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Design and Analysis of On-Demand Mobility Systems

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Design and Analysis of On-Demand Mobility Systems

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Design and Analysis of On-Demand Mobility Systems

Dissertation

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chair of the board of Doctorates

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The past four years of my PhD has been quite eventful (both professionally and personally). For someone who had never travelled outside his home country of India till then, everything was different when I first came to Delft. From shorter daytime, seeing sunlight at 8 in the evening to random people smiling and greeting me in the elevator and the supermarkets, the difference was quite overwhelming (mostly in a good way though). During those initial months of settling in, one of the factors that helped me immensely was the warm and welcoming nature of the Dutch community and I am grateful for that.

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Special thanks to my dear friends from Kerala, especially: Dileep, Kamath, Manu, AJ, and AM. From cooking our favourite meals together, those late night conversations, pulling each others' legs, Friday night drinks, playing dart till 4 in the morning, and our trips together; I have enjoyed each and every one of those immensly and will cherish them forever. To many more years of our friendship. Also, thanks to Amy, Syam, Ranjani, Prasanth, Anjana, Minu, Divya for all the memorable moments we have had together.

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Jishnu Narayan,
Delft, September 2020.

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Chapter 1

Introduction

The past decade has seen vast advancements in various ICT (Information Communication, and Technology) platforms. Such advancements include availability of reliable real-time information, advanced communication systems, and technolgy that enables users to access those information and communicate with each other. For the mobility sector, this translates to availability of real-time information regarding traffic states, schedules of public transport and their real-time locations, and vehicle-to-vehicle communication. These advancements also enabled the rise of innovative mobility solutions (on-demand transport services among many others). Such solutions offer flexible transport services to users in which users could enjoy tailor-made mobility solutions. Among the attractive attributes of such on-demand services are being able to make travel choices in real-time without having to plan for their trips well in advance or own a vehicle.

Increasing evidence from the literature indicates the effects of such innovative mobility solutions on urban mobility. The effects range from traditional modes such as privately owned cars and public transport losing their market share to on-demand services (M. P. Enoch, 2015; Conway et al., 2018), and the subsequent need for public transport systems to evolve to stay relevant (M. Enoch et al., 2020). Modelling tools for the design and assessment of such on-demand transport services therefore need to account for its effect on urban mobility by considering its interaction with other travel modes.

However, most previous studies that have looked into the design and assessment of on-demand services largely overlooked the impact of these services on other travel modes and vice-versa. This dissertation attempts to fill this research gap by developing an approach to the design and analysis of on-demand services by considering its effect on other travel modes and on urban mobility.

The remaining of the chapter is structured as follows. In the next section we present the various planning aspects of on-demand services. We then present the research objective and scope of the study by formulating the main research question. We identify the research sub-questions that needs to be answered in order to answer the main research question. Next, we present the research approach and the key modelling aspects. Finally, we present an outline for the remaining of the thesis.

1.1 Planning on-demand services in an urban mobility context

Planning on-demand services consists of three aspects, namely: *Strategic*, *Operations*, and *Assessment* (Figure 1.1). The *Strategic* aspect refers to the long term decisions regarding planning, such as fleet size dimensioning, determining the type of services (taxi-like or shared, door-to-door or stop-to-stop and so on), and fare of the services. The *Operations* aspect comprises of short term decisions regarding the daily operations of services such as assigning travel requests to vehicles, vehicle routing, and relocation strategies of vehicles in the network. The *Assessment* aspect refers to service quality evaluation in terms of the efficiency of service and level of service offered and is performed in tandem with *Tactical* and *Operations*.

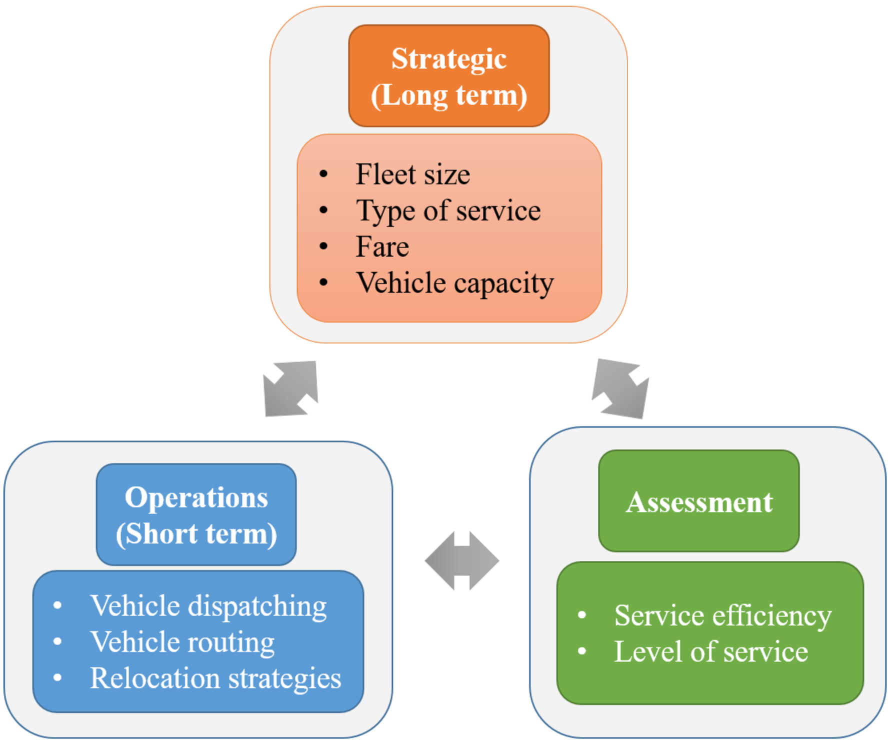


Figure 1.1: On-demand services' planning aspects

Numerous researchers have worked on each of these aspects of design and assessment of on-demand services. Works related to the *Strategic* aspect mostly dealt with fleet size and fare determination and is tackled as an optimisation problem in the literature. The objective of these studies is to determine the optimal fleet size and/or fare for the services to serve a set of travel requests with the objective of minimsing travel costs (Desrosiers et al., 1988; Gertsbach & Gurevich, 1977; Morisugi et al., 1997; Yang et al., 2002, 2005; Fu &

Ishkhanov, 2004; Z. Li & Tao, 2010). Fleet size optimisation at a city-wide context is also studied in the literature (Chang et al., 2012; J. Li et al., 2010; Vazifeh et al., 2018; Zhang & Ukkusuri, 2016). As in the previous case, the objective of these studies is to determine an optimal fleet size for a set of travel requests.

Studies related to *Operations* of on-demand services pertain to vehicle dispatching, assigning users to vehicles, and relocation of vehicles. Mathematical/analytical modelling of dispatcing and assignment is done in the literature as DARP (Dial-a-Ride Problem), and its many variations namely: DARPTW (Dial-a-Ride Problem with Time Windows), DARPT (Dial-a-Ride Problem with Transfers), PDPTW (Pickup and Delivery Problem with Time Windows); all of which are a generalisation of the classical VRP(Vehicle Routing Problem) and TSP (Traveling Salesman Problem). Additionally, request assignment has also been modelled as DVRP (Dynamic Vehicle Routing Problem) in literature. Excellent reviews of the existing advancements in modelling techniques in DARP and DVRP can be found in Cordeau & Laporte (2007), Psaraftis et al. (2016), and Ho et al. (2018). Due to the complexity of the problem (NP hard), heuristic and evolutionary optimisation methods have been used widely in the literature (Häme, 2011; Häme & Hakula, 2013, 2015; Cordeau & Laporte, 2003; Cordeau, 2006; Nanry & Barnes, 2000; Jaw et al., 1986). The general objective of all these studies is to determine a set of minimum cost paths to serve a set of requests subject to constraints related to time windows, travel time and capacity.

As is evident from the review, while there have been numerous works on the different aspects of planning, the existing works largely overlooked the interaction of on-demand services with other transport modes and their effects on urban mobility. However, in reality, mode specific demand is expected to depend on the service and also impacts the level-of-service offered. Supply-demand interactions and their impact on urban mobility need therefore to be explicitly accounted for during the planning stages of on-demand transport services. The assessment of on-demand services hence should consider the scenarios that stems from its interaction with other modes. This includes the scenarios of exploring on-demand scalability, its competition with conventional travel modes such as car, public transport, and active modes, and its combination with public transport. Design aspect which includes fleet size determination should also take into account this interaction with other modes and their influence on urban mobility. This dissertation aims to fill this research gap in the literature.

1.2 Research objective and scope

We develop a framework to the design (fleet size determination) and analysis of on-demand services by considering its interaction with other travel modes and consequentially, its effects on urban mobility. Hence, the objective of this study is the design and analysis of on-demand mobility systems in an urban mobility context. To this end, the main research question is:

How can the fleet size of an on-demand system be designed and its services be analysed in the context of urban mobility?

In order to answer this overarching research question, we need to answer a set of research sub-questions. Firstly, considering the impact of on-demand on urban mobility in general and on other modes, the analysis of on-demand services needs to performed for scenarios that stems from its interaction with other modes as illustrated in Figure 1.2.

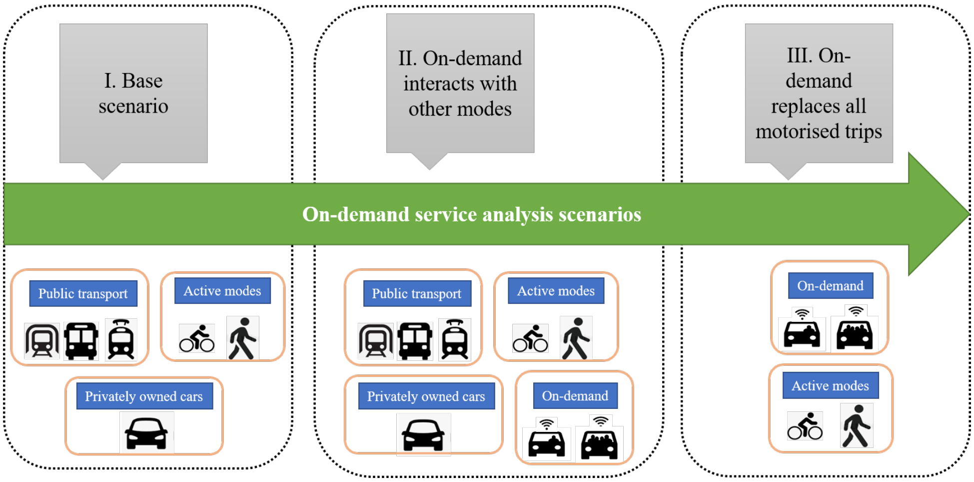


Figure 1.2: Scenarios of on-demand on urban mobility

As can be seen from the figure, we examine three scenarios of on-demand service on urban mobility. Scenario I is the base scenario where modes of car, public transport, and active modes are available. In Scenario II, on-demand services interact with the other travel modes. This includes stages where on-demand service competes with other travel modes and the one in which on-demand service is used by travellers combining it with public transport for their origin-destination trip. Scenario III represents a stage where on-demand service attracts all motorised trips - car and public transport. To this end, the research sub-questions related to scenario II is:

1. *What is the performance of on-demand mobility service offering competing services?*

2.*How can users' choice for combining public transport and on-demand services be modelled?*

The research sub-question related to scenario III is:

3.*What is the performance of on-demand transport services replacing car and public transport trips?*

This analysis part is followed by the design of on-demand services. This entails determining an optimal fleet size of an on-demand service. The research sub-question is formulated as:

4.*What is the optimal fleet size for an on-demand transport service, considering endogenous demand?*

A schematic representation of the framework developed in this study is shown in Figure 1.3.

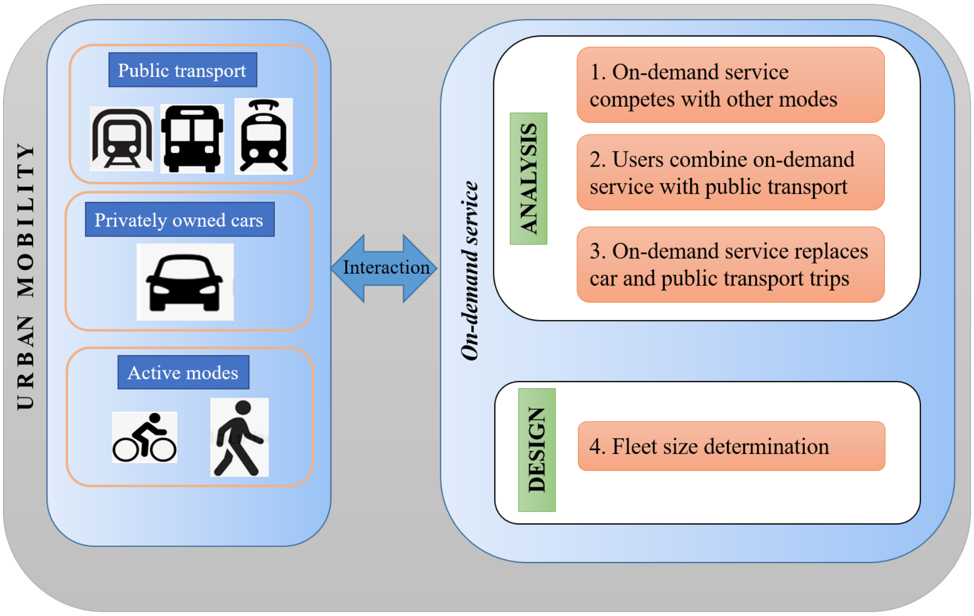


Figure 1.3: Design and analysis framework

In this thesis, on-demand transport services are modelled as a fleet of vehicles controlled by a central dispatching unit that offers door-to-door transport services to users in real-time. Hence there is no competition between the individual vehicles. Two types of on-demand services are considered, namely: private and pooled. The private on-demand transport service offers an individual taxi-like service and the vehicles are sequentially shared. The pooled on-demand transport service offers shared service where more than one passenger shares a ride.

1.3 Research approach

This section describes the research approach undertaken in this dissertation. The section is structured as follows. First the modelling approach is described. This is followed by the approach for design and analysis of on-demand services.

1.3.1 Agent-based simulation model

On-demand transport services are complex systems with real-time dynamics between users and vehicles. Hence, the modelling requirements of the system entails been able to capture the real-time dynamics and interactions. Even though mathematical and analytical models have been used extensively in the literature for planning of on-demand transport services, such models have an inherent inability to effectively capture the real-time dynamics of the on-demand transport system. Agent-based simulation models mitigate this issue to an extent; defined by Gilbert (2019) as: '...a computational method that enables a researcher to create, analyse, and experiment with models composed of agents that interact within an environment.' Agent-based simulation methods can effectively incorporate the user preferences into the system while providing insights into the operations of the system (Ronald et al., 2015). Recent works also illustrate the effectivemess of agent-based simulation models in modelling on-demand transport services (Kaddoura et al., 2012, 2015; Maciejewski, Horni, et al., 2016; Maciejewski & Nagel, 2013a; Neumann & Nagel, 2013; Hörl, 2016). Hence in this study, an agent-based simulation model, MATSim (Horni et al., 2016b) that incorporates the day-to-day learning of users is adopted for the design and assessment of on-demand transport services. Users are modelled as individual agents and are autonomous decision making entities. An overview of the agent-based simulation model adopted and adapted in this study is shown in Figure 1.4.

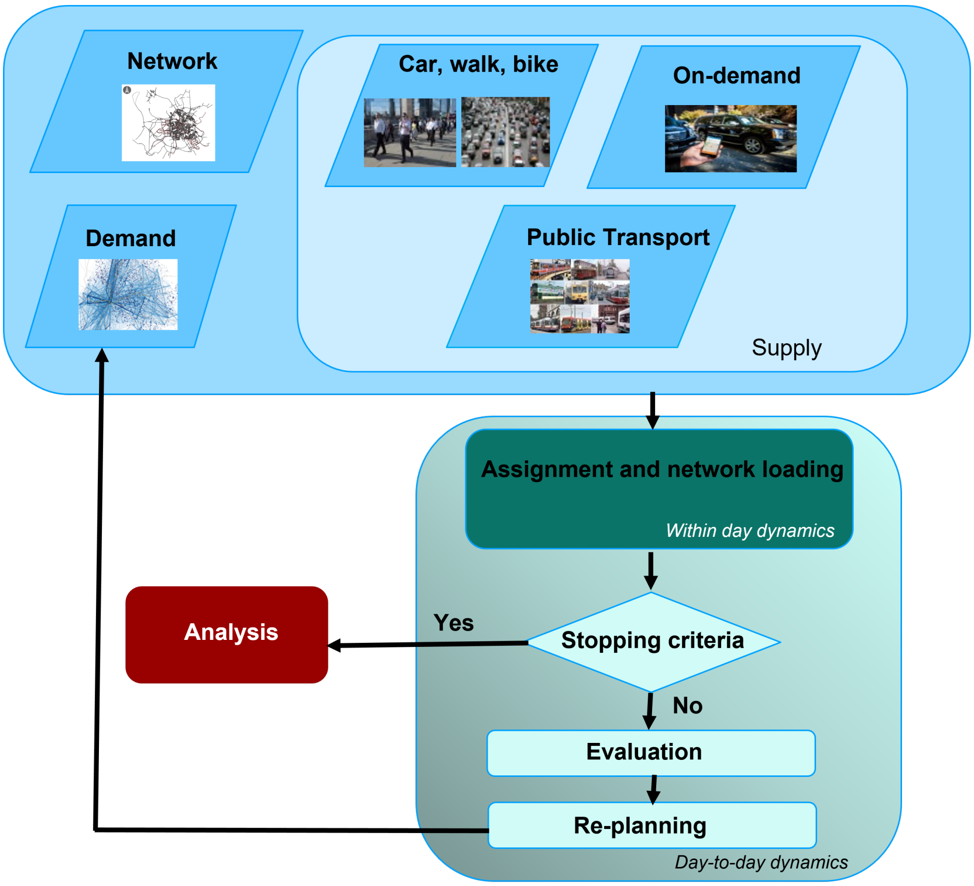


Figure 1.4: Agent-based simulation framework

The *Input* module comprises of the sub-modules of Network, Demand, and Supply. The Network sub-module comprises of data of the application network with nodes and connecting links. The Supply sub-module comprises of the transport services provided by the service providers and a default set of modes available to each user. The Demand sub-module comprises of passengers with a set of origin and destination points in the network. Each passenger has a set of travel plans as the demand data and each travel plan is represented as an activity-based travel demand data. Each plan comprises of two elements namely, *Activities* and *Legs*. Typical *Activities* include "home" (typically the first plan element of the day) and "work". Depending on the demand data, attributes that are usually associated with *Activities* include start and end time, minimum duration, location, earliest arrival time and latest departure time. The second element of the plan, *Legs* represents the connections between the *Activities*. The typical information that is stored in a *Leg* are the type of mode that the passenger use to travel from one activity to the next. Figure 1.5 shows a typical plan of an agent.

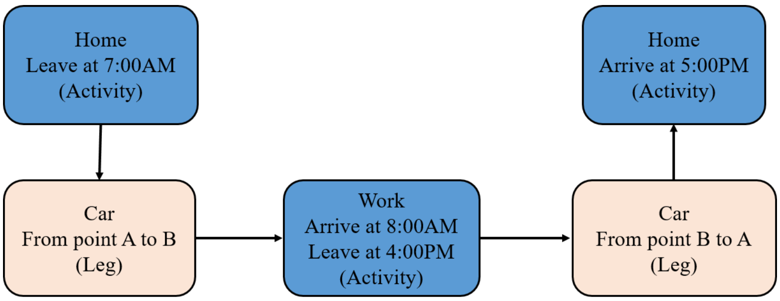


Figure 1.5: A typical plan of an agent

The *Input* module is followed by the *Assignment and network loading* module which constitutes the within-day-dynamics of the model. The agents are assigned to individual travel modes and loaded onto the network as per their travel plan. This is followed by the *Evaluation* module where agents evaluate their travel plans based on the experienced service. This is done in the form of a utility-based scoring of each plan based on the Charypar-Nagel scoring function (Horni et al., 2016b) as shown below:

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)} \tag{1.1}$$

In Equation 1.1, S_{plan} represents the score of an entire plan of the agent, $\sum_{q=0}^{N-1} S_{act,q}$ represents the score of all the activities performed, and $\sum_{q=0}^{N-1} S_{trav,mode(q)}$ represents the score of all the travel legs, and N represents the total number of activities performed. The plan of the agent is scored based on Equation 1.1 and that score is stored with that plan. The *Evaluation* module is followed by the *Re-planning* module which constitute the "learning" part of the model. In this module the agent alters his/her travel plan based on a set of predefined strategies for the next day (iteration). These strategies include selecting a plan with the best score, changing the departure time from an activity, changing the mode of travel, and changing the route of travel. The altered set of travel plans forms the demand data for the next iteation. The *Assignment and network loading* module, *Evaluation* module and the *Re-planning* module constitute the day-to-day dynamics of the model. This sequential process of *Assignment and network loading*, *Evaluation*, and the *Re-planning* is continued until a state of stochastic user equilibrium is achieved.

Replications

Since the model comprise of several stochastic elements and interactions between agents, multiple simulation runs are required to account for this stochasticity and subsequent output analysis. Considering the average waiting time of users of on-demand service as a key performance index, the required number of replications to account for stochasticity can be calculated by the following equation (Cats et al., 2010; Burghout, 2004; Dowling et al., 2004):

$$N(m) = \left(\frac{S(m) \cdot t_{(m-1), \frac{1-\alpha}{2}}}{\overline{\chi}(m) \cdot \varepsilon} \right)^2 \tag{1.2}$$

In the above equation, $N(m)$ represents the number of replications required given initial simulation run of m. $\overline{\chi}(m)$ and $S(m)$ represents the estimated mean and standard deviation from a sample of m simulation runs. Finally, ε and α represents the allowable percentage of error of estimate $\overline{\chi}(m)$ and level of significance respectively. Given an allowable percentage error, ε = 0.05 and level of significance, α = 0.05, a total number of 10 simulation runs were found to be sufficient to account for stochasticities for all of the simulation scenarios considered in this thesis.

1.3.2 Analysis and design of on-demand services

The analysis of on-demand services is performed for scenarios that stems from the interaction of on-demand services with traditional travel modes in an urban mobility context. First we consider the scenario where on-demand service competes with traditional modes of car, active modes, and public transport. Next we consider the scenario where users combnine on-demand services and public transport for their origin-destination journey. Finally we consider the hypothetical scenario where on-demand service replace all trips performed by car and public transport. Key performance indices related to level of service (average travel time), service efficiency (fraction of time spent by the on-demand vehicles to pick-up and drop-off users and without being assigned any requests), and modal share is analysed for system performance.

The design aspect of on-demand service considered in this study pertains to determination of optimal fleet size mix of private and pooled on-demand services. Other design elemets such as fare, capacity, and operational strategy are exogenously defined and form the input modules.

1.4 Contributions

In this section we highlight the scientific and practical contributions of this study.

1.4.1 Scientific contribution

The scientific contributions of this dissertation are:

1. *Insight into performance of on-demand transport service competing with car, PT, and walk* (Chapter 2): Scenarios where public transport, car, walk, and on-demand services (private and pooled) co-exist is considered. System performance for varying fleet size and cost ratio (ratio of fare of on-demand transport to public transport) of on-demand services are analysed.

2. *Integrated route choice and assignment model for public transport and on-demand transport service* (Chapter 3): An integrated route choice and assignment model that allows users to combine public transport and on-demand service on a single trip or use them as exclusive modes, is developed. Results related to market share and level of service of on-demand service when used as an exclusive mode and in combination with public transport are analysed.

3. *Insight into level of service and service efficiency of private and pooled on-demand services for urban mobility* (Chapter 4): The contribution include the analysis of service efficiency and level of service for private and pooled on-demand transport services serving motorised trips in Amsterdam.

4. *Optimal fleet mix of on-demand transport services with endogenous demand* (Chapter 5): A model to determine the fleet size of an on-demand service offering private service and pooled service, where the demand for these services is an outcome of modal choices, is developed. The model is applied to a network based on Amsterdam North. We explored the relation between the optimal fleet size of an on-demand system from the perspective of a transport planning authority (Agency) and a service provider (Operator). The Agency is assumed to be interested in minimising the travel time of all the users while the Operator is interested in maximising its profit.

1.4.2 Practical and societal contribution

The practical contributions of this dissertation are:

1. *Insight into implications of competing on-demand services in an urban mobility context* (Chapter 2): The study enables practitioners and policy makers to evaluate the implications of introducing competing on-demand services (both private and pooled) with traditional modes such as car, active modes and public transport. This includes insights into market share of on-demand service and modal shifts among the existing modes when on-demand service enters the market.

2. *Evaluation of services and identifying transfer locations when on-demand service and public transport interact* (Chapter 3): Potential applications of the model include identifying locations for transfers between on-demand services and public transport to support interchange facility design and assessing the performance and level of service of on-demand service as first/last mile under various public transport service attributes such as frequency. The application of the model to the area centered around Amsterdam shows that the model is scalable for large-scale real-world applications.

Hence the study provides a model allowing for the evaluation of on-demand and public transport services in contexts where on-demand services are expected to interact with conventional line-based services.

3. *Insight into scalability of on-demand services* (Chapter 4): Scenarios where private and pooled on-demand services replace car trips, PT trips, and car and PT trips are considered. Key performance indices where private and pooled on-demand services fare better and worse are identified and analysed. The insight enables practitioners and planners in fixing congestion surcharges and fares for on-demand services in urban areas.

4. *Optimal fleet size determination for a planning authority and service provider* (Chapter 5): In this chapter, fleet size required when taking either the perspective of a user cost minimising Transit Planning Authority (Agency) and profit maximising Service Provider (Operator) is determined. The results also provide insights into the most profitable operational strategy for the planning authority (whether to operate an on-demand service or not). The modeling framework can hence be used by on-demand service providers and also by transit planning authorities to determine the optimal fleet size in an urban context where these modes interact with the other modes such as car, public transport, and active modes.

1.5 Thesis outline

The remaining of the thesis is structured as follows. Chapters 2, 3, 4, and 5 address research sub-questions 1, 2, 3, and 4, respectively; and Chapter 6 concludes the thesis. In Chapter 2, we assess the performance of on-demand service providing private and pooled service, while competing with other travel modes (car, walk, and public transport). Performance of the system in terms of average travel time and mode share is assessed with varying fleet size and cost ratio of private and pooled service. In Chapter 3, we develop a route choice and assignment model that allows users to combine line and schedule based public transport and private on-demand service or use them as exclusive modes. In Chapter 4, we explore certain market share scenarios and the scalability of on-demand service in an urban mobility context. We perform a scenario analysis where private and pooled on-demand service replace car trips, public transport trips, and car and public transport trips. The objective of the study is to assess the service efficiency and level of service of on-demand service for certain hypothetical scenarios and its scalability. In Chapter 5, we develop a model for service design of on-demand service. Optimal fleet size for private and pooled on-demand service is determined. Finally, Chapter 6 summarises and concludes the work. An overview of the thesis outline along with the demand considered for on-demand service (endogenous or exogenous) and supply level (private or pooled) is given in Figure 1.6.

Chapter 2, 3, and 4 pertains to the *Analysis* part of on-demand services and chapter 5 pertains to the *Design* of on-demand services. The chapters are further classified on the basis of the demand for on-demand services considered and the supply of on-demand services. The demand for the on-demand service is either endogenous or exogenous. An endogenous demand for on-demand service entails that the demand is an outcome of model choices of users and is not externally defined. An exogenous demand for on-demand service on the other hand entails that the demand is externally defined as an input to the model and hence does not change. For the supply, two types of on-demand service is considered in this dissertation, namely private and pooled. Chapter 4 considers an exogenous demand and chapter 2, 3, and 5 considers an endogenous demand. Regarding the supply, a private on-demand service is considered in chapter 4 whereas both private and pooled on-demand services are considered in chapters 2, 3, and 5.

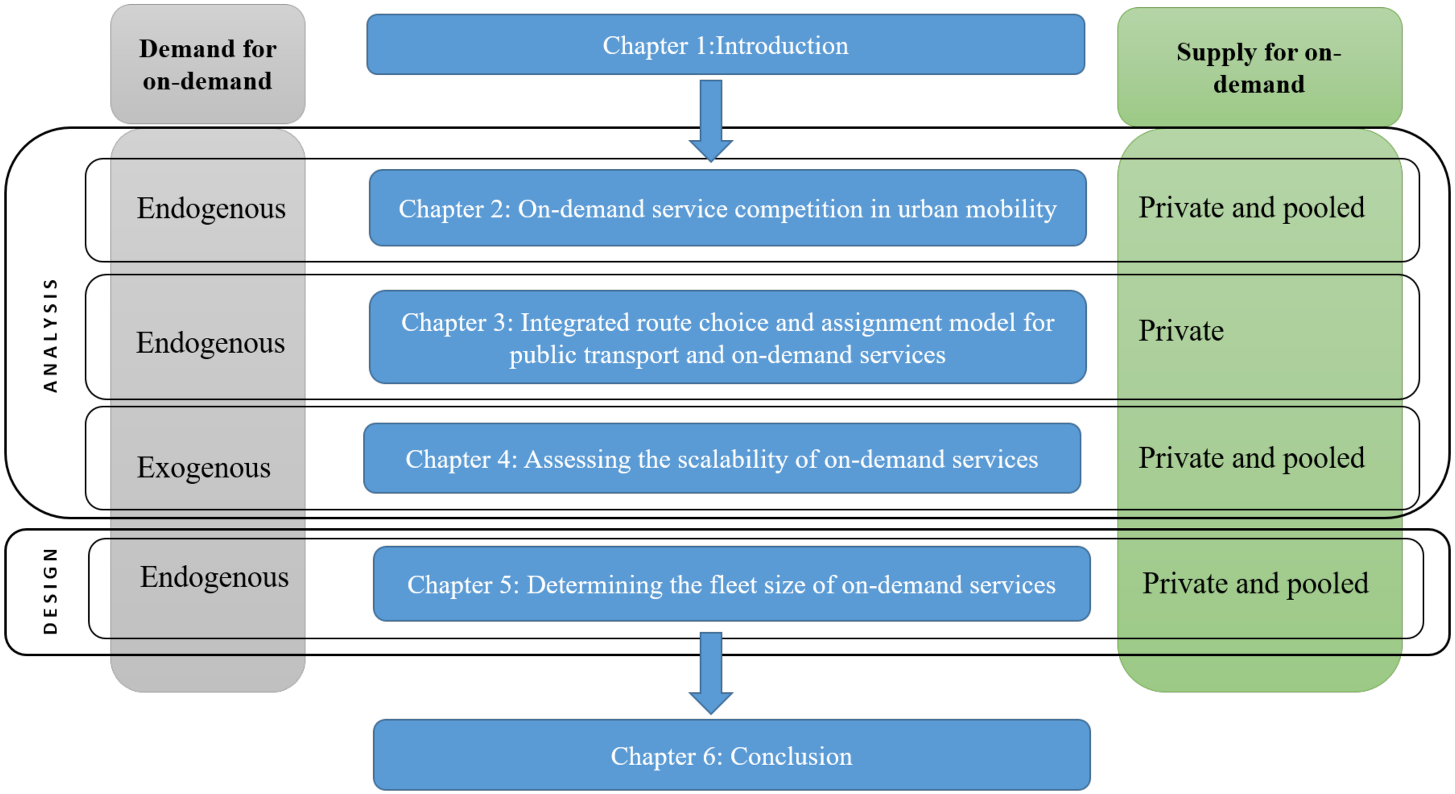


Figure 1.6: Thesis outline

Chapter 2

On-demand service competition in urban mobility

In this chapter we explore the scenario where on-demand service competes with modes of car, public transport, and active modes. We analyse the performance of the system comprising of users and services and the factors influencing them. Instances where on-demand transport offer private and pooled services are considered. The system performance is analysed for varying fleet size of on-demand service and ratio of fare of on-demand service to public transport.

The chapter is structured as follows. First we describe the methodology developed for this study, followed by the section which presents the simulation setup and the various scenarios that are investigated. This is followed by a section presenting the simulation results and analysis. The final section concludes the work with remarks and potential future direction of researchs. The term '*Fixed public transport*' in this chapter refers to a line and schedule based public transport and the term '*Flexible public transport*' in this chapter refers to an on-demand service.

The chapter is a modified version of the following published paper:

Narayan, J., Cats, O., van Oort, N., & Hoogendoorn, S. (2017). Performance assessment of fixed and flexible public transport in a multi agent simulation framework. *Transportation Research Procedia*, 27, 109-116.

2.1 Introduction

Conventional public transport systems are characterized by services that are line based and schedule based. They operate along routes and schedules which are mostly fixed during the day offering high frequency services during peak-hours and relatively low frequency services during off peak hours. This requires rigid planning and operations and does not consider the real time variations in demand. Furthermore, it is often not accessible to users from areas with low demand density. This in turn leads to longer waiting times for transit users and the demand from regions of low demand density not being satisfied.

Recent technological advancements, namely real-time fleet management and travel booking platforms, have enabled the emergence of innovative mobility solutions which offer on demand services. These types of flexible public transport services can relieve the disadvantages inherent to fixed public transport systems. The demand is typically specified as a travel request which the operator/driver of the service receives through an online platform. The fleet of vehicles operated by the system may offer door-to-door service picking up passengers from their origin and dropping them off at their destination, or stop-to-stop service in which passengers are picked up and dropped off from pre-defined pickup and drop-off locations. The service offered might be a sequentially shared type in which a vehicle is shared in sequence by many passengers such that at each given time there will be only a single passenger in the vehicle or a simultaneously shared service in which more than one passenger share the vehicle on a given trip. Note that the service discussed here is different from the car (or bike) sharing systems in which travelers pick up vehicles from dedicated stations near their origin and drop off the vehicles at dedicated stations near their destination.

The modelling of fixed and flexible public transport systems have been studied by researchers over the years. Designing fixed public transport systems requires satisfying conflicting objectives. Some of the pioneering works in the area include Baaj & Mahmassani (1995), Ceder & Wilson (1986), and Mandl (1980). The problem deals with determining a set of routes over a network comprising of a set of nodes and corresponding links so as to minimize objectives related to passenger travel time, operator's operating cost, or their combination. The modelling of flexible public transport systems has been studied by researchers as a Dial-a-Ride Problem (DARP) which is a generalization of the Vehicle Routing Problem (VRP), which in turn is a generalization of the Travelling Salesman Problem (TSP). The major objective of the DARP is to determine a set of minimum cost paths and schedules to satisfy a set of travel requests subject to a set of constraints on time windows or deviation from the least cost path. Depending on whether the travel requests are known upfront or not, the problem can be considered static or dynamic respectively. An excellent review of the models and algorithms used for DARP is given in Cordeau & Laporte (2007). Due to the complexity of both the problems (NP Hard), generating an exact analytical/mathematical solution becomes nearly impossible for large instances of the problem. Hence heuristic/metaheuristic or evolutionary optimization methods have been used to obtain optimal solutions or improve a set of initial feasible solutions in search for an optimal solution such as in Uchimura et al. (2002), Nanry & Barnes (2000), Neumann (2014), Kuan et al. (2006), Arbex & da Cunha (2015).

Due to the growing availability of technologies that facilitate the large-scale deployment of flexible public transport services, its interaction with fixed services has recently been a subject of research. An IDARP (Integrated Dial-a-Ride Problem), a generalization of the Dial-a-Ride Problem, was formulated as scheduling travel requests where some portion of the trips is covered by fixed services. In most of those studies, the flexible system is modelled as a complement to fixed public transport services or as a means of access to an extensive public transport network (Posada et al., 2017; Uchimura et al., 2002). In the literature which dealt with competing fixed and flexible systems, the flexible system was in some cases envisaged to consist of a fleet of fully-automated vehicles. The major focus of those works was on the simulation of such services in which fixed service was included as an alternative mode choice (Archetti et al., 2018; Hörl, 2017; Lima Azevedo et al., 2016). However these studies have not analyzed the effects of factors such as fleet size, operational strategy, and cost ratio on the performance of the system in the context of competing services. It is necessary to understand the extent to which these factors affect the dynamic demand-supply interactions. In this chapter, an attempt is made to study the effect of different operational strategies, level of service, and service costs on the overall performance of the system when considering the perspectives of users as well as the operators of both services.

2.2 Methodology

This section presents the developed methodology. An agent based simulation model is used for the study. The model is designed to represent the within day and the day-to-day dynamics of the system. An overview of the methodology is given in Figure 2.1. The major components of the model are:

- Input
- Modal split
- Assignment
- Evaluation
- Re-planning

The Input module comprise of a network (with nodes and connecting links), supply, and demand. The supply consists of transport services provided by service providers and a default set of modes available to each user. The transport services comprise of fixed public transport (with a description of a route and a schedule per line and a fleet of vehicles) and flexible public transport (fleet of vehicles with on-demand services serving real time requests). The default modes available to each user are car and walk. The input data is used in the Modal split module in which users choose from the modes available: car, walk, fixed public transport (fixed PT), and flexible public transport (flexible PT). In the Assignment module, the users are assigned to individual vehicles. If a user has chosen fixed PT then they walk from their origin to the nearest stop and wait for a vehicle to pick them up. The Modal split and Assignment form the daily dynamics of the system. The users then evaluate the service based on their experience in the Evaluation module. Based on the evaluation, the users re-plan their travel strategy for the following day in the Re-planning module.The users may change their existing travel strategy in the following ways: change to a different

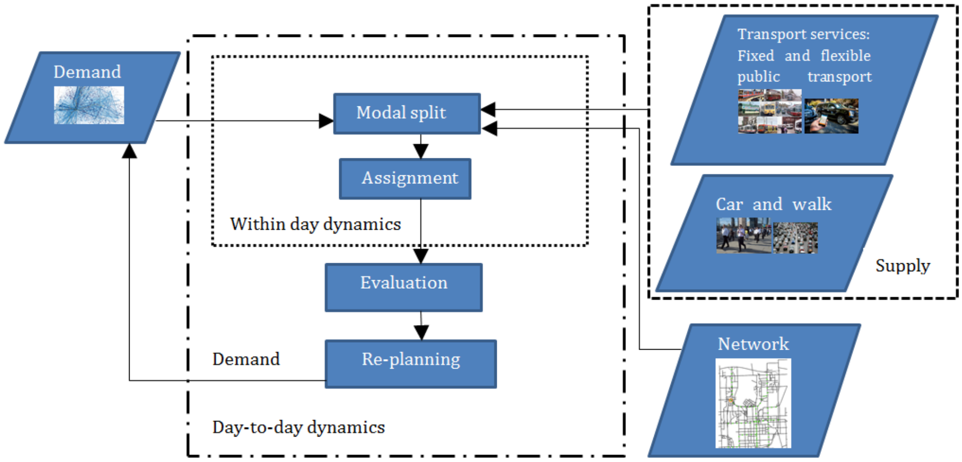


Figure 2.1: Overview of the methodology

mode, use a different route with the same mode, and change the departure time from their origin.

The open-source multi-agent traffic simulation framework MATSim (Horni et al., 2016b) was used in model implementation. Each user of the transport system is represented as an agent with a set of travel plans. Once the plans have been performed, each agent evaluates the executed travel plan based on the service experienced. The altered set of travel plans forms the demand for the subsequent simulation cycle. This sequence of network and agent choice simulation, scoring and re-planning forms an iteration which corresponds to a day. This process is continued till some set of convergence criteria is achieved. In MATSim, plans are scored according to the Charypar-Nagel scoring function (Horni et al., 2016b) as shown in the equation below:

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)} \tag{2.1}$$

In Equation 2.1, S_{plan} represents the score of an entire plan of the agent, $\sum_{q=0}^{N-1} S_{act,q}$ represents the score of all the activities performed, and $\sum_{q=0}^{N-1} S_{trav,mode(q)}$ represents the score of all the travel legs between each activities, and N represents the total number of activities performed. The score of performing an activity, $S_{act,q}$ is computed as shown in the following equation.

$$S_{act,q} = \beta_{dur,q} \cdot t_{dur,q} \tag{2.2}$$

In Equation 2.2, $\beta_{dur,q}$ represents the marginal utility for performing an activity q, and $t_{dur,q}$ represents the time spent performing the activity q. The score that represents the travel utility of the plan, $S_{trav,mode(q)}$ is computed as shown in the following equation.

$$S_{trav,mode(q)} = C_{mode(q)} + \beta_{trav,mode(q)} \cdot t_{trav,mode(q)} + \beta_{money} \cdot \gamma_{mode(q)} \cdot d_{trav,mode(q)}$$

$$+ \beta_{wait,mode(q)} \cdot t_{wait,mode(q)} \tag{2.3}$$

In the above equation, $C_{mode,q}$ represents the mode specific constant for traveling using mode q. It represnts a constant utility for choosing the mode for the leg. The term $\beta_{trav,mode(q)}$ represents the marginal utility of traveling using mode q and $t_{trav,mode(q)}$ represents the time spent traveling by mode q. The term β_{money} describes the marginal utility of money, $\gamma_{mode(q)}$ represents the monetary distance rate associated with mode q, and $d_{trav,mode(q)}$ represents the distance traveled with mode q. Finally, the terms $\beta_{wait,mode(q)}$ represents the marginal utility of waiting time (if any) for mode q and $t_{wait,mode(q)}$ represents the waiting time experienced (if any) for mode q.

2.3 Application

2.3.1 Network and demand data

The test network used in this study is based on the road network of the city of Sioux Falls in the United States (Figure 2.2). The population and detailed road network for simulation have been adopted from Chakirov & Fourie (2014) and Hörl (2017) respectively. The network comprise of 1,806 nodes and 3,335 links. The public transport network comprise of 5 bus lines with 150 stops (shown as red nodes in Figure 2.2) at an average distance and median of 520m and 566m respectively. The headway of service operation is 5 min. The public transport stops are spaced at a minimum and maximum distance of 218m and 847m respectively. The population consists of 84,110 persons with either home-work-home or home-secondary-home activities based on the employment status of each person. The modes used by the agents are either car, walk, or fixed PT. The agents perform their activities at locations of 24,718 facilities (blue nodes in Figure 2.2). Figure 2.3 shows the mode specific hourly trip distribution within the 24 hr period of the demand data. As can be seen from the figure, the daily trips of car, walk, and fixed PT are shows two distinct morning and evening peaks from 7:00 to 10:00 in the morning and 16:00 to 19:00 in the evening. The morning and evening peak is primarily composed of trips originating from the home-work-home activities and the off-peak trips are primarily the home-secondary-home trips.

2.3.2 Simulation scenarios

The scenarios considered are given in Table 2.1. Three scenarios in terms of service availability are considered. Under Scenario I, the users may choose between modes of car, fixed PT, and walk. In Scenario II, a fleet of vehicles is introduced which offer flexible PT serving real time requests. The type of service offered is a private (taxi-like) ride with no sharing among passengers. In Scenario III, in addition to the default modes of car, fixed PT, and walk, a fleet of vehicles serving real-time requests operates on a sharing basis, including possible detours for picking-up and dropping-off fellow passengers.

In addition to the three scenarios described above, system performance is analyzed for varying fleet size of vehicles serving as flexible PT and varying ratio of cost of flexible to fixed PT services. The simulation model is run for fleet size of 1000, 2000, 3000, 4000, and

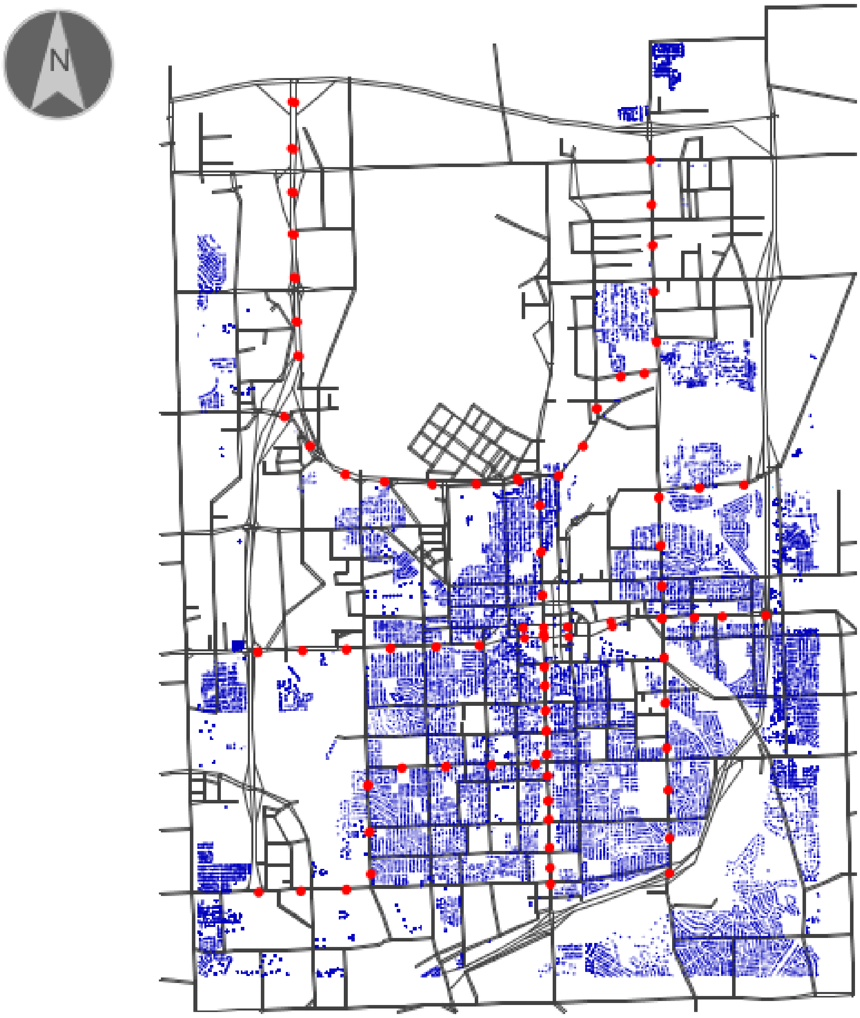


Figure 2.2: Application network of Sioux Falls

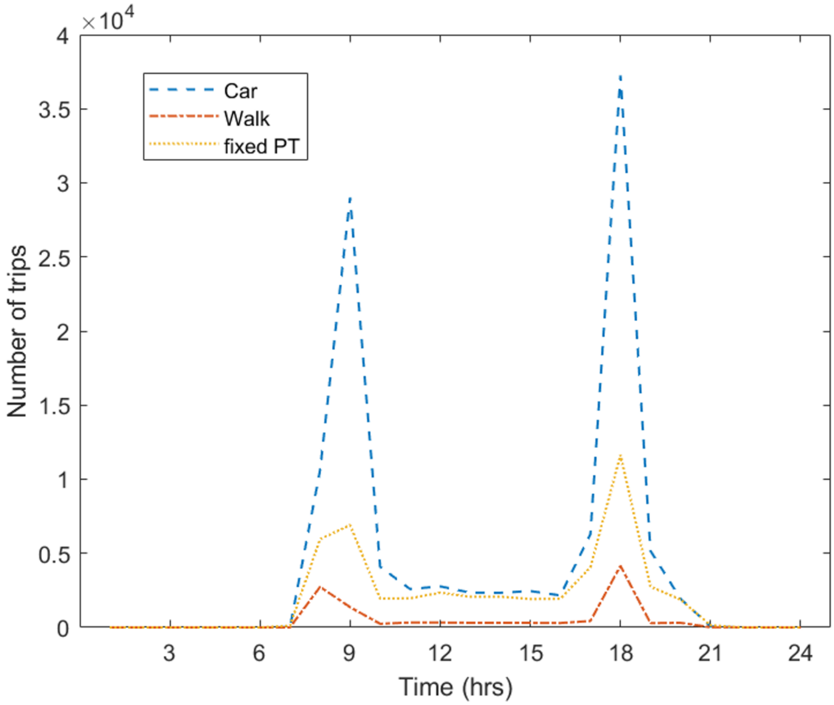


Figure 2.3: Hourly variation of trips in the Base Case

Table 2.1: Tabulation of the scenarios

Scenario	User mode choice
I	Car, Fixed PT, walk
II	Car, Fixed PT, Flexible PT (private), walk
III	Car, Fixed PT, Flexible PT (shared), walk

5000 and cost ratios (ratio of fare of flexible PT to fixed PT) of 2, 3, 5, and 10. The base case fleet size is 1000 and the base case cost ratio is 2.

2.3.3 Dispatching strategy of flexible PT

The flexible PT system comprises of a fleet of vehicles that are controlled by a central dispatching unit which assigns incoming requests to vehicles in the network. A vehicle that has been assigned with a request, drives to the pick-up location, picks up the passenger and drops off the passenger at their drop off location. The vehicle then stays at the drop-off location until further notice from the system dispatcher. The destination of the passenger is not known to the dispatcher while assigning the request. The dynamic vehicle routing algorithm used in this study is adopted from Hörl (2017) in which the framework developed by Maciejewski (2015) was extended.

2.3.4 Model specifications

The utility function coefficient values (Equations 2.2 and 2.3) have been based on a set of behavioral parameters adopted from Hörl (2017) and are converted to the MATSim implementation framework Horni et al. (2016a) and are detailed in Table 2.2.

2.4 Results and analysis

This section presents the simulation results and analysis. Section 2.4.1 presents the simulation results for fleet size variation for Scenarios II and Scenario III where Scenario I is considered as the Base Case and Section 2.4.2 presents the results for cost ratio variation for Scenario II and Scenario III where a cost ratio of 2 is considered as the Base Case.

2.4.1 Effects of the fleet size of flexible public transport

Table 2.3 presents the mode share variation for Scenario II and Scenario III with varying fleet size of flexible PT. From Table 2.3, it can be seen that in comparison to the Base Case, a large percentage of users shift from car and fixed PT and a relatively small percent from walking. This indicates that the introduction of flexible PT service can considerably reduce the number of personal car trips as well as cause a mode shift from fixed PT. It can also be seen that with increase in fleet size of flexible PT, there is a steady increase in its modal share. This can be explained from Figure 2.4 where the average waiting times per passenger using flexible PT are plotted as a function of its fleet size. It can be seen that the increase in

Table 2.2: Utility values used for simulation

Utility	Values
Marginal utility of money (β_{money})	1
Utility for performing an activity (β_{dur})	23.29
Car	
Mode specific constant (C_{car})	-4.21
Marginal utility of travel ($\beta_{trav,car}$)	0
Monetary distance rate (γ_{car})	-0.176
Walk	
Marginal utility of travel ($\beta_{trav,walk}$)	-9.91
Fixed PT	
Marginal utility of travel ($\beta_{trav,fixedpt}$)	8.86
Marginal utility of waiting time (β_{wait})	-0.84
Utility of transfer ($\beta_{transfer}$)	-1.67
Monetary distance rate ($\gamma_{fixedpt}$)	-0.265
Flexible PT	
Marginal utility of travel ($\beta_{trav,flexiblept}$)	8.86
Monetary distance rate (private) ($\gamma_{flexprivate}$)	-0.48
Monetary distance rate (shared) ($\gamma_{flexshared}$)	-0.28

fleet size causes a decrease in the average waiting time in both the scenarios hence making the service more attractive. There is a slight increase in average waiting time for Scenario II from 2000 to 3000 where the pace of increasing demand surpasses the increase in fleet availability. Another trend that becomes evident from Figure 2.4 is the rate of decrease of average waiting time for Scenario II and Scenario III. It can be seen that the rate of decrease of average waiting time for Scenario II is higher compared to that of Scenario III. This implies that the effect of fleet size on the average waiting time of users is more pronounced for a private service than a shared service.

An hourly distribution of the average waiting times of flexible PT for each fleet size instances considered in Scenario II and Scenario III are given in Figure 2.5 and 2.6 respectively. As with the trip distributions in the Base Case in Figure 2.3, Scenario II and Scenario III also shows two distinct morning and evening peaks. It can be seen that the increase in fleet size causes an overall decrease in waiting times throughout the day which is the result of improved level of service in terms of average waiting time as shown in Figure 2.4. It can also be seen that the effect of increase in fleet size on waiting time is more pronounced during peak hours than off-peak hours, indicating high demand for flexible services during peak hours. The average waiting time of zero in these figures indicate zero demand during those hours.

2.4.2 Effects of cost ratio between fixed and flexible public transport services

Table 2.4 shows the mode share results obtained by varying the ratio of cost of flexible PT to fixed PT. The ratios considered are 2, 3, 5, and 10. Figure 2.7 plots the mode share

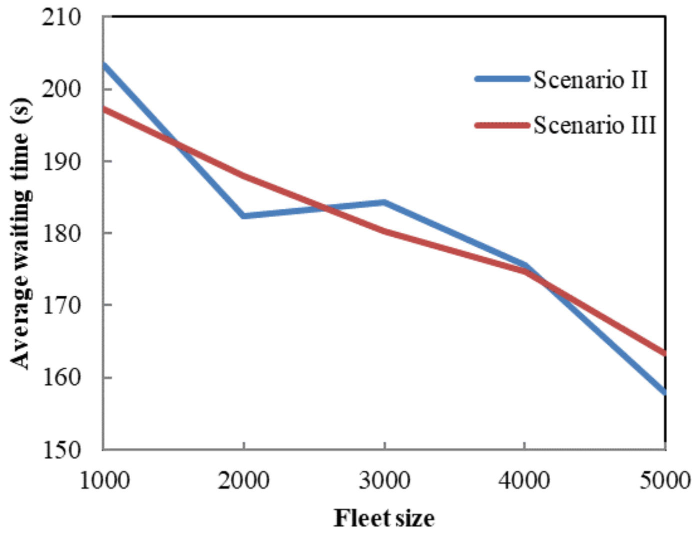


Figure 2.4: Variation of average waiting time for flexible PT with fleet size

Table 2.3: Mode share and travel statistic results for varying fleet size

Scenario	**Fleet size of Flexible PT**	**Car**	**Fixed PT**	**Walk**	**Flexible PT**
Base Case	NA	63.6	28.44	7.96	NA
	1000	52.17	17.88	5.43	24.52
	2000	48.47	17.13	5.24	29.16
Scenario II	3000	46.77	16.88	5.25	31.10
	4000	46.07	16.79	5.22	31.92
	5000	45.76	16.82	5.23	32.19
	1000	54.05	18.62	5.6	21.73
	2000	51.01	17.97	5.47	25.55
Scenario II	3000	50.34	17.84	5.43	26.39
	4000	50.03	17.77	5.44	26.76
	5000	49.60	17.76	5.45	27.19

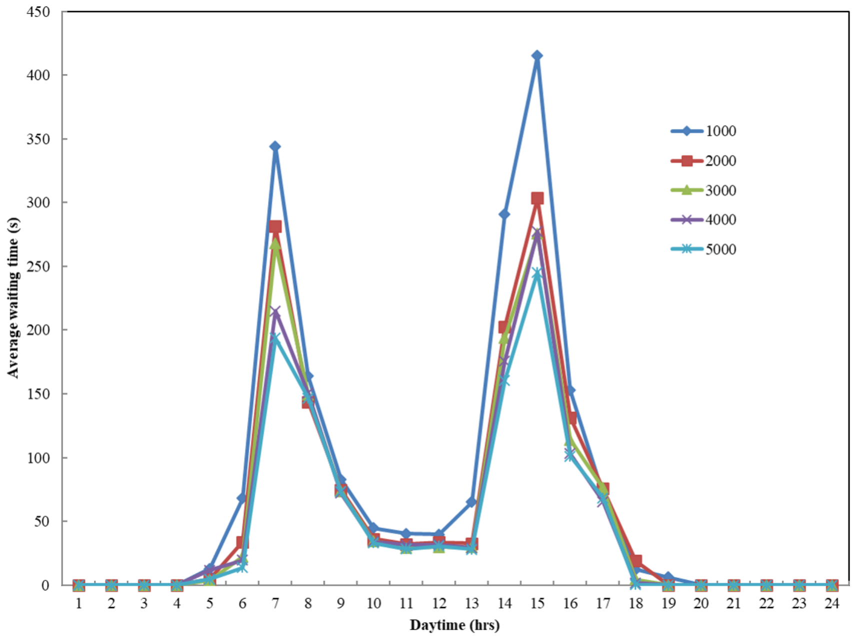


Figure 2.5: Hourly variation of average waiting time with fleet size for Scenario II

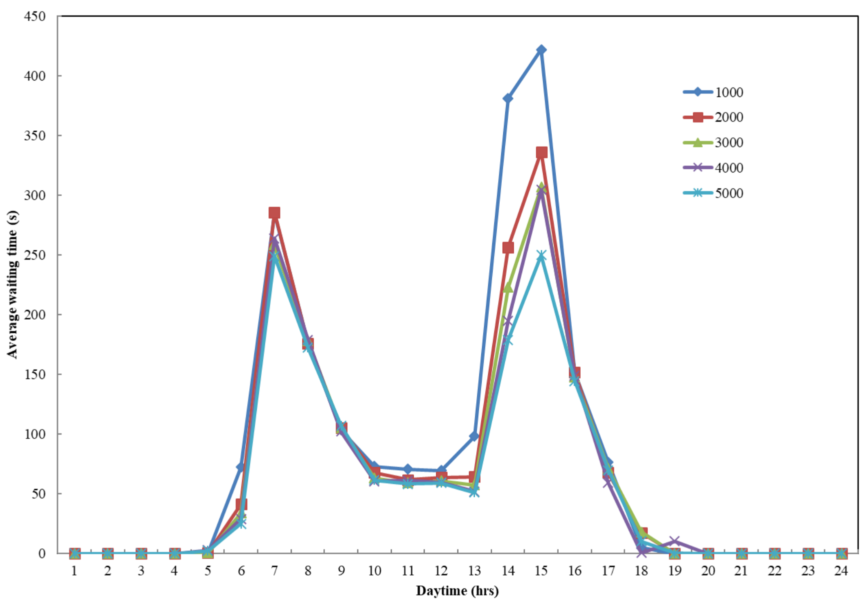


Figure 2.6: Hourly variation of average waiting time with fleet size for Scenario III

variation for fixed and flexible PT with the cost ratio. The scenarios in which the cost ratio is 2 is chosen as the Base Case. As can be seen from Table 2.4, there is a steady decrease of mode share for both individual and shared flexible PT services with increasing relative cost ratios. There is also a corresponding increase in the mode share of car and fixed PT when compared to the Base Case. Another interesting trend that emerge can be seen from Figure 2.7, is the rate of decrease of mode share of flexible PT for Scenario II and III. It can be seen that the rate of decrease of mode share of flexible PT without shared service is more than that of flexible PT with shared service at higher cost ratios. This is due to the lower average waiting time of shared services which makes it relatively attractive compared to individual flexible PT at higher relative cost ratios.

Table 2.4: Mode share and travel statistic results for varying cost ratio

Scenario	**Fleet size of Flexible PT**	**Car**	**Fixed PT**	**Walk**	**Flexible PT**
Scenario II	2 (Base Case)	52.30	17.96	5.42	24.32
	3	53.76	18.31	5.41	22.52
	5	56.95	19.28	5.43	18.34
	10	61.07	22.69	5.63	10.61
Scenario II	2 (Base Case)	55.46	19.21	5.72	19.61
	3	56.75	19.91	5.78	17.56
	5	59.17	21.05	5.90	13.88
	10	61.60	24.20	6.19	8.01

2.5 Conclusion

This chapter analysed the performance of a system when fixed and flexible public transport systems co-exist while offering competing services. The multi-agent simulation framework MATSim was chosen to implement the model. The system performance was analyzed for varying fleet size of flexible PT and varying cost ratio of flexible PT to fixed PT. The analysis showed that the increase in fleet size caused an overall increase in mode share for flexible PT which was caused due to an overall decrease in waiting time of passengers using flexible PT. It was found that the effect on waiting times of passengers by increasing fleet size is more pronounced when an individual taxi-like door-to-door service is offered. The variation of relative cost ratios showed a steady decline of mode share for flexible PT with increasing cost. The results also showed that at higher cost ratios, the relative gap in modal share between private and pooled flexible PT decreases. In addition to addressing the gaps in the scientific literature, the relations investigated in this study is relevant from a practical and policy perspective in the sense that it enables practitioners and policy makers to evaluate the implications of introducing competing flexible PT services with fixed PT services based on

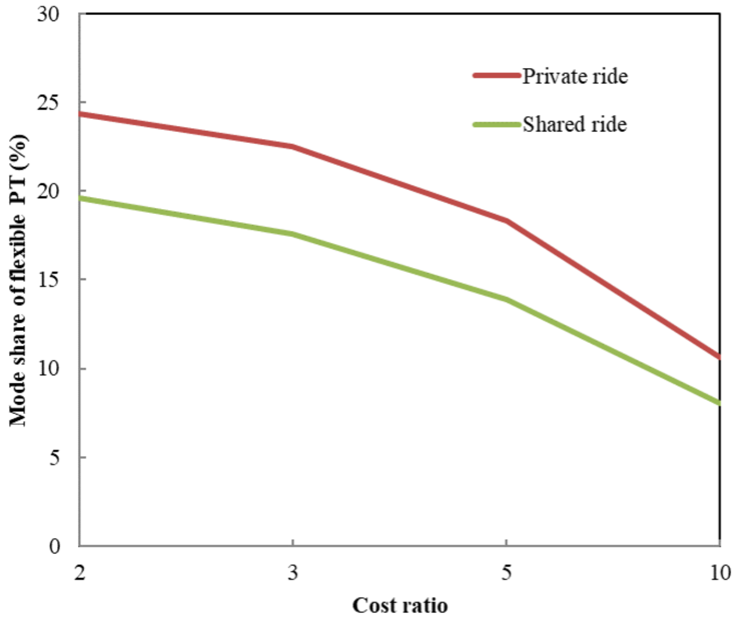


Figure 2.7: Variation of average waiting time for flexible PT with fleet size

the response of users. Another aspect from a modelling perspective is that, the mode share of users obtained from the model depends on the scoring of each plan of user which in turn depends on the values of utility parameters. An effective methodology to model the user behavioral preferences based on real world population is essential in representing passenger preference for future studies in the area. Moreover, the effect of operational aspects such as vehicle relocation strategy and destination knowledge to the dispatcher at the time of making a request on the system performance and the implications of using a flexible PT system for first/last mile travel of fixed PT was not investigated in the study and should form direction for future research.

Chapter 3

Integrated route choice and assignment model for public transport and on-demand service

In the previous chapter we looked into the scenario where on-demand service competes with traditional modes. In this chapter we consider the scenario where users combine on-demand services and public transport for their origin-destination journey. The objective of this chapter is to model the users' trip where on-demand service and public transport can be combined in a single trip or used as exclusive modes. To this end, an integrated route choice and assignment model is developed that allows users to combine on-demand service and public transport in a single trip or use them as exclusive modes. The model is applied to network of Amsterdam. Scenarios where on-demand transport competes with modes of car, public transport, and active modes and the one where users combine on-demand and public transport is considered.

In the first part we present the integrated route choice and assignment model that is developed, scenarios considered and application network. We then present results for modal usage, service performance, and fleet utilisation. Following this, we conclude the study providing key insights and direction for future research. The term '*Fixed public transport*' in this chapter referes to a line and schedule based public transport and the term '*Flexible public transport*' in this chapter refers to an on-demand service offering taxi-like services.

The chapter is based on the following published paper:

Narayan, J., Cats, O., van Oort, N., & Hoogendoorn, S. (2020). Integrated route choice and assignment model for fixed and flexible public transport systems. *Transportation Research Part C: Emerging Technologies*, 115, 102631.

3.1 Introduction

The emergence of innovative mobility solutions, brought about by ICT advancements, is set to change the public tranport landscape. Emerging mobility solutions offer on-demand services picking up and dropping off passengers from a pre-defined set of stops (stop-to-stop service) or between selected locations (door-to-door service) either controlled by a central dispatching unit (such as an app-based vehicle-travel request matching service) or as a competing fleet of vehicles with drivers having the discretion to accept or reject travel requests. Travelers may use these on-demand services to travel from their origin to destination or combine it with traditional line/schedule-based services. Fixed and flexible services may not only co-exist within a given urban area as alternative, mutually-exclusive, modes but may also be combined by passengers along a given journey. Fixed and flexible services may thus not only compete for market shares but also complement each other and potentially serve different parts of the journey which they are best suited depending on their characteristics such as speed, capacity and availability. From this perspective, it is important to understand the potential to combine on-demand services and line/schedule-based public transport services and the dynamic interaction between the demand (users) and supply (services). To this end, a model is developed for the integrated public transport route choice of users allowing for the combination of on-demand service (Flexible PT) and line/schedule-based public transport service (Fixed PT) along a single trip.

System analysis of a combined Fixed PT and Flexible PT comprise of two major components: Route choice modelling and Assignment (network loading). The Fixed PT comprises of a line/schedule-based service (such as train, tram, bus, or metro). Service network of Fixed PT involves route allignment and service frequencies. The Flexible PT comprises of a fleet of vehicles offering on-demand services to passengers along with their operational strategy. This is followed by the *Route choice modelling* phase in which the travel options of users are modelled. In the *Assignment* phase, passenger demand is distributed over the choice alternatives. The assignment procedure‘ is performed for the service network over several iterations (iterative network loading) until a steady-state (equilibrium) is attained. We study and classify the existing literature based on the modelling approaches that have been used for the Route choice and Assignment phase of service design.

A large number of studies have used analytical, mathematical programming, or simulation methods to model the assignment of travel requests to on-demand services (the matching problem). Notable works that used an analytical approach include Wilson et al. (1976) and Potter (1976). They modelled the assignment problem as an Integrated Dial-a-Ride Problem (IDARP) and used a passenger utility maximisation approach and modelled demand responsive services as feeder to fixed route service. Mathematical programming approach involve solving the assignment problem as an optimization problem by assigning travel requests to a fleet of on-demand vehicles (Posada et al., 2017; Häll et al., 2009; Salazar et al., 2018). Posada et al. (2017) and Häll et al. (2009) solved the assignment problem as Integrated Dial-A-Ride Problem (IDARP) and assigned travel requests of on-demand service to coordinate with the service of Fixed PT. Salazar et al. (2018) used a flow optimization model for assigning the travel requests while maximising the social welfare. Liaw et al. (1996) and Hickman & Blume (2001) solved for the combination of static and dynamic version of Dial-a-Ride Problem where part of the travel requests are known before the planning stage . However, such analytical models often fail to capture the real-time system dynamics.

Simulation and agent-based simulation methods mitigate this issue to an extent. Works that used simulation methods for on-demand service design include Edwards et al. (2011) and Horn (2004). Edwards et al. (2011) introduced the concept of network inspired transportation system (NITS) that routes passengers analogous to routing packets through a telecommunications network. Horn (2004) used a simulation model for planning journeys combining fixed route services and demand responsive services. The journey could be carried out by a single mode which includes walk, taxi, or fixed route service. The fixed route service included conventional services such as bus and lightrail and demand responsive modes. However, they considered an exogenous demand that was fixed throughout the assignment process. Neumann & Nagel (2013) presented an evolutionary algorithm for the design of an optimal paratransit service network. They designed the paratransit services as a competing mode with a Fixed PT service. Atasoy et al. (2015) designed an on-demand service in which a list of travel options is given to passengers in real-time. The travel options include using taxi service (single passenger with door-to-door service), shared taxi service (multiple passengers with door-to-door service), or minibus (multiple passenger with fixed routes but flexible schedules). Maciejewski & Nagel (2013b) and Maciejewski, Horni, et al. (2016) designed a framework for implementing dynamic transport services in an agent-based simulation framework. Hörl (2016) implemented an autonomous taxi service in competition with a Fixed PT service. The autonomous taxi service were modelled as a fleet of vehicles controlled by a central dispatching unit offering door-to-door service to passengers. The studies mentioned so far modeled on-demand transport in isolation with the demand for this services considered to be externally defined and independent of the level of service offered or as an alternative that fully substitutes public transport.

Another line of research has considered Fixed PT and Flexible PT as part of a joint passenger transport by introducing a flexible service as feeder to the high-capacity fixed route network such. Notable works include Potter (1976), Uchimura et al. (2002), M. M. Aldaihani et al. (2004), Vakayil et al. (2017), Y. Shen et al. (2017), Moorthy et al. (2017), T.-Y. Ma (2017), Charisis et al. (2017), Wen et al. (2018), Stiglic et al. (2018), K.-T. Lee et al. (2004), Cayford & Yim (2004), Pinto et al. (2019), and Luo & Nie (2019). Vakayil et al. (2017) designed an autonomous mobility on demand as a first/lst mile option when mass transit services are available. Their results indicated a 50% reduction in vehicle miles travelled of mobility on-demand vehicles when integrated with mass transit. Y. Shen et al. (2017) investigate the case of autonomous vehicles serving as first/last mile problem during morning peak for a public tranport sysem in Singapore. They suggested replacing low demand bus routes with shared autonomous vehicles. T.-Y. Ma (2017) presented a dynamic vehicle dispatching and routing algorithm for shared services in coordination with an existing public transport network. The objective was to attain optimal passenger-vehicle assignment. Wen et al. (2018) designed an integrated autonomous vehicle and public transport system. The autonomous services were designed to provide first/last mile connections to rail services and efficient mobility in low-density sub-urban areas. M. M. Aldaihani et al. (2004) presented an anlytical tool to determine the optimal number of zones to provide demand responsive services. The on-demand services either transfers passengers to a fixed route line or transports them from their final stop to their destination. Cayford & Yim (2004) designed a demand responsive system as a feeder service to a fixed route system for the city of Milbrae, California. Results showed that the demand responsive service is a feasible solution for downtown feeder system. X. Li & Quadrifoglio (2011) and A. Lee & Savelsbergh (2017) investigated the deployment of demand responsive services at a zonal level. X. Li & Quadrifoglio (2011) developed an anlytical model based on continuous approximations to address the optimal zone design problem. Assuming a two vehicle operation in each zone, the objective was to arrive at an optimal number of zones by considering level of service and operating cost. A. Lee & Savelsbergh (2017) considered a zone with multiple transfer points. They found out that the benefits of a more flexible system are substantial but depends on characteristics such as passneger and station density. Luo & Nie (2019) examined the basic trade-off of several transit systems involving fixed-route systems and hybrid systems that involve ride-pooling services. The purpose was to identify how ride-pooling might reshape mass transit in the era of mobility-as-a-service. Results indicated that mixing ride-pooling with fixed-route services leads to marginal improvements to the overall system efficiency. More recently, joint optimisation of capacity and headway of on-demand transit services with autonomous buses were carried out by Chen et al. (2019) and Dai et al. (2020). While Chen et al. (2019) solved the joint design as a mixed integer linear programming model with a homogeneous autonomous shuttle fleet, Dai et al. (2020) formulates the problem as an integer nonlinear programming model considering a heterogeneous fleet of autonomous and human driven buses. However, both the studies considered an exogenous demand for the services without considering integration with a line and schedule based public transport.

Neumann & Nagel (2013), Kalpakcı & Ünverdi (2016), and M. Aldaihani & Dessouky (2003) considered on-demand services in competition with a Fixed PT network. The on-demand services were modelled as paratransit services which operates on fixed routes but with no fixed schedules. The objective of these studies were to determine a set of optimal set of routes for the paratransit services.

From a demand perspective, determining the feasible conditions to operate a demand responsive service has been studied by Quadrifoglio & Li (2009) and X. Li & Quadrifoglio (2010). They developed analytical and simulation models to this end and the results indicated that the switching point between a demand responsive and a fixed route service is in the range from 10-50 customers/mi^2/hr.

A comparitive summary of the reviwed literature based on the modelling approach, operation of Flexible PT, and the objective is shown in Table 3.1. As can also be seen from the table, while these studies shed light on the interaction between fixed and flexible services and related design variables, all of them have considered fixed and flexible services as mutually exclusive. Consequently, the assignment process for fixed and flexible services was performed in isolation as passengers either had to choose between fixed and flexible services or had to combine them in a shuttle setting. In all cases, passengers' ability to choose the best sequence of legs connecting their origin and destination including possibly combining fixed and flexible services within a given journey was not accounted for in the model. From a demand perspective, most of the studies designed fixed and flexible services while considering demand as exogenous. In other words, none of the studies allowed users to choose between flexible services as first/last mile service or exclusive door-to-door service from their origin to destination.

In this chapter, a route choice model that allows users to combine fixed and flexible passenger services or use them as individual modes, with endogenous demand is proposed. This enables examining the share of the trip that users choose to travel using each of these services, as well as the share of travelers choosing to do so. Furthermore, the locations

Table 3.1: Comparitive summary of reviewed literature based on modelling approach and Flexible PT design

Paper	**Modelling approach**	**Flexible PT operation**	**Demand for Flexible PT**	**Objective**
Wilson et al. (1976)	Analytical	Feeder to Fixed PT	Exogenous	Assignment of travel requests
Potter (1976)	Analytical	Feeder to Fixed PT	Exogenous	Assignment of travel requests
Posada et al. (2017)	Mathematical programming	Feeder to Fixed PT	Exogenous	Optimal assignment of travel requests
Salazar et al. (2018)	Mathematical programming	Feeder to Fixed PT	Exogenous	Maximise social welfare
Quadrifoglio & Li (2009) and X. Li & Quadrifoglio (2010)	Analytical and simulation modelling	Exclusive mode	Exogenous	Determine the range of demand for Flexible PT operation
Neumann & Nagel (2013)	Agent based simualtion	Competing mode with Fixed PT	Exogenous	Determine a set of optimal routes for the services
Horn (2004)	Mathematical programming and simulation	Integrated design with Fixed PT	Exogenous	Planning of multi-leg journeys with Fixed PT and Flexible PT
Atasoy et al. (2015)	Mathematical programming and simulation	Exclusive mode	Exogenous	Planning of journeys with multiple Flexible PT services such as taxi, shared taxi and mini bus
Maciejewski & Nagel (2013b), Maciejewski, Horni, et al. (2016), and Hörl (2016)	Agent based simulation	Exclusive mode	Exogenous	Assignment of travel requests
X. Li & Quadrifoglio (2011)	Analytical and simulation	Feeder service to Fixed PT network	Exogenous	Determine the optimal number of zones for Flexible PT operation
M. M. Aldaihani et al. (2004)	Analytical method	Feeder service to Fixed PT network	Exogenous	Determine the optimal nmber of zones for Flexible PT operation
Dai et al. (2020)	Analytical and simulation	Exclusive mode	Exogenous	Joint optimisation of headway and capacity

where users choose to interchange between these services can be identified. All these choice dimensions become therefore an integral outcome of the integrated assignment model as opposed to part of the case settings or model assumptions. The route choice model is integrated in an agent-based transport assignment framework. The model allows combined journey with fixed and flexible service as well as a journey that consists exclusively of fixed or flexible transport; with endogenous demand. The model, implemented in MATSim, is applied to a network centered around the city of Amsterdam and provides insights on how an individual ride-hailing service will perform and its potential market share as a self-standing mode as well as in combination with the existing Fixed PT. Measures of performance of the system in terms of the passenger travel time, impact of fleet size and thus level of service (in particular waiting times) on the number of passenger trips performed using Flexible PT and their respective share of travel demand and fleet utilisation metrics is analysed under scenarios where Fixed PT and Flexible PT services are offered as mutually exclusive modes or can be combined into a single journey. This in turn may facilitate the efficient design of an integrated public transport system consisting of both Fixed PT and Flexible PT.

3.2 Methodology

This section presents the overall methodology developed. First, **System components** and **Integrated public transport route** of a user are defined. Second, the model developed for generating and evaluating public transit travel alternatives and the assignment procedure are described. Third, we provide details on model implemenation. Each of these points are detailed in the following sub-sections.

3.2.1 Definitions

System components

We first introduce the key system elements.

Network: Refers to the network which comprise of the sub-networks of road and fixed public transport. The sub-network of fixed public transport involve the route network for public transport modes (e.g. train, tram, metro, bus) with their respective stop locations.
Demand: Comprise of passengers with a set of origin and destination points in the network. In this study it is assumed that the passengers have full knowledge about the network and schedules of the Fixed PT system.
Supply: Comprise of the modes available to each user for travelling from their origin to their destination. The modes available are:

- **Fixed PT:** Comprise of line-based services that follow a pre-defined route and schedule operated by a fleet of vehicles.
- **Flexible PT:** On-demand services picking up passengers from their origin or a Fixed PT stop and dropping them off at their destination or a Fixed PT stop, operated by a fleet of vehicles. The fleet of vehicles are controlled by a central dispatching unit which assigns incoming travel requests to vehicles in real-time. Individual rides are offered by the on-demand services and all travel requests are generated in real-time i.e. no pre-booking is allowed.

Walk: Passengers may choose to walk from their origin to a Fixed PT stop, from a Fixed PT stop to their destination, or even from their origin to their destinaion.

Bike: Passengers may choose to bike from their origin to a Fixed PT stop, from a Fixed PT stop to their destination, or from their origin to their destinaion.

Car: Privately owned vehicles that may be used between the trip origin and destination.

Integrated public transport route

Integrated public transport route refers to the trip a passenger makes from an origin to a destination using one or more public transport services. It may thus consist of a Fixed PT service (or a combination of several modes - e.g. bus and metro), a Flexible PT service, or the combination thereof. Depending on the type of service used in the journey, integrated public transport routes are classified into one of the following types.

1. Walk/Bike+Fixed PT+Walk/Bike: A passenger walks/bikes from his/her origin to a Fixed PT stop, waits for a Fixed PT service, makes a Fixed PT trip to another Fixed PT stop, and finally walks/bikes from that stop to his/her destination.

2. Walk/Bike+Fixed PT+Flexible PT: A passenger walks/bikes from his/her origin to a Fixed PT stop, waits for a Fixed PT service, travels with Fixed PT trip to another Fixed PT stop, books a Flexible PT service, waits for the Flexible PT service, and finally makes a Flexible PT trip to his/her destination.

3. Flexible PT+Fixed PT+Walk/Bike: A passenger calls a Flexible PT service from his/her origin, waits for the Flexible PT service, makes the Flexible PT trip to a Fixed PT stop, waits for a Fixed PT service, makes a Fixed PT trip to another Fixed PT stop, and finally walks/bikes from that stop to his/her destination.

4. Flexible PT+Fixed PT+ Flexible PT: A passenger books a Flexible PT service from his/her origin, waits for the Flexible PT service, makes the Flexible PT trip to a Fixed PT stop, waits for a Fixed PT service, makes a Fixed PT trip to another Fixed PT stop, books a Flexible PT service, waits for the Flexible PT service, and finally makes a Flexible PT trip to his/her destination.

5. Flexible PT: A passenger orders a Flexible PT service from his/her origin, waits for the Flexible PT service, rides the Flexible PT trip to his/her destination.

Note that route composition options 1-4 are composed of three legs, whereas the fifth option consists of a single leg. A spatio-temporal representation of the different types of routes is given in Figure 3.1. The following section describes the method developed to generate, for each user, a set of integrated public transport routes and the process by which a particular route is chosen.

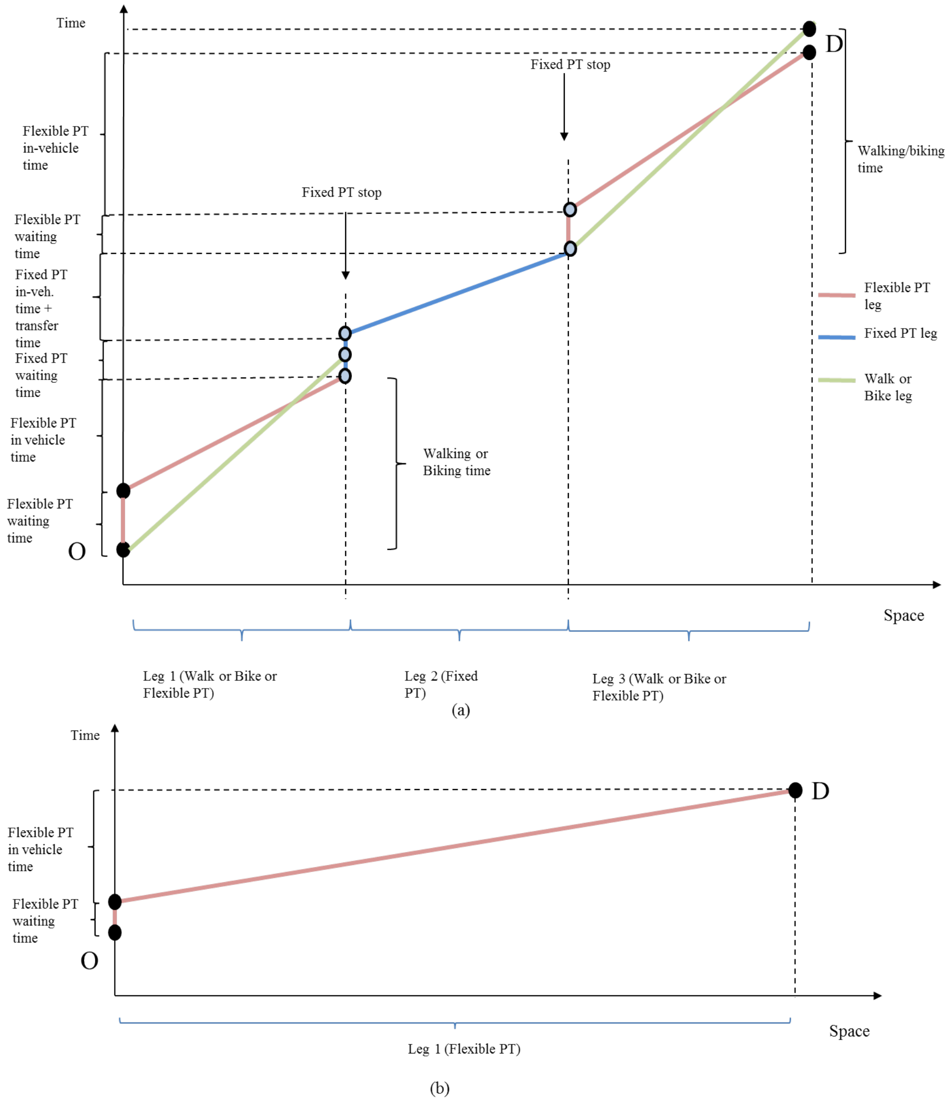


Figure 3.1: Spatio-temporal representation of integrated public transport route composition options

3.2.2 Integrated passenger transport assignment

For each origin-destination pair, first a set of integrated public transport routes (choice set) are generated in the module *Choice set generation*. Then for each of these options, a utility value is computed - which is a function of attributes of that particular route- in the module *Scoring of choice alternatives*. Finally, the origin destination demand is iteratively assigned to those paths based on the computed utility values in the *Assignment* module. The following sub-sections describe each of these modules.

Combined route choice set generation

A choice alternative here refers to the sequence of stops and services for realising the integrated public transport trip. A choice for a given origin-destination pair consists of a path connecting the origin and destination, transfer points if any, and the modes used to travel each leg of the path. Consider a route of a person traveling from origin location O to destination location D. It is assumed in this study that passengers search for Fixed PT stops in a circle (symmetric around their origin and desination). Let r be the radius (Euclidean distance) with which transit users search for Fixed PT stops from their origin and destination. Let d be the maximum distance (Euclidean distance) that a transit user chooses to walk to reach from their origin to a transit stop or from a transit stop to their destination. Thus r and d define the catchment area by on-demand transport and active modes, respectively. Based on the search radius r and walking distance limit d, the following sets are defined:

1. $S(r)_O$ = set of all Fixed PT stops within the radius r from origin O = $\{S_O^1, S_O^2, S_O^3, ... , S_O^m\}$
2. $S(r)_D$ = set of all Fixed PT stops within the radius r from destination D = $\{S_D^1, S_D^2, S_D^3, ... , S_D^n\}$
3. $S(d)_{O,walk/bike}$ = set of all Fixed PT stops in S_O with walking or biking distance from origin O to the stop, less than or equal to d
4. $S(d)_{D,walk/bike}$ = set of all Fixed PT stops in S_D with walking/biking distance from destination D to the stop, less than or equal to d
5. S_{OD} = set of all origin destination transit stop pairs = $\{(S_O^1,S_D^1), (S_O^1,S_D^2), ...(S_O^i,S_D^j), ...(S_O^m,S_D^n)\}$ where $S_O^i \in S_O(r)$ and $S_D^j \in S_D(r)$

We refer to the origin destination pair as OD demand pair and origin destination transit stop pair as OD transit pair. Following the process of generating these sets per OD demand pair, a set of feasible paths is generated by examining the feasibility of alternative route composition. If the stop S_O^i is in the set $S(d)_{O,walk/bike}$, then the path between origin and S_O^i is assigned the walk/bike mode. If the stop S_O^i is not in the set $S(d)_{O,walk/bike}$, then the path between origin and S_O^i is assigned the Flexible PT mode. Similarly the path between S_D^j and destination is also assigned a mode. The path between S_O^i and S_D^j is assigned the Fixed PT mode. The path chosen for the Fixed PT part is the shortest path (based on generalised travel cost) between the two stops using the Fixed PT network. The Fixed PT routing between an OD transit stop pair is based on Rieser (2010). The path obtained with modes assigned to it,

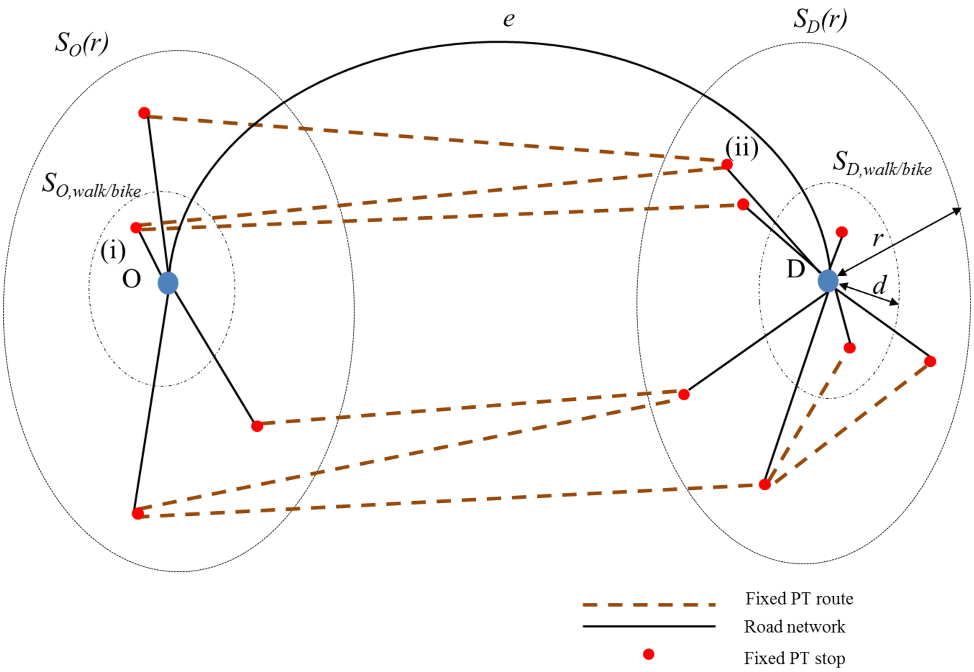


Figure 3.2: Illustration of integrated public transport routes with Fixed PT stop sets between origin O and destination D

is stored as a choice alternative for the respective OD demand pair. The assigned OD transit stop pair $\{(S_O^i, S_D^j)\}$ is then removed from the set S_{OD} and a new pair is chosen at random. This process of assigning modes is repeated for each of the OD transit stop pairs in S_{OD}. If either or both of the sets $S_O(r)$ and $S_D(r)$ are empty, then the path between origin and destination is assigned to Flexible PT. In this case the OD demand pair will have a single choice. Note that in any case assigning Flexible PT to the entire trip between O and D will be one of the alternative. An illustration of all the possible integrated public transport routes of a passenger with sets $S(r)_O$, $S(r)_D$, $S(d)_{O,walk/bike}$, and $S(d)_{D,walk/bike}$ is shown in Figure 3.2. We assume a connected Fixed PT network which implies that it is possible to reach a Fixed PT stop from any other Fixed PT stop in the network. The Fixed PT network in the figure indicates a schematic network and Fixed PT links may correspond to a direct line or a combination of lines involving interchanges.

Consider the origin-destination transit stop pair (i, ii). Following the process described above, the segment from O to i will be assigned walk/bike mode, the portion i to ii will be assigned Fixed PT mode, and the portion ii to D will be assigned Flexible PT mode. The public transit journey path e represents the trip covered entirely by Flexible PT. Table 3.2 provides the pseudocode for the algorithm for generating the choice set for the OD pair. Set C represents the choice set of integrated public transport routes for the origin-destination pair including the modes assigned to each of the journey legs.

Table 3.2: Pseudocode for generation of choice set for an origin destination pair

Step 1:	Consider an origin destination pair
Step 2:	Define $S_O(r)$, $S_D(r)$, $S(d)_{O,walk/bike}$, $S(d)_{D,walk/bike}$, Initiate $C = \emptyset$ and $k = 1$
Step 3:	$C_k = \{O, \text{Flexible PT}, D\}$
Step 4:	$if(S_{OD} = \emptyset)$
	Stop
	else
	$k{+}{+}$
	Randomly select a pair from S_{OD}
	Let the pair be (a,b)
	$if((a \in S(d)_{O,walk/bike}) \wedge (b \in S(d)_{D,walk/bike}))$
	$C_k = \{O, \text{walk or bike}, a, \text{Fixed PT}, b, \text{walk or bike}, D\}$
	Go to *Step 5*
	else
	$if((a \notin S(d)_{O,walk/bike}) and (b \notin S(d)_{D,walk/bike}))$
	$C_k = \{O, \text{Flexible PT}, a, \text{Fixed PT}, b, \text{Flexible PT}, D\}$
	Go to *Step 5*
	else
	$if(a \notin S(d)_{O,walk/bike})$
	$C_k = \{O, \text{Flexible PT}, a, \text{Fixed PT}, b, \text{walk or bike}, D\}$
	Go to *Step 5*
	else
	$C_k = \{O, \text{walk or bike}, a, \text{Fixed PT}, b, \text{Flexible PT}, D\}$
	Go to *Step 5*
Step 5:	Remove (a,b) from S_{OD}
Step 6:	Go to *Step 4*

Scoring of route choice alternatives

Once a choice set has been generated for an *OD* pair, the next task is to distribute the demand over the alternatives available. To this end, it is essential to evaluate each of the choice alternatives in the choice set. A utility function is developed which scores each choice alternatives based on the following attributes: number of transfers involved in the choice alternative, mode specific attributes such as fare, in-vehicle time and waiting time. The utility value of alternative i, U_i is given by,

$$\begin{aligned} U_i = &\beta^{walk/bike}_{travel}.t^{walk/bike}_{travel} + \beta_{transfer}.N_{transfer} \\ &+ \sum_{m=Fixed\ PT,Flexible\ PT} [\beta^m_{wait}.t^m_{wait} + \beta^m_{travel}.t^m_{travel} + \beta_{money}.\gamma^n.d^m] \end{aligned} \tag{3.1}$$

where,
$t^{walk/bike}_{travel}$ is the total walking/biking time for alternative i
t^m_{wait} is the waiting time for mode m
$t^m_{inveh.}$ is the total in vehicle time of mode m
γ^m is the fare per unit distance for mode m
d^m is the total distance travelled with mode m
βs are behavioral route choice parameters
$N_{transfer}$ is the total number of transfers between public transport services, regardless of their mode of operations

The computation of travel times and the waiting times of the user, with Fixed PT and Flexible PT is described as follows. The in-vehicle time of both the Fixed PT and Flexible PT is calculated using Dijkstra's algorithm using the length of each link in the network and mode specific speed. The waiting time of Fixed PT is computed from the schedule of the Fixed PT based on the arrival time of the user at the Fixed PT stop. The waiting time of Flexible PT is determined by the Flexible PT dispatching algorithm that assigns user travel requests to vehicles based on minimising their waiting time. The waiting time is computed as the time required for the Flexible PT vehicle to reach the user's pick-up location from its current location. The network travel time between an origin and destination travel time is computed using Dijkstra's algorithm. The travel time experienced by all users include the effect of congestion in the network.

Iterative Network Loading

Once the utilities of all the choice alternatives have been computed, the demand is assigned to the choice alternative with the lowest travel utility (*all-or-nothing* assignment). The *all-or-nothing* assignment implemented in this study is described as follows. Figure 3.3 shows a network with origin O and destination D and the sets $S_O(r)$, $S_D(r)$, $S(d)_{O,walk/bike}$, and $S(d)_{D,walk/bike}$ as described in the previous section. The number of possible paths for the user to travel from O to D is 3 as shown in Table 3.3 which also shows the individual travel time components and utility. The utility value of each path is computed as per Equation 3.1. The demand between O and D is then assigned to the path with the highest utility value.

Table 3.3: Travel time components of integrated routes of Figure 3.3

Path index	**Nodes in sequential order**	**Travel time components**	**Utility**
I	$\{O,(i),(ii),D\}$	Walking or biking time from O to (i) Fixed PT waiting time at (i) Fixed PT in-vehicle time from (i) to (ii) Flexible PT waiting time at (ii) Flexible PT in-vehicle time from (ii) to D	U_I
II	$\{O,(iii),(ii),D\}$	Flexible PT waiting time at O Flexible PT in-vehicle time from O to (iii) Fixed PT waiting time at (iii) Fixed PT in-vehicle time from (iii) to (ii) Flexible PT waiting time at (ii) Flexible PT in-vehicle time from (ii) to D	U_{II}
III	$\{O,D\}$	Flexible PT waiting time at O Flexible PT in-vehicle time from O to D	U_{III}

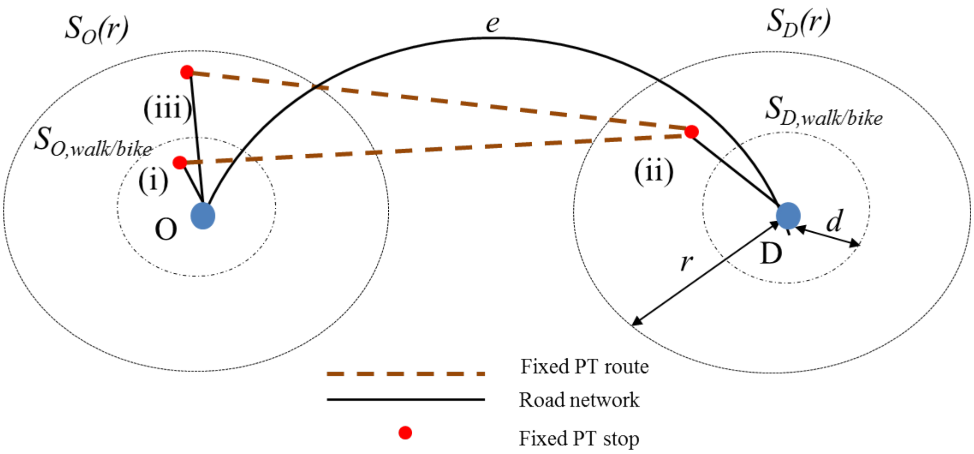


Figure 3.3: Network for all-or-nothing assignment illustration

3.2.3 Model implementation

The proposed model is embedded in a multi-agent transport simulation framework. It is implementd and integrated in the open source software MATSim (Horni et al. (2016b)). During the course of the iterative assignment, agents may undertake different strategies to alter their travel plans while making their trip from origin to destination based on the service experienced on past days. In this study, the strategies available to an agent are: changing the route of travel, changing the mode of travel, changing the departure time from an activity, and selecting a plan with the best score. An overview of the overall modelling framework with the developed multimodal route choice model is depicted in Figure 3.4. User assignment for the combined Fixed and Flexible PT takes place in the *Integrated public transport route choice and Assignment* module. The assigned users and vehicles are loaded to the network and simulated in the *Network Loading* module. The *Integrated public transport route choice and Assignment* and the *Network Loading* module comprise the daily dynamics of the system. Following the simulation, the users evaluate their executed travel plan based on the travel time experienced on the network in the *Evaluation* module. Travel time uncertainty such as a long waiting time and a possible increase in travel time due to congestion, is incorporated in the **Evaluation** module. For instance, if a user has to wait long for a service or experiences increased in-vehicle time due to congestion, this would lead to an increase in the overall travel time for that particular travel plan. Subsequently, that particular travel plan would receive a low score in the **Evaluation** module and the probability of that plan being selected in the following iterations diminishes. Consequently, modes of travel that consistently or even occasionally underperform due to inherent service uncertainty are less likely to be selected by users at equilibrium. The users make adjustments to their travel plans based on the strategies mentioned above in the *Re-planning* module. The selection of a strategy is based on a Logit function which is the default option in MATSim. The *Evaluation* and *Re-planning* modules entail the day-to-day dynamics of the system. The model has

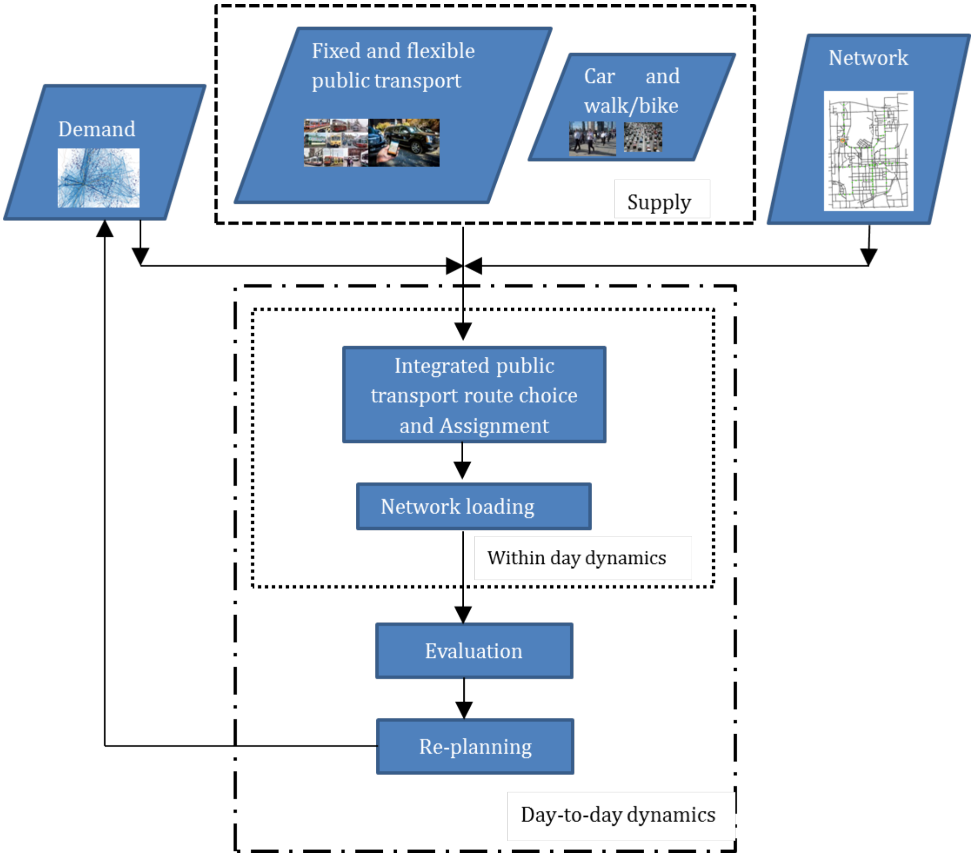


Figure 3.4: Overall modelling framework

been coded in Java, the documentation and source code of which are available on github[1].

3.3 Application

3.3.1 Network

The proposed integrated route choice model is applied to the network centered around Amsterdam, The Netherlands (Figure 3.5) and extends to the national airport, Schiphol, located at the south-east of the study area. The objective of the application is to gain insights into the implications of combining the Fixed PT service (which includes metro, tram, and bus) and Flexible PT service in Amsterdam. The network consists of 17,375 nodes, 31,502 links, and 2,517 public transport stops and includes train, tram, bus, and metro. The demand comprise of an activity based travel demand data with each agent performing a series of activity and travel leg for an entire day of simulation. It consists of 168,103 agents (repre-

[1] https://github.com/Jishnuns/IntegratedFixedFlexibleRouteChoiceAssignment.git

Figure 3.5: Road and public transport network of Amsterdam

senting 20% of the population), performing 556,437 trips and is adopted from the national activity-based demand model, Albatross (Arentze et al., 2000). Simulating a fraction of the population is found to provide meaningful simulation results as shown in Bischoff & Maciejewski (2016). The following modes are considered by the model: car, Fixed PT, walk, and bike.

3.3.2 Model settings

We introduce the various aspects of model settings under the following sub-sections, namely *Mode and route choice*, *Flexible PT dispatching algorithm*, and *Modal attributes*.

Mode and route choice

We calibrated the mode specific parameters by performing a sensitivity analysis on the alternate specific constants. We set the target modal share for all the modes to reflect a realistic modal split for the city of Amsterdam and arrived at values for the alternate specific constants that generated a realistic modal share at equilibrium. The marginal utility of performing an activity (β_{dur}), marginal utility of time spent by traveling (β_{travel}) for all the modes, marginal utility of arriving late for an activity ($\beta_{latear.}$) have been set to +6 utilities/hour, -6 utilities/hour, and -18 utilities/hour respectively. The behavioral parameter values were set to the default values set in MATSim following the calibration guidelines provided in Horni et al. (2016b). Marginal utility of money (β_{money}) is set to -0.685 utilities/€(based on the Dutch value of time). The radius of the catchment area for on-demand and active modes, r and d were set to 1000m and 500m, respectively, in accordance wih the average access and egress distances assumed for active modes.

Flexible PT dispatching algorithm

In this study, the Flexible PT system comprises of a fleet of vehicles controlled by a central dispatching unit that assigns vehicles to travel requests in real time. The vehicle dispatching algorithm has been adopted from Maciejewski, Horni, et al. (2016). The Flexible PT offers taxi-like individual door-to-door service and does not allow sharing. A vehicle that has been assigned a request by the dispatching unit, drives to the pick-up location, picks up the passenger, drives to the drop-off location, and drops the passenger. It then stays at the drop off location till further requests are assigned.

Modal attributes

The cost of the Fixed PT has been set according to the values provided by the incumbent public transport service provider. The Flexible PT is assumed to be 10 times as expensive as Fixed PT which is a reasonable assumption for taxi-like door-to-door service in Amsterdam. The distance based fares of Fixed PT ($\gamma^{FixedPT}$) and Flexible PT ($\gamma^{FlexiblePT}$) used in the model are 0.154 €/km and 1.54 €/km, respectively. The capacity of a Fixed PT vehicle is 100 whereas Flexible PT offers a taxi-like door-to-door service with a capacity of a single passenger. The speed of walk and bike modes were set to the default values in MATSim which are 3km/hour and 15km/hour, respectively.

Model calibration

In the absence of real data, we calibrated the utility functions following the calibration guidelines in MATSim. We methodically investigated the alternate specific constants of the available modes by fixing the marginal utility of traveling term to a fixed value as suggested in the calibration guideline for MATSim. We set the modal share for the modes to a realistic value for our case study area and obtained the ASCs which yielded the desired modal share. The obtained set of values was then fixed throughout the simulation runs.

3.3.3 Simulation scenarios

The simulation scenarios are summarised in Table 3.4. The scenarios are based on the type of public transport services offered and whether the combination of fixed and flexible services in a single trip is possible. In the **Base scenario**, the modes available to the user are car, walk, bike, and Fixed PT. In scenario **Fixed PT or Flexible PT**, a fleet of vehicles is introduced which offers Flexible PT. Fixed and flexible services are mutually exclusive in this scenario. Finally, in scenario **Fixed PT + Flexible PT**, in addition to the modes available in the previous scenario, users may also combine Fixed PT and Flexible PT when travelling from their origin to their destination.

From a planning perspective, it is important to investigate the effects of the fleet size of Flexible PT on the level-of-service offered to users and on system performance in general. To this end, a sensitivity analysis is conducted with respect to the fleet size of Flexible PT for both the second and third scenarios. The fleet sizes are equivalent to 0.1, 0.5, 1, 2, 3, 5, and 10 percentages of the simulated agent population.

Table 3.4: Scenario description with mode choice of users

Index	**Scenario**	**Car**	**Walk**	**Bike**	**Fixed PT only**	**Fixed PT and Flexible PT**	**Flexible PT only**
I	**Base Scenario**	Y	Y	Y	Y	N	N
II	**Fixed PT or Flexible** PT	Y	Y	Y	Y	N	Y
III	**Fixed PT + Flexible PT**	Y	Y	Y	Y	Y	Y

The simulations were run in the Dutch national supercomputer, Cartesius. The simulation timestep is 1s and the running time of a simulation run till convergence is approximately 32 and 42 hours for scenario **Fixed PT or Flexible PT** and **Fixed PT + Flexible PT** respectively. In order to account for stochasticity in the results, 10 runs for each simulation instance was carried out and the key performance indices were averaged over these runs.

3.4 Results and Analysis

The results are analysed with respect to *Modal usage*, *Service performance*, and *Fleet utilisation* related to the number of trips performed per mode, travel times for users, and fleet utilisation of Flexible PT, respectively. The results provide insights on the performance of a Flexible PT service and its market share, as a self-standing mode as well as in combination with a Fixed PT. The following sub-sections discuss these results in detail.

3.4.1 Modal usage

Table 3.5 shows the number of trips per mode and the vehicle-km travelled for the three scenarios considered. From the table, it becomes evident that with the increase in fleet size of Flexible PT, there is a steady increase in the number of trips with only Flexible PT in the scenario **Fixed PT or Flexible PT** and for trips with only Flexible PT as well as trips combining Flexible PT and Fixed PT in the scenario **Fixed PT + Flexible PT**. To further understand this trend, we look at the plots of number of PT trips versus Flexible PT fleet size for scenarios **Fixed PT or Flexible PT** and **Fixed PT + Flexible PT** as shown in Figures 3.6 and 3.7. It can be seen from the Figure 3.6 that the variation of number of trips by Flexible PT only is super-linear till a fleet size that is equivalent to 2% of the population after which the variation becomes sublinear with the number of trips stabilising around fleet size of 3%. Similary from Figure 3.7, it can be observed that the increase in the number of trips by Flexible PT only and trips combining Fixed PT and Flexible PT is sub-linear till 5% of fleet size after which the number of trips stabilises. This trend can be further explained by examining the average waiting time plots for scenarios **Fixed PT or Flexible PT** and **Fixed PT + Flexible PT** (Figure 3.8). The waiting time plots indicate a similar trend, indicating that the increase in number of trips for Flexible PT is primarily governed by the waiting time reductions. It can be also seen from Table 3.5 that there is an overall increase in the share of PT for the scenario **Fixed PT + Flexible PT** of about 12% (for a fleet size of 10% of the total demand) compared to the scenario **Fixed PT or Flexible PT** indicating that the integration of Fixed and Flexible PT makes the service more attractive. There is also a steady decrease in mode share of car and active modes (walk and bike) for scenarios **Fixed PT or Flexible PT** and **Fixed PT + Flexible PT** compared to the **Base Scenario**.

We further analyze modal shift by plotting the migration pattern when making the transition from the **Base Scenario** to **Fixed PT + Flexible PT** scenario (indicating the number of people shifting from the modes in **Base Scenario** to the modes in scenario **Fixed PT + Flexible PT**). As can be seen in Figure 3.9 that the trips with Fixed PT in the base case is absorbed by Flexible PT and the combination of Fixed PT and Flexible PT in scenario **Fixed PT + Flexible PT**. It can be also seen that the share of combined Fixed PT and Flexible PT trips comes predominantly from Fixed PT users from the **Base Scenario**. Most of the users who switch to Flexible PT, have previously traveled by car. A considerable portion of car users in the **Base Scenario**, switch to Flexible PT in the scenario **Fixed PT + Flexible PT**. There is also a considerable shift from the active modes (Walk and Bike) to Flexible PT. Most of the previous Fixed PT users choose the combination of Fixed PT and Flexible PT, Flexible PT only, or stay with Fixed PT only in the scenario **Fixed PT + Flexible PT**.

The total vehicle-kms travelled for scenario **Fixed PT or Flexible PT** steadily increases for fleet sizes of up to 3% after which it starts to stabilize. A similar trend is observed for scenario **Fixed PT + Flexible PT** albeit the vehicle-km steadily continues to increase for fleet sizes of up to 5%, after which it remains at the same level. This could be explained by the increase in the mode share of Flexible PT when possible to use it as either an exclusive mode or in combination with Fixed PT; and the decrease in modal share of active modes. The increase in mode share for Flexible PT translates into additional time spent by vehicles en-route to picking up passengers from their origins. Also, the decrease in mode share of active modes implies a shift from non-motorised to motorised modes. This can also be observed in Figure 9, which shows that Flexible PT attracts a considerable portion from trips previously performed by active modes. These factors results in additional vehicle-kms travelled as fleet size of Flexible PT increases. Beyond a fleet size of 3% for scenario **Fixed PT or Flexible PT** and 5% for scenario **Fixed PT + Flexible PT**, the increase in the modal share becomes marginal and thus does not induce further increase in vehicle-kms.

Table 3.5: Modal share per mode for the scenarios in percentages

Scenario	Fleet size	Car	Walk	Bike	Fixed PT only	Fixed PT and Flexible PT	Flexible PT only	Total PT	Vehicle-km($\times 10^6$)
Base Scenario	NA	28.35	30.33	22.15	19.17	NA	NA	19.17	2.49
Fixed PT or Flexible PT	0.5	18.75	29.61	14.98	19.34	NA	17.32	36.66	2.35
	1	16.10	28.49	13.18	17.68	NA	24.56	42.24	2.77
	2	13.40	23.57	10.88	12.08	NA	40.06	52.14	3.67
	3	12.36	19.94	10.66	9.15	NA	47.88	57.03	4.60
	5	12.28	18.45	10.66	8.43	NA	50.19	58.62	4.53
	10	12.07	17.87	10.39	7.94	NA	51.73	59.67	4.62
Fixed PT + Flexible PT	0.5	19.17	29.24	11.84	11.39	8.55	19.81	39.75	2.34
	1	17.83	28.72	12.30	8.20	9.53	23.43	41.16	2.78
	2	15.17	25.20	10.87	3.01	13.63	32.12	48.76	3.54
	3	12.30	20.52	8.12	0.87	18.51	39.69	59.07	4.17
	5	9.18	16.09	5.03	0.19	23.78	45.73	69.70	4.91
	10	8.54	15.26	4.94	0.16	24.55	46.55	71.26	4.88

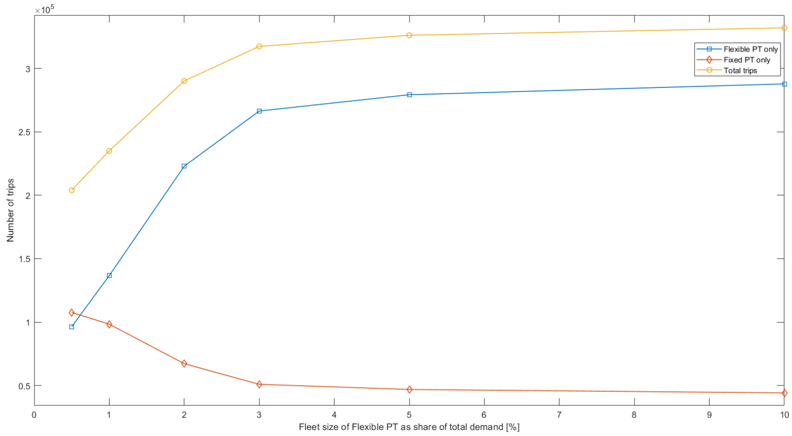


Figure 3.6: Number of PT trips versus fleet size of Flexible PT for scenario Fixed PT or Flexible PT

Further, we analyze how passengers combine Fixed PT and Flexible PT in a trip in scenario **Fixed PT + Flexible PT**. For all the trips combining Fixed and Flexible PT in **Fixed PT + Flexible PT**, Figure 3.11 plots the absolute frequency distribution for the ratio of Flexible PT trip lenghts to the total trip length. It can be seen from Figure 3.11 that among the trips that combine Fixed PT and Flexible PT, majority of the trips use Flexible PT to cover only about 10-20% of their trip lengths, indicating that Flexible PT is mostly used as an access or egress mode to Fixed PT. This trend is especially pronounced for larger

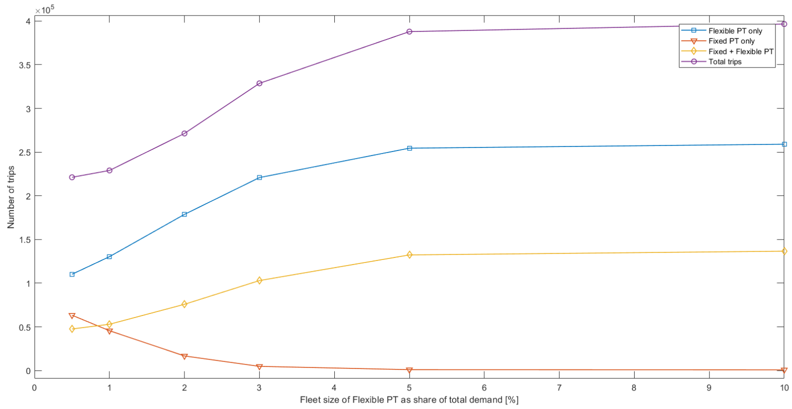


Figure 3.7: Number of PT trips versus fleet size of Flexible PT for scenario Fixed PT + Flexible PT

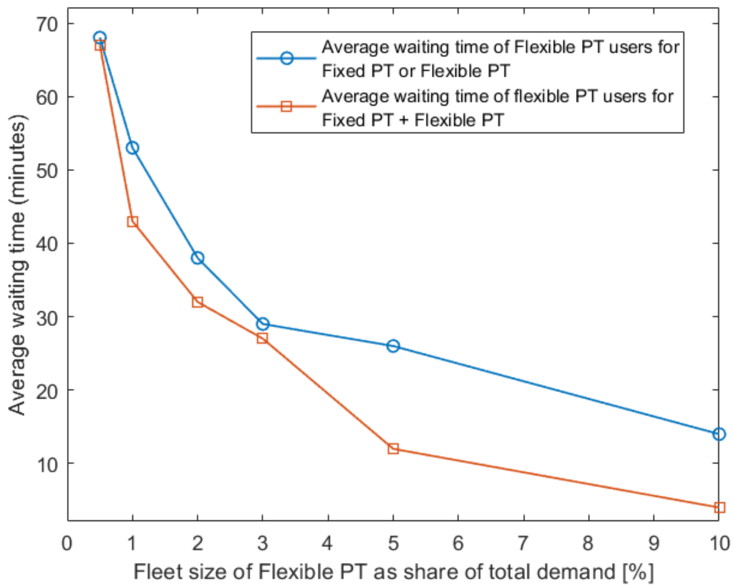


Figure 3.8: Average waiting time vs fleet size of Flexible PT for scenarios Fixed PT or Flexible PT and Fixed PT + Flexible PT

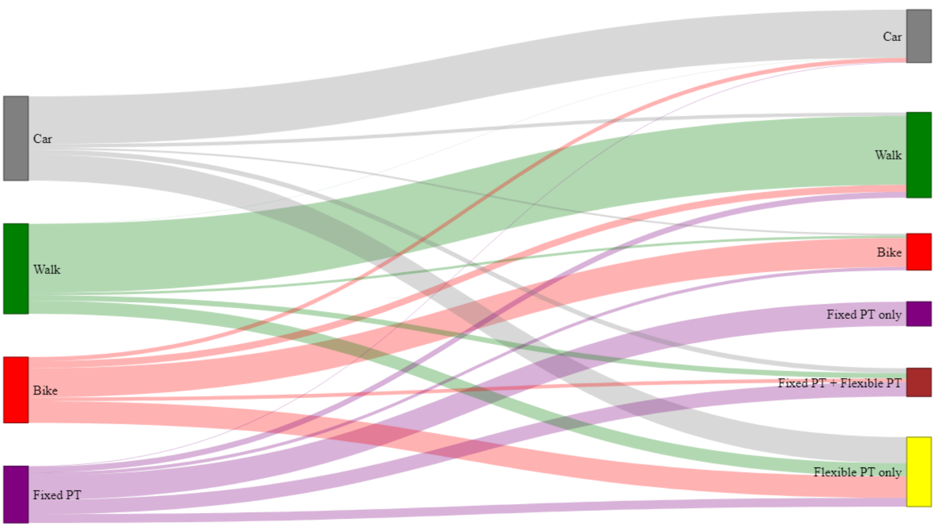


Figure 3.9: Migration plot for Base case to scenario Fixed PT + Flexible PT, fleet size = 1%

Figure 3.10: Transfer points between Fixed PT and Flexible PT

fleet sizes of Flexible PT. As the fleet size increases, there is an overall increase in the number of trips combining Fixed and Flexible PT. At the same time, this increase in the number of trips is skewed towards using Flexible PT for travelling less than 30% of their total trip length. Figure 3.10 shows a spatial representation of the transfer points between Fixed PT and Flexible PT for Flexible PT fleet size = 1% of the total demand. It can be seen from the Figure 3.10 that transfers between Fixed PT and Flexible PT and vice-versa take place throughout the network and in combination with all modes (such as bus, tram, metro, and train). We cluster the transfer points based on the volume of transfer as shown in Figure 3.10. While stops with fewer than 100 transfers are spread throughout the network, high volume transfer stops correspond to metro stations and public transport interchange locations within the ring area. Central station is the most popular transfer location between Fixed PT and Flexible PT.

Fare Sensitivity Analysis

In order to understand the effect of fare of Flexible PT on the modal share we perform a sensitivity analysis with varying fare for Flexible PT. We vary the fare of Flexible PT relative to the fare of Fixed PT. The ratio of fare of Fixed PT to Flexible PT considered are 1:1, 1:2, 1:5, 1:10 (considered in this study), 1:25, and 1:50. Figure 3.12 shows how the modal shares of Flexible PT, Fixed PT + Flexible PT, and Fixed PT under varying fare ratios. As can be seen from the figure, the modal share of Flexible PT decreases monotonically as

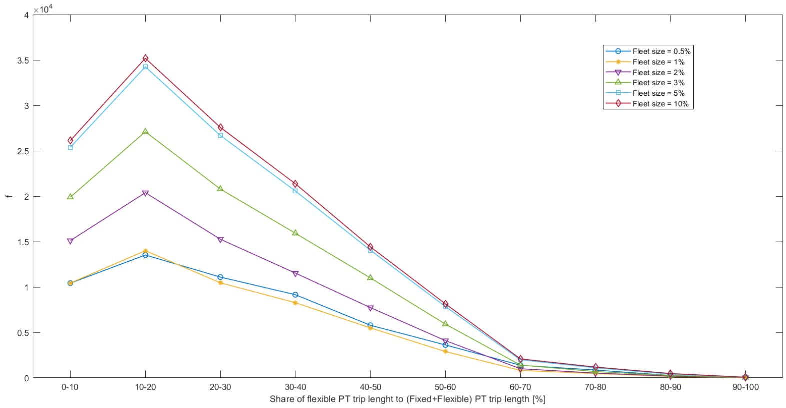


Figure 3.11: Frequency distribution of fraction of Flexible PT trip length in trips combinig Fixed and Flexible PT

the fare increases. The variation is sub-linear until a fare ratio of 1:10 after which the variation becomes super-linear. The share of Flexible PT + Flexible PT does not show considerable variation till a ratio of 1:5, after which the share increases monotonically up to a ratio of 1:25 and then decreases monotonically from 1:25 to 1:50. This implies that as the fare ratio increases, Fixed PT + Flexible PT becomes more attractive compared to Flexible PT, hence attracting passengers from Flexible PT. However, beyond a ratio of 1:25, using Flexible PT both as exclusive door-to-door travel and in the combination with Fixed PT becomes prohibitive for many users and hence the share of both Flexible PT and Fixed PT + Flexible PT decreases beyond the ratio of 1:25. The share of Fixed PT increases substantially beyond the ratio of 1:25, as it becomes more attractive compared to Flexible PT and Fixed PT + Flexible PT and hence attracts passengers from both these modes.

3.4.2 Service performance

Figures 3.13 and 3.14 plot the cumulative relative frequency distribution for travel time components of waiting time and total travel time, respectively, for Flexible PT users in the **Fixed PT + Flexible PT** scenario. As can be seen from Figure 3.14, an increase in fleet size of Flexible PT results in an overall increase in the fraction of short trips (travel time of up to 20 minutes). To further understand the effect of fleet size of Flexible PT on the travel time of its users, we look at the relative frequency distribution of average waiting time of its users. From Figure 3.13 it becomes evident that the increase in fleet size leads to an overall increase in the fraction of trips with waiting time shorter than 10 minutes (shift from 40% for Fleet size = 0.1% to more than 90% for fleet size = 10%). With the increase in fleet size, the fraction of trips with travel time 0-10 minutes increases whereas the fraction of trips for all other in-vehicle time range (>10 minutes) decreases. This overall gain in the percentage of shorter trips can be explained from the overall reduction in the number of active mode trips (bike and walk) when shifting from the **Base Scenario** to scenario **Fixed**

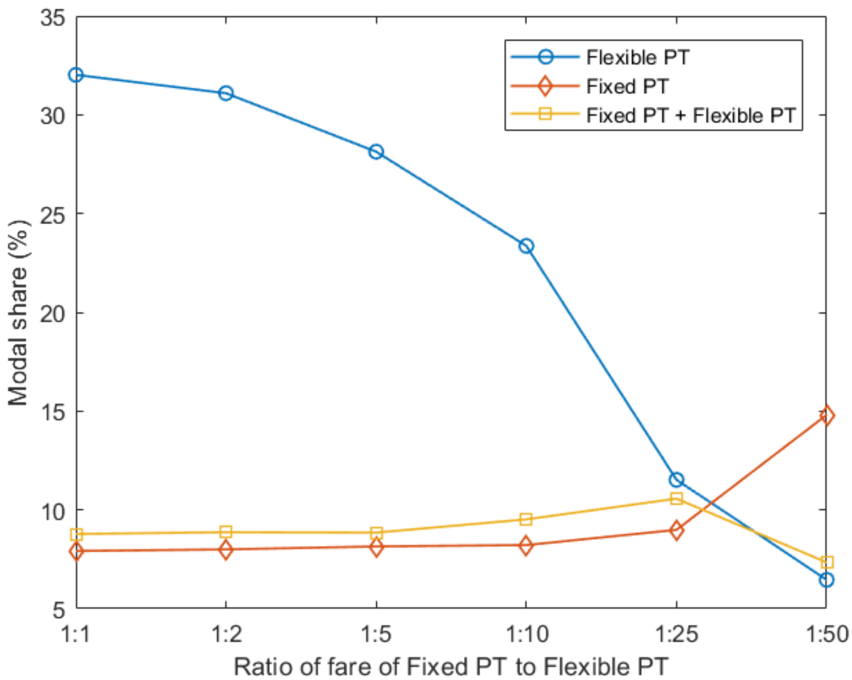


*Figure 3.12: Modal share of public transport alternatives under different fare settings in the scenario **Fixed PT + Flexible PT***

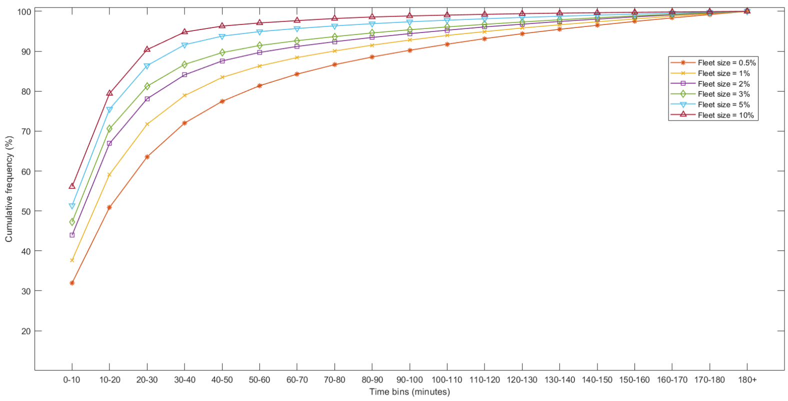


Figure 3.14: Cumulative frequency distribution of total travel time time for Flexible PT for scenario Fixed PT + Flexible PT

PT + Flexible PT (Table 3.5 and Figure 3.9). These trips are attracted by Flexible PT as the fleet size increases and hence leads to an overall increase in the number of shorter trips.

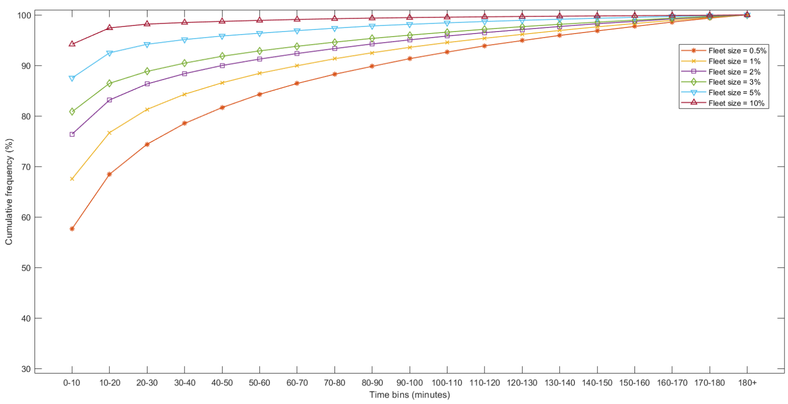


Figure 3.13: Cumulative frequency distribution of waiting time for Flexible PT for scenario Fixed PT + Flexible PT

3.4.3 Fleet utilisation

This section discusses the fleet utilisation of Flexible PT under the second and third scenarios. The performance indices considered in assessing the fleet utilisation are: *Idle ratio*, *Empty drive ratio*, and *Passenger drive ratio* defined as follows.

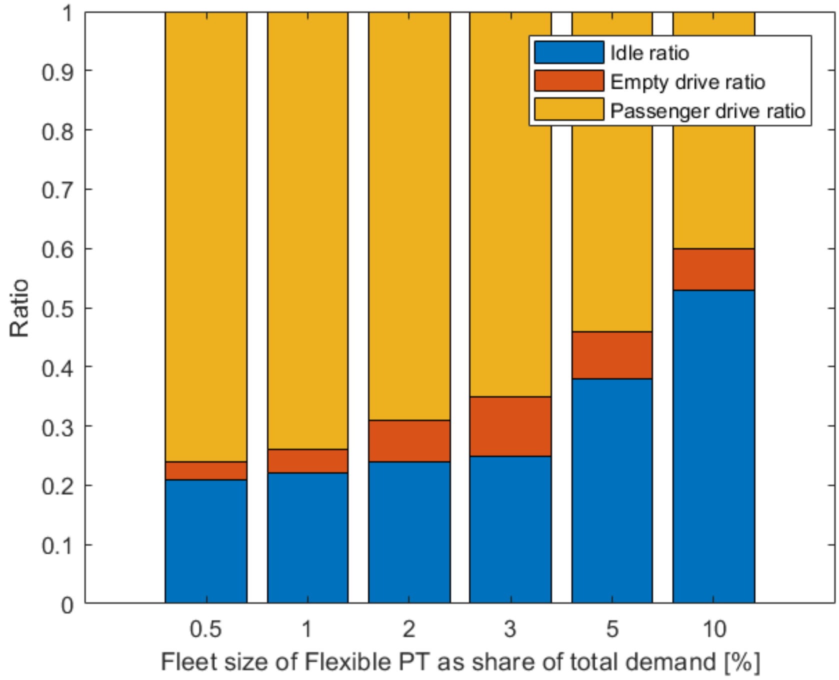


Figure 3.15: Flexible PT fleet utilisation for scenario ***Fixed PT or Flexible PT***

- *Idle ratio* is the fraction of time all the vehicles spend without being assigned a request, to the total time the vehicles are in service
- *Empty drive ratio* is defined as the fraction of time the vehicles spend driving in the network without a passenger on-board
- *Passenger drive ratio* is defined as the fraction of time all the vehicles spend driving in the network with a passenger on-board

We examine the breakdown of *Idle ratio*, *Empty drive ratio*, and *Passenger drive ratio* for the scenarios **Fixed PT or Flexible PT** and **Fixed PT + Flexible PT**, as displayed in Figures 3.15 and 3.16 respectively. The *Passenger drive ratio* decreases and *Idle ratio* increases in both scenarios with increase in fleet size of Flexible PT. This indicates that the vehicles spend more time in the network without being assigned a request and spend less time transporting passengers as the fleet size increases. In particular, the fleet of Flexible PT remains largely underutilised when the fleet size is equivalent to 10% of the travel demand.

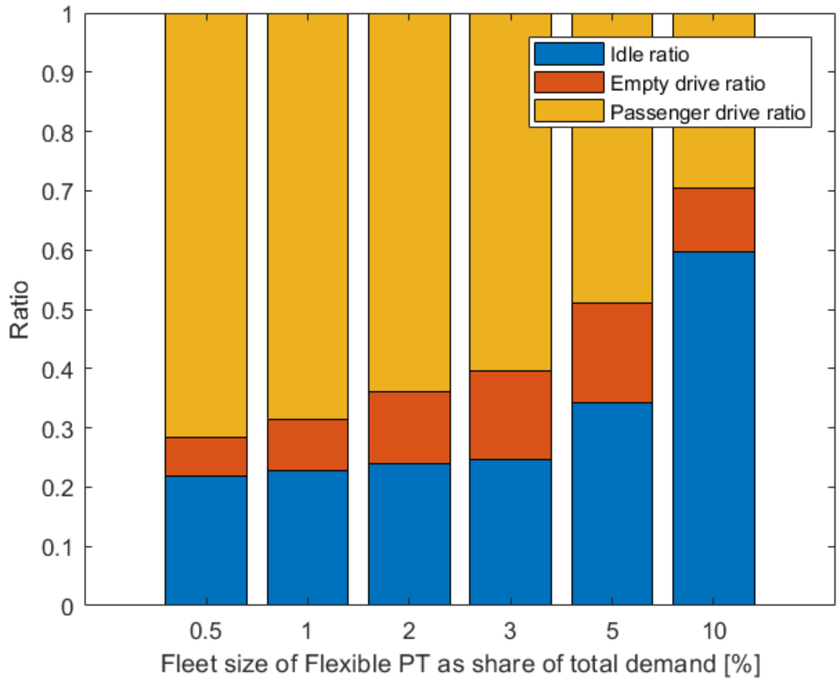


Figure 3.16: Flexible PT fleet utilisation for scenario ***Fixed PT + Flexible PT***

3.5 Conclusion

We developed an integrated multimodal route choice and assignment model that allows users to combine conventional line-based and on-demand passenger transport services so that their travel impedance is minimized. The model is implemented in an agent-based simulation framework which incorporates the day-to-day learning of users and was applied for the network based on the city of Amsterdam. Results are presented and discussed for scenarios where Fixed PT and Flexible PT are either mutually exclusive or facilitate their combination. Key performance indicators related to modal usage, service performance, fleet utilisation, and impact of fleet size and thus level of service on the number of passenger trips are discussed. Potential applications of the model include identifying locations for transfers between Fixed PT and Flexible PT to support interchange facility design and assessing the performance and level of service of Flexible PT services as first/last mile under various Fixed PT service attributes such as frequency.

Results indicate that Flexible PT is mainly used to cover $<30\%$ of the trip length, when the two modes of operations can be combined within a single passenger journey. Most of the users combining Fixed and Flexible PT services are otherwise using solely Fixed PT in the base case. Sensitivity analysis with respect to fleet size of Flexible PT indicate that no significant gains in level-of-service are made when increasing the fleet size beyond 5% of the travel demand. Fleet utilisation results indicates that the fleet of Flexible PT remains increasingly underutilised beyond a fleet size of 5% of the travel demand. This indicates a need for better relocation strategies for the fleet of Flexible PT.

The application of the model to the area centered around Amsterdam shows that the model is scalable for large-scale real-world applications. Hence the study provides a model allowing for the evaluation of fixed and flexible passenger services in contexts where on-demand services are expected to interact with conventional line-based services.

The limitations of the assignment model used in this study can be addressed in future research by employing a dynamic and stochastic assignment which accounts for correlations among public transport alternatives (e.g. in the form of path size logit). Furthermore, further research may include accommodating other modal combinations such as shared on-demand services, park and ride, kiss and ride, and car-sharing while considering supply adaptation in response to prevailing demand patterns. Future work may also enrich the model by incorporating the value of time and reliability in the behavioral modelling of passengers' preferences towards on-demand transport (Alonso-González et al., 2020).

Chapter 4

Assessing the scalability of on-demand services

This chapter explores several hypothetical scenarios of market share of on-demand transport in an urban mobility context. We adopt an agent-based simulation framework for modelling and evaluation of the on-demand services. We investigate scenarios where either private and pooled on-demand service replace private car trips, public transport trips, or both private car trips and public transport trips in Amsterdam. On-demand service performance in terms of level of service offered and service efficiency are analysed. Results provide insights into the scalability of the on-demand service and into the comparative analysis of operational aspects of private and pooled on-demand service and how it affects the level of service offered to users.

The chapter is structured as follows. First we describe the modelling framework adopted for assessing the mobility system, present the case study along with the experimental scenario design. This is followed by presenting the results for level of service offered and service efficiency and their analysis. We conclude the chapter work by discussing the key findings and offer directions for future research. This chapter concludes the analysis part of on-demand service and in the following chapter we move on to the design.

The chapter is based on the following paper that is currently under review:

Narayan, J., Cats, O., van Oort, N. & Hoogendoorn, S., On the scalability of private and pooled on-demand services for urban mobility in Amsterdam. (submitted on 04-05-2020 to IEEE Transactions on Intelligent Transportation Systems)

4.1 Introduction and Study Objective

Economic growth and rapid urbanisation around the world have caused an increasing need for efficient mobility of people in urban areas. The various advancements in ICT platforms have facilitated the emergence of innovative mobility solutions where users and service providers interact through an online platform such as a smart phone application. Such mobility systems provide flexible services to users (door-to-door or stop-to-stop, private or shared) and provide them with the flexibility to plan their trips. Preliminary empirical evidence suggests that traditional motorised modes of travel such as privately owned cars, line and schedule-based public transport are increasingly losing their market shares to such mobility solutions such as Cabify, Lyft, Uber, Car2Go, DriveNow, ZipCar (M. P. Enoch, 2015; Conway et al., 2018) and that public transport should evolve in the light of such emerging innovative solutions to stay relevant (M. Enoch et al., 2020). There is therefore a growing need to assess the impact of such services on urban mobility and their potential to substitute traditional motorised modes such as cars and public transport.

The literature relevant to this study pertains to the deployment of a large scale on-demand fleet in a city-wide context and their impact on urban mobility. One of the earliest works that looked into the problem include S. Ma et al. (2013). They developed a heuristic-based large-scale taxi ride-sharing service and demonstarted the efficiency and scalability of the model for large-scale instances. More recent studies that looked into the deployment of on-demand fleet for US cities include those for Manhattan (Santi et al., 2014; Alonso-Mora et al., 2017), New York (W. Shen & Lopes, 2015), New Jersey (Zachariah et al., 2014), Austin (Fagnant & Kockelman, 2018), and a series of diverse urban cases (Burns et al., 2013). The Manhattan study (Santi et al., 2014) concluded that all taxi trips in Manhattan could be served by pairing up two requests per taxi while minimising the travel time. This concept of shareability graph was later adopted by Alonso-Mora et al. (2017). They developed an algorithm that enables real-time high capacity ride-pooling for Manhattan. Simulation results indicate that 98% of the taxi demand can be served by 3000 vehicles (with a capacity of four) instead of the current fleet which is more than four times larger. The New York study (W. Shen & Lopes, 2015) developed scheduling strategies for dispatching autonomous vehicles and evaluated the model using New York City taxi data. Results showed that the model could achieve a reduction in passenger waiting time by around 30% and an 8% increase in the trip success rate. Implementation of stop-to-stop based autonomous taxis (ATaxis) was carried out for New Jersey by Zachariah et al. (2014). In the Austin study, the potential of SAVs (shared autonomous vehicles) to replace the trips performed by privately owned cars was performed and results indicated that a single SAV could serve the demand offered by 10 privately owned cars. Fleet implementation of shared, self-driving, and autonomous vehicles for three regional US cities was studied in Burns et al. (2013). The cities studied include Ann Arbor, Michigan (mid-sized US city), Babcock Ranch, Florida (low-density suburban development), and Manhattan, New York (large and densely populated urban area). Results for Ann Arbor indicated that a shared fleet could achieve a fleet reduction of 85%. The Babcock Ranch case study indicated a fleet of 3,000-4,000 vehicles for a population of 50,000 people. In the case of Manhattan, the study finds out that a fleet size of 9,000 vehicles could replace the trips performed by 13,000 vehicles.

On-demand fleet deployment for European cities was performed for Berlin (Bischoff & Maciejewski, 2016), Lisbon (L. Martinez & Crist, 2015), Munich (Moreno et al., 2018), Amsterdam (Narayan et al., 2019), and Stockholm (Rigole, 2014). These studies investigated the potential of SAVs to replace the trips performed by privately owned cars and/or public transport. Results from Berlin, and Lisbon indicate that a single SAV could replace the demand served by 10 privately owned cars. The Munich study suggests that four shared autonomous vehicles could serve the demand offered by 10 privately owned cars. The potential of ride-sourcing systems offering taxi-like service to serve all the demand currently served by either private car or public transport was performed in the Amsterdam study. It was concluded that one ride-sourcing vehicle could replace the trips performed by nine privately owned cars. In addition, the ride-sourcing fleet required to serve the PT demand amounted to 1.3% of the PT trips. The Stockholm study showed that a fleet of autonomous vehicle can potentially provide on-demand door-to-door transport with a high level of service, using less than 10% of private cars.

Similar studies were conducted for the cities of Melbourne (Dia & Javanshour, 2017) and Singapore (Spieser et al., 2014). The results of the Melbourne study show that deploying a fleet of shared autonomous vehicles can significantly reduce the total number of vehicles required. The Singapore study suggests that a fleet of self-driving vehicles could replace two thirds of the vehicles currently operating in Singapore while still delivering all the trips made by private vehicles.

The above-mentioned studies highlight the relevance of research on on-demand mobility and the potential of such services in improving overall urban mobility. Most of these studies (with the notable exception of L. Martinez & Crist (2015)) looked at the implemetation of on-demand mobility systems either as shared (simulataneously shared) or as private (sequentially shared). This study adds to the existing body of knowledge by testing the consequences of scaling the on-demand mobility system - private and pooled - and investigating its potential to replace privately owned car trips, public transport trips, or both car and public transport trips.

4.2 Modelling Framework

On-demand mobility services are characterised by the real-time dynamics of their operations. Mathematical/analytical models often fail to capture these real time dynamics. Conversely, agent-based simulation models allow capturing system dynamics and its operation. We therefore adopt in this study an open-source multi-agent traffic simulation framework MATSim (Horni et al., 2016b) as the modelling framework.

The modelling framework is shown in Figure 4.1. The input modules comprise of the *Network*, *Demand*, and *Supply*. The *Network* refers to the super-network which consists of the sub-networks of road and line/schedule based public transport. The sub-network of line/schdule based public transport involves the route network for public transport modes (e.g. train, tram, metro, bus) along with their stop locations. *Demand* includes all passengers with a set of origin and destination points in the network. Each user of the transport system is represented as an agent with a corresponding set of travel plans. *Supply* comprises of the modes available to each user for travelling from their origin to their destination. The modes available are: car (privately owned), walk, bike, public transport, and on-demand service. The public transport network pertains to line-based and schedule-based services that follow a pre-defined route and schedule operated by a fleet of vehicles. In the *Assignment and*

Network Loading module the passengers are assigned to their modes and loaded onto the network. This module pertains to the 24hr simulation period of a day. The simulation output from the *Assignment and Network Loading* module is used in the *Analysis* module.

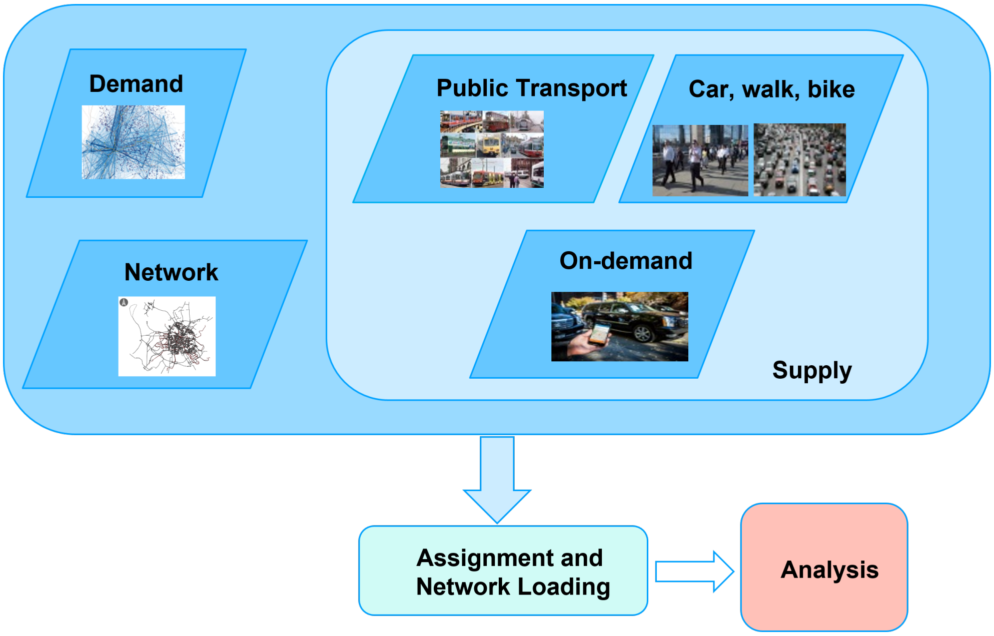


Figure 4.1: Modelling framework

On-demand service in this study is modelled as a fleet of vehicles operated by a central dispatching unit that assigns travel requests to vehicles in real-time and offers door-to-door service to passengers. Two types of on-demand service are considered in this study, namely:

- **Private on-demand**: Offering individual taxi-like service to passengers

- **Pooled on-demand**: Offering shared rides where passengers may share their ride with other passengers. Vehicle capacity is set to four.

The dispatching strategy of the on-demand system offering private service is as follows. A vehicle that has been assigned a request drives to the pick-up location, picks up the passenger, drives to the travel request destination, drops off the passenger and remains at the drop-off location until further requests are assigned. The dispatching strategy of the on-demand system offering pooled service is as follows. A vehicle that has been assigned a request drives to the pick-up location, picks up the passenger, possibly makes detour(s) to pick up other pooled requests, drives to their destination, drops off the passenger and stays at the drop-off location until further requests are assigned. The dispatching strategy of the on-demand vehicles has been adopted from Bischoff et al. (2017).

4.3 Application

In our experiments, we apply a series of scenarios for a network centered around Amsterdam, The Netherlands (Figure 4.2). The network consists of 17,375 nodes and 31,502 connecting links. The public transport network includes train, tram, bus, and metro with a total of 2517 stops and stations. The network is based on data extracted from OpenStreetMap (Haklay & Weber, 2008). The demand amounts to 168,103 agents which represent 20% of the population and is adopted from the national activity-based demand model, Albatross (Arentze et al., 2000). The travel modes considered next to public transport are: car, walk, bike, and private and pooled on-demand services.

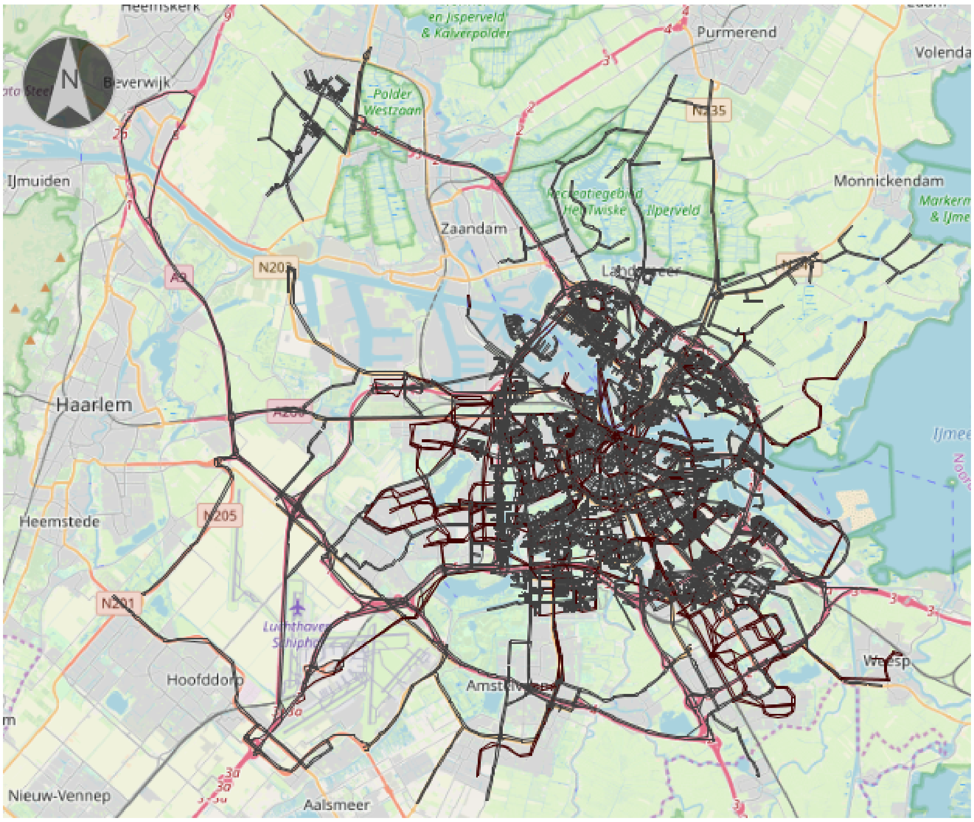


Figure 4.2: The model application network of Amsterdam

4.4 Simulation scenarios

We devise seven simulation scenarios to investigate the potential of on-demand services to serve motorised trips in Amsterdam, The Netherlands (summarised in Table 4.1). The first scenario is the **Base case**. The modes available to the users are: car, walk, bike, and PT. In the second scenario (scenario 2(a)), all the car trips performed in the **Base case** are served instead by a fleet of private on-demand vehicles. In the third scenario (scenario 2(b)), all the car trips from the **Base case** are served by a fleet of pooled on-demand vehicles. Next, all the public transport trips from the **Base case** are served with a fleet of private on-demand vehicles in scenario 3(a), or alternatively by a fleet of pooled on-demand vehicles in scenario 3(b). This is followed by scenarios where both car and public transport trips are substituted by on-demand services. In scenario 4(a), all the car and PT trips from the **Base case** are served with a fleet of private on-demand vehicles. Finally, by scenario (4(b)), all the car and PT trips from the **Base case** are served wih a fleet of pooled on-demand vehicles. The mode share (%) at equilibrium in the *Base Scenario* is as follows: Car (29%), Walk (28%), Bike (22%), public transport (21%). The mode shares reflect the actual modal share in the study area of Amsterdam, The Netherlands.

Table 4.1: Experimental scenario design

Index	**Scenario**	**Description**
1	Base case	Available modes are car, walk bile, and PT
2(a)	Car $\rightarrow$ private on-demand	All the private car trips from Base case are served with private on-demand
2(b)	Car $\rightarrow$ pooled on-demand	All the private car trips from Base case are served with pooled on-demand
3(a)	PT $\rightarrow$ private on-demand	All the PT trips from Base case are served with private on-demand
3(b)	PT $\rightarrow$ pooled on-demand	All the PT trips from Base case are served with pooled on-demand
4(a)	Car and PT $\rightarrow$ private on-demand	All the private car and PT trips from Base case are served with private on-demand
4(b)	Car and PT $\rightarrow$ pooled on-demand	All the private car and PT trips from Base case are served with pooled on-demand

Figure 4.3 shows the scenarios considered along with the modal share in the Base case.

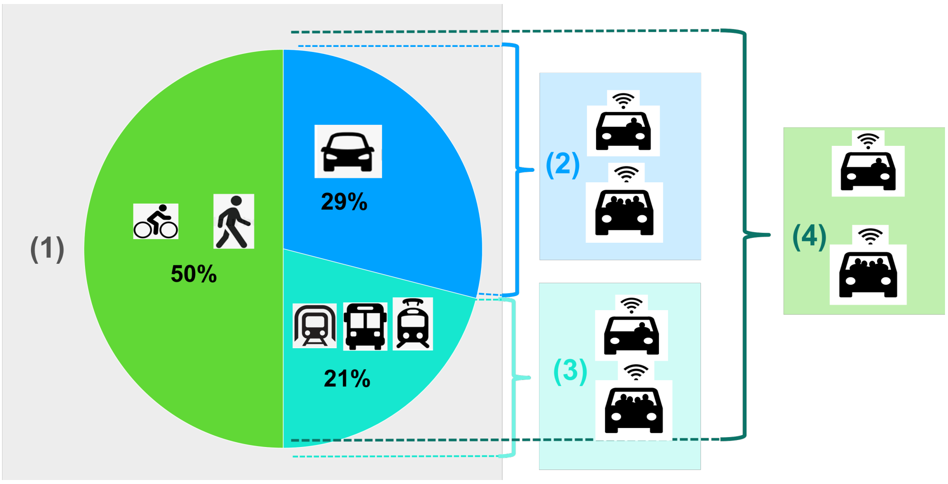


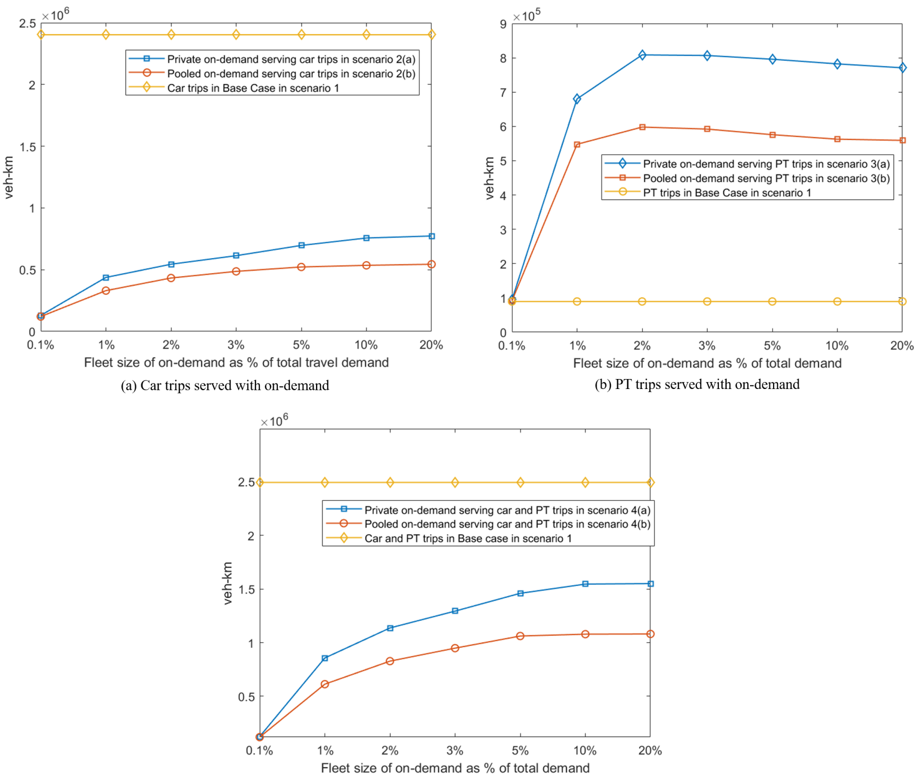
Figure 4.3: Simulation scenarios

4.5 Results and Analysis

This section presents the results and analysis of the scenarios detailed in the previous section. For all the scenarios we consider two aspects of system performance namely, *Service efficiency* and *Level of service*. *Service efficiency* is analysed using key performance indicators that pertain to veh-km travelled, occupancy rate, and empty drive ratio. *Level of service* is investigated from a user's perspective with key performance indices such as travel time (in-vehicle time and waiting time) and share of demand satisfied. For all scenarios, we consider various instances of on-demand fleet size, represented as a percentage of total demand. We test the impact of fleet sizes corresponding to 0.1%, 1%, 2%, 3%, 5%, 10%, and 20% of total demand.

4.5.1 Service efficiency

Figure 4.4 shows the veh-km traveled for all scenarios. Figure 4.4(a) shows the veh-km travelled by car trips in *Base case* and when those are substituted by an on-demand service. Similarly, Figures 4.4(b) and 4.4(c) depicts the veh-km for PT trips and car and PT trips in the base case scenario and the respective private and pooled on-demand services scenarios. As can be seen from Figure 4.4(a) the veh-km travelled by private car trips in *Base case* is significantly higher than that when either private or pooled on-demand services serve car trips. The difference between veh-km travelled for private and pooled on-demand service notwithstanding, the difference of the veh-km for the two on-demand services from the *Base case* can be explained from Figure 4.5. It shows the rejection rate for the on-demand travel requests for scenarios when car trips, PT trips, and car and PT trips are replaced with private and pooled on-demand services. As can be seen from the figure, for scenario when on-demand services serve car trips, the rejection rate is still significant (0.3). Hence a considerable portion of the car trips in *Base case* is not satisfied in for the scenario when on-demand serves car trips; which then results in the lower veh-km travelled.



(a) Car trips served with on-demand

(b) PT trips served with on-demand

(c) Car and PT trips served with on-demand

Figure 4.4: Vehicle-kilometers travelled in all the scenarios

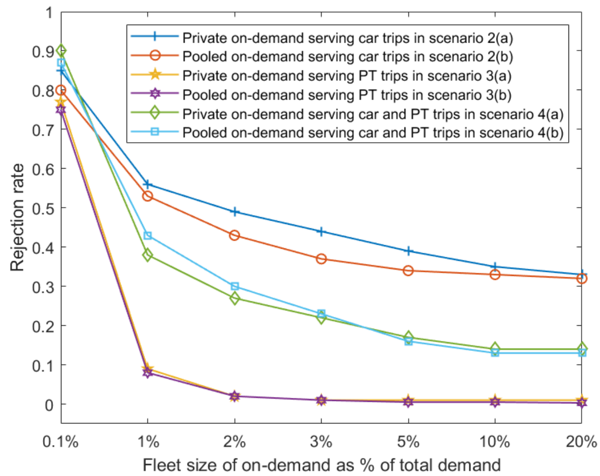
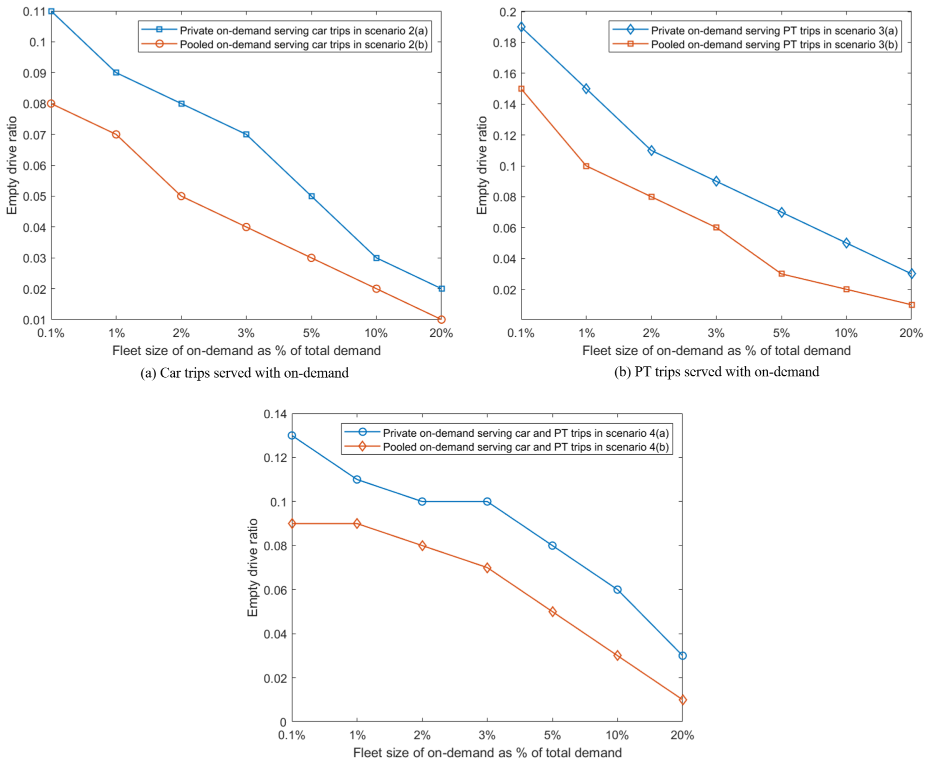


Figure 4.5: On-demand rejection rate

In the case of substituting public transport with on-demand transport, we observe from Figure 4.4(b) that the total veh-km travelled by on-demand services is significantly higher than that travelled by the PT vehicles in *Base case*. The total veh-km travelled when private and pooled services serve PT trips are approximately 8 times and 6 times respectively, more than the *Base case*. As can be seen from the Figure 4.5, the rejection rate for scenario 3 drops rapidly from 0.7 to < 0.1 when the fleet size increases from 0.1% to 1%. This indicates that majority of the PT demand is satisfied when the fleet size amounts to 1% of the total demand. The rejection rate drops further when the fleet size increases to 2% and thereafter stabilises at a negligible rejection rate. This also explains the trend of veh-km travelled by on-demand visible in Figure 4.4(b). The veh-km also marginally decreases beyond a fleet size of 2%. This is explained by a reduced pick-up distance travelled by on-demand vehicles due to an increase in the number of vehicles in the network. This along with a stable share of satisfied demand beyond a fleet size of 2% results in a reduction in veh-km travelled.

Similarly, in case travel demand for both car and PT is to be served by the on-demand service, we observe from Figure 4.4(c) that the total veh-km of car and PT trips in the *Base case* is higher than when car and PT trips are replaced by on-demand services. This reduction is also attributed to the unsatisfied demand as can be observed from Figure 4.5. In all cases, it can be observed that the veh-km travelled by private on-demand services is higher than that by pooled on-demand. At the fleet size instances where the rejection rates starts to stabilise, private on-demand services generate 43%, 38%, and 44% more veh-km than pooled on-demand when on-demand services replace car trips, public transport trips, or car and public transport trips, respectively. This is attributed to the extra veh-kms travelled by private on-demand services in order to pick-up passengers compared to pooled on-demand services.

In order to further analyse the operational efficiency, we plot the empty drive ratio (Figure 4.6) which is the fraction of time the on-demand vehicles spend moving in the network in order to pick-up passengers. From the figure it can be seen that for all the scenarios, the fleet size of on-demand is inversely proportional to the empty drive ratio, indicating that with an increase in fleet, the vehicles spend less time driving in the network to pick-up passengers. The empty drive ratio of pooled on-demand is lower than private on-demand under all scenario pairs, indicaing that pooled on-demand spend less time in the network to pick-up passengers compared to private on-demand. The results and analysis of veh-km travelled and empty drive ratio indicate that pooled on-demand service fares better than private on-demand service with respect to those key performance indices.



(a) Car trips served with on-demand

(b) PT trips served with on-demand

(c) Car and PT trips served with on-demand

Figure 4.6: Empty drive ratio of on-demand services

Following these results, we turn to analyzing of the service performance of the on-demand fleet. We investigate the performance over a 24 hours period. For the fleet of vehicles, we investigate the vehicle status and occupancy which may at any moment be one of the following categories:

- *Empty drive*: Time spent to pick-up passengers
- *Stay*: Time spent without being assigned any request
- *1 passenger*: Time spent with a single passenger in the vehicle

- *2 passengers*: Time spent with two passengers in the vehicle
- *3 passengers*: Time spent with three passengers in the vehicle
- *4 passengers*: Time spent with four passengers in the vehicle

We plot these key performance indices of the on-demand vehicles in Figure 4.7 for all on-demand scenarios for select fleet size rates. The fleet size instances are selected as follows. For each of the scenarios we look at the occupancy levels for two instances of fleet size. One with the highest unsatisfied demand and one where the addition of more vehicles does not induce a significant increase in demand satisfaction. To this end, we choose the fleet size instance where the rejection rate is maximum and one where the rejection rate starts to stabilise. For the scenarios when car trips and car and PT trips are replaced with on-demand, the range is from 0.1% to 5% and for the scenario when PT trips are replaced with on-demand services, the range is from 0.1% to 2%. We plot the occupancy levels of the on-demand vehicles for all these cases in Figure 4.7.

We use the *Stay* ratio as a fleet utilisation index with higher *Stay* ratio indicating lower fleet utilisation levels and hence higher service efficiency. As can be seen from the figure, the highest fleet utilisation (lowest *Stay* ratio), is achieved for the case when the rejection rate is highest (fleet size = 0.1%). For private on-demand and a fleet size of 0.1%, the majority of the fleet operates with a passenger on-board throughout the day (and hence low shares of vehicles in states *Stay* and *Empty drive*). Similary, for pooled on-demand and a fleet size of 0.1%, the majority of the fleet operates with a single passenger on board followed by increasing passenger loads, from two to four in descending prevalence. For all these cases, the *Stay* ratio is considerably low.

For the scenario when car trips are served with on-demand services, the occupancy level of private and pooled for fleet size of 5% indicate that a large fraction of the fleet remains without being assigned any request throughout the day. This trend is observed again for the scenario when car and PT trips are served with on-demand. However, the fleet utilisation is much higher in the scenario when car and PT trips are replaced compared to the one where car trips are replaced with on-demand. The highest fleet utilsation is attained in the case of substituting demand for PT only. This can be explained by the public transport demand pattern. Unlike car trips, the public tranport trips are characterized by greater directionality, which offers more opportunities for pooling travel requests.

The trends in the occupancy plots in Figure 4.7 indicate a high level of fleet utilisation for the lower bound of fleet size considered; and that the fleet at the upper bound remains largely underutilised. When comparing private and pooled on-demand services, it can be seen that for the same fleet size rate, private on-demand service have a higher *Empty drive* ratio than pooled on-demand service. However, pooled on-demand service have a higher *Stay* ratio than private on-demand service. This indicates that while vehicles offering a private on-demand service spend more time en-route to pick-up passengers, vehicles offering pooled on-demand services have a higher share of the fleet being unassigned with requests throughout the day.

4.5.2 Level of service

In this section, we analyse the level of service experienced by the users. We analyse the in-vehicle time and waiting time for private and pooled services for all the scenarios along

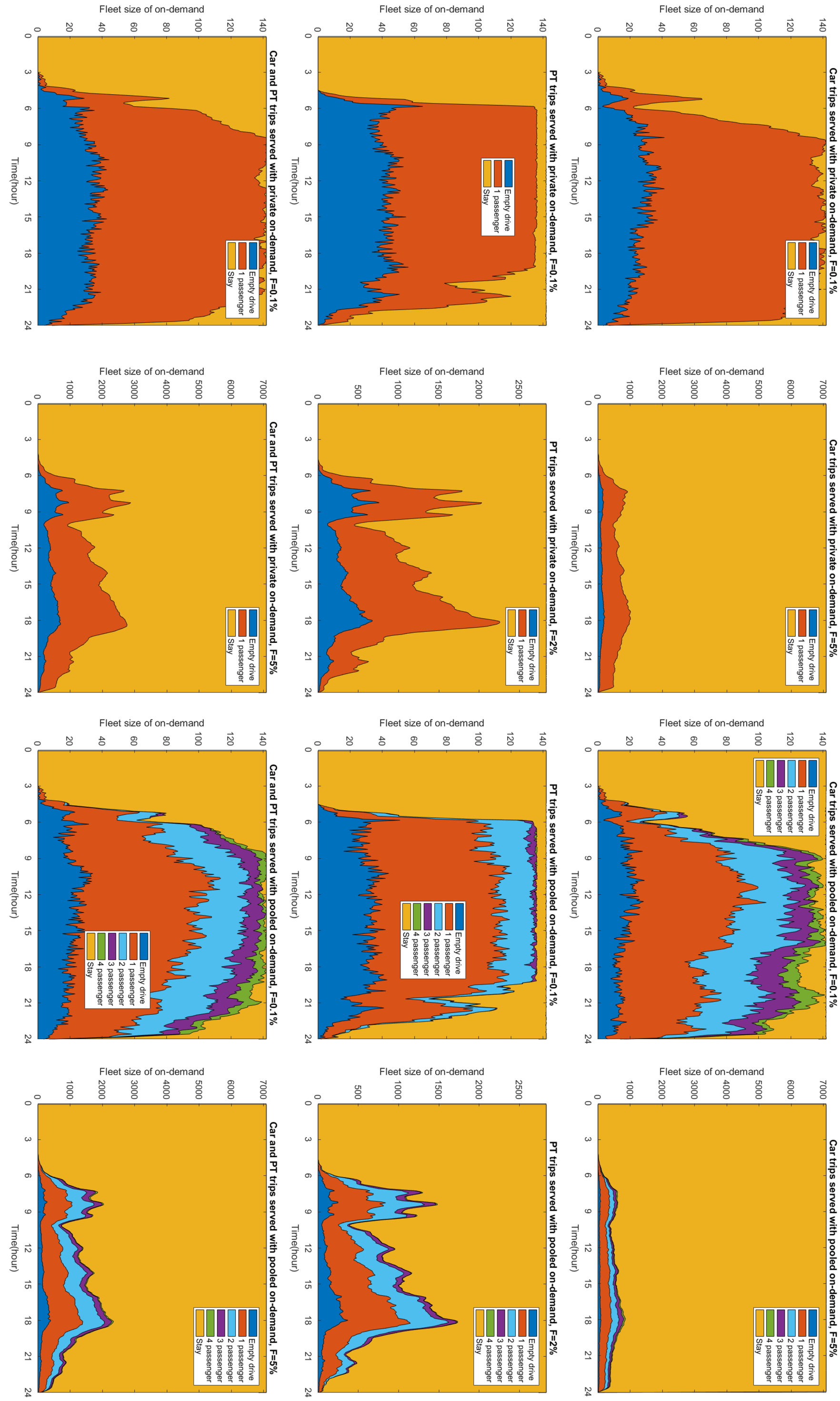


Figure 4.7: Occupancy level of on-demand services for select cases

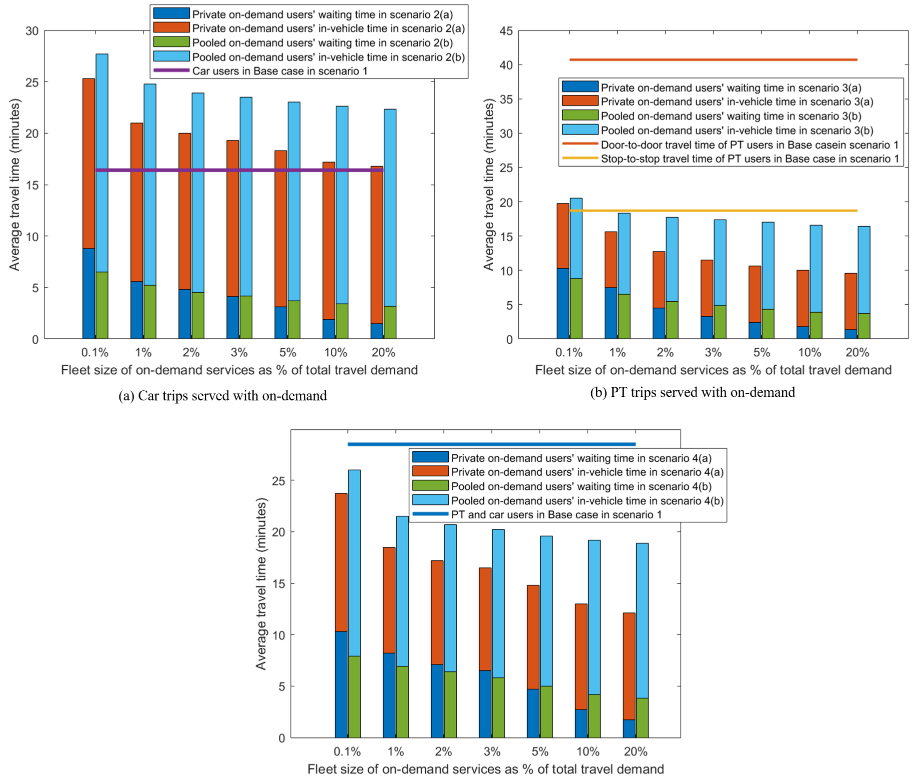
with the average travel time experineced by car users, PT users, and car and PT users in the *Base case* and discuss the underlying trends. We start by investigating travel time split experienced by the users for all the scenarios considered. Figure 4.8(a) shows the travel time of car trips in *Base case* and those when on-demand service replaces car trips. Figure 4.8(b) plots the travel time of PT users in *Base case* (stop-to-stop and door-to-door) and those when on-demand service replaces PT trips. Similarly, Figure 4.8(c) displays the travel time of car and PT users in the *Base case* and those when on-demand service replace car and PT trips.

As can be seen from Figure 4.8, increasing the on-demand fleet size results in an overall reduction of travel time in all scenarios for both private and pooled services. The in-vehicle time of pooled on-demand users is higher than that of private on-demand users for all fleet sizes. This could be explained by the detours performed by pooled on-demand services to pick-up other passengers which results in additional in-vehicle time. The private on-demand service being a direct door-to-door service does not involve such detours. Furthermore, the in-vehicle time remains stable for different fleet sizes for both service types indicating that vehicle congestion does not come into effect for the fleet sizes considered. It can also be observed that the average waiting time of on-demand users decrease with the increase in fleet size for both private and pooled service. However, the effect of increasing fleet size on average waiting time is more pronounced for private on-demand users than pooled on-demand users. This is due to the direct door-to-door service provided by private on-demand service without any detours. Hence an increase in fleet size entails more vehicles to serve the demand and hence a subsequent reduction in waiting time. While this is true for both private and pooled on-demand services, for pooled on-demand services, the reduction in waiting time becomes less pronounced because of the detours performed.

We now compare the waiting times experinecd by private and pooled service users and analyse the underlying trend. It can be seen from the figure that at lower fleet size, pooled on-demand users experience shorter waiting times on average compared to private on-demand users. However, as the fleet size increases, the average waiting time of private on-demand users decreases at a higher rate than pooled on-demand users. Consequentially, with larger fleet sizes private on-demand users experinece shorter waiting time than pooled on-demand users.

Travel time comparison with the base case indicate that in the case of substituting car trips (Figure 4.8(a)), the *Base case* performs better for all the fleet size instances for both private and pooled on-demand services. Among private and pooled on-demand services it can be seen that private on-demand provides lower travel time. In the case of replacing PT trips (Figure 4.8(b)) it can be seen that both private and pooled on-demand services perform better than the *Base case* for all fleet size instances in terms of total door-to-door travel time. In terms of stop-to-stop time both private and pooled on-demand services perform better than the *Base case* for all fleet size instances, with the exception of a very small fleet size (fleet size of 0.1%). Even in the case of combined car and PT trips being replaced (Figure 4.8(c)), both private and pooled on-demand services outperform the level of service offered in the *Base case* for car and PT users, albeit at a persistently high rejectio rate.

The level of service analysis indicates that on-demand services could effectively absorb all PT trips from the *Base case* by providing improved travel times (both stop-to-stop and door-to-door). In contrast, car trips cannot be substituted without leading to considerable rejections of 30% and 10% for the cases of car trips and car trips and PT trips, respectively.



(a) Car trips served with on-demand

(b) PT trips served with on-demand

(c) Car and PT trips served with on-demand

Figure 4.8: Travel time of users in all the scenarios

For all the the scenarios and fleet size instances, private on-demand services offer shorter travel times than pooled on-demand. Similar to the comparitive analysis of veh-km, travel time analysis of on-demand users at the fleet size instances where the rejection rates starts to stabilise was performed. Pooled on-demand users' travel time was 33%, 39%, and 48% more than that of private on-demand users when on-demand services replace car trips, public transport trips, or car and public transport trips, respectively.

4.6 Conclusion

This chapter investigated the potential of an on-demand service to serve the motorised trips in Amsterdam. An agent-based simulation model was adopted for model implementation. Scenarios where private and pooled on-demand services replace private car, public transport, and combined private car and public transport (all motorised trips) were analysed. On-demand service performance in terms of level of service offered and service efficiency were analysed. Results indicated that pooled on-demand service were more efficient in terms of veh-km travelled and empty drive ratio and that private on-demand vehicles spend more time picking up passengers than pooled service for the same fleet size instance. Private on-demand services generate 43%, 38%, and 44% more veh-km than pooled on-demand when on-demand services replace car trips, public transport trips, or car and public transport trips, respectively. Occupancy levels of on-demand service for the scenarios indicated an under-utilisation of fleet for higher fleet sizes.

While there was a significant share of unsatisfied demand for the scenario when car trips were served by on-demand service, it was found that the entire PT trips could be served with a relatively low fleet size of on-demand for both private and pooled services. Analysis of travel time indicated that the travel time of car users in the *Base case* was lower than when on-demand service were used for both private and pooled services. However, the travel time of PT users was found lower when on-demand was used to serve the trips than the *Base case*. The combined average travel time of car and PT users was also lower when on-demand served the trips than the *Base case*. In all these scenarios, the travel time of private on-demand users was lower than that of pooled on-demand users. Pooled on-demand users' travel time was 33%, 39%, and 48% more than that of private on-demand users when on-demand services replace car trips, public transport trips, or car and public transport trips, respectively. While the in-vehicle time was stable throughout the fleet size instances, the increase in fleet size resulted in the reduction of average waiting time for both private and pooled service users. However, the effect of fleet size increment on waiting time of users was more pronounced for private on-demand than pooled on-demand.

The study illustrates the scalability of an on-demand system on a city-wide level and its potential to serve trips performed by private car and public transport. The on-demand service includes a fleet of vehicles that are randomly distributed in the network and the vehicle stays at the drop-off location till further requests are assigned. This leads to an under-utilsation of the fleet as shown in the occupancy analysis. Hence a more efficient vehicle distribution and relocation strategy based on demand anticipation could be a potential model improvement.

Chapter 5

Determining the fleet size of on-demand services

In the previous three chapters, we looked into the analysis of on-demand services in an urban mobility context. In this chapter, we now move on to the design of on-demand services in an urban mobility context. In this chapter we determine the optimal fleet size of an on-demand system with private and pooled services where demand for these services are endogenously determined. An optimisation model with the fleet size of private and pooled on-demand service as decision variables is developed. The model is applied to the network of Amsterdam North. We determine the optimal fleet size from two perspectives. One being a profit maximising service provider and other being a travel cost minimising planning agency.

In the first part of the chapter, we introduce the topic of service design of on-demand systems and perform a review of the existing literature. We then present the modeling framework comprising of the agent-based simulation framework with day-to-day learning of users that is embedded in the optimisation model. In the last part we provide the results and their analysis where we present the optimal fleet size for the private and pooled on-demand service for both the service provider and the agency and provide directions for future research.

The chapter is based on the following published paper:

Narayan, J., Cats, O., van Oort, N. & Hoogendoorn, S., Fleet size determination for a mixed private and pooled on-demand system with elastic demand. *Transportmetrica A: Transport Science* (in press)

5.1 Inroduction

The emergence of innovative mobility solutions, brought about by advancements in various ICT platforms and increasing urbanisation is changing the mobility landscape in urban areas. Service providers and users of such innovative mobility systems often interact with each other through an online platform such as an application in a smartphone. They offer users the flexibility to plan their trips in real-time and potentially address some of the inherent issues with a line- and schedule-based public transport (bus, tram, or metro) such as large waiting time during off-peak hours and low accessibility in rural areas.

Such services have impacts on urban mobility at several levels. From a demand perspective, there is some evidence in the literature to suggest that, traditional modes of transport such as privately owned car, line- and schedule-based public transport are increasingly losing their market shares to disruptive mobility solutions such as Cabify, Lyft, Uber, Car2Go, DriveNow, ZipCar (M. P. Enoch, 2015; Conway et al., 2018). The operations of such services also have an impact at the network level in terms of additional vehicle-kilometers travelled which in turn influence the levels of congestion across the network. Hence, the dimensioning of these mobility services needs to be designed considering demand elasticity and their impact on overall urban mobility.

Multiple stakeholders with different objectives are involved in the planning stage of such services such as transit planning authority and service operator. The planning authority can play an instrumental role in planning integrated multi-modal transport services. This includes setting priorities, policies and regulations so as to stimulate synergy between fixed line-based services and flexible on-demand services by means of tendering procedures, incentive schemes, integrated ticketing, pricing and travel information platforms, setting level-of-service standards, designate space for vehicle fleets and curbside management. In case of a tendered on-demand service, a transit planning auhority would be interested in making the overall mobility portfolio more efficient (i.e. reducing the overall travel time and operation cost) whereas a service operator would be interested in profit maximisation. Depending on the number of competing operators, the market is either monopolistic (one service operator) or oligopolistic (multiple service operators compete for market share). Insights into levels of service of such systems based on these distinctive objectives are crucial in planning, operation, and the possible regulation of such services.

In this study, we develop a model to design the service of an on-demand mobility system offering both private and pooled door-to-door services. We determine the optimal fleet size of the on-demand system required when taking two distinctive perspectives. The first one being a transit planning authority interested in improving the travel time of all the users and the second being a single service provider operating in a monopolistic market and interested in maximising its own profit. We conduct our analysis using an agent-based simulaion framework that models the day-to-day learning of users.

5.2 Literature review

In this section we review the literature pertaining to planning and operations of on-demand mobility systems. While planning pertains to service design aspects such as fleet size and fare determination, operations pertain to the day-to-day aspects of the on-demand service such as fleet dispatching, relocation, and the assignment of travel requests to vehicles. We classify the literature based on the aspects addressed (objective), the methodology employed for design and analysis, and the key findings.

Mathematical and simulation methods have been used in the literature to model the operations of on-demand services. The objective is commonly defined as optimally assigning travel requests to vehicles while satisfying certain constraints. Notable early works that used an analytical approach for the assignment of tavel requests include Wilson et al. (1976) and Potter (1976). They used a passenger utility maximisation approach and modeled the assignment to travel requests to vehicles as an Integrated Dial-a-ride Problem (IDARP). More recently, Posada et al. (2017), Häll et al. (2009), and Salazar et al. (2018) used mathematical programming approach that involves solving the assignment problem as an optimization problem by assigning travel requests to a fleet of on-demand vehicles. Posada et al. (2017) and Häll et al. (2009) solved the assignment problem as an Integrated Dial-A-Ride Problem (IDARP). They developed a model to assign travel requests to on-demand vehicles by coordinating with the line-based transit service. Salazar et al. (2018) used a flow optimization model for assigning the travel requests to on-demand vehicles while maximising the social welfare. The pitfall of such analytical models is their inherent inability to capture the real-time system dynamics of the on-demand system.

Agent-based simulation methods mitigate this issue to an extent. Notable recent works that used agent-based simulation methods to model the operations of on-demand systems include Neumann & Nagel (2013), Maciejewski, Horni, et al. (2016), Maciejewski & Nagel (2013b), and Atasoy et al. (2015). Neumann & Nagel (2013) presented an evolutionary algorithm for optimal paratransit service network design by designing the paratransit services as a competing mode with a line and schedule based public transport service. Atasoy et al. (2015) designed an on-demand service which gives a list of travel options to travellers in real-time. The travel options include choosing between using a private taxi service, shared taxi service, or minibus (multiple passenger with fixed routes but flexible schedules). Danaf et al. (2019) provide a good overview of how behavioural models can be applied in real-time to generate customized recommendations which facilitates the usage of an integrated fixed and flexible public transport system. Notwithstanding, these studies did not determine the service parameters of on-demand service such as fleet size. Moreover, the demand for these services was considered an exogenous value, independent of the level of service offered.

One of the earliest works which looked into the design of a large scale on-demand fleet was performed by S. Ma et al. (2013). They developed a heuristic based taxi dispatching system for large urban fleets. Later works that looked into the concept of ride-pooling include Santi et al. (2014) and Alonso-Mora et al. (2017). The former developed the concept of shareability graph and concluded that all taxi trips in Manhattan could be served by pairing up two requests per taxi while keeping the passenger discomfort low in terms of travel time. The latter adopted the concept of shareability grapth from Santi et al. (2014) and developed an algorithm that enables real-time high capacity ride-pooling for Manhattan. Results indicate that 98% of its taxi demand can be served by 3000 vehicles (with a capacity of 4 passengers each) instead of the current fleet which is more than four times larger. Several studies have examined the hypothetical case of city-wide replacement of all private vehicles or even all other transport modes with shared autonomous vehicles. The fleet size requirements for this boundary case were determined for Berlin (Bischoff & Maciejewski, 2016), Austin (Fagnant & Kockelman, 2018), Lisbon (L. M. Martinez & Viegas, 2017), and Melbourne (Dia & Javanshour, 2017). The prime interest of these studies was the potential of shared autonomous vehicles to replace private car trips, indicating that one shared autonomous vehicle could replace the demand served by 10 privately owned cars. In contrast, more recent studies, for the cities of Munich (Moreno et al., 2018) and Amsterdam (Narayan et al., 2019), suggests a replacement ratio of 10 to 4 and 9 to 1, respectively. However these studies considered a fixed demand for on-demand systems and supply parameters were exogenous to the model.

Numerous works in the past have studied the service design of on-demand transport sysems in terms of their optimal fleet size and fare determination. The objective of such studies was to determine the optimal fleet size required to carry out a set of travel requests with the objective of minimising travel costs. Some of the early works that used anlytical and mathematical models includes Gertsbach & Gurevich (1977) and Desrosiers et al. (1988). Gertsbach & Gurevich (1977) determined the minimum fleet required to serve a set of travel requests by introducing the concept of a deficit function which is defined as the difference between departures and arrivals at a station. The fleet size required was then proved to be equal to the total deficit. Desrosiers et al. (1988) determined the minimum fleet size required to visit a set of nodes once, subject to time window constraints. The objective was to minimise the travel cost while using Lagrangian relaxation techniques. More recent works that used mathematical models for fleet size determination include Morisugi et al. (1997), Yang et al. (2002) and Yang et al. (2005). Morisugi et al. (1997) determined the optimal pricing and fleet size of GPS enabled taxis by considering passengers' willingness to pay and adding an equal net revenues constraint. Yang et al. (2002) and Yang et al. (2005) introduced a mathematical model to optimise the taxi fare and fleet size by considering the demand-supply equilibrium road network and congestion externality. Notable works that used heuristics for optimal fleet size determination include Fu & Ishkhanov (2004) and Z. Li & Tao (2010). Fu & Ishkhanov (2004) developed a heuristic method for determining the optimal fleet size mix for a set of travel requests by maximising the service productivity in terms of (trips/vehicle/hour). They determined the optimal number of vehicles required for different vehicle categories with varying seating capacity and showed the existence of a critical point beyond which additional capacity becomes ineffective. Z. Li & Tao (2010) developed a two stage dynamic programming model to determine the optimal fleet size and vehicle transfer policy for a car rental company that serves two cities by maximising the income of the rental company. None of these studies considered an elastic demand for the on-demand services. From a planning perspective, none of the studies optimised service parameters from an Agency and Operator perspective.

Fleet size optimisation at city-wide level was studied by Chang et al. (2012) and J. Li et al. (2010). Chang et al. (2012) considered profit maximisation and cost minimisation for Taipei Metropolitan Area, while J. Li et al. (2010) considered user cost and operating cost minimisation for port of Rotterdam. Vazifeh et al. (2018) addressed the 'minimum fleet problem' for on-demand system with fixed demand in New York City. They provided a computationally efficient solution by introducing the idea of 'vehicle sharing network'. The model was tested for the taxi demand data for New York City for a period of one year. More recently, Zhang & Ukkusuri (2016) developed a leader follower Stackleberg game model between transport authorities, taxi drivers, and passsengers to optimise the fleet size and fare setting. The results provided valuable insights into current NYC taxi market regulation policies.

Studies that have considered elastic demand for on-demand services include Hörl et al. (2016), Narayan et al. (2019), Araldo et al. (2018), and Wen et al. (2019). Hörl et al. (2016) presented a framework for simulation of autonomous vehicles in an intergrated network and population based traffic environment. The model allows the demand to evolve dynamically from the traffic situation. Narayan et al. (2019) adopted an agent-based simulation framework to explore hypothetical scenarios that involve ride-sourcing replacing private car and public transport trips for Amsterdam. Araldo et al. (2018) presented a flexible automated mobility on-demand (AMoD) model developed within an agent-based simulation platform. Wen et al. (2019) studied the value of information on passenger demand in an on-demand mobility system at both individual and aggregate levels. Their results indicate that information on aggregate demand can lead to a better service (more requests served and shorter waiting time) while improving system performance and yielding a higher profit. However, these studies did not optimise the supply side parameters while considering an elastic demand. To the best of our knowledge, the work by Liu et al. (2018) addressing fare and fleet size optimisation for a mobility on-demand system with inelastic demand, is the one of most direct relevance to this study. They developed a Bayesian model to optimise the fleet size and fare of a mobility-on-demand system and considered a profit maximisation objective from the perspective of a service provider.

Our review suggests that, while fleet size optimisation has been studied in the literature, most of the studies assumed a fixed (inelastic) demand for on-demand services. However, in reality, demand is expected to depend on fleet size due to its impacts on the level-of-service. Supply-demand interactions need therefore to be explicitly accounted for to identify the steady-state conditions. Furthermore, the extent to which demand is elastic depends on the availability and quality of service offered by alternative transport modes, including car, bike and lined-based public transport. From a planning and policy perspective, none of the works designed optimal service parameter from the perspective of a transport operator (profit maximisation) and a transit authority (system cost minimisation) with elastic demand. This study attempts to fill the gap in the literature by determining the fleet size required for an on-demand service with elastic demand while considering both service profit maximization and integrated planning perspectives. In addition, the study provides novel insights into the service design of on-demand systmes from a planning perspective. The study analyses the fleet size of two competing on-demand services, one which offers private service and another which offers a pooled service. We analyse and compare the results from the perspective of a service provider (*Operator*) and a transit planning authority (*Agency*). The objective of the *Operator* is to maximise the profit while the *Agency* aims to minimise the total system cost.

5.3 Modelling framework

This section presents the modelling framework, details the individual components, and presents the optimisation formulation. Figure 5.1 shows the overall modelling framework. The input modules comprise of *Demand*, *Network*, and *Supply*. The *Demand* data comprise of passengers with a set of origin destination points in the network. The *Network* data comprise of the road network and public transport network respresented by a set of nodes and connecting links. The *Supply* data comprise of the modes available to each user to travel from their origin to their destination. The modes available are: car, walk, bike, schedule and line-based public transport (PT), and on-demand service (private and pooled). On-demand

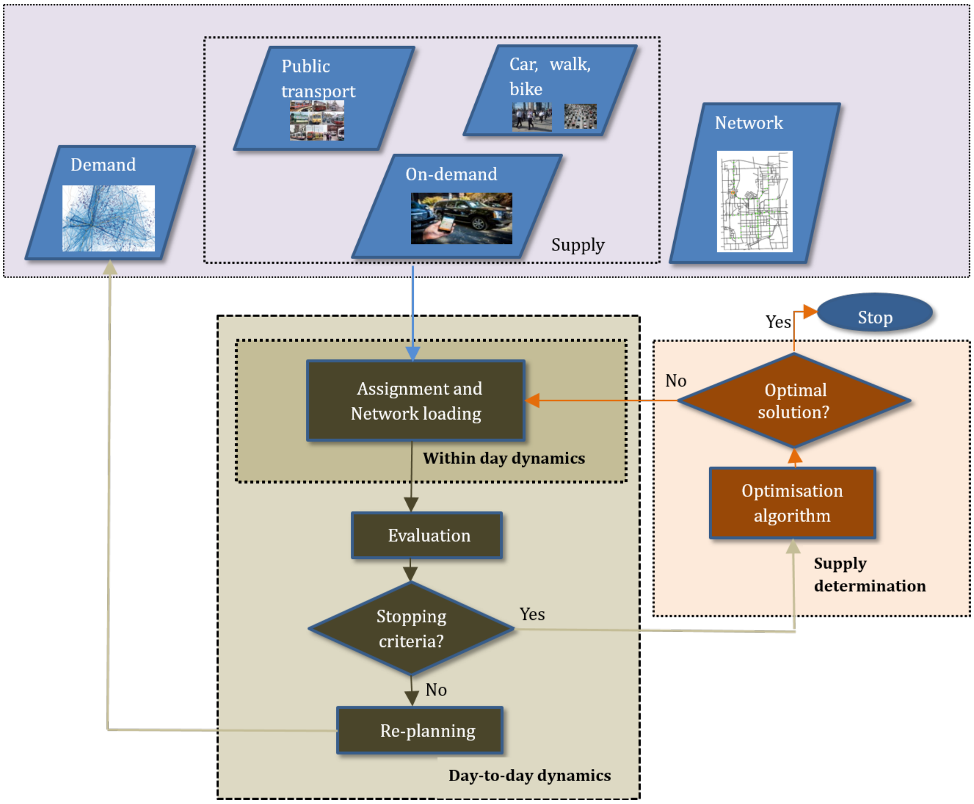


Figure 5.1: Modelling framework

service in this study is modelled as a fleet of vehicles operated by a central dispatching unit that assigns travel requests to vehicles in real-time and offers door-to-door service to passengers.
Two types of on-demand service are considered in this study based on the type of service offered. The types of services are:

- **Private on-demand**: This service offers individual taxi-like service to passengers
- **Pooled on-demand**: This service offers shared rides where passengers may share their ride with an occupancy of 4 passengers

Each user starts with a set of travel plans that define their performing activity (type, duration, and departure time) and travel modes. The 'Assignment and Network loading module' comprise the within day dynamics of the system. The users evaluate the services in the 'Evaluation' module by assigning a score to the executed plan and replan their travel strategies accordingly in the 'Re-planning' module. This sequence of assignment, network loading, scoring and re-planning forms an iteration which corresponds to a day. The process continues until a convergence criterion is achieved. Nagel & Marchal (2003) show that while day-to-day learning may not satisfy the mathematical definition of equilibrium conditions, the iterative process results in a stochastic user equilibrium. During an iteration, users may undertake different strategies to alter their travel plans while making their trip from origin to destination based on service experience. In this study, the strategies available to an agent are: changing the route of travel, changing the mode of travel, changing the departure time from an activity, and selecting a plan with the best score. The demand at equilibrium along with the supply configuration, is the input data to the 'Supply determination' module where they are scored and evaluated. The proposed model is embedded in a multi-agent transport simulation framework. It is implementd and integrated in the open source software MATSim (Horni et al., 2016b).

In the context of this study, the objective of the 'Supply determination' module is to set an optimal fleet size for the two on-demand services offering private and pooled rides. The desired fleet size for on-demand service is explored and analysed from two different perspectives, namely:

1. **Agency's perspective**: A public authority interested in setting the fleet size of on-demand services so as to minimise the generalised travel cost of users and the operator's operating cost.
2. **Operator's perspective**: A transport service provider interested in finding the fleet size of on-demand service so that its total profit - defined as the difference between revenue and expenditure - is maximised.

In the following sub-sections, we present the mathematical formulaion of the objective function, decision variables, and constraints for the two perspectives: the Agency and the Operator.

5.3.1 Agency perspective

The Total Agency Cost is formulated as follows:

$$\begin{gathered}\text{Total Agency Cost}(TAC) = \text{User's travel Cost}(UC) + \text{Operator's operating cost}(OC) \\ UC = \sum_{i \in U} (\delta \cdot f\colon (\theta_1, \theta_2) \mapsto t_i) \\ OC = \sum_{m \in \{1,2\}} (\alpha_m \cdot \theta_m + \sigma_m \cdot g_m\colon (\theta_1, \theta_2) \mapsto \zeta_m)\end{gathered} \tag{5.1}$$

The Total Agency Cost (TAC) is defined as the summation of the User's travel cost (UC) and the Operator's operating cost (OC) as shown in Equation 5.1. The User's travel cost is a function of the travel time experienced by all the users ($\sum_{i \in U} t_i$). The passenger travel time t_i, is in turn the summation of all the travel time components experienced by the user. This includes the mode specific travel time components such as walking time, in-vehicle time and waiting time. The travel time of all the users ($\sum_{i \in U} t_i$) in turn is a function (f) of the decision variables of the optimisation model which are the fleet size of private and pooled on-demand services, θ_1 and θ_2 respectively. The Operator's operating cost (OC) is a function of the fleet size of the two on-demand services (θ_1 and θ_2) and the distance travelled by the on-demand vehicles, ζ_m. The distance travelled by each of the on-demand service

(ζ_m) is a function (g_m) of the fleet size of the two on-demand services. The travel time of the users (t_i) and the distance travelled by the on-demand service ζ_m are obtained as an output from the simulation. The optimisation problem is formulated as follows, subject to two constraints:

$$\begin{aligned} \min_{\theta_1 . \theta_2} \quad & TAC \\ \text{s.t.} \quad & \theta_1^{min} \leq \theta_1 \leq \theta_1^{max} \\ & \theta_2^{min} \leq \theta_2 \leq \theta_2^{max} \end{aligned} \tag{5.2}$$

where,

U is the set of all passengers
m is the on-demand service, where $m = 1$ represents private and
$m = 2$ represents pooled service
t_i is the total travel time of passenger i in hr
δ is the value of travel time in $€/hr$
α_m is the maintenance cost of on-demand service m in $€/vehicles$ which
corresponds to the leasing cost
of the fleet of vehicles
θ_1 is the fleet size of private on-demand service
θ_2 is the fleet size of pooled on-demand service
σ_m is the operating cost of on-demand service m in $€/km$ which corresponds to
the fuel cost
ζ_m is the total distance travelled by all vehicles of on-demand service m in km
θ_1^{min} is the minimum required fleet size of private on-demand service
θ_1^{max} is the maximum required fleet size of private on-demand service
θ_2^{min} is the minimum required fleet size of pooled on-demand service
θ_2^{max} is the maximum required fleet size of pooled on-demand service

5.3.2 Operator perspective

The Profit (P) of the operator is formulated as:

$$\begin{aligned} \text{Profit}(P) &= \text{Revenue}(R) - \text{Operating Cost}(OC) \\ R &= \sum_{m \in \{1,2\}} \sum_{i \in \Gamma_m} (\mu_m + \gamma_m \cdot h_m \colon (\theta_1, \theta_2) \mapsto \xi_{m,i}) \\ OC &= \sum_{m \in \{1,2\}} (\alpha_m \cdot \theta_m + \sigma_m \cdot g_m \colon (\theta_1, \theta_2) \mapsto \zeta_m) \end{aligned} \tag{5.3}$$

The Profit(P) is defined as the difference between the Revenue (R) and the Operating cost (OC) as shown in Equation 5.3. The Revenue(R) is a function of the the demand for each of the on-demand service (Γ_m) and the distance travelled by the users of the on-demand service ($\xi_{m,i}$). The distance travelled by the users of the on-demand service ($\xi_{m,i}$) in turn is a function (h_m) of the decision variables of the optimisation model which are the fleet size of private and pooled on-demand services, θ_1 and θ_2 respectively. The distance travelled by the on-demand users ($\xi_{m,i}$), the total distance travelled by the vehicles (ζ_m), and the demand for each of the on-demand service (Γ_m) are obtained as the output from the simulation. The optimisation problem is formulated as, subject to two constraints:

$$\begin{array}{rl} \max\limits_{\theta_1.\theta_2} & P \\ \text{s.t.} & \theta_1^{min} \leq \theta_1 \leq \theta_1^{max} \\ & \theta_2^{min} \leq \theta_2 \leq \theta_2^{max} \end{array} \tag{5.4}$$

where,

μ_m is the base fare of mode m in €
Γ_m is the set of all passengers using mode $'m'$
γ_m is the distance based fare of mode m in $€/km$
$\xi_{m,i}$ is the total distance travelled by passenger i using mode m in km

5.4 Application

5.4.1 Network and demand data

The model is applied for a network centered around the northern district of the city of Amsterdam, the Netherlands. The network is developed using data extracted from OpenStreetMap (Haklay & Weber, 2008). A layer of links and nodes was first selected in OpenStreetMap that included the road infrastructure (motorway, trunk, primary, secondary, tertiary, and minor) and public transport stops. The network was then cleaned for reduntant/duplicate links and unconnected nodes. The total number of nodes and links in the final network is 11,399 and 24,396 respectively. The demand data is adopted from the national activity-based demand model, Albatross (Arentze et al., 2000). Albatross is an learning-based model of activity-based travel behavior. The model predicts the time, place, and duration of activities of users and the travel modes involved. The demand data hence comprise of an activity based travel plan for each user in the Netherlands and comprise of activities (type, duration, arrival and departure time) and travel modes (type, route, and travel time). The data was then converted to a format to be consistent with MATSim (Winter & Narayan (2019)). Next, the demand data located within the network of Amsterdam North was extracted. The final demand data consists of 4,169 agents with a total number of daily trips as 20,996. Figure 5.2 shows the case study network.

5.4.2 Simulation scenarios

Two scenarios are considered based on the type of service available for users. In the **Base Scenario**, the modes available consists of car, walk, bike, PT (line- and schedule-based public transport including bus, tram, and metro). In the **On-demand** scenario, an on-demand mobility operator enters the market with two types of on-demand services: private on-demand and pooled on-demand. These new services compete with each other as well as with other modes for travel demand. In order to account for stochasticity in the results, 10 runs for each simulation instance was carried out and the key performance indices were averaged over these runs.

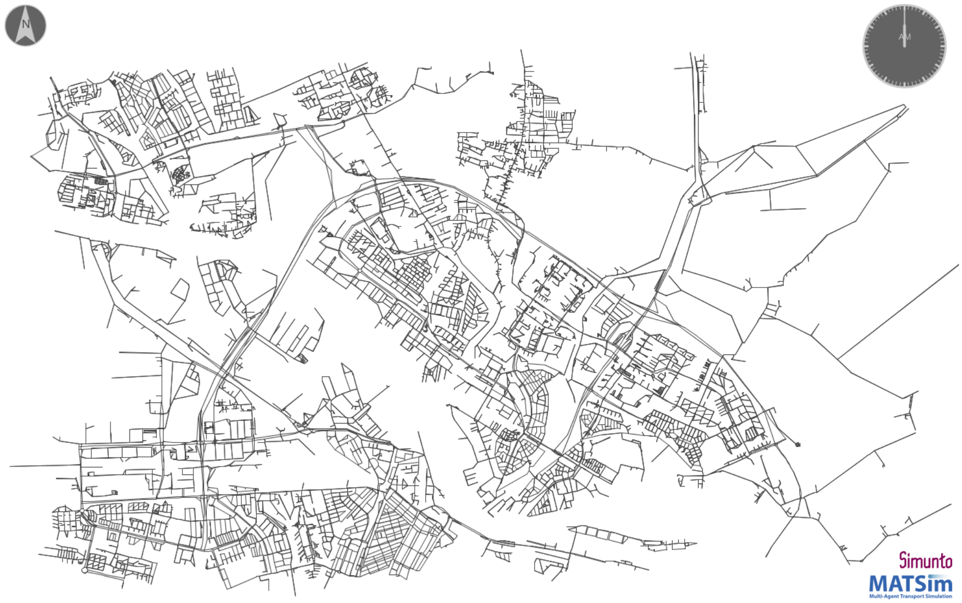


Figure 5.2: Application network of Amsterdam North

5.4.3 Dispatching strategy of on-demand service

The dispatching strategy of the on-demand system offering private service is as follows. A vehicle that has been assigned a request drives to the pick-up location, picks up the passenger, drives to the travel request destination, drops off the passenger and stays at the drop-off location until further requests are assigned. The dispatching strategy of the on-demand system offering pooled service is as follows. A vehicle that has been assigned a request drives to the pick-up location, picks up the passenger, makes detours to pick up other pooled requests, drives to their destination, drops off the passenger and stays at the drop-off location until further requests are assigned. The dispatching strategy of the on-demand vehicles has been adopted from Bischoff & Maciejewski (2016) and Maciejewski, Salanova, et al. (2016).

5.4.4 Model specifications

Objective function parameters

The values of the parameters included in the objective function are given in Table 5.1.

Fare setting

The ratio of fare of public transport, pooled on-demand, and private on-demand is set to 1:5:10 which is a reasonable assumption for line- and schedule-based, private, and pooled services in Amsterdam. The fare of public transport provided by GVB (the public transport operators in Amsterdam) is used in this study *GVB Exploitatie B.V.[NL]* (2019).

Table 5.1: Parameter value specification

δ	8.75 €/hr (Bates, 2012)
α_1	9.4 €/vehicles (LeasePlanDirect, 2019)
α_2	9.4 €/vehicles (LeasePlanDirect, 2019)
σ_1	0.079 €/km (LeasePlanDirect, 2019)
σ_2	0.079 €/km (LeasePlanDirect, 2019)
μ_1	3.19 €
μ_2	3.19 €
γ_1	1.62 €/km
γ_2	0.81 €/km

Calibration and parameters of mode choice model

Calibration of the model and parameter setting plays a crucial part in system performance and simulation output, particularly because the system comprise of dynamic transport services such as private and pooled services where travel time variability plays an important part in mode choice of users (Alonso-González et al., 2020). For instance, for pooled on-demand services this entails longer travel time for its users as the service becomes popular and attract more users. The model hence has to be adequately calibrated considering these feedback effects between travel demand and service performance. In the absence of real data, the choice model (utility function) was calibrated following the calibration guidelines in MATSim. This was done by means of investigating the alternate specific constants of the available modes methodically following the calibration guidelines provided in MATSim (Horni et al., 2016b). The modal share for all the available modes (car, walk, bike, public transport) were set correspond to the actual value for the case study area, thus obtaining the ASCs (alternate specific constants) that yielded the respective modal shares. The set of values obtained for the ASCs was then kept fixed throughout the simulation runs.

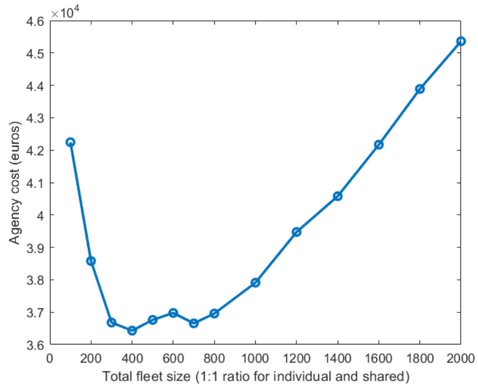
The marginal utility of performing an activity (β_{dur}), marginal utility of time spent by traveling (β_{travel}) for all available modes, marginal utility of arriving late for an activity ($\beta_{latear.}$) have been set to +6 utilities/hour, -6 utilities/hour, and -18 utilities/hour, respectively. Finally, the marginal utility of money (β_{money}) was set to -0.685 utilities/Euro based on the Dutch value of time.

5.5 Results and Analysis

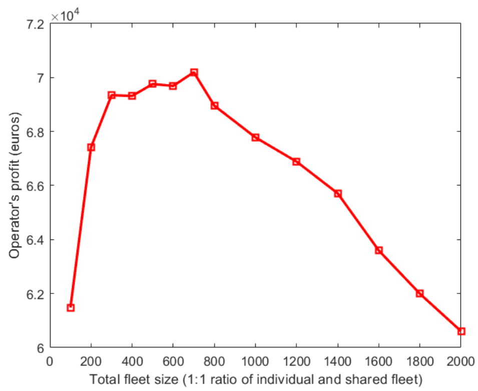
In the following, we investigate the relation between the fleet size of on-demand services (both private and pooled) and the individual objective functions from the Agency and Operator perspective. The objective of this investigation is to determine the upper and lower bound of the fleet size values of the two alternative on-demand services. Then we present the objective function values for Agency and Operator in relation to the fleet size of private and pooled services exploring all possible fleet size combinations for the two alternative on-demand services, assuming a reasonable fleet size increment. We also present the contributing components of each objective function for alternative fleet size solutions of the two services, analyse the underlying trends of the objective function values, and their relation with the fleet size.

5.5.1 Upper and lower bound of fleet size

Figure 5.3 shows the variation of Agency and Operator cost for various total fleet size of on-demand services. The ratio of fleet size of private and pooled on-demand services is 1:1 here. As can be seen from Figure 5.3(a) the Agency cost decreases monotonically until a fleet size of about 400 and increases monotonically from a fleet size of 800 till 2000. Similarly, we learn from Figure 5.3(b) that the Operator cost increases monotonically until a fleet size of 300 and thereafter decreases monotonically from a fleet size of 700 to 2000.



(a) Agency cost in relation to fleet size



(b) Operator cost in relaion to fleet size

Figure 5.3: Agency and Operator cost variation with fleet size of on-demand services with a 1:1 ratio of private and pooled services

The trends also reveal the presence of an optimal value of fleet size for both Agency and Operator in the range considered. Hence we truncate the solution space by excluding all fleet size combinations involving a total fleet size less than or equal to 200 and greater than or equal to 1600.

We further investigate this trend by examining the mode share and travel times for all possible fleet size combinations of private and pooled service wihin a total fleet size range from 200 to 1600 with an increment of 100 vehicles. We plot the travel times and mode shares for all possible fleet size combinations within the range for both private and pooled on-demand users (Figure 5.4, 5.5, and 5.6). Figure 5.4 and Figure 5.5 plots the average waiting time and average in-vehicle time respectively for private and pooled on-demand service users and Figure 5.6 plots the mode share for private and pooled on-demand service.

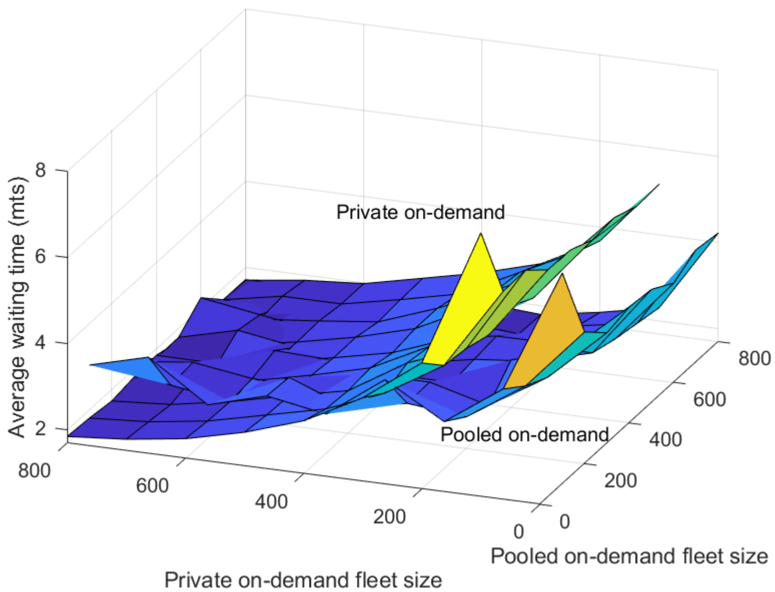


Figure 5.4: Average waiting time variation with fleet size of on-demand vehicles

The initial decrease in the Agency cost in Figure 5.3(a) is attributed to an overall increase in mode share of on-demand service as shown in Figure 5.6. The increase in fleet size causes an overall reduction in waiting time as shown in Figure 5.4, which makes the service more attractive. Also, majority of the mode share for on-demand are active mode users in the **Base Scenario**. This shift results in an overall decrease in the travel time of users which in turn results in a decrease in the *Users's travel cost* component of the Agency cost. During this range, the reduction in the travel time component outweighs the increase in the *Operator's operating cost* component caused due to the increase in fleet size. However, beyond a certain point, the increase in fleet size does not yield a significant reduction in travel time of users and the operating cost outweighs the travel time component. This explains the monotonic increase in Agency cost beyond a certain point.

Similarly, the initial increase in the Operator cost in Figure 5.3(b) is attributed to an overall increase in mode share of on-demand service (Figure 5.6) thereby also increasing the *Revenue*. The increase in the *Revenue* outweighs the increase in *Operating cost* within this range. However, beyond a certain point the increase in fleet size does not cause significant increase in the *Revenue* and the *Operating cost* outweighs the *Revenue*. During the entire

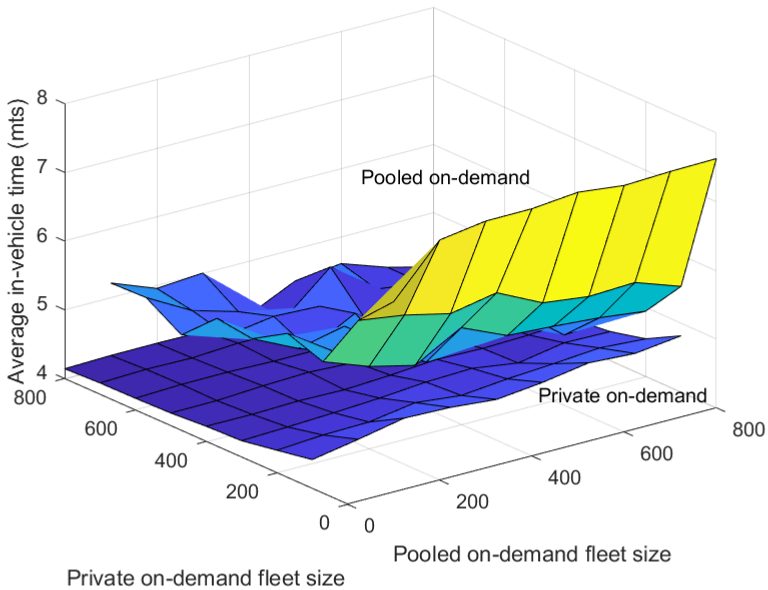


Figure 5.5: Average in-vehicle time variation with fleet size of on-demand vehicles

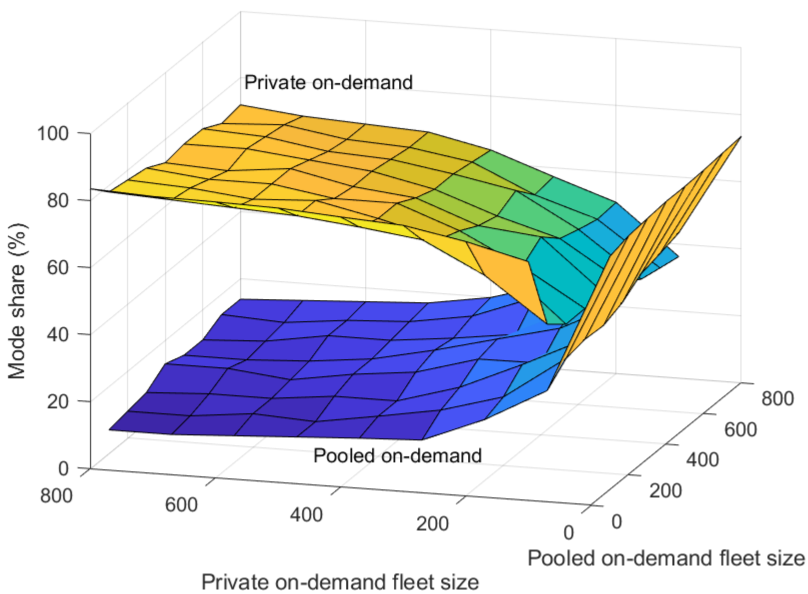


Figure 5.6: Mode share variation with fleet size of on-demand vehicles

range of fleet size considered, the *Revenue* exceeds the *Operating cost*.

As can be seen from the Figure 5.6, the mode share of private and pooled on-demand service increases monotonically when operated as the sole on-demand service. When the private and pooled on-demand services start operating in competition, the combined mode share of the private on-demand service and the pooled on-demand service decreases compared to when they operate in isolation. This can be seen from the trends of the the mode share of the two on-demand services which shows a decrease along the fleet size axis of the competing on-demand service. However, as can be seen from the figure, this decrease is more pronounced for pooled on-demand users where the rate of reduction is more along the private on-demand axis. This indicates that the effect of increase of fleet size on mode share is more pronounced for private on-demand users. The effect of fleet size on mode share also decreases for higher fleet size as shown in Figure 5.6 indicating that the increase in fleet size does not attract significant mode share beyond a ceratin point.

This trend can be further explained by Figure 5.4 and 5.5. As can be seen from Figure 5.4 the waiting time for private on-demand users decreases along the private on-demand fleet size axis and that of pooled on-demand users decreases along the pooled fleet size axis. The trend is more pronounced when the two services operate as the sole on-demand service. It can also be seen from the figure that the decrease in average waiting time is more pronounced for private on-demand service compared to pooled on-demand service indicating that the waiting time of on-demand users is more sensitive to fleet size increment as compared to pooled service. From Figure 5.5 it becomes evident that the in-vehicle time of private on-demand users is less sensitive to fleet size as compared to pooled on-demand users. The marginal increase in in-vehicle time of pooled on-demand users along the pooled on-demand fleet axis indicates inadequate supply for the corresponding demand which results in more detours for pooled on-demand users. The in-vehicle time for pooled on-demand users also decreases along the private on-demand axis which is due to the rapid decline in mode share of pooled service when private service enters the market as shown in Figure 5.6.

5.5.2 Optimal private and pooled fleet size

In this section we explore the effect of fleet size of private and pooled on-demand service on the Agency cost and the Operator cost. Figure 5.7 shows the split of the Agency cost along with its individual components as shown in Equation 5.1. We plot the Agency cost along with its individual contributing components in relation to the fleet size of the two on-demand services (private and pooled). The *Users's travel cost* in the figure corresponds to the total travel time cost of all the users. *Operator's operating cost* corresponds to the operational cost of the on-demand services. *Total agency cost* corresponds to the summation of the two components. As can be seen from the figure, the *Users's travel cost* decreases monotonically along the axis of private and pooled on-demand services. However, the rate of decrease is more along the private on-demand fleet size axis than that for the pooled on-demand fleet axis. The *Operator's operating cost* increases monotonically along the axis of private and pooled on-demand services. As expressed in Equation 5.1, the *Operator's operating cost* is a linear function of the total fleet size and the vehicle-km travelled. The leasing cost which is assumed the same for the the two on-demand services (Table 5.1) is the dominant factor compared to the cost incurred by vehicle-kms driven. Hence the *Operator's* *operating cost* shows a unifrom variation along the two fleet size axes. As can be seen from the range of values for the two components of the Agency cost, the *Users's travel cost* is the dominant factor in the Agency cost.

The decrease in *Users's travel cost* is attributed to the modal shift of users when comparing the **Base Scenario** and the **On-demand scenario**. The mode share of active modes in **Base Scenario** is close to 75% and that of on-demand services in **On-demand scenario** ranges between 60% and 90%. Hence a considerable share of active mode users in the **Base Scenario** shift to on-demand services in **On-demand scenario**, thus resulting in an overall reduction in travel time of users. This results in the decrease in *Users's travel cost*.

As can be seen from Figure 5.5, the average in-vehicle time of private on-demand service users is marginally lower than that of pooled on-demand service. This is due to the possible detours that pooled on-demand vehicles perform in order to pick up other passengers. The private on-demand service being a direct door-to-door service, does not have such detours and this results in a lower in-vehicle travel time. From Figure 5.4 it can be seen that the average waiting time of pooled on-demand service is initialy lower than that of private on-demand service up to a fleet size of 500. Beyond this point the average waiting time of private on-demand users is lower than that of pooled on-demand users. The initial gain in average waiting time for pooled on-demand users is attributed to the number of vehicles in service in relation to the demand for that service. Initially, the number of private on-demand vehicles is not sufficient enough to cater for its demand as compared to the pooled service. However, as the fleet size increases this gain in waiting time decreases and beyond a certain point, the waiting time for private on-demand service becomes lower than for pooled on-demand service. This could be explianed by the rate of decrease of average waiting time for private on-demand users and pooled on-demand users. The rate of decrease of average waiting time for private service users is higher than that of pooled on-demand users. Thus the effect of increase in fleet size on the average waiting time is much more pronounced for private on-demand service than that for pooled on-demand service.

Similarly, Figure 5.8 shows the split of Operator's Profit along with its individual components as shown in Equation 5.3. *Revenue* corresponds to the revenue generated from the on-demand service, *Operating cost* corresponds to the operational cost of the on-demand system, and *Profit* corresponds to the overall profit which is the difference between the revenue and the operational cost. The *Revenue* monotonically increases as the fleet size increases along both axes of private and pooled on-demand services. However the rate of increase of revenue is higher along the private on-demand axis than the pooled axis. This can be explained by the trends observed in Figure 5.4, Figure 5.5, and Figure 5.6. As can be seen in Figure 5.4, the rate of decrease of average waiting time for private on-demand users is higher than that for pooled on-demand users, thus making the service increasingly more competitive compared with the pooled service with an increase in fleet size. This is also visible in Figure 5.6, which indicates that the mode share of private on-demand service is significantly higher than the shared service for all possible fleet sizes. We also observe that the rate of increase of mode share for private service is higher than for the pooled service and that the private service is more competitive than pooled service. This also explains the shape of the plot of *Revenue* and *Profit* in Figure 5.8. The maxima of *Revenue* and the *Profit* are skewed towards the private on-demand axis. The range of values for *Revenue* and *Operating cost* indicates that the *Profit* is primarily governed by the *Revenue*.

The fleet size configuration of private and pooled on-demand service that yields the op-

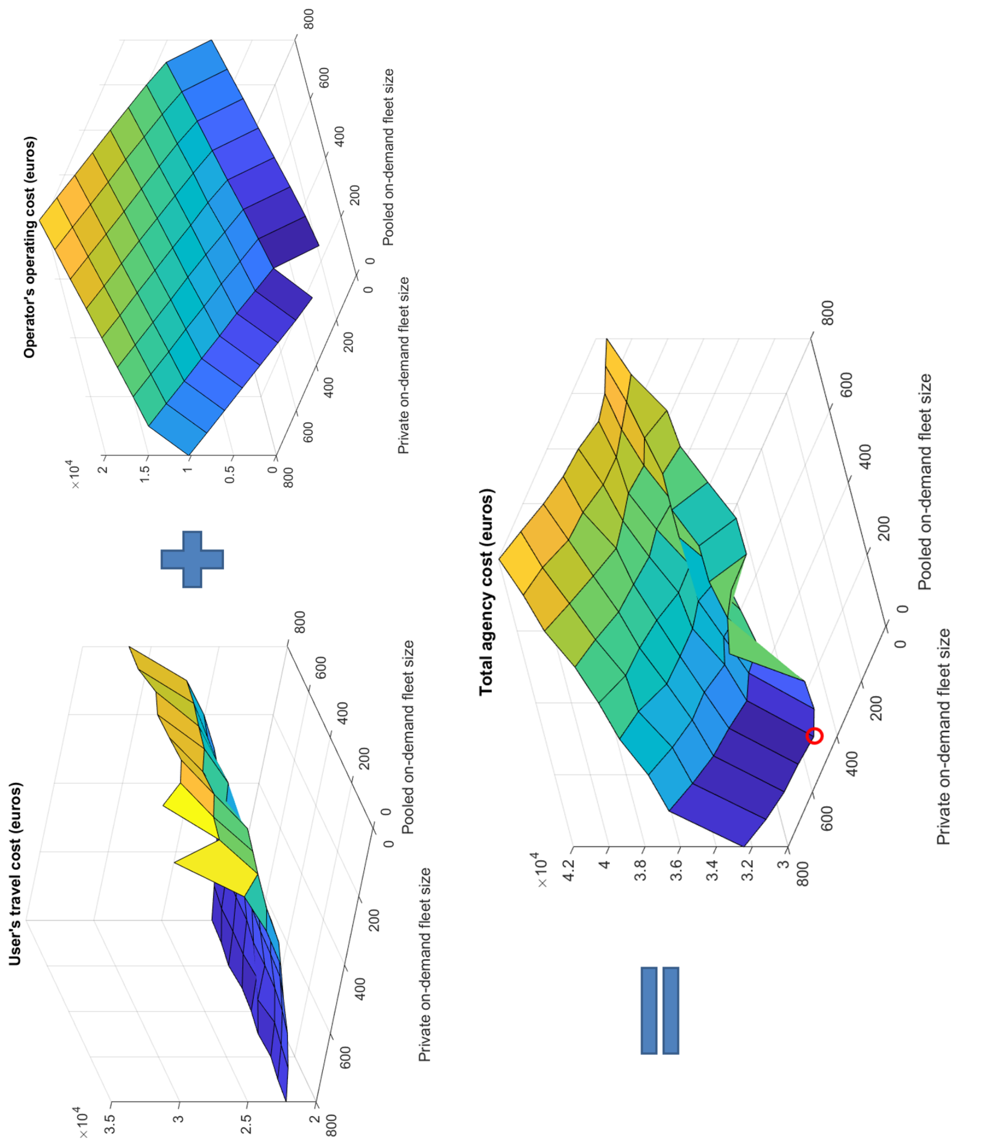


Figure 5.7: Plot of Agency's objective function values

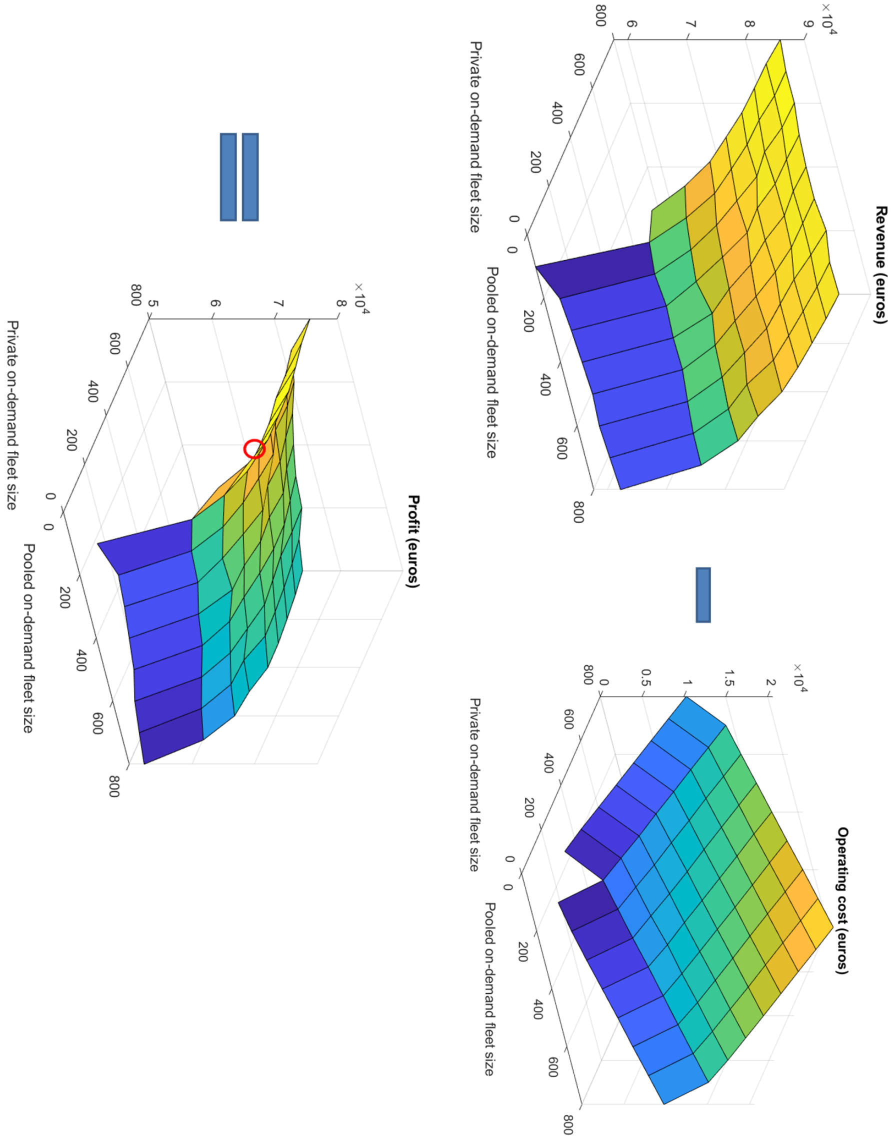


Figure 5.8: Plot of Operator's objective function values

timal values are 400 and 0 respectively for Agency and 300 and 0 respectively for Operator. Hence both from an Agency perspective and from an Operator perspective, the ideal strategy would be to operate a private on-demand service only. The increase in fleet size from 300 to 400 cause an increase in the operating cost and revenue and decrease in the overall travel cost of users. However from an Agency perspective, during the increase in fleet size from 300 to 400 the travel time savings of the users outweighs the increase in operating cost. However, from an Operator's perspective the additional operational cost outweighs the increase in Revenue. This explains the difference in optimal values for the Agency and the Operator. Hence from a planning perspective, the Agency allowing the Operator to determine the fleet size would result in sub-optimum solution for the Agency.

Finally, we compare the Agency cost in the **Base Scenario** and **On-demand** scenario. The Agency cost at the optimal solution of 400 private vehicles is 31,300 €and that in the **Base Scenario** is 55,359 €. Hence, the Agency cost at **Base Scenario** yields a higher cost than the Agency cost at optimal solution for scenario **On-demand**. This shows that from an Agency perspective, the optimal scenario would be the **On-demand** indicating that the best plan of action from an Agency perspective would be to operate an on-demand service as opposed to the **Base Scenario**.

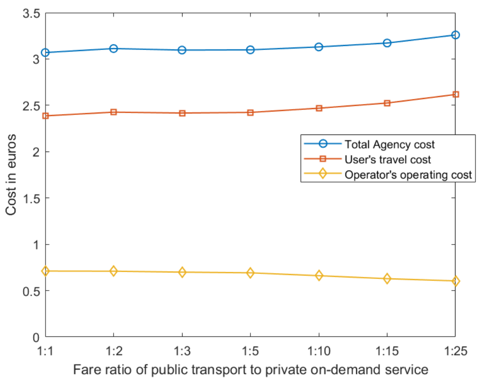
5.5.3 Fare sensitivity analysis

In this section, we perform a fare sensitivity analysis for the private and pooled on-demand services. To this end, we consider 4 fleet size instances. First, we consider the fleet size instance that yield the optimal Agency cost (private on-demand fleet size = 400 and pooled on-demand fleet size = 0). Next, we consider the fleet size instance that yield the optimal Operator cost (private on-demand fleet size = 300 and pooled on-demand fleet size = 0). For the two fleet size instances we vary the fare ratio of public transport to private on-demand service by varying the fare of private on-demand service. The ratios of fare of public transport to private on-demand service considered are: 1:1, 1:2, 1:3, 1:5, 1:10, 1:15, and 1:25.

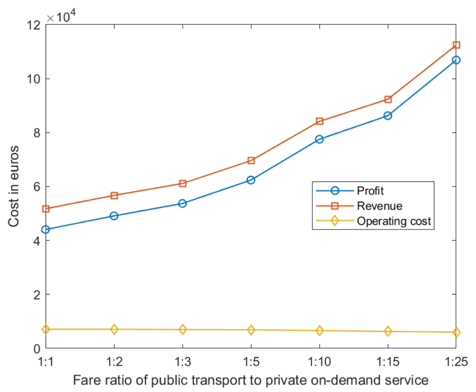
In addition, we consider two fleet size instances with both private and pooled on-demand service. The first one being the mixed fleet size instance with the lowest fleet size (private on-demand fleet size = 100 and pooled on-demand fleet size = 100) and the next being the mixed fleet size instance with the highest possible fleet size (private on-demand fleet size = 800 and pooled on-demand fleet size = 800). For both instances of the mix fleet size, we vary the fare of pooled on-demand service relative to public transport and private on-demand service. The ratios of fare of public transport to pooled on-demand service to private on-demand service considered are: 1:1:10, 1:2:10, 1:3:10, 1:5:10, and 1:10:10.

Agency and Operator optimal fleet size instances

Figure 5.9 and 5.10 shows the variation of Agency cost and Profit of operator along with their individual components with varying fare ratios for the optimal fleet size configuration for Agency and Operator, respectively. As can be seen from the two figures, the Agency cost remains relatively stable during the initial increments in fare ratio (till 1:5) and then monotonically increases beyond this point. The total Agency cost follows the trend of User's travel cost which is the dominant part in the Agency cost. The Operator's operating cost monotonically decreases for all the fare increments. The increase in fare ratio makes the on-demand service relatively less attractive and consequentially the mode share of private on-demand service decreases with the increase in fare ratio. However, during the initial increments, the decrease in mode share is marginal and not sufficiently high to cause an overall decrease in total Users' travel cost (and thus Agency cost). The decrease becomes substantial for higher fare ratios which cause an increase in the Users travel cost and Agency cost at higher fare ratios. This also explains the decrease in operating cost component for both the optimal fleet size instances. In both cases the optimal pricing strategy for the Agency would be to keep the fare of private on-demand service as low as possible (comparable to public transport).



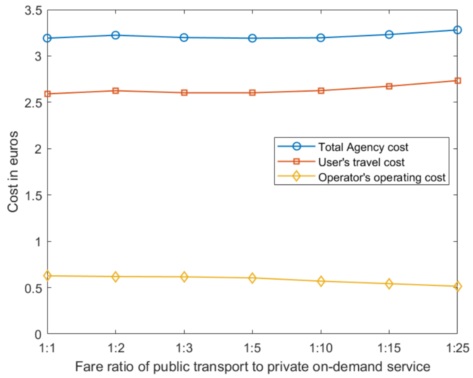
(a) Agency cost components



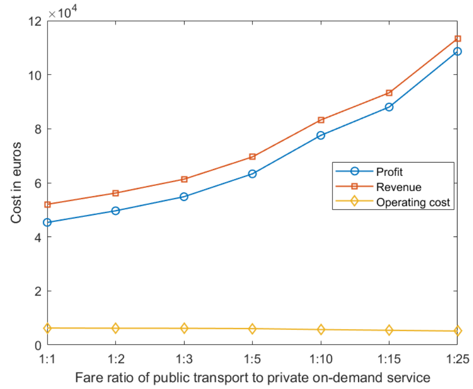
(b) Operator cost components

Figure 5.9: Agency and Operator cost variation with fare ratio of public transport to private on-demand services at optimal Agency fleet size

The Profit for the Operator increases monotonically for both optimal fleet size instances with an increase in the fare ratio. Although the mode share of the private on-demand service decreases the more its fare increases, the increase in its revenue caused by the fare increment outweighs the revenue loss caused by the decrease in its modal share. Consequently,



(a) Agency cost components



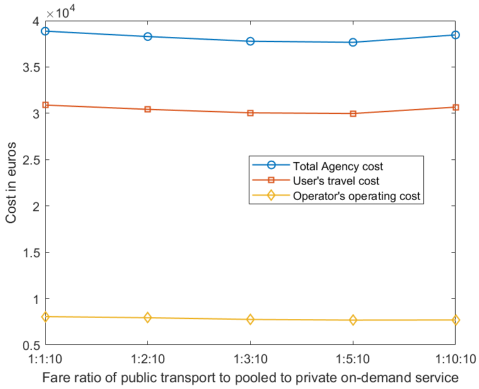
(b) Operator cost components

Figure 5.10: Agency and Operator cost variation with fare ratio of public transport to private on-demand services at optimal Operator fleet size

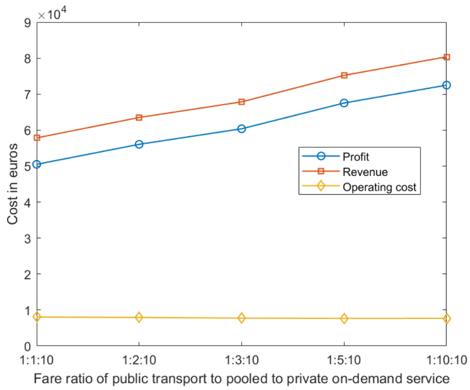
the Operator sees an overall increase in its profit when it becomes increasingly expansive relative to public transport despite the decrease in its modal share.

Mixed fleet size instances

Figures 5.11 and 5.12 plots the Agency cost and Profit of operator along with its individual components for the mixed fleet size instances of 100 and 800. As can be seen from the two figures, as the fare of pooled on-demand service increases, the total Agency cost and the users travel cost decreases till a ratio of 1:5:10 and then increases from 1:5:10 to 1:10:10. The Agency cost is primarily governed by the market share of the on-demand service and the share of private and pooled on-demand services. As the fare of pooled on-demand service increases, the service becomes less attractive and there is a modal shift from pooled on-demand to private on-demand service. Private on-demand service being a direct door-to-door service, the increase in its market share causes an overall decrease in the travel time of its users which yields also to a decrease in the Agency cost. This decrease in travel time caused due to the shift from pooled service to private service outweighs the effect of an overall decrease in on-demand modal share till a ratio of 1:5:10. Conversely, beyond this point, the decrease in the market share of the on-demand service caused by the increase of fare ratio from 1:5:10 to 1:10:10 is substantial enough to outweigh the effect of travel time reduction caused due to the shift from pooled to private. The minimum Agency cost is hence achieved for a fare ratio of 1:5:10.



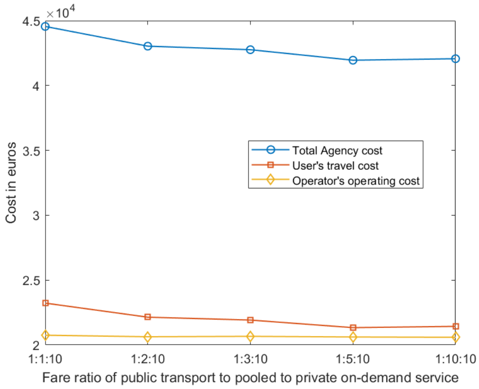
(a) Agency cost components



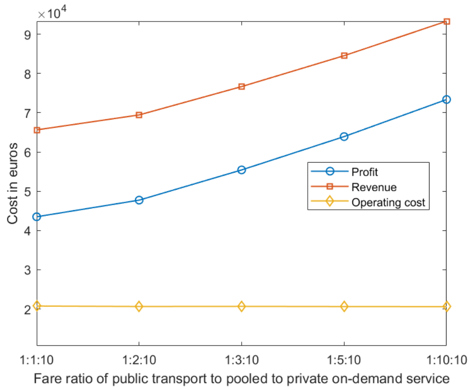
(b) Operator cost components

Figure 5.11: Agency and Operator cost variation with fare ratio of public transport to pooled to private on-demand services (private and pooled on-demand fleet size = 100)

As in the previous case, the Profit for the operator increases monotonically for both mixed fleet size instances with an increase in the fare ratio of public transport to pooled to private service. Although the overall market share of on-demand services decreases with an increase in the fare ratio, the increment in Revenue due to an increase in its fare, outweighs the decrease in its market share. This results in an overall increase in its the Profit for the operator despite an overall decrease in its market share.



(a) Agency cost components



(b) Operator cost components

Figure 5.12: Agency and Operator cost variation with fare ratio of public transport to pooled to private on-demand services (private and pooled on-demand fleet size = 800)

5.6 Conclusion

This chapter explored the relation between the optimal fleet size of an on-demand system with elastic demand form the perspective of a transport planning authority (*Agency*) and a service provider (*Operator*). An agent-based simulation framework was adopted for implementing the model with day-to-day learning of users (which corresponds to the elastic demand). The model was implemented in the real world network based on Amsterdam North. Results indicated that operating a private on-demand service is more profitable for both *Agency* and *Operator* than a pooled on-demand service. Analysis of travel time of on-demand passengers also indicated that the effect of increase in fleet size on travel time is more priominent for private on-demand as compared to pooled on-demand. Comparitive analyses of optimal fleet size for *Agency* and *Operator* indicated different total fleet size with the *Agency* perspective requiring a larger fleet than would have been required if it is to be set by the *Operator*. The analysis also showed different dominant parts of the individual objective functions with revenue dominating the *Operator's* cost and user's travel cost dominating the *Agency* cost. An analysis of the *Agency* cost indicated the optimal scenario for the *Agency* would be the **On-demand** scenario in which the *Agency* operates a fleet of private on-demand vehicles as opposed to a scenario where no on-demand service is offered. This is due to an overall reduction in travel time of users in **On-demand** scenario compared to the **Base Scenario**. Fare sensitivity analysis of private and pooled on-demand service indicated that the optimal pricing strategy for the Agency would be to keep the fare of private on-demand service as low as possible (comparable to public transport).

In this chapter, we determined the private and shared fleets of an on-demand service provider with elastic demand. However, the service levels of line- and schedule-based services was exogenously defined. Passengers were also not allowed to combine on-demand and line- based services in a single trip, albeit unlikely in the application considered in this study. Also, the cost components considered in this study does not include costs beyond the transit system such as societal costs (emissions and health). Moreover, a monopolistic market where only one on-demand service provider prevails, was considered in this study. However, the market of on-demand services may consist of multiple competing operators offering competing services that cater for different segments in the market and differ in price, level of service (travel time and comfort), and types of service offered (private or pooled). Competition between such services will affect the optimal fleet size configuration. Future research directions and model improvement include thus developing a model which jointly optimises the service parameters of line-based public transport and an on-demand service while considering costs beyond the transit system, developing a route choice model that allows users to combine line-based public transport and on-demand services in a single trip, and considering oligopolistic markets where multiple on-demand operators prevail and a scenario where there is no overseeing authority and tendering of services.

Chapter 6

Conclusions and recommendations

The objective of this thesis was developing models for the design and analysis of on-demand mobility systems in an urban context. To this end, four research questions were formulated pertaining to various aspects of design and analysis of on-demand mobility systems, which are reposed and discussed in the sections below.

In answering these research questions, we examine certain scenarios of on-demand mobility on urban transport. First, we examine the scenario where on-demand mobility competes with other travel modes such as car, public transport, and active modes. Then we consider the scenario where users combine on-demand service and public transport for their origin-destination journey. Next, we examine the hypothetical scenario where on-demand mobility services replace the trips performed by car and public transport. This is followed by the design of on-demand transport services where we determine the optimal fleet size mix of a private and pooled on-demand transport system.

In the following sections, we highlight the scientific contributions which stems from answering the research questions pertaining to the analysis and design of on-demand mobility systems. Furthermore, we discuss the practical implications of the study, and provide direction for future research.

6.1 Scientific contributions

In chapter 1, the following research questions (RQs) were presented and answered subsequently in this thesis. The answers to the questions constitute the scientific contributions, which are described in this section. An agent-based simulation model was adopted and adapted for model implementation in order to answer all the research sub-questions.

RQ1: What is the performance of on-demand mobility service offering competing services with traditional modes of car, public transport, and active modes?

Answering the research question provided insights into the performance of on-demand service when they compete with traditional modes such as car, active modes, and public transport. Results showed that an increase in fleet size of on-demand transport caused an overall increase in its mode share. This was caused due to an overall decrease in waiting time of passengers using on-demand transport. It was also found that the effect on waiting times of passengers by increasing fleet size is more pronounced when a private door-to-door service is offered compared to that for pooled on-demand service. This is due to the direct door-to-door service provided by private on-demand service without any detours. An increase in fleet size therefore entails more vehicles to serve the demand and hence a subsequent reduction in waiting time. While this is true for both private and pooled on-demand services, for pooled on-demand services, the reduction in waiting time becomes less pronounced because of the detours performed. The variation of relative cost ratios showed a steady and considerable decline of mode share for on-demand transport with increasing cost. When the fare of on-demand service varies from 2 to 10 times that of public transport, the mode share of private and pooled on-demand service decreases by 54% and 60% respectively. Finally, results indicated that at higher relative cost ratios, the relative gap in modal share between private and pooled on-demand service decreases. Next, we considered the scenario where users combine on-demand transport and public transport, and the subsequent research question is as follows.

RQ2: How can users' choice for combining public transport and on-demand services be modelled?

To answer this question, we developed an integrated multi-modal route choice and assignment model that allows users to combine conventional line- and schedule-based and on-demand passenger transport services or use them as exclusive modes so that their travel impedance is minimized. An on-demand transport service offering private taxi-like service was considered for this study. We considered scenarios where public transport and private on-demand are a) either mutually exclusive or b) used in combination in a single trip. Key performance indicators related to modal usage, service performance, fleet utilisation, and impact of fleet size and thus level of service on the number of passenger trips were discussed.

The results indicate that private on-demand service is mainly used to cover $\leq 30\%$ of the trip length, when the two modes of operations can be combined within a single passenger journey. It was also found that most of the users combining public transport and private on-demand service are otherwise using only public transport in the base case scenario, whereas car and active mode users generally stick to their modes. This is because the majority of the trips that combine public transport and private on-demand service, use private on-demand service as access egress modes to public transport implying that those were the trips that were originally performed by public transport. Sensitivity analysis with respect to fleet size of private on-demand service indicate that no significant gains in level-of-service are made when increasing the fleet size beyond 5% of the travel demand and consequentially the fleet of private on-demand service remain increasingly underutilised beyond this point.

Having considered the two scenarios where on-demand transport co-exists with other modes, we turn into considering the hypothetical scenario where the entire car and public transport trips are served with on-demand transport. The research question that is related to this issue is answered below.

RQ3: What is the performance of on-demand transport services replacing car and public transport trips?

In this part, we investigated the potential of an on-demand service to serve all the motorised trips (car and public transport) in Amsterdam. We considered scenarios where private and pooled on-demand transport services replace private car, public transport, and combined private car and public transport trips (all motorised trips). On-demand service performance in terms of level of service offered and service efficiency were analysed.

Our results indicate that pooled on-demand service were more efficient in terms of veh-km travelled and empty drive ratio than private on-demand service for the same fleet size instance. Occupancy levels of on-demand indicated an under-utilisation of the fleet for higher fleet sizes for both private and pooled on-demand services. Results also suggest that while there was a significant unsatisfied demand for the scenario when car trips were served by on-demand, the entire PT trips could be served with a relatively low fleet size of on-demand for both private and pooled services. Analysis of travel time indicate that the travel time of car users in the Base case was lower than when on-demand service were used for both private and pooled services. However, the travel time of public transport users were lower when on-demand service was used to serve the trips than the Base case. The combined average travel time of car and public transport users was also lower when on-demand served the trips than the Base case. In all these scenarios, the travel time of private on-demand was lower than that of pooled on-demand users. While the in-vehicle time was stable throughout the fleet size instances, the increase in fleet size resulted in the reduction of average waiting time for both private and pooled service users.

Last, we design the services of on-demand service by determining the optimal fleet size mix of private and pooled on-demand service. The research question is as follows.

RQ4: What is an optimal fleet size composition of private and pooled on-demand services?

In this final study, we explored the relation between the optimal fleet size of an on-demand system from the perspective of a transport planning authority (Agency) and a service provider (Operator). The Agency is assumed to be interested in minimising the travel time of all the users while the Operator is interested in maximising its profit. An optimisation model was developed and implemented in an agent-based simulation framework with day-to-day learning of users (which corresponds to the endogenous demand). The model was applied to the network of Amsterdam North. Results indicate that operating a private on-demand service is more profitable for both Agency and Operator than a pooled on-demand service. Analysis of travel time of on-demand passengers also indicates that the effect of increase in fleet size on travel time is more prominent for private on-demand as compared to pooled on-demand. Comparative analyses of optimal fleet size for Agency and Operator indicate different total fleet size with the Agency perspective requiring a larger fleet than would have been required if it is to be set by the Operator. The analysis also showed different dominant parts of the individual objective functions. For Operator's cost, the revenue is the dominant part and for Agency cost, user's travel cost is the dominant part. Introducing a fleet of private on-demand services was found to reduce the overall travel time of all the users compared to the base scenario where no on-demand service is offered. Consequentially, the optimal operating scenario for the Agency is the one where the Agency operates a fleet of private on-demand vehicles as opposed to a scenario where no on-demand service is offered.

6.2 Implications for practice

This section highlights the practical recommendations of the study. All the developed models were applied to networks based on real-world urban areas, namely *Sioux Falls*, *Amsterdam metropolitan area*, and *Amsterdam North* thereby providing relevant insights into the implementation of on-demand transport services in these respective urban contexts. We highlight the practically relevant insights pertaining to each of the scenarios considered in analysis phase and design phase.

Impact of introducing on-demand services

In the analysis phase, first we examined the scenario where on-demand transport competes with other modes such as car, public transport, and active modes. The study enables practitioners and policy makers to evaluate the implications of introducing competing on-demand services (both private and pooled) with other travel modes. Insights into system performance include effect of varying fleet size and fare ratio of on-demand service on travel time of users and modal share of on-demand service. Results showed that the increase in fleet size of on-demand service improved the waiting time of its users and increased its mode share. The variation of relative cost ratios showed that at higher relative cost ratios, the on-demand service that operate without sharing becomes less attractive than the one with sharing. The insights enables on-demand service operators and transit planners to understand the system performance under various service levels and fare setting thus aiding in the process of service design - fleet size determination and fare setting.

Identification of transfer locations

Next we considered the scenario where users combine on-demand transport and public transport for their origin-destination journey. The key practical contribution here is a model for evaluation of services and identifying transfer locations when on-demand service and public transport interact. This helps to support interchange facility design and to assess the performance and level of service of on-demand service as first/last mile under various public transport service attributes such as frequency. The application of the model to the area centered around Amsterdam also shows that the model is scalable for large-scale real-world networks.

Insight into scalability of on-demand services

We then considered certain hypotetical scenarios of on-demand transport on urban mobility where the entire car and public transport trips in Amsterdam were served with on-demand transport services. Two on-demand transport services, private and pooled, were considered. The study illustrates the scalability of an on-demand transport system on a city-wide level and its potential to serve trips performed by private car and public transport. Scenarios where private and pooled on-demand services replace car trips, public transport trips, and car and public transport trips were analysed. While there were significant unsatisfied demand for the scenario when car trips were served by on-demand, it was found that the entire public transport trips could be served with a relatively low fleet size of on-demand for both private and pooled services. From an operational perspective, results indicated that veh-km and empty drive ratios are indices where pooled on-demand fare better and private on-demand fare better for travel time indices. This implies that private on-demand service spends more time driving in the network, produce more induced traffic and is likely to contribute more to congestion levels in the city compared to pooled service. This insight enables practitioners and planners in fixing congestion surcharges and fares for on-demand services in urban areas.

Determining optimal fleet size

Finally in the design phase, an optimal fleet size mix of private and pooled on-demand transport service was determined. Fleet size determination of an on-demand transport service is a process that involves multiple stakeholders with different objectives. This includes a service provider who would be interested in maximising the revenue and a planning authority who would be interested in minimising the total travel cost of the users. Our results suggest that the decision on the fleet size would yield different values if made by either of the two stakeholders, where the planning authority requires a larger fleet. The results also provide insights into the most profitable operational strategy for the planning authority (whether to operate an on-demand service or not). The modeling framework can hence be used by on-demand service providers and also by transit planning authorities to determine the optimal fleet size in an urban context where these modes interact with the other modes such as car, public transport, and active modes.

Use of activity-based modelling

Last but not least, the study highlights the effectiveness of agent-based simulation tools in design, analysis, and implementation of large scale on-demand transport services in a city-wide context. Key performance indicators analysed in the study indicate that agent-based simulation tools are effectively able to capture the complexities of the system and real-time dynamics of on-demand transport services.

6.3 Recommendations for future research

In addition to the specific future research directions mentioned in the individual chapters, we now highlight the key limitations of the study and directions for future research.

Model calibration and validation

The study adopts an agent-based simulation tool where users are modelled as individual agents with autonomous decision making capabilities and an assignment based on the concept of stochastic user equilibrium. How the agents behave in the model is governed by a set of behavioral parameters values. Model improvements and hence the direction of future research should focus on enriching the behavioral model by incorporating behavioral parameters that reflect the actual preferences of users towards emerging mobility systems such as on-demand transport services.

Testing more efficient vehicle dispatching strategies

The on-demand transport service modelled in this study includes a fleet of vehicles controlled by a central dispatching unit and are randomly distributed in the network. After picking up a passenger from their origin, and dropping them off at their destination, a vehicle stays at the drop-off location till further requests are assigned. This leads to under-utilisation of fleet as shown in the occupancy analysis of the individual studies. Hence a more efficient vehicle distribution and relocation strategy based on demand anticipation could be a potential model improvement and could largely improve service efficiency.

Combined service design of public transport and on-demand service

In this thesis the service design pertains to fleet size determination of a private and pooled on-demand service. A more elaborate service design that includes a combined service design of on-demand service and public transport service is a possible future direction of research. Service design of public transport could include route alignment, frequency of services, scheduling and so on. Such a service design would also enable users to combine the on-demand service and public transport services.

Service design and analysis in a market setting with competing service providers

Throughout the thesis, a single service provider in a monopolistic market setting was considered. However, in reality that might not be the case. There might be multiple service providers who compete for market share. Service design and analysis in such an oligopolistic market setting is a another direction for future research.

Design and analysis of other innovative mobility systems

This thesis considered an on-demand mobility system which comprise of a fleet of vehicles offering private and pooled door-to-door services in real-time to passengers. possible future direction of research therefore could consider the design and analysis of other innovative mobility systems such as carsharing, paratransit services, carpooling and stop-to-stop on-demand services in the context of urban mobility and their possible integration with public transport.

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Samenvatting

In het afgelopen decennium is er enorme vooruitgang geboekt op verschillende ICT-platforms (informatiecommunicatie en technologie). Deze ontwikkelingen hebben de opkomst van innovatieve mobiliteitsoplossingen mogelijk gemaakt, zoals vraaggestuurde vervoersdiensten. Dergelijke oplossingen bieden gebruikers flexibele vervoersdiensten, waarbij gebruikers mobiliteitsoplossingen op maat kunnen krijgen. Onderzoek wijst in toenemende mate op de potentieel ontwrichtende effecten van dergelijke innovatieve mobiliteitsoplossingen op stedelijke mobiliteit. De effecten variëren van traditionele modaliteiten, zoals particuliere auto's en openbaar vervoer, die hun marktaandeel verliezen aan on-demand diensten, tot de daaropvolgende behoefte voor openbaarvervoersystemen om te evolueren om relevant te blijven. Modelleringsinstrumenten voor het ontwerp en de evaluatie van dergelijke vraaggestuurde vervoersdiensten moeten daarom rekening houden met de implicaties ervan voor stedelijke mobiliteit door ook de interactie met andere vervoerswijzen in beschouwing te nemen.

In bestaande onderzoeken naar het ontwerp en de analyse van on-demand diensten werd de impact van deze diensten op andere vervoerswijzen, en vice-versa, grotendeels over het hoofd gezien. Dit betekent dat studies tot nog toe het ontwerp en de analyse van on-demand systemen zonder dit effect van on-demand diensten op andere vervoerswijzen en hun algemene impact op stedelijke mobiliteit hebben onderzocht. Deze studie tracht deze onderzoekskloof te dichten door een benadering te ontwikkelen voor het ontwerp en de analyse van on-demand diensten in een stedelijke mobiliteitscontext. In dit proefschrift worden twee soorten vraaggestuurde diensten in beschouwing genomen: namelijk particuliere en gepoolde (gedeelde) diensten. Zowel particuliere als gepoolde vraaggestuurde diensten worden gekenmerkt door een wagenpark dat wordt aangestuurd door een centrale dispatchingeenheid. Ze bieden een real-time deur-tot-deur service aan in respons op reisverzoeken van passagiers. De particuliere on-demand service biedt een taxiachtige service aan individuele passagiers, terwijl bij een gepoolde on-demand service meerdere passagiers de service kunnen delen.

Figuur 6.1 toont een conceptuele weergave van de doelstelling, bijdrage en context van het onderzoek. In het gedeelte Analyse stellen we verschillende scenario's voor van de interactie van on-demand services met stedelijke mobiliteit, zoals weergegeven met I, II en III in Figuur 1. In (I) kijken we naar het scenario waarin on-demand service concurreert met auto, openbaar vervoer en actieve vervoerwijzen. In II kijken we naar het scenario waarin gebruikers on-demand service en openbaar vervoer combineren voor hun reis van herkomst naar bestemming. In III kijken we naar scenario's waarin on-demand service alle verplaatsingen met auto en openbaar vervoer vervangt. In het Ontwerp gedeelte bepalen we de optimale mix van vlootomvang van een on-demand service bestaande uit particuliere en gepoolde services.

Voor de modelimplementatie is een agent-based simulatie-framework gehanteerd, waarbij sprake is van een stochastisch equilibriummodel inclusief lerend vermogen van gebruikers. De wetenschappelijke bijdragen en praktische implicaties van de Analyse en Ontwerp aspecten van on-demand diensten worden in de volgende sectie samengevat.

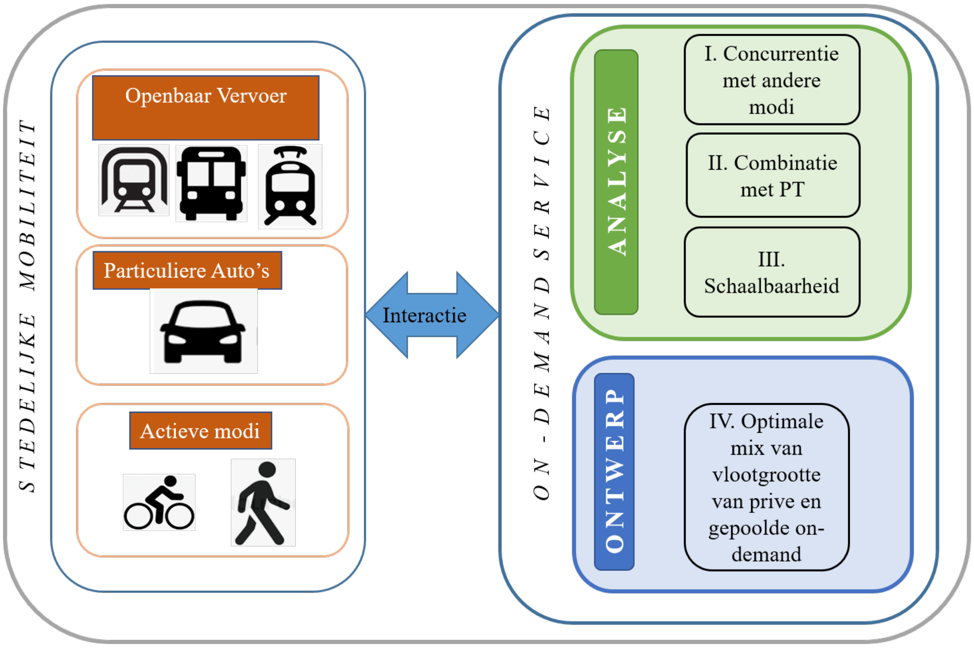

Figure 6.1: Conceptuele weergave van de kernthema's die in het proefschrift en de studiecontext aan bod komen

Analyse van on-demand services

Eerst kijken we naar het scenario waarin de on-demand service concurreert met auto, openbaar vervoer en actieve vervoerwijzen. De prestaties van een particuliere en gepoolde on-demand service zijn geanalyseerd voor een variërende vlootomvang en met verschillende kostenratios van de on-demand service in vergelijking met openbaar vervoer. Uit de analyse bleek dat het effect van een grotere vloot op de wachttijden van passagiers meer zichtbaar is wanneer een particuliere deur-tot-deur-service wordt aangeboden, in vergelijking met een gepoolde on-demand service. De resultaten toonden ook aan dat bij hogere relatieve kostenratios (wanneer het tarief van de on-demand service meer dan 5 keer dat van openbaar vervoer is), het relatieve verschil in modal split tussen particuliere en gepoolde on-demand service afneemt . De studie stelt beleidsmakers in staat om de implicaties te evalueren van het introduceren van concurrerende on-demand diensten (zowel particulier als gepoold) op andere vervoerwijzen op basis van de reactie van gebruikers op de ervaren diensten.

Vervolgens kijken we naar het scenario waarin gebruikers on-demand service en openbaar vervoer combineren in hun totale reis van herkomst tot bestemming. We hebben een geïntegreerd multimodaal routekeuze- en toedelingsmodel ontwikkeld waarbij gebruikers conventionele, aanbodgestuurde en on-demand vervoersdiensten kunnen combineren of deze apart als vervoerwijze kunnen gebruiken, zodat hun reisweerstand geminimaliseerd wordt. De resultaten laten zien dat de meeste gebruikers die openbaar vervoer en particuliere on-demand diensten combineren in het basisscenario oorspronkelijk alleen openbaar vervoer gebruikten, terwijl de vervoerwijzekeuze voor automobilisten en gebruikers van active modes over het algemeen ongewijzigd blijft. De belangrijkste praktische bijdrage hier is de beschikbaarheid van een model voor de evaluatie van vervoerdiensten en het identificeren van overstaplocaties van vraaggestuurde diensten naar openbaar vervoer en vice-versa. Dit helpt het ontwerp van de overstapfaciliteiten te ondersteunen en de prestaties en het serviceniveau van on-demand service als first / last mile te beoordelen op basis van verschillende kenmerken van openbaarvervoersdiensten, zoals de frequentie.

Tenslotte kijken we naar de scenario's waarin particuliere en gepoolde on-demand diensten de privéauto, openbaar vervoer en gecombineerde auto- en openbaar vervoerverplaatsingen (alle gemotoriseerde verplaatsingen) vervangen. De on-demand serviceprestaties wat betreft het aangeboden serviceniveau en de service-efficiëntie werden geanalyseerd. Aspecten waarbij elk van de twee on-demand services (particulier en gepoold) beter of slechter presteren qua aangeboden serviceniveau en service-efficiëntie werden geïdentificeerd. Onze resultaten geven aan dat een gepoolde on-demand-service efficiënter is wat betreft afgelegde voertuigkilometers en lege ritten en dat particuliere on-demand voertuigen meer tijd kwijt zijn aan het ophalen van passagiers dan gepoolde service voor dezelfde wagenparkomvang. Particuliere on-demand diensten genereren 43%, 38% en 44% meer voertuigkilometers dan gepoolde on-demand diensten wanneer on-demand diensten respectievelijk autoritten, openbaar vervoer of auto- en openbaar vervoerverplaatsingen tezamen vervangen. Ook kon worden vastgesteld dat de reistijd van particuliere on-demand gebruikers lager was dan die van gepoolde on-demand gebruikers. De reistijd voo gepoolde on-demand gebruikers was 33%, 39% en 48% meer dan die van particuliere on-demand gebruikers, wanneer on-demand diensten respectievelijk autoritten, openbaar vervoer of auto- en openbaar vervoer vervangen. Het onderzoek laat zien dat een on-demand vervoersysteem schaalbaar is naar een geheel stedelijk en illustreert het potentieel ervan om verplaatsingen met de auto en het openbaar vervoer te verzorgen.

Ontwerp van on-demand services

Na het Analyse gedeelte wordt het Ontwerp van on-demand services belicht. Hier hebben we de relatie onderzocht tussen de optimale vlootomvang van een on-demand systeem vanuit het perspectief van zowel de vervoersautoriteit (Agency) als de vervoerder (Operator). Er wordt verondersteld dat de vervoersautoriteit als doelstelling heeft om de reistijd van alle gebruikers te minimaliseren, terwijl de vervoerder beoogt zijn winst te maximaliseren. De studieresultaten laten zien dat het exploiteren van een particuliere on-demand dienst voordeliger is dan een gepoolde on-demand dienst voor zowel de Agency als Operator. Analyse van de reistijd van gebruikers van on-demand diensten laat daarnaast zien dat het effect van de toename van de vlootomvang op de reistijd groter is bij particuliere on-demand diensten, dan voor gepoolde diensten. Een vergelijking van de optimale vlootomvang tussen het perspectief van de Agency en de Operator laat een verschillende totale vlootomvang zien, waarbij vanuit het perspectief van het Agency een grotere vloot benodigd zou zijn dan wanneer geoptimaliseerd door de Operator. De resultaten bieden ook inzicht in de meest winstgevende operationele strategie voor de vervoersautoriteit (om al dan niet een on-demand service te exploiteren). Het ontwikkelde model framework uit deze studie kan dus worden gebruikt door zowel aanbieders van on-demand vervoerdiensten, als door vervoersautoriteiten, om de optimale vlootgrootte te bepalen in een stedelijke context waar deze diensten interacteren met auto, openbaar vervoer en actieve vervoerwijzen.

Gevolgtrekking

Innovatieve mobiliteitssystemen zoals vraaggestuurde vervoersdiensten veranderen de manier waarop mensen reizen: studies laten in toenemende mate hun potentieel verstorende effecten op stedelijke mobiliteit zien. Daarom is de interactie van dergelijke diensten met andere vervoerwijzen cruciaal voor het ontwerp en de analyse ervan. Het doel van dit proefschrift was het ontwikkelen van modellen voor het ontwerp en de analyse van on-demand mobiliteitssystemen in een stedelijke context, daarbij deze interactie met andere vervoerwijzen expliciet in beschouwing nemend. Een agent-based simulatie framework met een stochastisch equilibriummodel inclusief lerend vermogen van gebruikers is gehanteerd en aangepast voor modelimplementatie. Meerdere scenario's van de wijze waarop on-demand services interacteren met stedelijke mobiliteit zijn ontwikkeld en geanalyseerd, waarvoor ook het netwerkontwerp is uitgevoerd met het oog op deze interactie. Het eerste scenario gebruikt voor deze analyse betreft een scenario waarin de on-demand service concurreert met traditionele vervoerwijzen. De resultaten toonden aan dat het effect van een grotere vloot op de wachttijden van passagiers groter is wanneer een particuliere deur-tot-deur-service wordt aangeboden, in vergelijking met het aanbieden van een gepoolde on-demand-service. Het tweede scenario was een scenario waarin gebruikers het openbaar vervoer en de dienst op aanvraag combineren voor hun totale reis van herkomst naar bestemming. Hiervoor is een geïntegreerd routekeuze- en toedelingsmodel ontwikkeld waarmee gebruikers openbaar vervoer en on-demand-diensten kunnen combineren. Resultaten toonden aan dat de meeste gebruikers die openbaar vervoer en particuliere on-demand diensten combineren oorspronkelijk alleen het openbaar vervoer gebruikten in het basisscenario, terwijl automobilisten en gebruikers active modes over het algemeen vasthouden aan hun oorspronkelijke vervoerwijze. Het laatste scenario betreft een scenario waarbij on-demand services alle ritten met de auto en het openbaar vervoer vervangen. De resultaten geven aan dat gepoolde on-demand-service efficiënter is qua afgelegde voertuigkilometers en lege ritten en dat de reistijd voor gebruikers van particuliere on-demand services lager is dan die van gepoolde on-demand gebruikers. De studie illustreert ook de schaalbaarheid van een on-demand transportsysteem naar geheel stedelijk niveau. Betreffende het ontwerp van dergelijke diensten hebben we de relatie onderzocht tussen de optimale vlootomvang van een on-demand systeem vanuit het perspectief van een vervoersautoriteit en een vervoerder. Resultaten geven aan dat het exploiteren van een particuliere vraaggestuurde dienst gunstiger is voor zowel de Agency als Operator dan een gepoolde on-demand dienst. Onze resultaten versterken daarom de bevindingen in de literatuur over de effecten van, en de impact op, on-demand diensten op stedelijke mobiliteit.

Modelverbeteringen en toekomstige onderzoeksrichtingen omvatten onder meer het verrijken van het gedragsmodel, het testen van efficiëntere dispatchingstrategieën, het overwegen van concurrerende dienstverleners in een oligopolistische markt, het optimaliseren van diensten voor het openbaar vervoer en on-demand service en het ontwerp en de analyse van andere innovatieve mobiliteitssystemen zoals car-sharing en car-pooling.

Summary

The past decade has seen vast advancements in various ICT (Information Communication, and Technology) platforms. These advancements have enabled the rise of innovative mobility solutions e.g. on-demand transport services. Such solutions offer flexible transport services to users in which users can receive tailor-made mobility solutions. Increasing evidence from the literature points at the potentially disruptive effects of such innovative mobility solutions on urban mobility. The effects range from traditional modes such as privately owned cars and public transport losing their market share to on-demand services, to the subsequent need for public transport systems to evolve to stay relevant. Modelling tools for the design and assessment of such on-demand transport services therefore needs to account for its implications for urban mobility by considering its interaction with other travel modes.

Existing studies that have looked into the design and analysis of on-demand services largely overlooked the impact of these services on other travel modes and vice-versa. The existing literature hence considered the design and analysis of on-demand systems without investigating this effect of on-demand services on other travel modes and their overall impact on urban mobility. This study attempts to fill this research gap by developing an approach to the design and analysis of on-demand services in an urban mobility context. Two types of on-demand services are considered in this thesis, namely private and pooled. Both private and pooled on-demand services are characterised by a fleet of vehicles controlled by a central dispatching unit. They provide door-to-door service to passengers' travel requests in real time. While the private on-demand service provides taxi-like service to passengers, pooled on-demand service allows multiple passengers to share the service.

Figure 6.2 shows a conceptual representation of the objective, contribution, and context of the study. In the *Analysis* part, we envision several scenarios of on-demand service interaction in an urban mobility shown as I, II, and III in Figure 6.2. In (I), we consider the scenario where on-demand service compete with car, public transport, and active modes. In II, we consider the scenario where users combine on-demand service and public transport for their origin-destination journey. In III, we consider scenarios where on-demand service replaces all trips performed by car and public transport. In the *Design* part, we determine the optimal fleet size mix of an on-demand service comprising of private and pooled services.

An agent-based simulation framework with day-to-day learning of users and a stochastic user-equilibrium model is adopted for model implementation. The scientific contributions and practical implications under the *Analysis* and *Design* aspects of on-demand service are summarised in the following section.

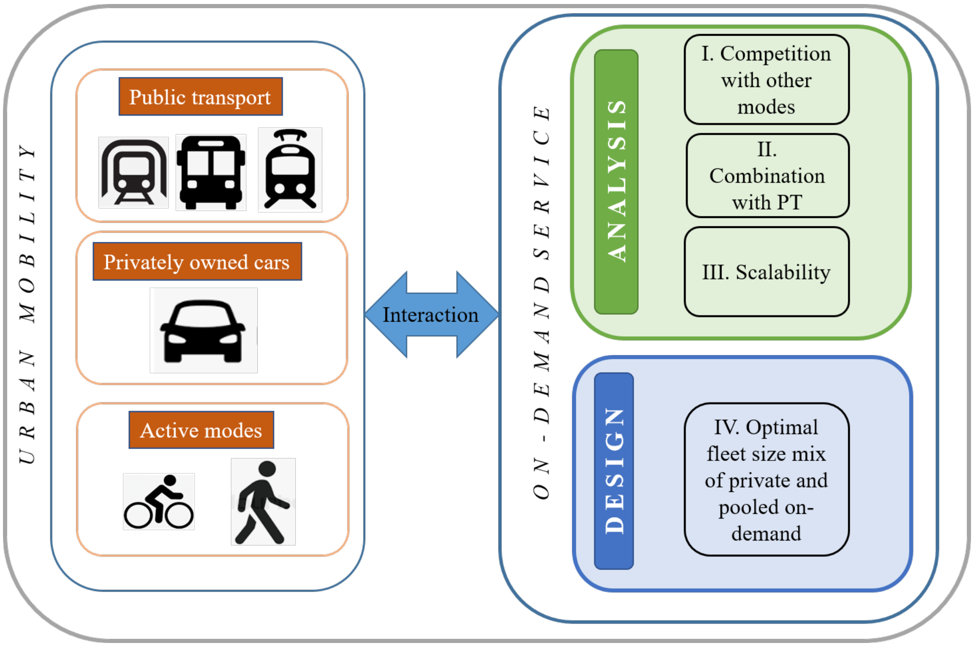

Figure 6.2: Conceptual representation of the core topics addressed in the thesis and the study context

Analysis of on-demand services

First we consider the scenario where the on-demand service competes with car, public transport, and active modes. Performance of a private and pooled on-demand service was analyzed for varying fleet size and varying cost ratios of the on-demand service compared to public transport. The analysis showed that the effect of increased fleet size on passengers' waiting times is more pronounced when a private door-to-door service is offered compared to that for pooled on-demand service. Results also showed that at higher relative cost ratios (when the fare of on-demand service is more than 5 times that of public transport), the relative gap in modal share between private and pooled on-demand service decreases. The study enables practitioners and policy makers to evaluate the implications of introducing competing on-demand services (both private and pooled) with other travel modes based on the response of users to the services experienced.

Next, we consider the scenario where users combine on-demand service and public transport in their origin-destination journey. We developed an integrated multi-modal route choice and assignment model that allows users to combine conventional line- and schedule-based and on-demand passenger transport services or use them as exclusive modes so that their travel impedance is minimized. The results indicate that most of the users combining public transport and private on-demand service are otherwise using only public transport in the base case scenario, whereas car and active mode users generally stick to their modes. The key practical contribution here is a model for evaluation of services and identifying transfer locations from on-demand services to public transport and vice-versa. This helps to support interchange facility design and to assess the performance and level of service of on-demand service as first/last mile under various public transport service attributes such as frequency.

Finally, we consider the scenarios where private and pooled on-demand services replace private car, public transport, and combined private car and public transport trips (all motorised trips). On-demand service performance in terms of level of service offered and service efficiency were analysed. Aspects where each of the two on-demand services (private and pooled) fare better or worse, in terms of level of service offered and service efficiency were identified. Our results indicate that pooled on-demand service were more efficient in terms of veh-km travelled and empty drive ratio and that private on-demand vehicles spend more time picking up passengers than pooled service for the same fleet size instance. Private on-demand services generate 43%, 38%, and 44% more veh-km than pooled on-demand when on-demand services replace car trips, public transport trips, or car and public transport trips, respectively. Also, the travel time of private on-demand users was observed to be lower than that of pooled on-demand users. Pooled on-demand users' travel time was 33%, 39%, and 48% more than that of private on-demand users when on-demand services replace car trips, public transport trips, or car and public transport trips, respectively. The study illustrates the scalability of an on-demand transport system on a city-wide level and its potential to serve trips performed by private car and public transport.

Design of on-demand services

The *Analysis* part is followed by the *Design* of on-demand services. Here, we explored the relation between the optimal fleet size of an on-demand system from the perspective of a transport planning authority (Agency) and a service provider (Operator). The Agency is assumed to be interested in minimising the travel time of all the users while the Operator is interested in maximising its profit. Results indicate that operating a private on-demand service is more beneficial for both Agency and Operator than a pooled on-demand service. Analysis of travel time of on-demand passengers also indicates that the effect of increase in fleet size on travel time are more prominent for private on-demand as compared to pooled on-demand. Comparative analyses of optimal fleet size for Agency and Operator indicate different total fleet size with the Agency perspective requiring a larger fleet than would have been required if it is to be set by the Operator. The results also provide insights into the most profitable operational strategy for the planning authority (whether to operate an on-demand service or not). The modeling framework can hence be used by on-demand service providers and also by transit planning authorities to determine the optimal fleet size in an urban context where these modes interact with car, public transport, and active modes.

Conclusion

Innovative mobility systems such as on-demand transport services is changing the way people travel; with increasing evidence from the literature indicating its potentially disruptive effects on urban mobility. Hence the interaction of such services with other modes are critical aspects to its design and analysis. The objective of this thesis was developing models for the design and analysis of on-demand mobility systems in an urban context considering its interaction with other modes. An agent-based simulation framework with day-to-day learning of users and stochastic equilibrium model was adopted and adapted for model implementation. Multiple scenarios of on-demand service interaction with urban mobility were envisioned for the analysis and finally the service design was carried out considering this interaction. The scenarios envisioned for the analysis include the one where on-demand service competes with traditional modes. Results showed that the effect of increased fleet size on passengers' waiting times is more pronounced when a private door-to-door service is offered compared to that for pooled on-demand service. The second scenario was one where users combine public transport and on-demand service for their origin-destination journey. An intergrated route choice and assignment model that enables users to combine public transport and on-demand service was developed and results showed that most of the users combining public transport and private on-demand service are otherwise using only public transport in the base case scenario, whereas car and active mode users generally stick to their modes. And the final scenario was the one where on-demand service replaces all trips performed by car and public transport. Results indicate that pooled on-demand service were more efficient in terms of veh-km travelled and empty drive ratio and that travel time of private on-demand is lower than that of pooled on-demand users. The study also illustrates the scalability of an on-demand transport system on a city-wide level. For the design part, we explored the relation between the optimal fleet size of an on-demand system from the perspective of a transport planning authority and a service provider. Results indicate that operating a private on-demand service is more beneficent for both Agency and Operator than a pooled on-demand service. Our results therefore reinforce the findings in the literaure about the effects of, and impact on, on-demand services on urban mobility.

Model improvements and future direction include enriching the behavioral model, testing more efficient dispatching strategies, considering competing service providers in an oligopolistic market setting, service optimisation of public transport and on-demand service and design and analysis of other innovative mobility systems such as carsharing and carpooling.

About the Author

Jishnu Narayan was born in Kerala, India on the 24th of August 1989. After completing higher secondary level education in 2007, he pursued Bachelors' degree at National Institute of Technology, Calicut; where he studied Civil Engineering. He completed his Bachelors' in 2011; after which, he started his Masters' in Transportation Engineering at Indian Institute of Technology, Kanpur. He graduated in 2013. His thesis focused on optimal route network design and fleet size allocation for urban transit systems using genetic algorithms.

After Masters', he joined the consultancy firm VR Techniche Consultants Pvt. Ltd. based in Delhi, India as an Assistant Transport Planner where he worked as a data analyst and transport modeller. Following this, he joined the National Transportation Planning and Research Centre (NATPAC) in Trivandrum as a Project Engineer. He primarily worked on road safety projects of State Highways at NATPAC.

In June 2016, he moved to Delft to start his PhD at the Transport & Planning Department at Delft University of Technology. His research focussed on service design and analysis of on-demand transport systems, and its interaction with other travel modes. His research interests include application of agent-based simulation modelling, and evolutionary optmisation algorithms for service design of on-demand transport and public transport systems.

During his PhD, Jishnu has presented his research at a number of national and international scientific conferences, organised workshops, and served as reviewer for several conferences and journals. His research was also shortlisted among the top 10 submissions for the TRA VISIONS 2020 Young Researcher Competition.

List of Contributions

Journal Articles

- **Narayan, J.**, Cats, O., van Oort, N., & Hoogendoorn, S. (2020). Integrated route choice and assignment model for fixed and flexible public transport systems. *Transportation Research Part C: Emerging Technologies*, 115, 102631. https://doi.org/10.1016/j.trc.2020.102631

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Data Sets

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- **Narayan, J.**, Cats, O., van Oort, N. & Hoogendoorn, S. (2020) ”On-demand public transport systems: Service design and impact on urban mobility,” Doctoral Research workshop at the *99th Transportation Research Board (TRB) 99th Annual Meeting*, Washington D.C., USA.

- **Narayan, J.**, Cats, O., van Oort, N. & Hoogendoorn, S. (2019) ”Does ride-sourcing absorb the demand for car and public transport in Amsterdam?,” 2019, *6th International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*, Cracow, Poland, 2019

- **Narayan J.**, Cats O., van Oort N. & Hoogendoorn S. (2018) “Passenger Route Choice and Assignment Model for Combined Fixed and Flexible Public Transport Systems”. *Conference on Advanced Systems in Public Transport and TransitData (CASPT)*, Brisbane, Australia. July 2018.

- **Narayan J.**, Cats O., van Oort N. and Hoogendoorn S. (2017). ”Performance Assessment of Fixed and Flexible Public Transport in a Multi Agent Simulation Framework”. *EWGT2017 (20th Euro Working Group on Transportation)*, Budapest, Hungary.

- **Narayan, J.** (2016) ”Are Demand Responsive Public Transport Systems the future of Public Transportation?” *TRAIL conference*, Utrecht, The Netherlands.

Professional Contributions

- **Narayan J.**, Cats O., and Hoogendoorn S. (2018). On-demand diensten onderzoeken met agent-based model. In : *NM Magazine*. 3, p. 19-21 [Article]

- **Narayan J.** (2019). Implications of On-Demand Services on Urban Mobility, Smart Mobility & Urban Development in Haven-Stad, Amsterdam *AMS Summer School* [Lecture]

- Winter, K., **Narayan, J.** (2018) Flexible and Smart Public Transport. *Smart Public Transport Lab kick-off event*, Delft, Netherlands. [Workshop]

- Winter, K., **Narayan, J.** (2019) Operating autonomous public transport: a MaaS perspective. *MaaS@AMS Event*, Amsterdam, The Netherlands. [Workshop]

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