan en verschillende scenario's efficiënt en nauwkeurig kunnen doorrekenen. Hiertoe wordt een aantal methodes ontwikkeld gericht op bovenstaande uitdagingen, gevolgd door een grootschalige case study, die het potentieel van het ABM-raamwerk tezamen met de ontwikkelde methodes demonstreert. Hieronder beschrijven we de methodes die zijn ontwikkeld en de case study die is uitgevoerd in de verschillende hoofdstukken van dit proefschrift.

De eerste uitdaging betreft het efficiënt modelleren van zowel traditionele als nieuwe vervoerwijzen. Om deze uitdaging het hoofd te bieden, introduceert Hoofdstuk 2 een MaaS-georiënteerde, flexibele structuur voor vervoerwijzekeuzemodellering in het ABM. Het gebruik van deze structuur maakt het mogelijk om zowel nieuwe unimodale vervoerwijzen als nieuwe multimodale vervoerwijzencombinaties toe te voegen voor de hele keten van verplaatsingen in een tour. De unimodale en multimodale alternatieven worden afzonderlijk niet-genest gemodelleerd, hetgeen het ABM helpt om numeriek zo efficiënt mogelijk te blijven. Het hoofdstuk beschrijft ook een procedure voor consistentiecontrole om onmogelijke vervoerwijzecombinaties te voorkomen, waardoor de numerieke efficiëntie verder wordt verbeterd. Het onderzoek laat zien dat het filteren van mogelijke vervoerwijzeketens het aantal te evalueren ketenalternatieven effectief vermindert. Daarnaast introduceert Hoofdstuk 3, ook in een poging om de eerste uitdaging te adresseren, een categorisering in zeven vervoerwijzecategorieën, waarin zowel traditionele als nieuwe vervoerwijzen kunnen worden opgenomen. Deze categorisering beperkt opnieuw het aantal keuzemogelijkheden voor het vervoerwijzekeuzemodel, wat de numerieke efficiëntie wederom ten goede komt, terwijl de heterogeniteit tussen de verschillende categorieën wordt gemaximaliseerd. Als bijkomend voordeel vermindert deze categorisering mogelijke selectiebias.

Zoals hierboven vermeld, is het hoge detailniveau één van de gewenste kenmerken van het ABM-raamwerk. Dit detailniveau brengt echter ook een grote rekenlast met zich mee. Dit leidt ertoe dat het evalueren van scenario's computationeel een zeer intensieve onderneming is, terwijl voor beleidsvorming een groot aantal aan scenario's snel moet kunnen worden geëvalueerd. Hoofdstuk 4 maakt daarom gebruik van de GPU van een computer om de rekensnelheid van het ABM te versnellen. Aangezien de activiteitenschema's van individuele reizigers, die leiden tot vervoervraag, meestal niet gecorreleerd zijn, kunnen deze schema's parallel worden gegenereerd. Dit maakt de schemageneratie uitermate geschikt voor een GPU, die is ontworpen om parallelle berekeningen uit te voeren. Analyse in dit hoofdstuk laat zien dat op deze manier versnellingsfactoren tot 50 kunnen worden verkregen, waarmee het probleem van de hoge rekentijd van een ABM voor een groot deel wordt opgelost.

De vorige hoofdstukken laten de derde uitdaging open wat betreft de stabiele resultaten van een ABM. Dat wil zeggen, aangezien een ABM gebruik maakt van simulatie, is de output ervan gevoelig voor stochastische fouten. Om ervoor te zorgen dat deze fouten de uitvoer niet onbetrouwbaar maken, is een veelgebruikte strategie om het aantal simulatieruns te verhogen. Deze strategie is echter gebrekkig in die zin dat het ook de rekentijd aanzienlijk kan verhogen, mogelijk in een te hoge mate. Als alternatieve strategie stelt Hoofdstuk 5 het gebruik van 'common random numbers' (CRN) in het ABM-raamwerk voor. Met deze strategie worden bij het evalueren van meerdere scenario's dezelfde getrokken random getallen gebruikt voor gemeenschappelijke kenmerken in de scenario's. Op deze manier kan het verschil in de output tussen scenario's worden toegeschreven aan scenarioverschillen, in plaats van aan onderling variërende random getallen. De experimenten die in dit hoofdstuk zijn uitgevoerd, laten zien dat CRN de rekentijd die nodig is om een stabiele output te verkrijgen, aanzienlijk verder verkort.

Na implementatie van bovenstaande methodologieën wordt een grootschalige case study uitgevoerd in Hoofdstuk 6, die betrekking heeft op de metropoolregio rond de steden Rotterdam en Den Haag in Nederland. Deze case study toont niet alleen het potentieel van het ABM-raamwerk aan, maar geeft ook inzicht in de mogelijke impact van nieuwe mobiliteitsdiensten in dit gebied. De case study laat bijvoorbeeld zien dat mobiliteitsknooppunten bij de introductie van deelmobiliteit aantrekkelijk kunnen zijn voor autogebruikers. Tegelijkertijd neemt het totale aandeel verplaatsingen als autogebruiker (zowel bestuurder als passagier) af, terwijl het aandeel verplaatsingen per e-bike of multimodale vervoerwijzecombinatie toeneemt. Het gebruiksgemak van gedeelde diensten kan reizigers echter ook ontmoedigen om korte afstanden te lopen. Verder suggereert de case study dat het verbeteren van de infrastructuur en de prestaties van bepaalde diensten het gebruik van openbaar vervoer en multimodale vervoerwijzecombinaties via mobiliteitshubs kan stimuleren, en dat het verminderen van de parkeercapaciteit en/of het verhogen van de parkeerkosten in de stadscentra de auto minder populair maakt in de stadscentra.

Author contributions

1. Author contribution for the article (Zhou et al., 2020b) in Chapter 2:

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3. Author contribution for the article (Zhou et al., 2019) in Chapter 4:

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5. Author contribution for the article (Zhou et al., 2022b) in Chapter 6:

H. Zhou	Conceptualization, Methodology, Software, Data Curation, Validation, Writing Original draft
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M. Mandjes	Conceptualization, Writing, Reviewing and Editing, Supervision
M. Snelder	Conceptualization, Writing, Reviewing and Editing, Supervision