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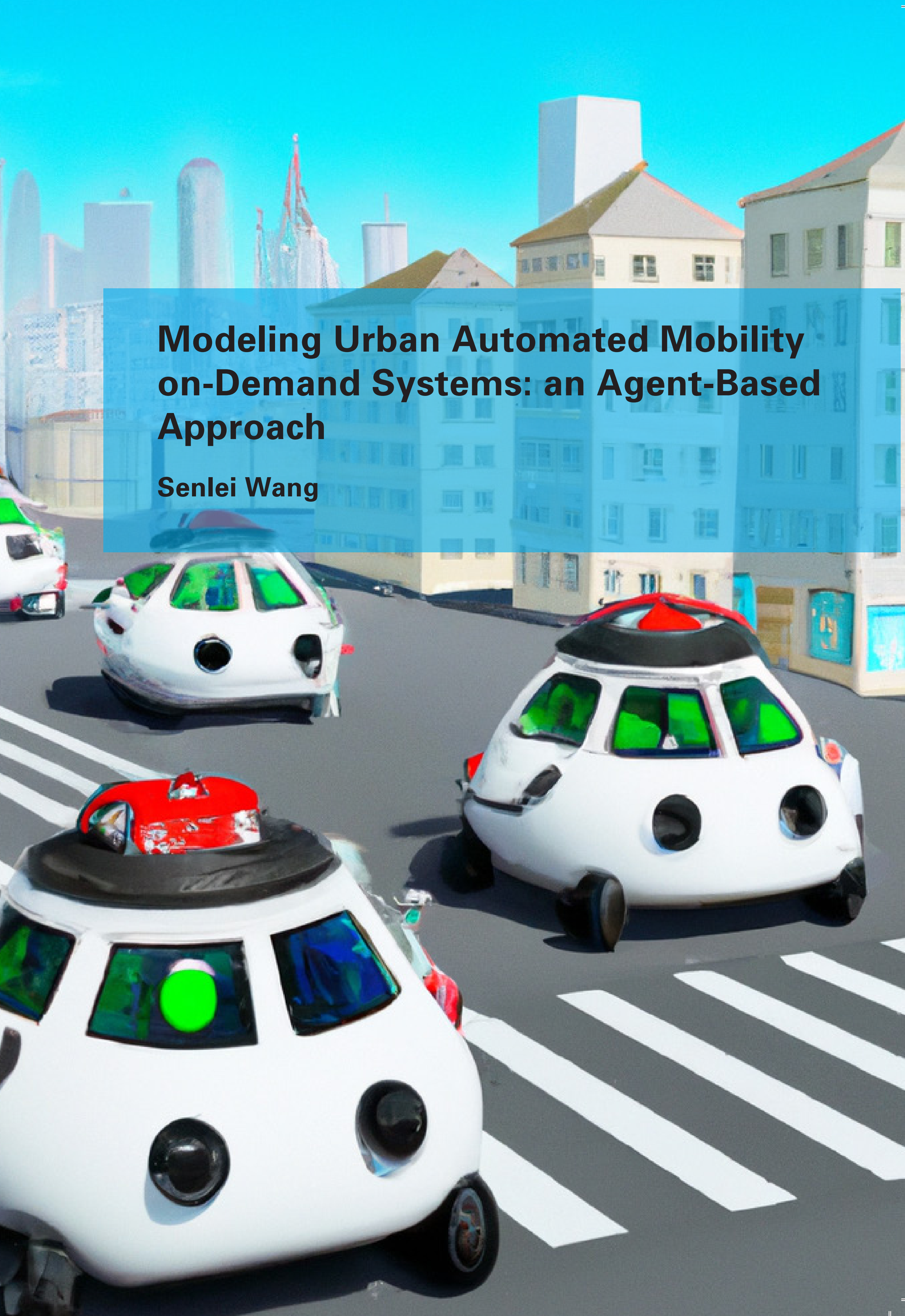
Senlei Wang



Modeling Urban Automated Mobility on-Demand Systems: an Agent-Based Approach

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Dissertation

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at Delft University of Technology
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by

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Dedicated to my parents.

Preface

I would like to thank my promotor, Hai Xiang Lin, for giving me the opportunity to conduct my Ph.D. research and for allowing me to dance with my spirit and reach for the stars. I am also very grateful for your patience and support for my research, career development, and personal life.

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Senlei Wang

Delft, the Netherlands, 2022

Summary

Automated Mobility-on-Demand (AMoD) systems, where a fleet of automated vehicles (AV) provides on-demand service, are expected to revolutionize urban mobility systems. Yet we are at a fork on the road to the emerging autonomous future. The expectation is that AMoD systems could transform urban personal transportation into sustainable, efficient, and accessible transportation services. However, there are considerable uncertainties in the planning and operations of the AMoD systems, which are not yet known and may even lead to negative results on urban mobility performance.

Research on AMoD systems and field trials of this technology are underway. Agent-based modeling, which describes a system at the level of its constituent entities, could provide a high level of detail in realistically representing the interaction between system entities and allow for changes to model assumptions, given the flexibility of this modeling approach. This is very important in the context of the uncertainty around the AMoD systems. Thus, in this thesis, we deem agent-based modeling as being well suited for investigating future AMoD systems with multiple interacting entities (e.g., travelers, shared AVs, and AMoD operators) and therefore shed some light on the uncertainties about the operations and the effects of such systems.

To begin with, one of the possible AMoD application scenarios is that many micro AVs will function as taxi systems to provide direct on-demand mobility solutions to travelers (e.g., morning commuters) in urban areas. In this thesis, service schemes are designed according to what is best for the service providers and travelers. With the help of a new agent-based modeling framework, simulation experiments are conducted in an urban area to explore the potential of different AMoD service schemes (e.g., door-to-door service, station-to-station service, simultaneous operation of two services).

Along with emerging AMoD services, micro AVs equipped with automated driving systems can be coordinated in platoons through connectivity and automated driving functions. Platoon operations provide an innovative way of operating vehicles. Briefly, we can envision a future urban mobility system in the 2030s or 2040s whereby individual micro AVs could carry commuters from one place to another, while swarms (platoons) of micro AVs could transport many commuters together with potential energy savings. Platoon-enabled AMoD systems could provide a solution to create a futuristic mobility system with better service quality, traffic efficiency, and energy efficiency. We have extended our modeling framework by allowing platoon operations to take place when AVs circulate across the urban road network. We delve into how the formation of platoons in AMoD systems may affect people's traveling but also system-wide performance indicators such as energy consumption of the fleet, which will most likely be constituted by electric vehicles.

Moreover, with the rapid development of AMoD systems, it will be natural to see fleets of micro AVs operated by multiple companies (e.g., Waymo, Baidu, Mercedes-Benz), which may drive a new urban mobility ecosystem. Motivated by the rapid development of AMoD solutions delivered by self-driving car companies, we have again extended our agent-based framework for allowing a multiple-operator AMoD system. We study the future scenarios of multiple-operator AMoD systems with exogenous demand to explore the potential effects of operating strategies (e.g., relocation strategies) in a competitive market. Furthermore, the decision-making mechanism of the travelers is considered by incorporating a mode choice component into the agent-based framework. The extended modeling framework is used to study the coexistence phenomena of multiple AMoD operators competing for customers. The modeling framework has been implemented and tested in a case study city.

Overall, with advanced agent-based models applied to emerging AMoD systems and developed algorithms, this thesis aims to advance the understanding of AMoD technologies and address uncertainties in future urban AMoD applications. It is critical for stakeholders to know exactly how AMoD systems should be operated in urban or regional mobility systems. Recommendations to various stakeholders (e.g., city government, original equipment manufacturers, service providers) are provided through the different contributions.

A significant commitment across agent-based modelers, analytical modelers, urban planners, and transport researchers is still needed in further research to answer the questions that arise regarding future AMoD systems. Pioneering investigations should continue to infuse sustainability and operating efficiency into the planning and operating AMoD systems to aid a smooth transition to a future transportation system.

Content

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List of Abbreviations

Abbreviation	Explanation
AV	Automated Vehicle
SAV	Shared Automated Vehicle
AMoD	Automated Mobility-on-Demand System
DARP	Dial-a-Ride-Problem
POV	Privately-Owned Vehicles
SAEV	Shared, Automated and Electric Vehicle
ICEV	Internal Combustion Engine Vehicle
EV	Electric Vehicle
TNC	Transportation Network Companies
ABM	Agent-Based Model
FCFS	First-Come, First-Served
OEMs	Original Equipment Manufactures
AI	Artificial Intelligence
PT	Public Transportation
MNL	A Multinomial Logit
VKT	Vehicle Kilometre Travelled
SSS	Station-to-Station Service
DDS	Door-to-Door service
TVTS	Time-Varying Transit Service
PTS	Parallel Transit Service

Chapter 1

Introduction

This introductory chapter introduces the background information on the future application of AMoD systems, briefly describes the current state of knowledge on modeling AMoD systems, and discusses the research challenges in planning and operating future AMoD systems that have been tackled in this thesis.

The chapter is organized as follows. In section 1.1, we give background information about AMoD systems. Section 1.2 presents the research challenges that need to be addressed in planning and operating AMoD systems. Section 1.3 formulates the research questions of the Ph.D. project. The main scientific and practical contributions of this thesis are summarized in Section 1.4. The outline of the thesis is presented in Section 1.5.

1.1 Background

As the urbanization process continues, the world population keeps concentrating more and more in the main cities. One of the biggest challenges for many cities worldwide is to provide transport infrastructure and mobility services to serve an increasing number of travelers.

Three-quarters of the population in Europe live in cities but still the number of people in most cities is expected to increase by more than 10% in the next 30 years (https://ec.europa.eu/). The growing number of inhabitants is putting extra pressure on transit supply and road infrastructure. Continuously, road traffic is increasing, and demand for public transit systems is growing. City authorities face the challenge of providing citizens affordable and efficient mobility options and are urgently seeking smart and innovative solutions for sustainable, efficient, economic, and inclusive transport.

With changes in mobility behavior and lifestyles, advances in urban mobility technology are opening up new opportunities for a sustainable and efficient urban transport system. AVs bring a unique opportunity for changing urban mobility, leading to significantly better mobility services with reduced costs of negative road transport externalities (accidents, congestions, emissions and oil dependence).

As we continue to witness the accelerating roll-out of AVs, transportation is experiencing the fastest and most far-reaching disruption in the new era of automation. The automotive industry is on an accelerating change curve with AVs and leads the transformative trend towards driverless mobility.

The Society of Automotive Engineers (SAE) has defined six levels of vehicle automation, from Level zero (fully manual) to Level 5 (full automation). The term AVs used in this thesis refers to vehicles equipped with SAE-level 5 automated driving systems: AVs (SAE-level 5), known as self-driving cars or driverless cars, are capable of driving everywhere in all conditions with no need for any human intervention.

Combining AVs with ride-hailing services is steering the paradigm shift of urban mobility systems. The transition towards AMoD or automated ride-hailing systems for both people and goods is already underway. Urban commuters may relinquish POV ownership and access the AMoD service in the foreseeable future.

Given the great potential of AMoD systems and the expected disruptive transformations of the urban transport system, there has been great interest in exploring the impacts of AV operations in passenger transport systems over the last few years.

A broad spectrum of research focuses on investigating the potential of operating AMoD systems on *operational cost*, *transport levels of service offered to travelers*, *environment*, *traffic congestion*, *energy consumption*, *pricing*, *and parking*. Some studies provided an assessment of operating AMoD systems when combining *public transportation options*. Several studies focused on deploying control or optimal strategies to manage AMoD systems (Hörl et al., 2019; Hyland & Mahmassani, 2018; Oh et al., 2020a). Existing studies demonstrated that the convergence of vehicle automation, electrification, and shared mobility in AMoD systems could provide sustainable, economical, and efficient transportation options (Hensher et al., 2021; Milakis et al., 2017). However, there are considerable uncertainties about achieving these benefits (Anania et al., 2018; Paddeu et al., 2020).

1.2 Research challenges raised in urban AMoD systems

As vehicle automation technology advances, new transportation use cases will emerge that are primarily driven by factors such as vehicle types (e.g., different vehicle sizes and automation levels), service schemes, and the organization of AMoD services (e.g., single operators or multiple operators). Planning and operations of AMoD systems require the establishment of guidelines to be prepared to meet the mobility needs of travelers in urban areas. However, in the future application of AMoD systems, there are still many uncertainties as to how AMoD systems are operated and organized to provide significant benefits to system users, fleet operators, and cities. Therefore, there is an urgent need to explore the potential impact of innovative operations in various forms of AMoD systems on serving urban travel demand in response to driverless disruption, which has great potential to transform the existing urban passenger transport system. Below, we describe four areas that require further research.

First, little attention has been paid to exploring the implementation of efficient AMoD systems in terms of the different service schemes in which they might be operated and the potential synergies between them. For example, services provided to travelers can be switched between a door-to-door service and a station-to-station service; two services could be operated simultaneously to provide services in the same urban area according to what is best for service providers and travelers. Flexible service schemes enabled by vehicle automation need to be designed and compared; at the time of the start of this thesis, little was known in the literature.

Second, the impact of platoon operations on urban and highway traffic has been studied, assuming that AVs are already in platoons. Some studies investigated the problem of coordinating vehicles in platoons on highways. However, the impact of the creation and operations of such platoons on urban passenger AMoD systems has not been the subject of much research. Hence, there is a lack of evidence on how the creation and operations of such platoons affect people’s travel and energy usage in urban passenger AMoD systems.

Third, existing studies focus on examining the impact of a single-operator AMoD system with and without consideration of public transportation options. With the rapid development of emerging AMoD services, it will be natural to see fleets of AVs operated by multiple independent companies. Existing models and tools lag behind the rapid developments in urban multiple-operator AMoD systems. So, there is a need to develop a new modeling framework to simulate emerging AMoD systems with multiple independent operators and fill the knowledge gap of multiple-operator AMoD systems by exploring the potential of operations (e.g., relocations) in the competitive market.

Fourth, current research has focused primarily on the impact of introducing the urban AMoD service that is provided by a single AMoD operator into urban mobility systems while considering supply and demand interactions. However, the phenomena associated with the coexistence of multiple AMoD operators competing for customers in a situation where information is completely shared is overlooked. There is no modeling framework to study this complex phenomenon, and insights into how to develop effective strategies by AMoD operators competing for customers are lacking.

The thesis addresses these research needs by developing a new agent-based modeling framework. The impacts of innovative operations in different urban AMoD systems can be quantified within the modeling framework; recommendations for different stakeholders can be presented through scenarios and case studies.

1.3 Research questions

AMoD systems are envisaged for the future, probably in operation between 2030 to 2040 when vehicle automation technology has matured enough and AVs have become affordable. We may see a situation in the foreseeable future where hundreds and even thousands of micro AVs will function as taxis or MoD systems to provide on-demand service to serve clients in urban areas. The main objective of this thesis is to study new phenomena of *providing different service schemes, forming platoons, transporting travelers in multiple-operator settings with and without relocations, and competing for travelers in urban AMoD systems comprised of different AV operators.* More specifically, this thesis addresses the following main research questions and associated sub-research questions.

Question 1: What are efficient ways of operating SAVs under different on-demand service schemes within the urban service area?

Sub-question 1: Which service schemes in terms of pickup points and doorstep service should be provided when serving demand in urban areas?

Sub-question 2: How can available vehicles and passengers be effectively matched?

Sub-question 3: How does ride-sharing operation affect the service offered to customers and fleet efficiency?

These questions are answered in ***Chapter 3.***

Question 2: What are the impacts of forming platoons in AMoD systems on travelling and energy efficiency?

Sub-question 1: What are the impacts of the formation and operation of urban platoons on the service quality offered to travelers and traffic efficiency related to road network travel times?

Sub-question 2: How do changes in traffic conditions by platoon operations affect the travel-related energy consumption of traffic participants across the urban road network?

These questions are answered in ***Chapter 4.***

Question 3: What are effective operating strategies for independent operators to gain a competitive edge in a situation without information sharing?

Sub-question 1: How do changes in supply (vehicle fleet) affect the performance (e.g., service levels, fleet efficiency, and profit) of an operator and its competitors coexisting in the same urban area?

Sub-question 2: How do relocation strategies of an operator affect the operator's performance?

These questions are answered in ***Chapter 5.***

Question 4: How do operators compete for clients in multiple-operator AMoD systems where information (travel requests, vehicle fleet, prices) are completely shared within a platform?

Sub-question 1: How do changes in pricing strategies affect travelers' choice of AMoD services and the operating performance of competing operators?

Sub-question 2: How do changes in assignment methods affect travelers' choice of AMoD services and the operating performance of competitors?

Sub-question 3: How do changes in fleet sizes affect travelers' choice of AMoD services and the operating performance of competitors?

These questions are answered *in* ***Chapter 6.***

To answer these questions, a new modeling framework was developed for different forms of emerging AMoD systems proposed in ***Chapters 3 through 6.***

1.4 Thesis contributions

This thesis has made contributions to the literature by developing an agent-based modeling framework to answer specific questions raised in future AMoD systems. We examine the practical effects of operating such systems from different perspectives (e.g., service operators, travelers). This section highlights the main contributions of this thesis to the literature and practice.

1.4.1 Contributions to the literature

In **Chapter 3,** we propose *four different AMoD service schemes*, and a simulation framework has been developed to evaluate the performance of AMoD services under different service schemes. We examine the potential of the AMoD systems and compare their performance. Moreover, a ridesharing mechanism and two different optimal assignment methods are developed and implemented. We demonstrate the effectiveness of the ridesharing operations for different AMoD services.

Our study in **Chapter 4** is the first to assess the potential of the *strategic formation* and operations of such platoons in future urban AMoD systems. For such a study, we develop an advanced modeling framework to tackle the challenges raised in the formation of urban platoons by detailing the behavior of travelers and vehicles as well as their interactions. Through the novel framework, in which the platoon-formation operations are modeled at different levels of detail, we can delve into how the formation of platoons in AMoD systems may affect people's traveling but also system-wide performance indicators such as energy consumption of the electric AMoD fleet. The findings of this study contribute to the growing body of literature on the study of SAVs planning and operations by assessing the travel impact of forming platoons in urban AMoD systems. Furthermore, we shed light on the energy aspect of innovative platoon operations in urban AMoD systems to complement the existing studies on the fuel consumption of platoons on highways.

Chapter 5 first models *multiple independent operators* coexisting in the same urban area to complement state-of-the-art literature relevant to a single urban AMoD operator. Notably, we have studied relocation operations and evaluated the potential of relocating vehicles for an operator compared to their competitors in a multiple-operator AMoD system. It adds to a growing body of studies related to relocation operations in the multiple-operator carsharing system, which differs from multiple-operator AMoD systems in terms of the system operations (optimal assignment and relocation mechanism) and operating costs. Performance is evaluated within the new modeling framework to provide insights into the competitive dynamics through a set of key performance indicators in terms of service quality offered to travelers, system efficiency, and the operators' profits.

Chapter 6 is the simulation study to investigate the problem of competing for customers between multiple AMoD operators. One of the main contributions is that a customer decision-making mechanism is designed as part of the modeling framework to allocate customers to different AMoD services. Using the agent-based modeling framework, we dig into travelers' considerations of when to choose the services offered by which competing AMoD operators under different operating strategies (fleet sizes, pricing, assignment strategies).

1.4.2 Contributions to practice

The framework presented in the thesis provides a risk-free, time- and cost-saving virtual environment. This reduces the cost, takes less time, and improves safety compared to field trials. Simulation studies of different AMoD systems can be performed for service providers to test different realistic scenarios with the objective of finding an efficient way to provide their services. For example, the effectiveness of the vehicle-to-passenger assignment algorithms in **Chapter 3,** the platoon formation algorithm in **Chapter 4**, the relocation algorithm in **Chapter 5,** and the pricing structures in **Chapter 6** are tested. The performance evaluation can help service providers avoid the risk of failure and assist them in developing effective strategies to improve the transport level of service, fleet efficiency, and profit. The operations that have been demonstrated to be effective can be incorporated into AMoD system design as key functionalities of management systems.

Introducing AMoD systems in urban areas can pose challenges for policy-making. Policy recommendations are formulated from different perspectives. Based on the quantitative analysis of the findings of simulating platoon formations, **Chapter 4** discusses the policy recommendation regarding whether to coordinate vehicles in platoons and the energy aspect of platoon operations. Also, simulation results allow policymakers (e.g., city authorities) to understand the impact of forming platoons in urban AMoD systems. Fostering an understanding of the potential can help them gain a deeper insight into how to take advantage of AMoD technology with a view to achieving mobility and energy goals.

As a case study, we apply the urban multiple-operator AMoD systems to the city of The Hague, the Netherlands. In **Chapter 5**, simulation experiments are performed to generate a spectrum of possible outcomes. Based on insights gained from simulation outcomes, we provide recommendations for city authorities on how to regulate the emerging AMoD market and for service providers on how to gain a competitive edge over their counterparts.

Through the simulation experiment **in Chapter 6**, we explore a variety of possible future application scenarios around the core issues of the competition for customers between AMoD operators. We gain insights into how the operating strategies affect people’s travel (e.g., travel times and choices to go to different AMoD services) in a competitive market that gives customers multiple AMoD options. In this way, we inform policymakers (e.g., city authorities and service providers) about the decision-making process to prepare for the arrival of AMoD services in cities.

1.5 Outline

This thesis consists of seven chapters.

Chapter 2 discusses the methods used to address the challenges in planning and operating AMoD systems. We divided the methods into two categories: analytical methods and simulation methods. Notably, we show the suitability of agent-based modeling in tackling the urgent problems of operating AMoD systems characterized by multiple entities and complicated interactions.

As a first attempt to study the impacts of AMoD operations under different service schemes, **Chapter 3** simulates the on-demand operations of SAVs in the proposed urban AMoD systems. Simulation experiments are conducted in a hypothetical urban area (roughly the size of Delft in the Netherlands) to demonstrate the potential of different AMoD service schemes.

In the continuation of the research, new functionalities related to platoon formations, energy consumption, and mixed traffic simulation are developed in **Chapter 4.** A novel study was performed on the real-size urban road network of The Hague, The Netherlands, to assess the travel and energy impact of forming platoons in urban AMoD systems.

Chapter 5 presents a study of multiple independent AMoD operators without sharing information, which may drive a new mobility ecosystem. Operating strategies (e.g., vehicle relocation) in the future multiple-operator AMoD systems with exogenous demand are investigated.

In **Chapter 6**, an urban AMoD system formed by multiple AMoD operators is defined. A sophisticated modeling framework for multiple-operator AMoD systems with endogenous demand in urban areas has been developed to evaluate individual operators' performance in a competitive market in which an AMoD operator changes service prices and fleet sizes.

Chapter 7 concludes with the main findings and provides recommendations for future research.

Chapter 2

Research Methodology

This chapter explains the research methodology that has been followed in this thesis with an emphasis on the agent-based modeling technique; in particular, the strengths and limitations of agent-based modeling are discussed.

This chapter is organized as follows. In section 2.1, we describe the agent-based technique as a modeling approach. Section 2.2 provides a summary of existing agent-based model development software. Conclusions are drawn in Section 2.3.

2.1 Agent-based modeling

The three most widely used simulation-based modeling techniques are system dynamics, agent-based, and discrete event modeling (Birta & Arbez, 2019). Each method serves a particular range of abstraction levels. System dynamics, typically used for strategic modeling, require a very high level of abstraction. Discrete event modeling supports an intermediate level of abstraction. System dynamics and discrete event modeling use a top-down view of system functions, while agent-based modeling is a bottom-up approach.

This thesis uses the agent-based modeling technique to answer the research questions. Agent-based modeling is a modeling paradigm that describes a system at the level of its constituent units (entities) (Bonabeau, 2002; Macal & North, 2015). In agent-based modeling, a system is modeled as a collection of agents. In order for the agent to interact, the interaction mechanism (a set of specified rules or equations) must be designed. The global or collective behavior of the modeled system emerges as a result of the interactions of individuals.

2.2.1 Strengths and limitations of agent-based modeling

Agent-based modeling is becoming a popular modeling method and is used in various disciplines, from social sciences, biology, political science, and transportation. The strengths of agent-based modeling are summarized as follows:

First, agent-based models can be populated with data that are being collected. Agent-based models can have a high level of detail whereby attributes of agents are initiated based on the data. In particular, the approach can model both travel demand and transport supply with the same level of detail. The more detail that is included in the simulation, the higher the resolution.

Second, the systems that we need to analyze and model are complex in terms of their interdependencies. There is a desire to gain deeper insights into systems. Agent-based modeling can explicitly model the entities and their interactions that occur in a real-world situation. With realistically represented interactions, the model structure can reflect the system structure. Therefore, agent-based modeling can provide a realistic view of systems.

Third, the development process is scalable, incremental, and modular. This results in the flexibility of the agent-based approach. One dimension of flexibility means that the modeling approach can provide different levels of description of the target system to be modeled. (e.g., vehicles and platoons formed by vehicles; relocation vehicles and relocation decision by operators) to evaluate different aspects of the system. Another dimension is that it is easy to make changes to assumptions (e.g., formation policies) and strategies (relocations, platoon formations, vehicle-to-passenger assignment, pricing) for different scenarios, given the flexibility of this modeling approach.

Fourth, agent-based models have the ability to be represented in a visual animation. Model animation is very useful for model demonstration, verification, validation, and debugging.

Modelers can measure variables and track entities, and add measurements and statistical analysis at any time. Overall, the main advantages of agent-based modeling are higher resolution, fidelity (model matches reality), flexibility, visualization, and traceable results.

There are some limitations associated with the application of the agent-based approach in the field of transport planning. One general limit is that simulating individual agents requires significant computational power, especially when individual agents have complex characteristics and decisions, as in the case of humans. Rapid advances in computing power and memory make large-scale simulations (thousands of AVs in AMoD systems in case-study cities) plausible. Large-scale agent-based simulations can be performed for different scenarios to simulate the operations and interactions of a group of entities.

Another limitation has to do with the nature of the system being modeled. Agent-based models often require behavioral data, which can be difficult and costly to obtain. It is also difficult to validate such a model, especially if the goal is to predict the behavior of an untested system. Moreover, building agent-based models requires a lot of programming and verifications to assure the functional components work as intended. Hence, building an agent-based model takes time.

2.2.2 Agent-based modeling and simulation

In this section, we briefly explain modeling and simulation in general and the connection between agent-based modeling and simulation in particular. The general development process in modeling and simulation goes through five phases of a cycle: 1) system definition (defining a system under investigation), 2) a model, 3) simulation (execute a model on a computer for experimentation), 4) analyzing the simulation results, and 5) making inferences about the modeled system. The modeling and simulation development process in Figure 2.1 will require a number of iterations of the development cycle.

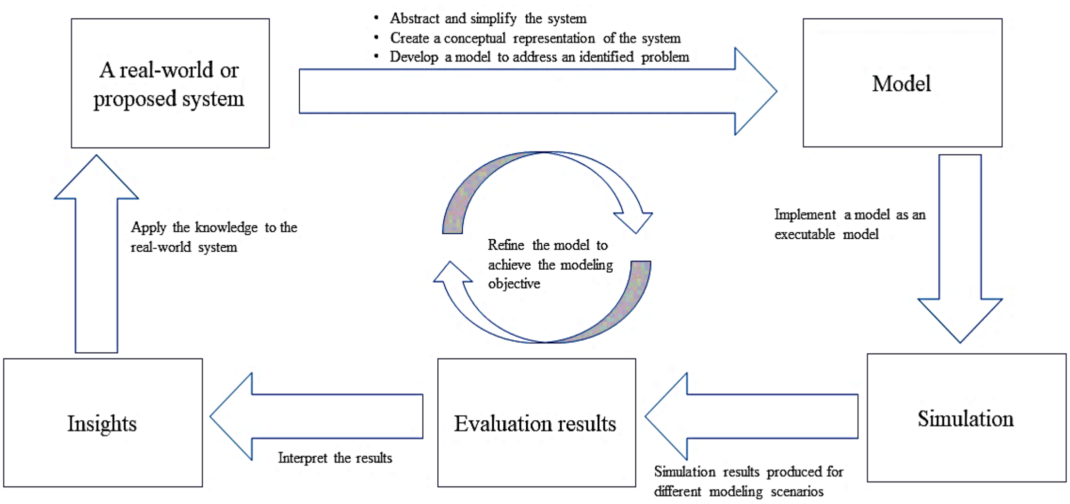

Figure 2.1 Model and simulation development process

The system definition refers to defining the subject being investigated. To develop a model, data and knowledge about the system are required. Modelers must study the system and collect the data for model development with a clear statement of the identified problem. A conceptual model is required to give descriptions of modeling objectives, model assumptions and simplifications, model input and output, and model specifications (e.g., functionalities, entities). The conceptual model aims to abstract the model from the system based on the understanding of the problem situation. The result of this conceptualization process is a non-software description of the model to be developed. A conceptual model could be a textual or graphical representation of a real-world system.

At the heart of the development process are models. A model is a representation of real-world (actual or proposed) systems with abstractions and simplifications. A model is not intended to represent all aspects of the system being studied; however, the model should be created, capturing the essential aspects that affect the performance of the system under investigation.

More broadly, simulation can be considered a method for studying systems. In this thesis, modeling and simulation, including the simulation step, are considered comprehensive methods for studying a system. Therefore, simulation refers to the software implementation of a model that allows the model to be run on a computer. For example, numerical simulation refers to a calculation running on a computer following a program that implements a mathematical model (Sommariva et al., 2021). Simulation is the process of executing a model to develop data or produce outputs regarding the behavior of the modeled system in order to make informed decisions. An agent-based model is a computer executable model. Therefore after the agent-based model is developed, simulation experiments can be designed to evaluate the system performance according to the modeling objective.

The system performance can be measured by defined indicators that are suitable to answer the questions. When obtaining the simulation results, the modeler can perform an analysis of the model output. These indicators are often called key performance indicators.

The objective of the modeling and simulation study is to generate insights by interpreting the evaluation results and applying the knowledge to the real-world system. Then, we can better understand the complexity of the system and improvements to the system. By utilizing the obtained knowledge, useful information can be provided for refining and modifying the model to bring it in line with the modeling objective.

2.2 Agent-based model development software and toolkits

Agent-based modeling can be performed using general-purpose software, proprietary software, and programming languages. ABM development environments such as Netlogo, MATLAB, and Mathematica can be used to learn the agent-based approach and perform basic analysis. General-purpose languages (Python, Java, C++) can be used directly. However, modelers will spend a lot of time developing templates of fundamental building blocks (e.g., for creating agents or defining agent states). Large-scale agent development toolkits are more efficient in developing an agent-based model. Repast, Swarm, Mason, and Anylogic are the most commonly used development toolkits.

This thesis developed the agent-based modeling framework from scratch in the Anylogic proprietary platform (Borshchev et al., 2002). AnyLogic is a flexible simulation software and provides several options for developing simulation models. The creation of AnyLogic was strongly inspired by Java, which is an efficient language for modelers. Java is a high-level language where you do not have to care about memory allocation, distinguishing between objects and references, etc. Moreover, Java is a full-featured object-oriented programming language with high performance. Furthermore, Java is more straightforward and easier to use than C++, especially for beginners. Finally, Java is supported by industry leaders, and as Java gets better AnyLogic modelers automatically benefit.

2.3 Conclusions

This chapter gives a detailed explanation of agent-based modeling and shows the advantages of the agent-based modeling technique. Notably, agent-based modeling can model a system with a high level of detail, leading to a high model resolution. Moreover, an agent-based model can realistically represent the interactions of system entities and their dynamic dependencies. Furthermore, it is flexible to make changes to the model (e.g., assumptions and specifications). Agent-based modeling is well suited to our study on modeling urban AMoD systems characterized by multiple entities and complicated interactions between entities.

Many agent-based development software toolkits have been designed to support agent-based model development. Modelers can choose the development environment depending on their background knowledge, project time, and available resources (e.g., computing clusters or funding).

The agent-based model development cycle provides the steps of developing models to answer specific questions. Generally speaking, modelers need to build and refine models until models are good enough (e.g., appropriate levels of detail, realistically represented interactions) to answer the specific questions.

Chapter 3

Modeling Different Service Schemes in Single-Operator AMoD Systems

The developed ABM aims to simulate the on-demand operations of AVs in a parallel transit service (PTS) and a tailored time-varying transit service (TVTS). The proposed TVTS system can switch service schemes between a door-to-door service (DDS) and a station-to-station service (SSS) according to what is best for service providers and travelers. In addition, the proposed PTS system that allows DDS and SSS to operate simultaneously is simulated. To test the conceptual design of the proposed AMoD system, simulation experiments are performed in a hypothetical urban area to show the potential of different AMoD systems. The impact of ride-sharing on operational efficiency is examined according to the designed operational rules. We provide an analysis of how different vehicle assignment methods impact system performance related to the level of service and fleet efficiency. [1]

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[1] *This chapter is based on the published paper: Wang, S., Correia, G.H.D.A., Lin, H.X. (2019). Exploring the Performance of Different On-Demand Transit Services Provided by a Fleet of Shared Automated Vehicles: An Agent-Based Model. J. Adv. Transp. https://doi.org/10.1155/2019/7878042*

3.1 Introduction

It is being said that we are at the dawn of the next mobility revolution with the introduction of automated driving. However, there are aspects of automated vehicles (AVs) that still need to be understood. For example, there are many legal, regulatory, and technical problems that are delaying the deployment of AVs. A fleet of shared automated vehicles (SAV), which functions as a centralized taxi service system, will probably bring the most disruptive changes in urban mobility. The real potential of SAVs is that they make the implementation of an entirely new public transportation system possible. That is, SAVs might have the power to transform transportation mobility fundamentally and revolutionize the transport system, given the added degrees of freedom of operating shared taxi systems (Bösch et al., 2018b; Greenblatt & Saxena, 2015; Jager et al., 2018).

A fleet of SAVs operated in a centralized way in AMoD systems could function as an efficient taxi system to provide demand-responsive service for travel demand during a day, especially in urbanized areas. The AMoD system could be used to provide station-to-station service (SSS) (services between pickup points) to transport as many people as possible in busy routes in a demand-responsive fashion. However, the AMoD system could also be operated as a door-to-door service (DDS), giving great convenience to travelers as of today's Transport Network Companies such as Uber, Lyft and Didi Chuxing. In this chapter, we aim to take into consideration these two ways of operating urban automated transport systems, both in parallel and in sequence, and propose a simulation tool to assess their impact on an urban network.

Building upon the on-demand DDS and on-demand SSS, two extra on-demand transit service systems are proposed and simulated. Time-varying transit service (TVTS) that can switch service schemes between DDS and SSS depending on the time of day (peak hours and off-peak hours, for example), and the simultaneous operation of DDS and SSS, allowing both of them to operate in parallel (designated as parallel transit service: PTS).

In addition, AMoD systems could facilitate the implementation of dynamic ride-sharing, which aims to pool multiple travelers with similar origins, destinations, and departure times in the same vehicle. Dynamic ride-sharing has the potential to improve the performance of proposed AMoD systems in terms of energy-saving, waiting time reduction, VKT reduction, etc (Alonso-Mora et al., 2017; Farhan & Chen, 2018; Furuhata et al., 2013). More importantly, the dynamic ride-sharing could enable the AMoD system to accommodate more travel demand with the same number of vehicles. The proposed AMoD systems offering various service schemes with dynamic ride-sharing could eliminate the problems in past attempts to provide demand-responsive transit services (Daganzo, 1984).

Few studies have explored the operation of variations in the service schemes of AMoD systems in which they could be operated and the potential synergies among those. This chapter attempts to fill that gap through a simulation study in a hypothetical city as a first approach to the problem. The ABM describes the AMoD system with its details and complexity by modeling the travel requests and vehicle movements, and especially interactions between vehicles and travelers. With the help of ABM, conceptual design and a preliminary study are presented for different AMoD systems as defined above: SSS system, DDS system, TVTS system, and four PTS systems. The ABM is used to explore the trade-offs in different AMoD systems between the service levels, captured by the waiting time and service time (in-vehicle travel time) and the system efficiency in terms of VKT, system capacity, and served trips.

The model allows us to understand how the system components of the AMoD system behave over time and find the potential of AMoD systems by studying the most efficient ways of operating them under different service schemes. Therefore, the preliminary look at the performance of AMoD systems could provide useful information for transport operators when deciding to adopt an AMoD system in the future. Nevertheless, it also provides support for future more detailed simulation studies whereby these schemes might be important to test.

The remainder of the chapter is organized as follows. Section 3.2 presents the model specifications. Section 3.3 gives a detailed description of the experiments that have been run. Section 3.4 provides an analysis of the simulation results. Conclusions are drawn in section 3.5.

3.2 Model Specifications

The ABM is intended to simulate the operations of SAVs and their interactions with travelers' real-time requests within a hypothetical city area. We simulate tailored AMoD systems with various service schemes as already described. In this study, the fleet operator has no information about the travel requests in advance. In other words, the fleet operator has no information about travelers before they request service. After a traveler requests a vehicle, the fleet operator knows the information of the traveler. The fleet operator only assigns the idle vehicles to serve the travelers in a real-time fashion, and therefore scheduled assignment in a pre-booking fashion is not possible. As shown in Figure 3.1, the fleet operator is responsible for real-time vehicle assignment, dynamic ride-sharing, and managing and monitoring information of travel requests and vehicles. In addition, the central operator is designed for route assignments for SAVs. Vehicle assignment means that the fleet operator finds idle vehicles to serve real-time travel requests. The route assignment is to find a route either for en-route pickup vehicles or en-route drop-off vehicles. We distinguish the functions between the fleet management center and the central routing center, enabling the designed system to keep an expanded capability for multiple operators.

The interactions of system components between SAVs and time-dependent travel requests are shown in Figure 3.1. The fleet management center controls the assignment of SAVs to serve real-time travel requests. After the assignment of SAVs, communications will take place between travel requests and SAVs until travelers arrive at their destination. After SAVs receive the essential information (origin, destination, identification) of travel requests, each

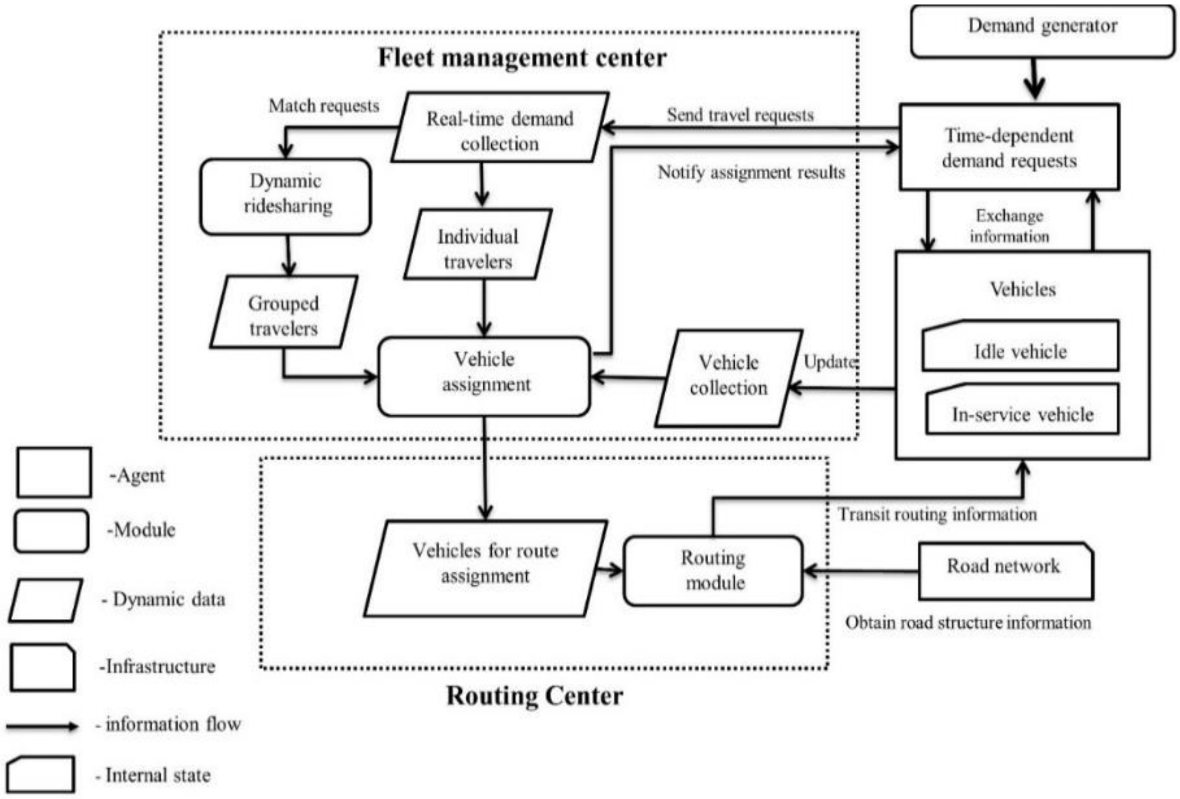


Figure 3.1 Interaction between system components

SAV will communicate with targeted travel requests for pickups and drop-offs. The dynamic ride-sharing module in the fleet operator aims to group travelers according to the matching rules. The routing module is responsible for the route calculation for real-time vehicle routing. The central operator will transit routing information to the in-service vehicles. The model contents include dynamic generation of time-dependent requests, real-time vehicle assignment, and dynamic ride-sharing. To deal with the lack of some essential information, we give the detailed description of model assumptions:

- No induced travel demand is taken into account;
- All the travelers are willing to share rides with strangers;
- The battery capacity can support full-day operations for each SAV;
- The parking spaces are enough for all the SAVs in each station.

For easier model implementation, we simplify the following model specifications:

- SAV speed is predefined on road segments and updated for peak hours and off-peak hours, respectively;
- Cancellation of assigned SAV is not allowed;
- Travelers will give up a request when the waiting time for being assigned a vehicle exceeds a specific time threshold;

- Travelers' choices between door-to-door service and station-based service are based on a fixed willingness to use a certain service, which is an experimental parameter (20%, 40%, 60%, and 80%).

3.2.1 Real-time SAV assignment

In this model, two assignment methods are designed. The first vehicle assignment method is to assign the nearest idle vehicles to serve the real-time travel requests according to the first-come, first-served (FCFS) principle. We define the first vehicle assignment method as the FCFS vehicle assignment method. The second is an optimal assignment method that assigns a group of idle vehicles to bundled travel requests with the objective of minimizing the total empty travel distance for the pickups.

3.2.1.1 FCFS vehicle assignment method

We design a fleet operator to assign the idle and nearest SAVs to serve real-time travel requests. The rules of the design are as follows:

The fleet operator will find an idle and nearest SAV in the same sub-region as the request departure location based on the FCFS principle;

- If there is no available SAV close to the request, the fleet operator will find an idle SAV from the whole study area to serve it;
- The fleet operator only gives top priority to shared riders. That is, the travelers who will share their rides are sorted from the waiting list and assigned an idle and nearest SAV as soon as possible.

3.2.1.2 Optimal vehicle assignment method

The optimal vehicle method can assign a group of idle vehicles $V = \{v_{1,} \dots , v_n\}$ to bundled travel requests $R = \{r_{t1,} \dots , r_{tn}\}$. That means that the fleet operators can bundle a certain number of travel requests, each of which is specified with a timestamp, and assign a group of available vehicles to them with the objective of minimizing the total empty travel distance of the assignment. The size of bundled travel requests varies along the day according to the demand that coincides with the same time interval. The collection of idle vehicles participating in the optimal assignment is found by searching the nearest vehicles for each travel request in the set R. The assignment problem can be formulated as a bipartite matching problem between bundled travel requests and selected idle vehicles in every dispatching time interval. The Hungarian algorithm (Kuhn, 2010) is used to solve the problem.

Nevertheless, a travel request can be assigned a vehicle by the FCFS principle without calling the Hungarian algorithm only when the fleet operator failed to find adequate idle vehicles as input for the Hungarian algorithm or when there is only one request for vehicle assignment in a certain dispatching time interval.

After the SAV assignment, the vehicle will have the essential information about requests (location, requested service, ride-sharing status) and communicate with travelers by sending an assignment message. After that, the traveler waits for the SAV's arrival. Therefore, the waiting time can be composed of waiting time for vehicle assignment (due to the unavailability of a SAV) and waiting for the SAV' arrival while it is en-route for picking up the traveler.

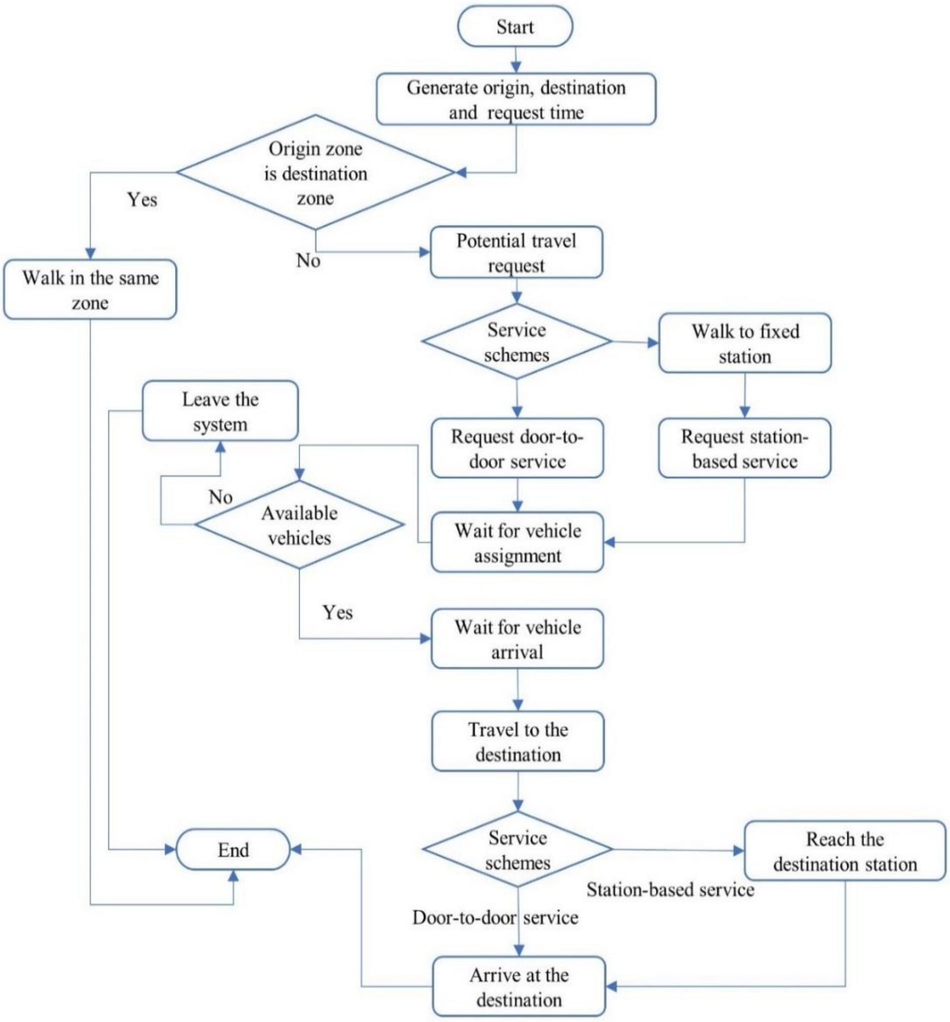


Figure 3.2 The state of individual travel requests

3.2.2 Dynamic generation of time-dependent travel requests

Based on the aggregate travel demand, individual travel requests are generated with spatial-temporal characteristics. In this study, the demand generation process can be divided into the following two steps.

- Generating a fixed number of time-dependent travel requests for each zone over each time interval

Total production of travel requests for each zone is calculated based on an origin-destination (OD) matrix, and then demand production per one-hour interval for each zone is estimated by using the departure time distribution and total demand production per zone for 24 hours. At the beginning of each time interval, a fixed number of travel requests are generated, and then the generated travel requests are distributed within this time interval by following a discrete uniform distribution. As a result, all the generated requests for each time interval will be associated with a specified time.

- Finding a destination zone for each travel request

It is assumed that observations of travel requests in each zone over other traffic analysis zones in the whole study area are known in the OD matrix table. That is to say, the number of requests ending in every other zone is known. Based on these observations of travel requests over traffic analysis zones in the OD matrix table, the destination zone of each travel request will be drawn by using the Monte Carlo simulation process. In the end, each request will have a destination zone. We give a detailed overview of departure time distribution and total travel requests for each zone in the section of detailed travel demand.

As shown in Figure 3.2, the statechart diagram, one of the five Unified Modeling Language diagrams, is used to model the dynamic nature of travelers. The statechart diagram can define different states of a traveler during a lifetime and these states are changed by events. By using statecharts, traveler behavior can be visually shown. The statechart has states and transitions. Transitions may be triggered by user-defined conditions (timeouts or rates, agent's arrival, messages received by the statechart, and Boolean conditions). For example, After the SAV assignment, the vehicle will have the essential information about requests (location, requested service, ride-sharing status) and communicate with the clients by sending an assignment message (state transition by receiving a message). After that, the traveler waits for the SAV's arrival (state transition by vehicle arrival). The travel request will give up waiting for vehicle assignment when waiting assignment time exceeds a time threshold (state transition by timeout event).

3.2.3 Fleet size

The fleet size is an experimental parameter in the ABM. We simulate the operations of AMoD systems with different fleet sizes. In addition, in order to illustrate the relations between multiple system characteristics, we estimate a small fleet size for keeping an acceptable service quality for AMoD systems.

3.2.4 Dynamic ride-sharing

The SAV can facilitate the implementation of dynamic ride-sharing. Dynamic ride-sharing aims to pool multiple travelers with similar temporal and spatial characteristics.

In this model, we design a set of rules for the implementation of dynamic ride-sharing. Travelers who have common OD zones are allowed to share a SAV. Note that the grouped travelers with a common OD zone may have different departing and arriving specific locations within each zone. The travel requests can be served at a service station or at their doorstep.

From the service scheme point of view, we design a set of rules for dynamic ride-sharing.

- If both of the shared rides need to be served at a station, the assigned SAV will pick them up at the origin station and then drop them off at the destination station.
- If both of the shared rides need to be served in a door-to-door fashion, the assigned SAV will first pick up the passenger who is closer to it and then pick up another one. Based on the trip distance of the passengers, the SAV will first drop off the passenger who has a shorter trip distance, and then it will drop off the second passenger at its specific destination of the same zone. If the assigned SAV has the same estimated travel distance from the two passengers in two different locations, the SAV will first pick up the passenger who sent the request earlier and then pick up the second passenger at his or her doorstep. After reaching the first passenger's destination, the second passenger will be dropped off.
- If one of the shared rides needs to be served at a station and the other one is to be served at the doorstep, the SAV will first pick up the passenger who is closer to it and then pick up the other passenger. Based on the trip distance of the passengers, the SAV will first drop off the passenger who has a shorter trip distance, and then it will drop off the second passenger at its destination (designated station or specific location) of the same zone. If the assigned SAV has the same estimated travel distance from the two passengers in two different locations, the SAV will first pick up the passenger who sent the request earlier and then pick up the second passenger at his or her doorstep. After reaching the first passenger's destination, the second passenger will be dropped off.

In this ABM, a ride-sharing agent type is introduced to delegate the grouped travel requests. That is, once the ride-sharing agent is created, it is responsible for the interaction with an assigned vehicle. Each ride-sharing agent records the information of grouped travelers, the OD of the travelers, and the assigned vehicles for grouped travelers. According to the designed rules for dynamic ride-sharing, the fleet operator dynamically adds and removes ride-sharing agents in the simulation process.

3.2.5 Service scheme

We have defined four types of on-demand AMoD systems in terms of variations of service schemes as described above: DDS system, SSS system, TVTS system, and PTS system. In all AMoD systems, we did not simulate user choices for different services based on attributes such as price or travel distance; however, we assume that individual requests have various levels of willingness to use the station-to-station service in the proposed PTS systems. According to the different willingness to choose the station-to-station service, the PTS system can be divided into PTS-20%, PTS-40%, PTS-60%, and PTS-80%. This would result from the prices of both services; otherwise, travelers would naturally prefer to use the door-to-door system only because it is more convenient.

3.3 Model Application

The simulation model was developed from scratch in Anylogic proprietary ABM platform with Java programming language. In this study, AMoD systems with different service schemes are tested in a hypothetical urban road network.

3.3.1 Urban road network

The road network of a city in a scale of 5 Km × 5 Km (roughly the size of Delft in the Netherlands) is used for testing the operations of different AMoD systems. The network is taken from the UDES (Urban Dynamics Educational Simulator) model. The road network topology includes 78 links and 77 nodes (see Figure 3.3). Stations for the drop-off and pickup service in AMoD systems are uniformly distributed among the traffic analysis zones (TAZs) in the whole study area. The scale is graphically defined in the agent simulation environment as: one pixel corresponds to ten meters. The SAVs shortest routes are computed using the Dijkstra algorithm.

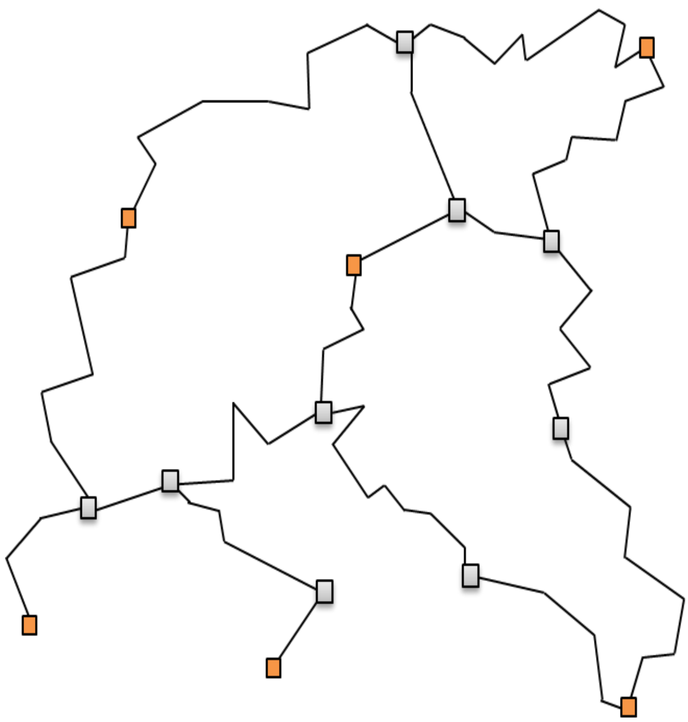
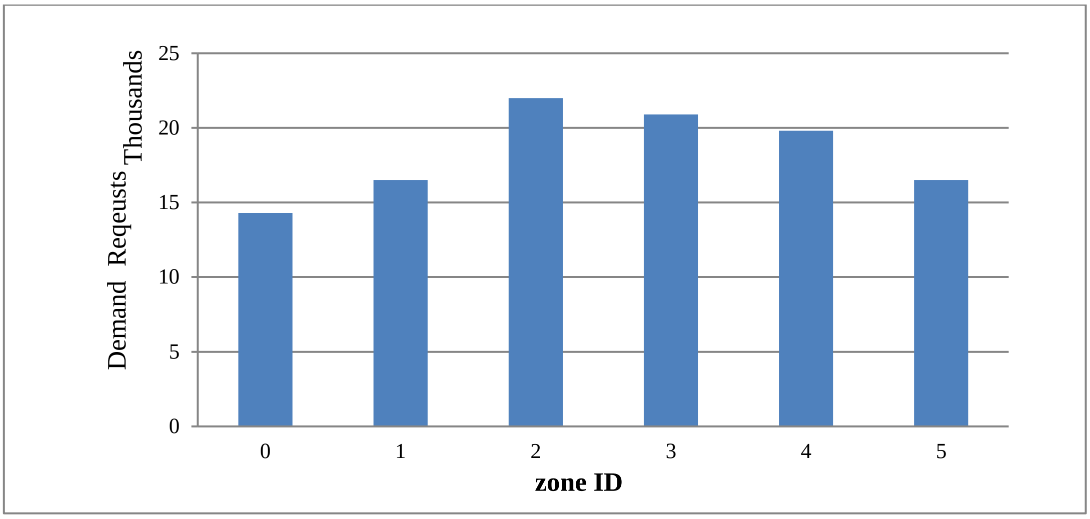


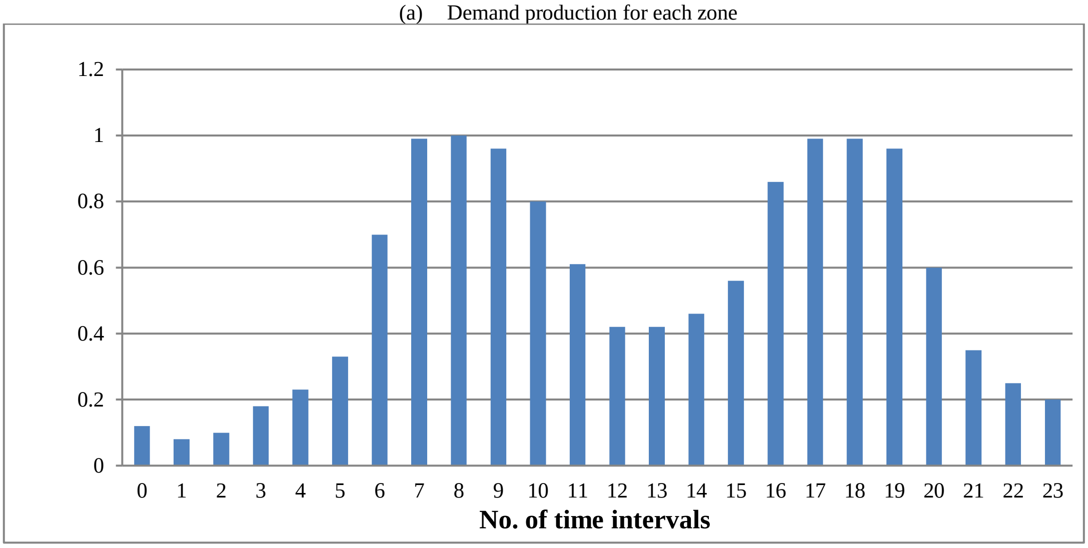
Figure 3.3 The road network

3.3.2 Detailed travel Demand

The AMoD systems will serve a total demand of 110 000 trips in a full day. Figure 3.4 depicts the departure time distribution of the demand and the total production of travel requests for each zone that are used as input in the simulation model, as explained in section 3.



(a) Demand production for each zone



(b) Departure time distribution

Figure 3.4 The departure time distribution and total demand for each zone

To mimic the commuting patterns, OD matrices with different assumed observations are used: one in the first half of the day and the other for the rest of the day. The destination zones are found by using the Monte Carlo simulation process. Therefore, heterogeneous observations in the trip table enable the simulation to generate different results.

Travel demand is not only generated and attracted in the centroid of each TAZ but specific points inside the zones are used, in order to simulate the operation of different service schemes. That means that travelers would walk from/to the station when using the station-based service or waiting for their pickup at their places of residence if there is a door-to-door service.

3.3.3 Simulation parameters

Table 3.1 shows basic input parameters for the SAV simulation. The vehicle speed is predetermined in all AMoD systems in peak hours and off-peak hours, respectively. Based on the research conducted by Wang et al. (X. Wang et al., 2016) in terms of speeds during the different times of the day, the reduction of the speed in peak hours ranges between 10% to 30%. Therefore, we assume that the speed of the SAV is 20% lower than that in off-peak hours. In this ABM, we assume the SAV speed in off-peak hours is 36 km/h. The energy efficiency of different electrical vehicles roughly ranges from 1 kWh per 7.16 km to 1 kWh per 4.82 km (https://pushevs.com/electric-car-range-efficiency-nedc/). Therefore, for energy consumption, we adopt a rate of electricity consumption of 1 kWh per 7 kilometers that is reasonable for a two-seat, light-weight vehicle. We assume that travelers will give up requesting a SAV when the waiting time for a vehicle assignment exceeds 5 minutes. We assume that the maximum number of travelers in a shared car is two. The time interval being used for the assignment is 5 seconds.

Table 3.1 Input parameters

Category	**Value**
City scale	5 Km × 5 Km
Road links	78
Road nodes	77
Travel requests	110 000
Vehicle off-peak speed	36 km/h
Vehicle peak-hour speed	28.8 km/h
Vehicle capacity	2 persons
Time threshold for client drop-out	5 minutes
Time interval for optimal assignment	5 seconds
Operation hours	Around the Clock
AM peak	7 AM-9 AM
PM peak	4 PM-6 PM
Fleet size	[2000,4500]
Fleet size step	500

3.4 Results and Discussion

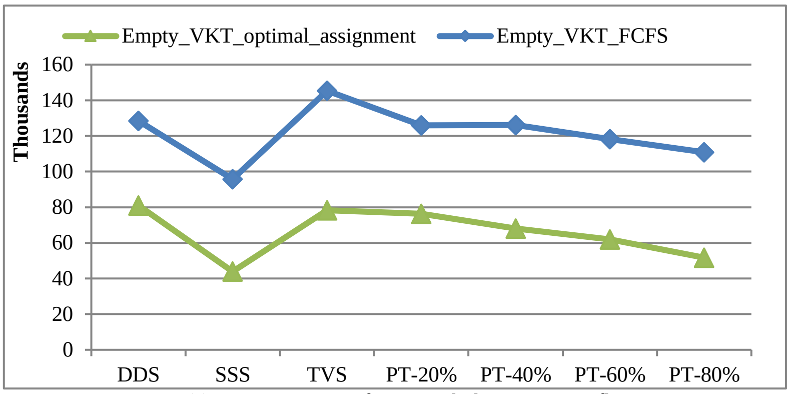
3.4.1 Analysis of the impact of vehicle assignment methods

To look at how the optimal vehicle assignment method impacts the performance of different SAVs systems. Seventy scenarios for different AMoD systems with variations in fleet size are simulated (see Table 3.2).

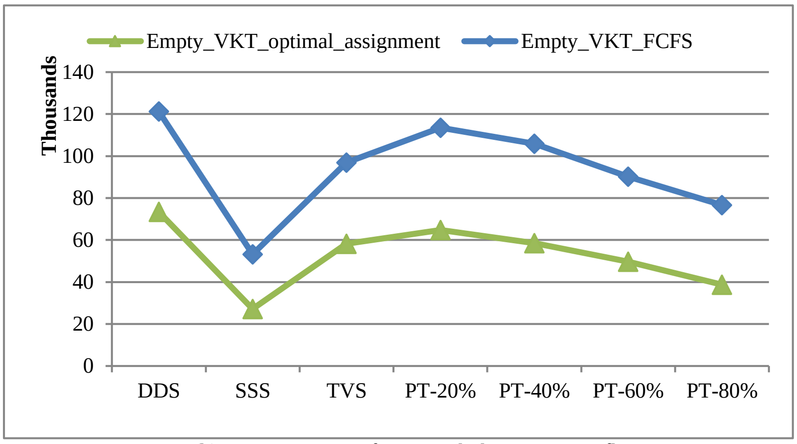
Table 3.2 Combinatorial scenarios for the simulation of optimal vehicle assignment

Assignment method	Optimal assignment method and FCFS assignment method						
AMoD systems	DDS	SSS	TVS	PTS-20	PTS-40	PTS-60	PTS-80
Fleet size	2000	2500	3000	3500	4000		

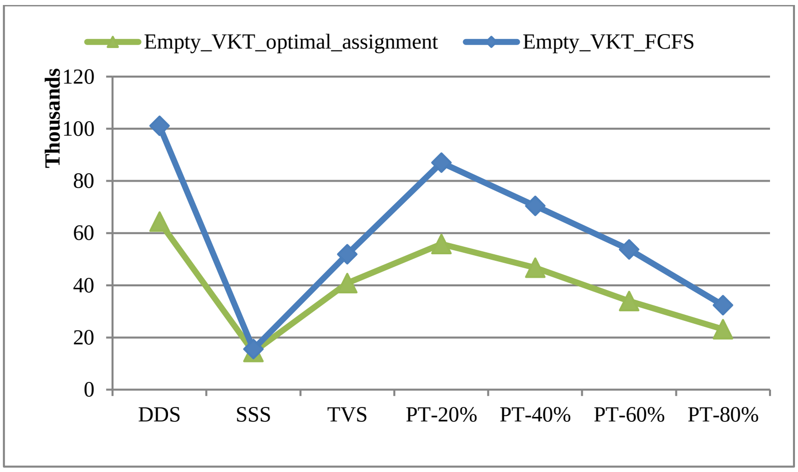
The simulation results in Figure 3.5 indicate that the optimal vehicle assignment algorithm can reduce empty VKT. The fleet operator can optimally assign idle vehicles to serve the travelers while minimizing the total empty travel distance for the pickups. The degree of reduction of empty VKT greatly depends on the fleet size. In Figure 3.5(a), the optimal assignment can reduce the empty VKT for all the AMoD systems in about 40 %, while there is almost of the same empty VKT for both assignment methods with a 4000-SAV fleet size in Figure 3.5 (e). Moreover, we found that the trend of the generated empty VKT over different AMoD systems for both vehicle assignment methods is similar to each other. That means that although the optimal assignment method can reduce the generation of empty VKT, the difference of generated empty VKT across AMoD systems remains the same to some extent.



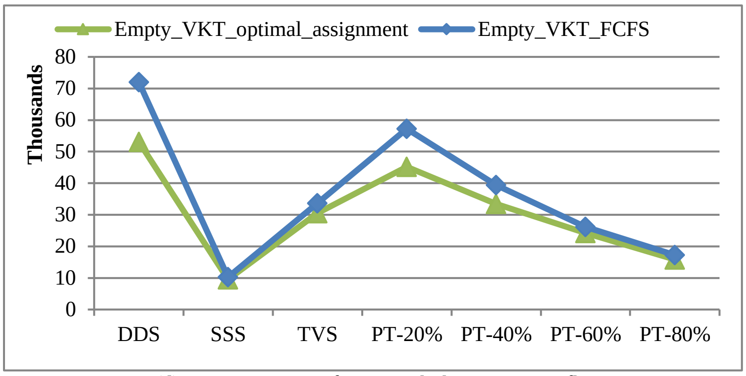
(a) Comparisons of VKT with the 2000-SAV fleet size



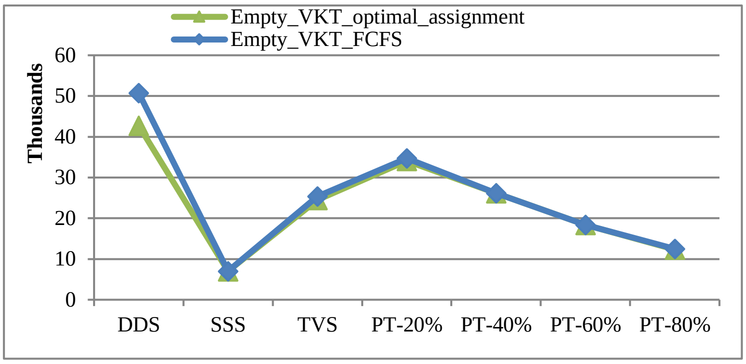
(b) Comparisons of VKT with the 2500-SAV fleet size



(c) Comparisons of VKT with the 3000-SAV fleet size



(d) Comparisons of VKT with the 3500-SAV fleet size



(e) Comparisons of VKT with the 4000-SAV fleet size

Figure 3.5 Comparisons of empty VKT for different assignment methods with variations in fleet sizes

Considering the number of drop-outs (unsatisfied trips), it is possible to see the simulation results in Figure 3.6 and Figure 3.7 for the total number of drop-outs with both vehicle assignment methods and for all tested systems. Results indicate that the optimal vehicle assignment can enable the AMoD systems to transport considerably more travelers. This can be explained because of a reduction in the waiting time due to the higher efficiency of the optimal vehicle assignment method.

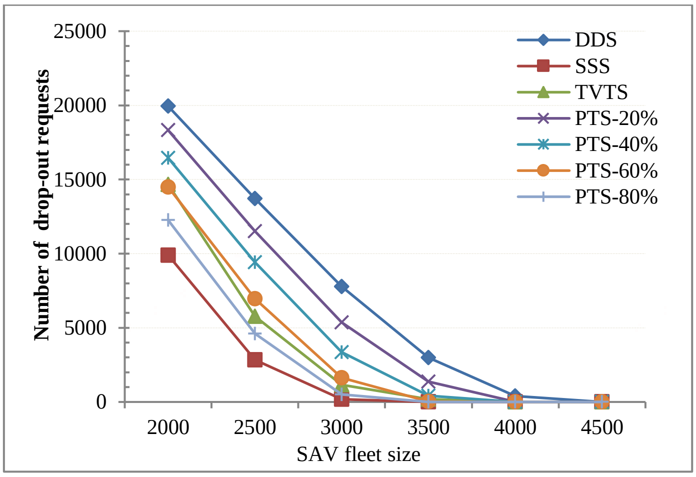


Figure 3.6 Unsatisfied requests for AMoD systems with variations of fleet sizes by the optimal assignment

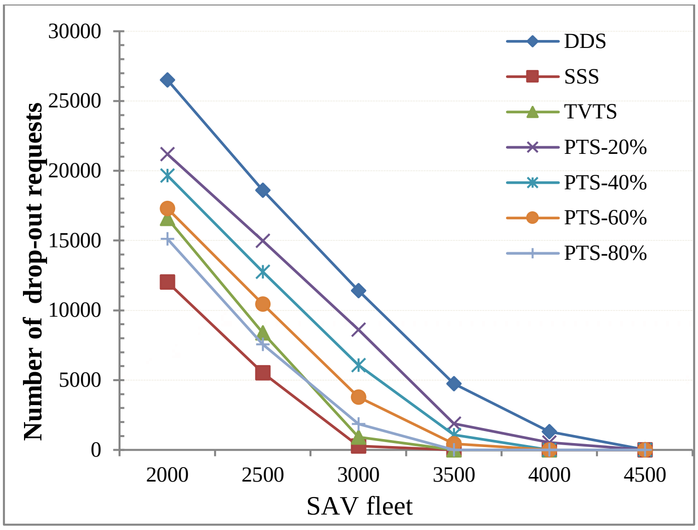


Figure 3.7 Unsatisfied requests for AMoD systems with variations of fleet sizes by the FCFS assignment

3.4.2 Analysis of fleet size variations

We provide a performance analysis of the AMoD system for different fleet sizes. In addition, a small fleet size for the base scenario to keep an acceptable level of service quality is determined to analyze the other characteristics of different AMoD systems. As shown in Table 3.3 and Table 3.4, the average peak-hour waiting time in all systems with dynamic ride-sharing ranges from 8.68 minutes to 13.17 minutes when we adopt the 2000-SAV fleet size. For smaller fleet sizes, the service quality would be lower. Furthermore, there is little difference in the average waiting time in the four-PTS system when the fleet size is reduced from 3500 to 2000, as shown in Figure 3.7. Therefore, we could analyze the AMoD systems' performance starting from the estimated 2000-SAV fleet size.

Table 3.3 Performance indicators for DDS, SSS, and TVTS systems with a 2000-SAV fleet size

AMoD system	**DDS**		**SSS**		**TVTS**	
Ridesharing	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Avg. waiting time (min)	14.79	7.21	9.84	4.41	12.87	6.43
Avg. peak-hour waiting time (min)	20.53	11.22	16.82	8.68	19.68	9.08
waiting time > 10 minutes (trips)	47 849	29 766	42 962	16 624	48 188	23 773
Avg. service time (min)	26.76	19.01	19.15	11.95	23.67	15.311
Avg. peak-hour service time (min)	33.65	24.34	26.94	16.99	28.56	16.22
Total VKT (km)	769 099	681 432	673 892	600 751	661 443	617 767
Energy consumption (Kwh)	109 871	97 347	96 270	85 821	94 491	88 252
Total SAV trips	131 355	117 999	141 076	125 544	138 487	131 901
Request dropouts	24 328	24 554	12 358	12 027	19 066	16 322
Percentage of dropouts (%)	22.1%	22.3%	11.2%	10.9%	17.3%	14.8%
Percentage of shared rides (%)	0%	34.4%	0%	15.6%	0%	20.1%

3.4.3 Analysis of the impact of dynamic ride-sharing

AMoD systems allow travelers to share their rides according to the designed rules. In this analysis, we analyze the impact of dynamic ride-sharing in the AMoD system. Compared with a non-ridesharing system in

Table 3.3 and Table 3.4, AMoD systems with ride-sharing significantly reduce at least 50% of the average waiting time, 6.0 % of VKT and 4.7% of total SAV trips. The dynamic ride-sharing could improve the performance of all proposed systems.

The DDS system reaches a peak of approximately 34.4% of shared rides, while the SSS system has the lowest percentage of shared rides (around 15.6%). Four-PTS systems have slightly high percentages of shared rides from 18.7% to 25.9%. Especially, the TVTS system is about the same as the PTS-60% for the percentage of shared rides with a 2000-SAV fleet size, reaching 20.1% of total serviced trips. The PTS systems and TVTS system, providing two service schemes, can achieve a relatively high sharing rate of trips. Although the simulation results for dynamic ride-sharing may not give conclusive evidence under designed matching rules to group travelers, the preliminary investigations of the impact of dynamic ride-sharing on different AMoD systems provide useful insights into the deployment of different AMoD systems.

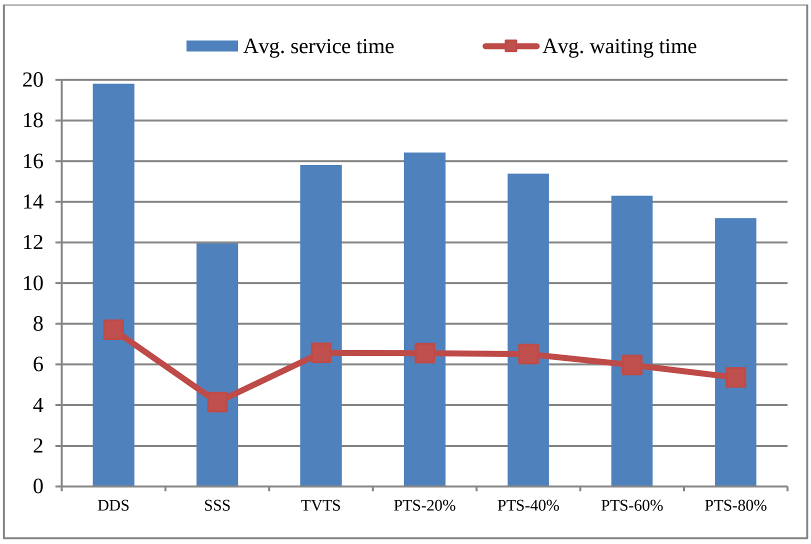
Table 3.4 Performance indicators for four-PTS systems with a 2000-SAV fleet size

AMoD system	**PTS-20%**		**PTS-40%**		**PTS-60%**		**PTS-80%**	
Ridesharing	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Avg. waiting time (min)	15.07	6.61	14.33	5.78	13.53	5.06	12.06	4.71
Avg. peak-hour waiting time (min)	22.48	13.20	21.79	11.92	21.08	11.11	19.54	9.77
waiting time > 10 minutes (trips)	5 108	2 408	5 078	2 331	5 129	2 123	4 820	1 921
Avg. service time (minute)	26.49	16.32	25.22	15.11	23.88	14.01	21.85	13.12
Avg. peak-hour service time (min)	34.88	23.11	33.58	22.14	32.35	20.67	30.18	18.77
Total VKT (km)	651 423	568 632	659 864	564 712	674 841	565 322	675 645	589 666
Energy consumption (Kwh)	93 060	81 233	94 266	80 673	96 405	82 022	96 520	84 238
Total SAV trips	136 548	118 441	138 086	118 301	141 295	119 849	141 729	121 721
Request dropouts	22 130	21 095	20 083	19 290	17 842	17 085	15 103	14 233
Percentage of dropouts (%)	20.1%	19.2%	18.3%	17.5%	16.2%	15.5%	13.7%	12.9%
Percentage of shared rides (%)	0%	18.7%	0%	19.6%	0%	20.1%	0%	25.9%

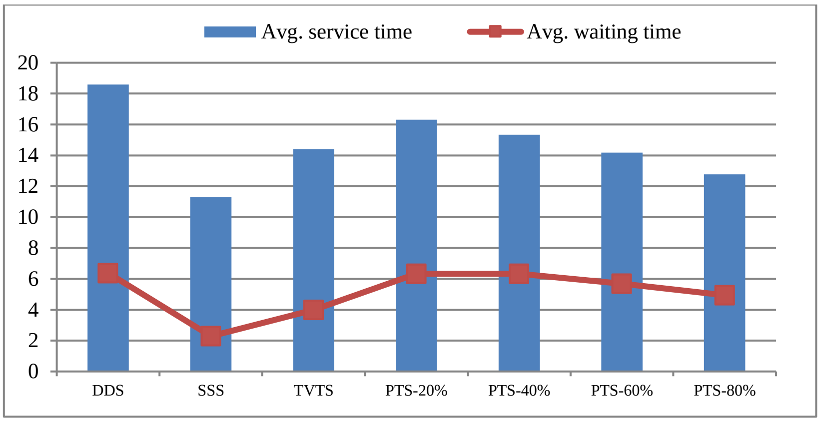
3.4.4 Analysis of waiting time and service time

Simulation results in Figure 3.7 (a) indicate that the average waiting time in the four PTS systems with dynamic ride-sharing has little difference, approximately 40% to 42% of average service time (in-vehicle travel time) in case of the 2000-SAV fleet size. TVTS system has a similar performance in terms of average waiting time and service time with the PTS-20% and PTS-40% system. We can infer that the AMoD systems, e.g., PTS-20% and PTS-40% system, that allows two service schemes to operate in parallel with a degree of restricted access to the door-to-door service, could provide a similar system performance than the TVTS system which only offers station-based service in peak hours.

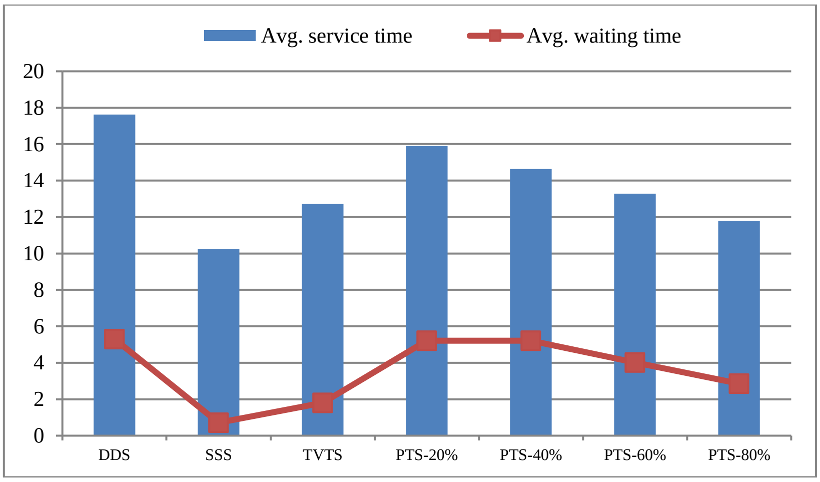
When a total fleet size of 3500 SAVs is adopted (Figure 3.7 (d)), the average waiting time in the PTS systems with 80% willingness to request station-based services could achieve a similar value with that of the TVTS system with approximately 22.8% of average service time. This means the system performance in terms of average waiting time and average service time achieved by the sequential operational rules in the TVTS system can be obtained by the proposed parallel modes of service schemes in the PTS-80% system.



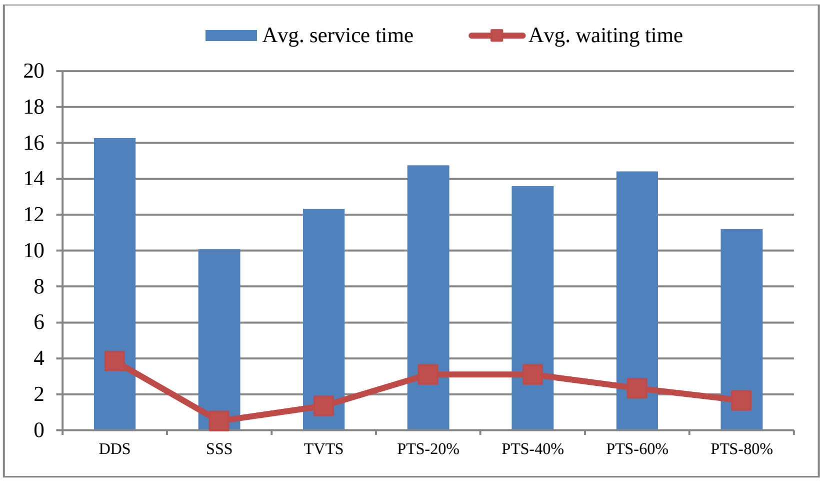
(a) 2000-SAV fleet size



(b) 2500-SAV fleet size



(c) 3000-SAV fleet size



(d) 3500-SAV fleet size

Figure 3.7 Avg. waiting time and Avg. service time with variations of fleet sizes for seven AMoD systems

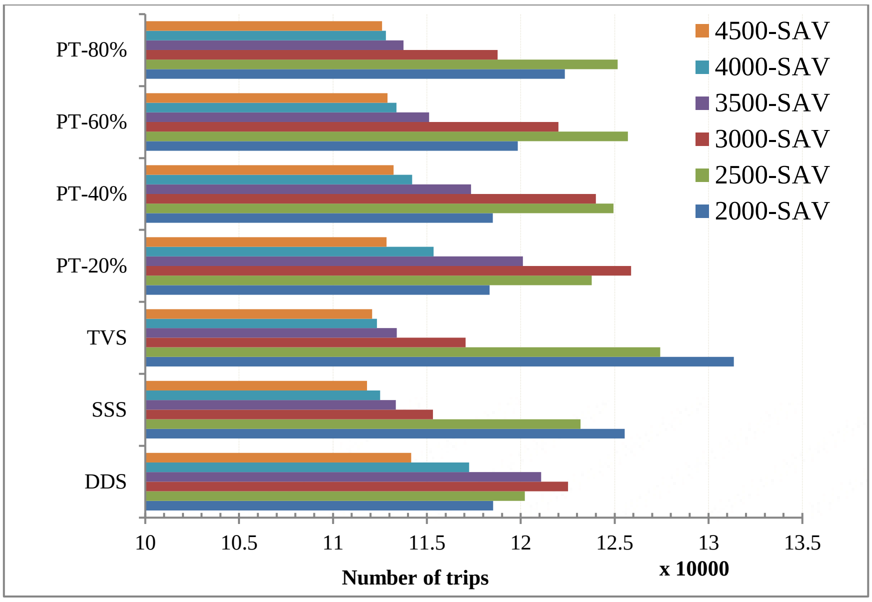
3.4.5 Analysis of VKT and energy consumption

The DDS system has more VKT and energy consumption than other AMoD systems, as can be seen in Figure 3.8 (c) and Figure 3.8 (d). Except for the DDS system, other proposed systems converge to the same amount both in VKT and energy consumption respectively, when fleet size approaches 4000 vehicles. Both VKT and energy consumption experience a growing trend in four PTS systems with an increase in fleet size from 2000 to 2500, while the TVTS system has a high level of energy consumption and VKT. Nevertheless, with the continued growth of fleet size to 4000, the TVTS system decreases the energy consumption and VKT to a relatively low level compared to the energy consumption on the PTS systems. TVTS system could operate a relatively large fleet size to provide quality service while consuming less energy.

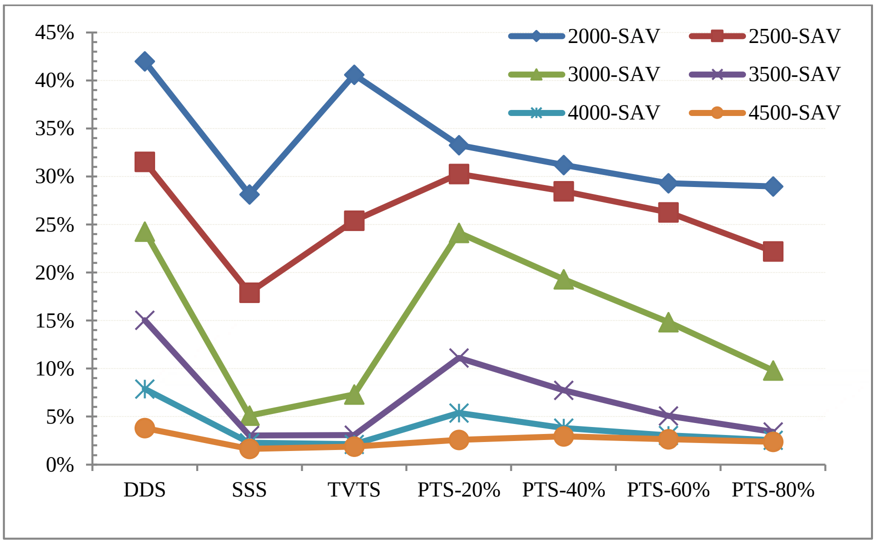
Figure 3.8 (a) showing the number of total SAV trips indicates that total SAV trips rise first, then fall for each system with an increment of fleet sizes for each AMoD system. One of the possible explanations is that with the increase of the SAV fleet size, fewer travel requests drop out of the AMoD system. Therefore, the AMoD system satisfies many more trips that result in an increase in the total number of SAV trips. On the other hand, the gradually increased fleet size will potentially reduce the empty SAV trips for pickup. The decline of empty (unoccupied) SAV trips for en-route pickups appears to reduce the total SAV trips. As a result, the total SAV trips rise first and decline for each AMoD system. The peak number of total SAV trips is about 131342 trips in the TVTS system, while the DDS, PTS-20% and PTS-40% systems only reach about 118000 trips with the 2000-SAV fleet size.

Results in Figure 3.8 (b) indicate that the empty trips with a 2000-SAV fleet size for each AMoD system occupy 30% to 40% of the total trips served. The percentage of empty trips in the SSS system has a minimum of 28.1% of the total served 97973 trips with 2000-SAV fleet size, while the DDS reaches a peak of 42.0% with a total of 83480 trips. The percentage of extra empty trips in the TVTS system is the second-largest percentage (40.6%). With a total fleet size of 2000 SAVs, AMoD systems seem to generate a higher percentage of empty trips.

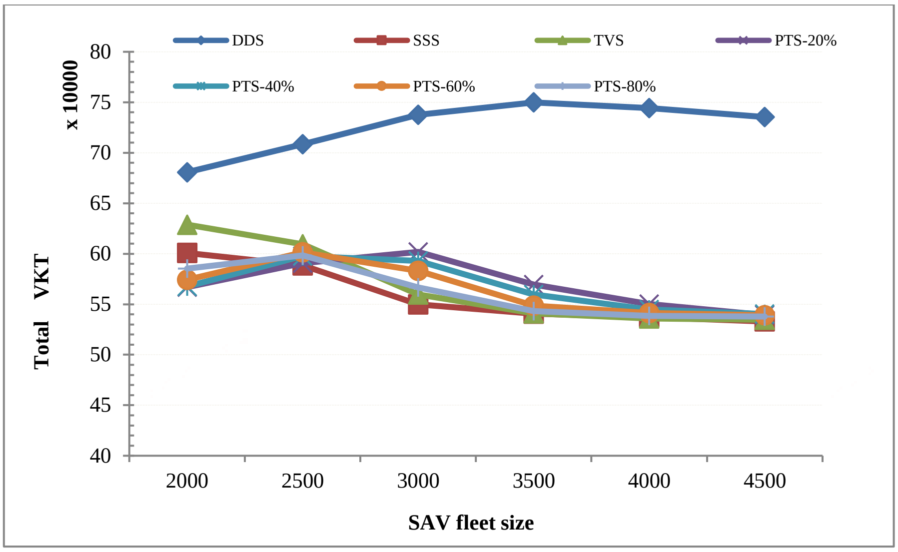
The high percentage of empty vehicle trips in DDS and TVTS has the potential to cause heavy traffic congestion.



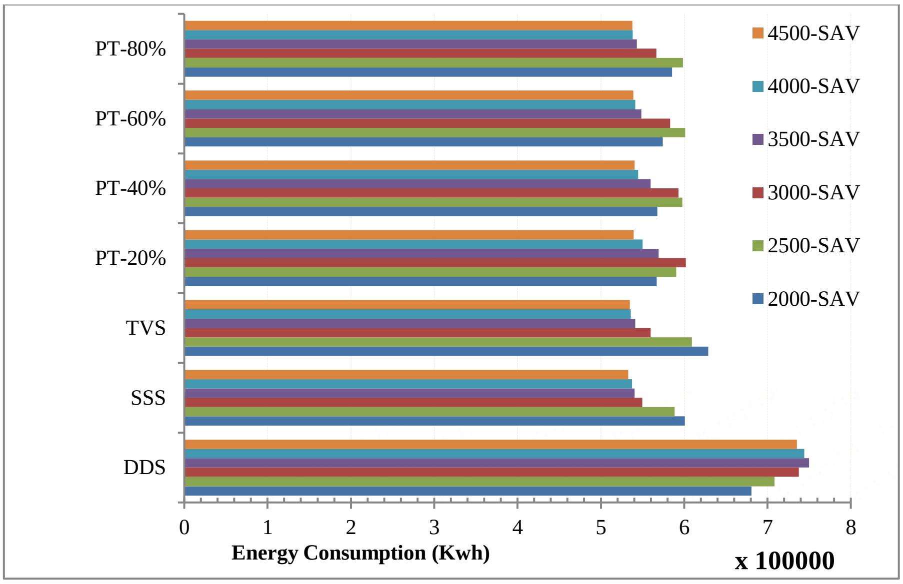
(a) Total SAV trips



(b) Percentage of extra empty trips



(c) Total VKT



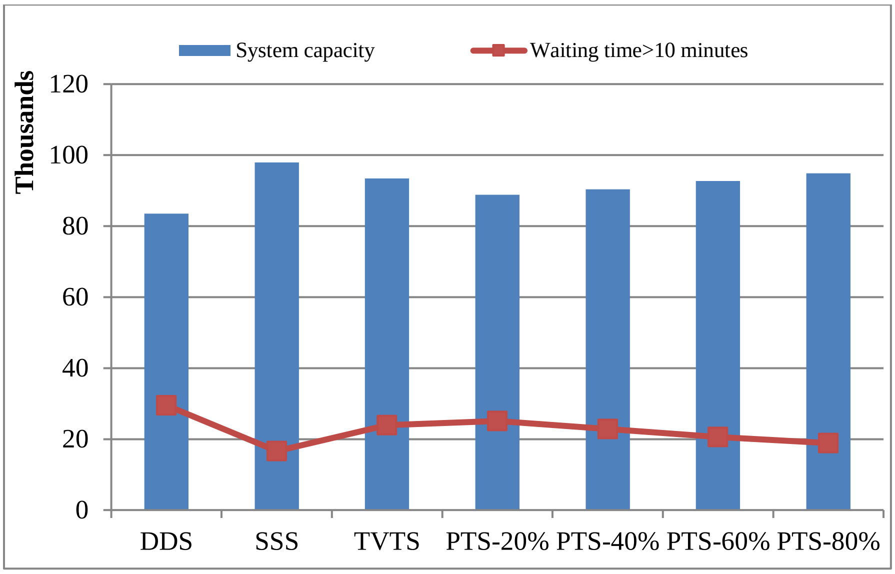
(d) Energy consumption

Figure 3.8 VKT, SAV trips, empty trips of SAVs and energy consumption for seven AMoD systems

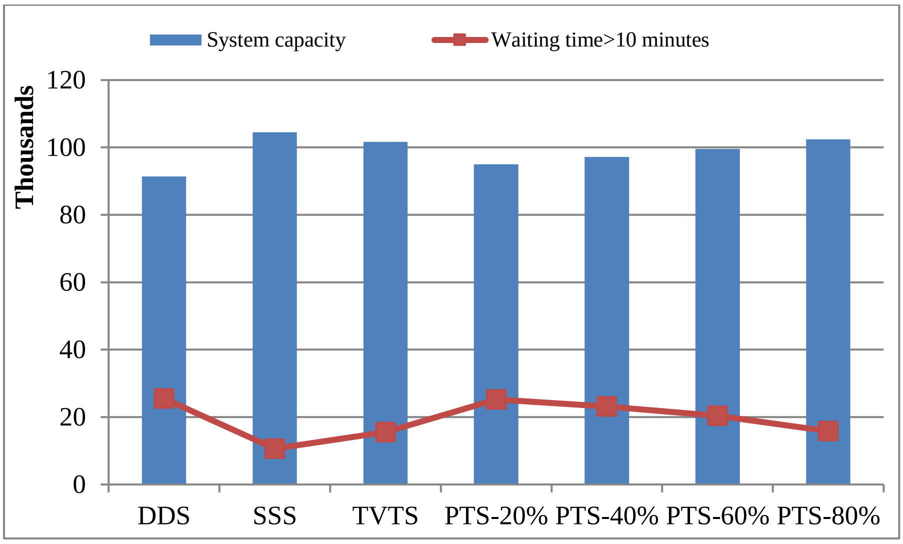
3.4.6 Analysis of system capacity and drop-out requests

With the 2000-SAV fleet in Table 3.3 and Table 3.4, the peak number of drop-outs is 24554 trips corresponding to 22.3% of the total number of requests (110000) in the DDS system, while in the SSS system this number goes down to 12027 drop-outs, only accounting for 10.9% of the 110000 requests. The drop-out rate in the TVTS system approximates that of PTS-60% system with a 2000-SAV fleet size, reaching 15% of the total number of requests (110000). The PTS-80% system has the lowest number of drop-outs. It is evident that the PTS system with a relatively high percentage of willingness to choose station-based service would be able to accomplish the performance of the TVTS system.

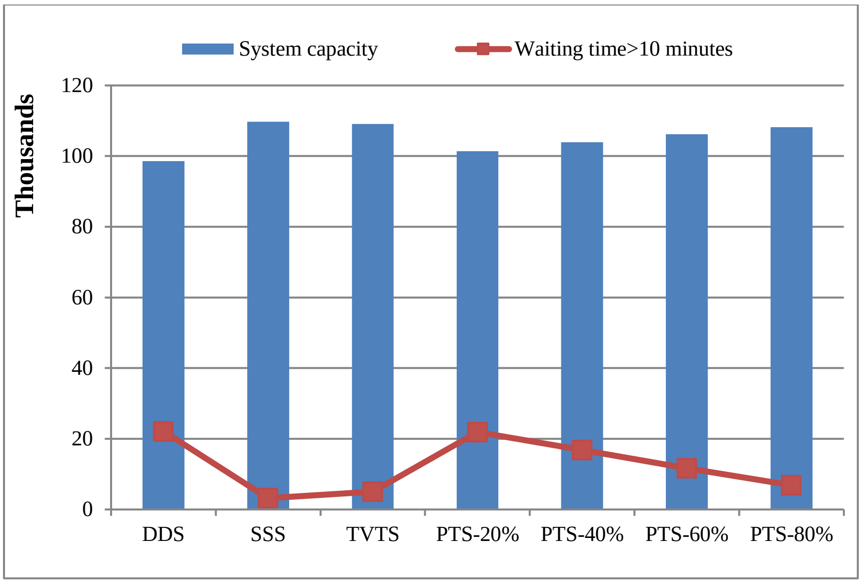
Results in Figure 3.9 indicate that the number of trips whose waiting time exceeds 10 minutes is between 29493 trips and 16624 trips, going down from 35.3% to 16.9% of system capacity (total number of served trips) with a 2000-SAV fleet size. The percentage of trips whose waiting time exceeds 10 minutes is about 25% in both PTS-40% and TVTS system, which are slightly larger than that of PTS-60% and PTS-80%. Both the TVTS system and PTS system with a relatively smaller fleet size can roughly keep 75% of the travelers waiting 10 minutes or less. With the shifts of SAV fleet size to 3500, DDS system still has a peak of 14.1% requests whose waiting time is larger than 10 minutes. Results indicate that PTS-20% still maintains a high percentage of travelers whose waiting time exceeds 10 minutes with a 3000-SAV fleet size (21%). Therefore, we can infer that the PTS system with a low willingness to choose the station service will lead to a long wait.



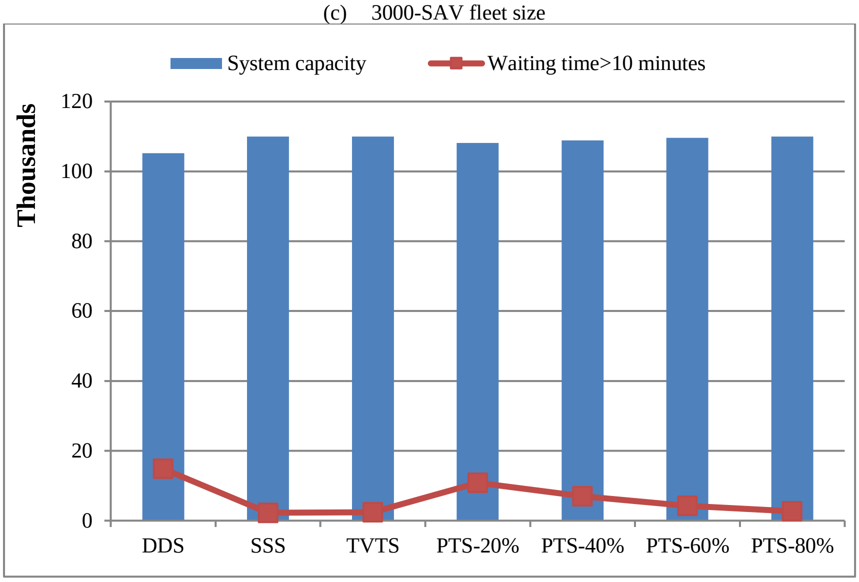
(a) 2000-SAV fleet size



(b) 2500-SAV fleet size



(c) 3000-SAV fleet size



3500-SAV fleet size

Figure 3.9 system capacity and waiting time>10 minutes trip number

Simulation results in Figure 3.7 indicate that the number of travelers who give up waiting for a SAV assignment has a significant descending trend with the increase of SAV flee sizes in seven AMoD systems. Except for the system with DDS, a fleet of 3500 SAVs can accommodate almost all of the requests. The fleet size that accommodates the total 110000 requests in the DDS is approximately 4500 SAVs. Therefore, The AMoD system only with door-to-door service needs many more SAVs to handle the high demand. A large number of vehicles has the potential to reduce vehicle utilization. Simulation results in Figure 3.10 reveals that the DDS system has the lowest number of served trips per SAV in all scenarios. In addition, the numbers of served trips per SAV are from 41.7 trips to approximately 49.0 trips in the AMoD system with a 2000-SAV fleet size. We find out that the PTS-60% and PTS-80% systems present about the same number of served trips as the TVTS system at about 47 trips per SAV. We compared the number of served trips per SAV with Fagnant et al.

(2015)'s study. Their study indicates that the AMoD system considering ride-sharing can serve 56324 person-trips with 1715-SAV fleet size within a network in the scale of 12 miles × 24 miles. That is, each SAV can approximately serve 32.8 trips. The served trips per SAV are relatively lower than ours. One reason is that the road network in Fagnant's study is relatively larger than that of this study. Another reason is that a relatively large number of vehicles are deployed in Fagnant’s study that leads to a relatively small average waiting time. The average waiting times ranges from 4.41 to 7.70 minutes with a 2000-SAV fleet size that are relatively larger than the 1.18-minute average waiting time in Fagnant’s study.

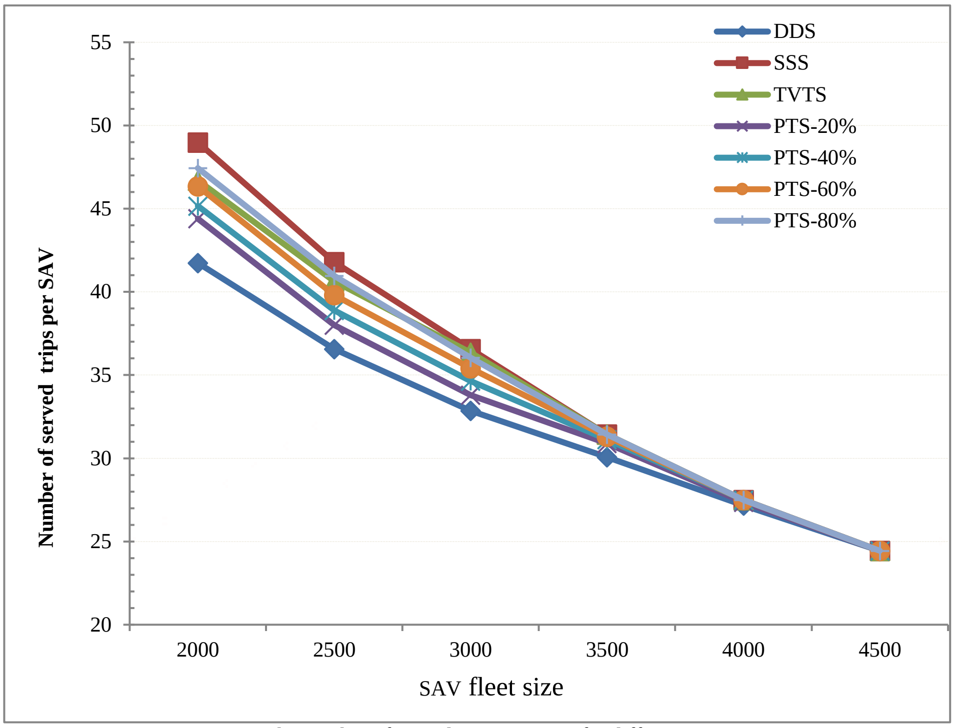


Figure 3.10 The number of served trips per SAV for different AMoD systems

3.4.7 Analysis of empty trips

Unlike human-driven vehicles parking at the destinations, SAVs could have an unoccupied journey to pick up the next request (no pro-active rebalancing in anticipation of future demand are considered in this study). Therefore, additional empty trips will be generated to satisfy the next trip. In this study, the additional empty trips by the vehicle movement between different zone stations are calculated. These empty trips have the potential to influence traffic congestion to a great extent. Therefore, it is of importance to know the number of empty trips by SAVs. As shown in Figure 3.11, dynamic ride-sharing can significantly reduce the generation of empty trips. PTS systems have the greatest reduction, reaching a peak of 23% in PTS-60% system; however, there is a large number of additional empty (unoccupied) trips in all AMoD systems. DDS and TVTS system with dynamic ride-sharing generate many more empty trips at around 40.5% of total served trips. The PTS systems with dynamic ride-sharing generate relatively fewer empty trips than that of the TVTS system.

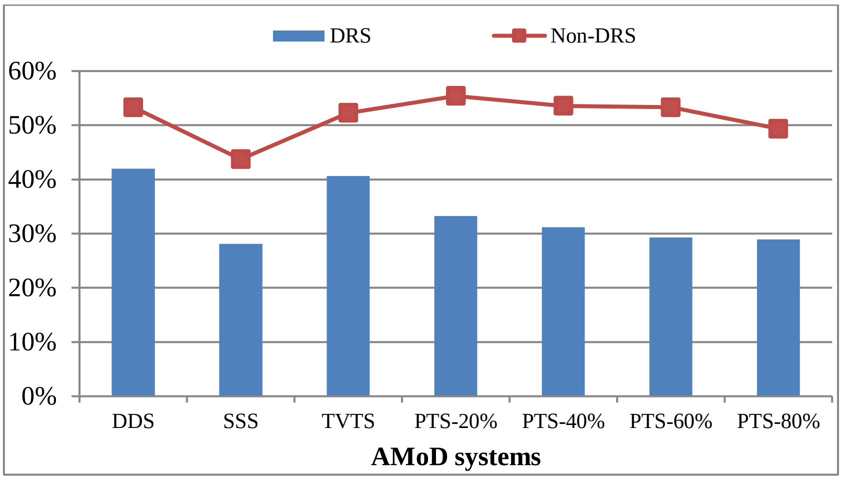


Figure 3.11 The percentage of empty trips with dynamic ride-sharing for a 2000-SAV fleet size

Simulation results in Figure 3.12 indicate the generation of empty trips with dynamic ride-sharing is sensitive to the fleet size. As the fleet size increases, the percentage of empty trips experiences a downward trend. The percentage of empty in all AMoD systems drops below 5% when the fleet size is 4500. In addition, it depicts that the SSS system, TVTS system, and PTS-80% system have low numbers of empty trips by SAV, compared with other systems.

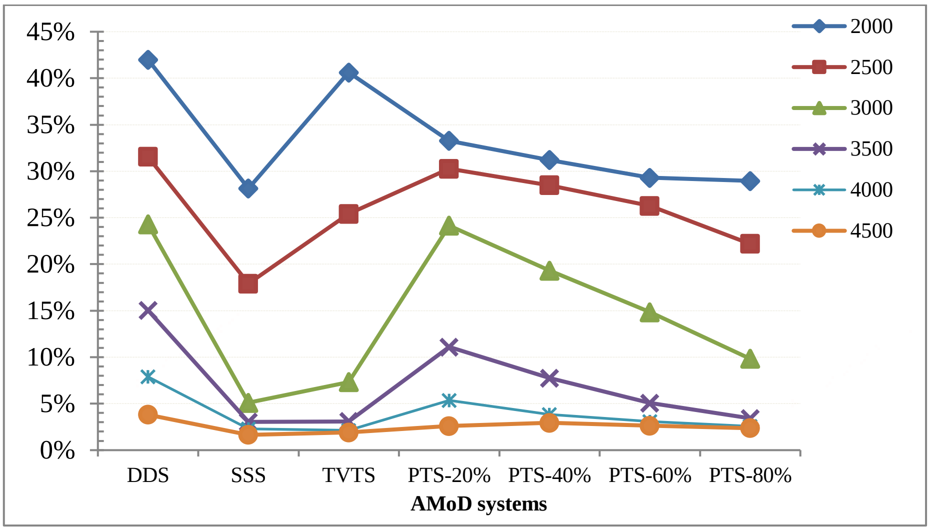


Figure 3.12 The percentage of empty trips with the variations of fleet size

3.5 Conclusions

This chapter developed an agent-based simulation model to assess the potential of on-demand AMoD systems with various service schemes. With the help of developed ABM, we understand what the performance of AMoD systems with different service schemes is and how the associated factors (variation of fleet size, dynamic ride-sharing, different vehicle assignment methods) influence the service quality of AMoD systems. Our study shows that the promotion of ride-sharing can significantly improve the performance of proposed AMoD systems in terms of reducing the average waiting time, VKT and empty trips. Moreover, compared to the FCFS vehicle assignment method, the optimal assignment can reduce the generation of empty VKT for all tested systems and enable the AMoD systems to transport considerably more travelers.

Although the DDS system brings great convenience of doorstep service for real-time requests; it is evident that DDS generates extra almost 13% of VKT than that of the PTS system with a fleet size of 2000 SAVs. In addition, the DDS system generates approximately 42% additional empty trips. The percentage of drop-out requests takes up 22.0% of the total 110000 person-trips. That is, the DDS system cannot transport many more travelers as the other AMoD systems do. Compared to the DDS system, the TVTS system and PTS systems can reduce at least 14.6% and 14.8% of the average waiting time respectively. The empty trips in TVTS and PTS systems system with dynamic ride-sharing account for 41.0% and 33.3% of total served trips respectively. The TVTS and PTS system provides a significant gain in terms of system capacity, waiting time and additional trips by empty SAVs. In other words, the AMoD systems that include two different on-demand services have the most significant improvements in system performance above.

DDS system ranks the highest in total energy consumption and VKT. Compared to the VKT in the DDS system, the TVTS system and PTS system can reduce at least 7.6% and 14.0% of the VKT with 2000-SAV fleet size. On the other hand, the DDD system transports a relatively small amount of travel requests and reduces vehicle utilization that is the average number of served trips per day per vehicle. Based on the analysis of proposed AMoD systems, TVTS and PTS systems are a promising alternative to be implemented to satisfy the intra-city transportation needs. In both systems, a SAV can serve many more trips per day with relatively less waiting time. The PTS systems with a relatively high percentage of choosing station-to-station service show a high level of service that could transport many more requests with less waiting time and empty trips. Although the TVTS system could generate many more VKT and consume much more energy, this system still has a relatively small waiting time and fewer drop-outs with providing doorstep convenience. In the future deployment of AMoD systems, the station-based service combing with the door-to-door service paralleling in time and space is of importance since blended service could make the system operating in a relatively high degree of service quality without inconvenient access.

Chapter 4

Modeling the Strategic Formation of Urban Platoons in a Single-Operator AMoD System

This chapter addresses the problem of studying the impacts of the strategic formation of platoons in AMoD systems in future cities. Forming platoons has the potential to improve traffic efficiency, resulting in reduced travel times and energy consumption. However, in the platoon formation phase, coordinating the vehicles at formation locations for forming a platoon may delay travelers. In order to assess these effects, an agent-based model has been developed to simulate an urban AMoD system in which vehicles travel between service points transporting passengers either forming or not forming platoons. A simulation study was performed on the road network of the city of The Hague, The Netherlands, to assess the impact on traveling and energy usage by the strategic formation of platoons. Results show that forming platoons could save up to 9.6% of the system-wide energy consumption for the most efficient car model. However, this effect can vary significantly with the vehicle types and strategies used to form platoons. Findings suggest that, on average, forming platoons reduces the travel times for travelers, even if they experience delays while waiting for a platoon to be formed. However, delays lead to longer travel times for the travelers in the platoon leaders, similar to what people experience traveling in highly congested networks when platoon formation does not happen. Moreover, the platoon delay increases as the volume of AMoD requests decreases; in the case of an AMoD system serving only 20% of the commuter trips (by private cars in the case study city), the average platoon delays experienced by these trips increase by 25%. We conclude that it is beneficial to form platoons to achieve energy and travel efficiency goals when the volume of AMoD requests is high.[2]

4.1 Introduction

A primary research priority is studying different operational aspects of urban passenger AMoD systems in future cities. Recent advances in vehicle automation have enabled vehicles to drive and connect without human intervention. With the help of connectivity and automation technology, AVs can exchange information for coordinated movements in platoons at closer following distances.

Vehicle platooning has been a popular research theme in recent applications of intelligent transportation systems. The impact of platoon operations on urban traffic has been studied, assuming that AVs are already in platoons. However, the impact of the creation and operations of such platoons on the future urban AMoD system is not researched. To fill this gap, an agent-based model has been developed to provide performance evaluations of forming platoons in urban passenger AMoD systems of the future.

The chapter is organized as follows. In Section 4.2, we summarize the existing literature on platoon operations and the formation of platoons, identify the challenges of forming platoons in urban AMoD systems, and present the main contributions of this chapter. Section 4.3 gives an overview of the modeling framework and discusses the model specifications. A detailed description of the model implementation and its application are provided in Section 4.4. Section 4.5 analyzes the simulation results. The main conclusions and policy implications are presented in Section 4.6, and Section 4.7 recommends future work directions.

4.2 Background

Platooning systems have attracted increasing attention with the rapid progress in automated and connected vehicle technologies. Much work has been done to investigate platoon communication technologies and platoon control strategies (Kavathekar & Chen, 2011). Recent literature has focused on platoon planning: at a low level (e.g., trajectory level), detailed platoon maneuvers (e.g., merging and splitting) are designed and simulated (Hao et al., 2022); at a high level, planning and optimization of routes and schedules in the platoon formation are studied(Bhoopalam et al., 2018). Moreover, vehicles with synchronized movement in platoons can have faster reaction times to dangerous situations and fewer human errors, reducing rear-end crashes. For a detailed analysis of platoon safety issues, the reader is

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[2]*This chapter is based on the published paper: Wang, S., Correia, G. H. de A., & Lin, H. X. (2022). Assessing the Potential of the Strategic Formation of Urban Platoons for Shared Automated Vehicle Fleets. Journal of Advanced Transportation, vol. 2022, Article ID 1005979, 20 pages, 2022. https://doi.org/10.1155/2022/1005979*

referred to the literature review research by Axelsson (2017) and Wang et al. (2020). In this study, we address the problems of forming platoons and assessing the travel and energy impact on a future urban mobility system. We herein provide background information about the potential implications of platoon operations on energy consumption and traffic efficiency. Besides, we review the literature on the strategic formation of platoons.

4.2.1 Energy impact of platoon operations on highways

Platoons of vehicles provide significant potential for energy savings on highway driving. The close-following mechanism can considerably reduce the energy consumed by platoon vehicles to overcome the adverse aerodynamic effect (Alam et al., 2015). Several field experiments in research projects, such as the COMPANION project, the PATH platoon research, the SARTRE project, and the Energy ITS project, have been conducted to investigate the potential of platoon operations in reducing energy consumption (Bergenhem et al., 2012).

4.2.2 Impact of platoon operations on highway and urban traffic

Platoon operations can improve highway throughput due to the shorter headways between platoon vehicles (van Arem et al., 2006). Using communication technologies (e.g., vehicle-to-vehicle or vehicle-to-infrastructure technologies), platoons of vehicles can also smooth out the vehicle-following dynamics on highways (Shladover, 2018). Besides, platoon operations can improve urban road capacity and reduce delays when crossing signalized intersections (Santana et al., 2021).

4.2.3 The platoon formation on highways

In the above literature, the energy and traffic studies on platooning systems considered vehicles that are already in platoons and used platoon operations to increase road throughput and reduce energy consumption. Some studies investigated the problem of coordinating vehicles in platoons on highways. Hall and Chin (2005) developed different platoon formation strategies to divide vehicles waiting at highway entrance ramps into different groups according to their destinations. Once formed at the highway entrance ramp, platoons remain intact to maximize the platoon driving distance. Saeednia and Menendez (2016) studied slow-down and catch-up strategies for merging trucks into a platoon under free-flow traffic. Larsson et al. (2015) defined the platoon formation problem as a vehicle routing problem to maximize the fuel savings of platoon vehicles. Studies by Liang et al. (2016) and van de Hoef (2016) investigated the problem of coordinating many trucks in platoons to maximize fuel savings. In the formation of platoons, trucks can adjust their speed without regard to traffic conditions. Larson et al. (2013) developed a distributed control system in which trucks can adjust speed to form platoons to save fuels. Johansson et al.(2021) developed two game-theoretic models to study the platoon coordination problem where vehicles can wait at network nodes to form platoons. In Table 4.1, we compare the newly developed functional components and the performance analysis of the AMoD system with the new components in our modeling framework with the referred studies in the literature.

Table 4.1 Comparison of the strategic platoon formation studies at the route level

Studies	Modeling components								Impact analysis				
					Platoon policies		*Coordination strategies*				*Energy consumption*		
	Many vehicles	Road network level	Demand and supply interaction	Mixed traffic	*Platoon sizes*	*Formation time constraints*	*Speed adjustment (Slow down or catch up)*	*Hold-on strategy*	Platoon vehicles	Traffic throughput	*Traffic*	*Aerodynamics*	Service levels (waiting and travel times)
Hall and Chin (2005)	✓				✓	✓		✓	✓	✓			
Larson et al., (2013)	✓	✓				✓	✓		✓			✓	
Saeednia and Menendez (2016)						✓	✓		✓				
Larsson et al. (2015)	✓	✓				✓			✓			✓	
Liang et al. (2016)						✓	✓		✓			✓	
van de Hoef (2016)	✓	✓				✓	✓		✓			✓	
Johansson et al.(2021)	✓	✓				✓		✓	✓				
Our approach	✓	✓	✓	✓	✓	✓		✓	✓		✓		✓

4.2.4 Urban AMoD system characteristics in future cities

The AMoD systems envisaged for the future will probably be available in the 2030s to 2040s when SAEV fleets have become common and affordable (Nieuwenhuijsen et al., 2018a). SAEVs, in this chapter considered to be purpose-built micro-vehicles, are intended to cover the whole trips of commuters. While providing on-demand services for morning commuters in lieu of private cars, SAEVs can be coordinated in platoons at service points. Although purpose-built SAEVs could occupy less space, SAEVs cannot form platoons anywhere because of urban driving conditions characterized by narrow streets and traffic congestion. One idea is to define what in this chapter is designated as service points which are platoon formation locations across the service area. Examples of service points for the platoon formation in today's urban transportation systems could include public parking garages, public charging service points, petrol service points, and some parking spaces along the canals in cities. The AMoD systems envisaged for the future will probably be available in the 2030s to 2040s, when SAEV fleets have become common and affordable (Nieuwenhuijsen et al., 2018b; Puylaert et al., 2018b). SAEVs, in this chapter considered to be purpose-built micro-vehicles, are intended to cover the whole trips of commuters. While providing on-demand services for morning commuters in lieu of private cars, SAEVs can be coordinated in platoons at service points. Although purpose-built SAEVs could occupy less space, SAEVs cannot form platoons anywhere because of urban driving conditions characterized by narrow streets and traffic congestion. One idea is to define what in this chapter is designated as "service points": platoon formation and dissolution (platoon is disassembled) locations across the service area. Examples of service points for the platoon formation in today's urban transportation systems could include public parking garages, public charging service points, petrol service points, empty bus stops, and some parking spaces along the canals in cities.

4.2.5 Challenges for the platoon formation in urban AMoD systems

The formation of platoons in urban AMoD systems poses challenges. First, the current state-of-the-art models consider the traffic demand for the platoon formation in an oversimplified way. Travel demand is generated according to trip lengths, destination distributions, and vehicle arrival patterns. Different distributions could be used to generate travel demand while capturing its uncertainty. However, in AMoD systems, the zero-occupancy vehicle trips of picking up the assigned travelers introduce uncertainty in the traffic demand on the road network. This uncertainty, therefore, requires explicit modeling of the interaction between SAEVs and travelers.

Second, existing studies overlook the effect of forming platoons on travelers in the platoon vehicles. In the future AMoD system that we are studying, a fleet of SAEVs directly provides on-demand services to travelers between service points. The formation of platoons requires the synchronization of different vehicles in the same coordinates. In the formation of platoons, vehicles may wait for other vehicles to form platoons, causing delays for travelers. The impact of forming platoons on the travelers in the platoon vehicles must be captured.

Third, existing studies investigate the effect of reduced aerodynamic drag via platooning on energy consumption in highway driving. However, due to higher traffic demand on the urban transport network, the potential for energy efficiency is primarily influenced by traffic conditions rather than by reducing air resistance. Coordinated movements of platoon vehicles could improve traffic throughput. As a result, the energy consumption of traffic participants (SAEVs) will be affected by platoon operations. Moreover, current studies aimed to investigate the traffic impact of platoon vehicles using predefined platoons. Therefore, the impact of forming platoons on travel conditions and energy consumption of SAEVs in urban driving needs to be assessed for future scenarios.

Fourth, platoon sizes (the maximum number of vehicles in a platoon) and the maximum time spent forming platoons are not restricted. This relaxation can lead to overestimation of the platoon driving distances and energy savings by forming long platoons. In AMoD systems, forming a long platoon may cost travelers more time in a situation where vehicles wait for other vehicles. Setting limits on platoon sizes and time spent in the formation can prevent long platoons from disrupting urban traffic and causing long delays for travelers. Therefore, the platoon size restriction and maximum time spent in the formation of platoons need to be taken into account when coordinating SAEVs in platoons. The impact of the time and platoon size restrictions on the formation of platoons, the level of service offered to travelers and on energy consumed needs to be studied.

4.2.6 Research contributions

This chapter aims to develop an agent-based model to study the impact of forming platoons in future urban AMoD systems on people's travel and energy usage. Agent-Based Modeling is suitable for our research questions. The agent-based modeling has the advantage of representing entities at a high resolution; the interaction of entities (e.g., vehicles and travelers) can be captured realistically; it is flexible to model a system at different description levels (e.g., vehicles and platoons formed by vehicles) to evaluate different aspects of the system and to make changes to assumptions (e.g., formation policies) for different scenarios. Taking into consideration the limitations of current studies identified above, we summarize the main contributions of this chapter as follows:

First, the ABM originally developed in this chapter includes a high level of detail. The individual travelers are modeled, and their attributes are initiated according to the regional travel demand data and the realistic departure time data. The interaction between SAEVs and travel requests is explicitly modeled by developing a vehicle-to-travelers assignment component, in which SAEV pickup trips and drop-off trips are represented. The modeled interaction between vehicles and travelers captures the uncertainty of traffic demand between areas of origin and destination.

Second, the formation behavior of waiting at service points, defined as the hold-on strategy, is explicitly simulated for platoon leaders and their followers. The platoon formation policies that determine when a group of vehicles leaves a service point as a platoon are: the maximum elapsed time of the platoon leader and the maximum platoon size. Either one of the two policies can trigger a release of a platoon. The AMB simulates platoon formation operations of vehicles, which allows us to measure the impact of forming platoons on travelers. Moreover, the formed platoons are flexibly represented with specified information (e.g., the platoon route, the vehicle sequences, the speed) at an aggregate level to model platoon driving and its impact on traffic conditions.

Third, a mesoscopic traffic simulation model is used to represent the traffic dynamics throughout the road network. The mesoscopic traffic simulation model can simulate each vehicle's movement, while a macroscopic speed-density relationship is used to govern congestion effects. The traffic simulation model can incorporate the impact of all SAEV trips, including unoccupied pickup trips and occupied drop-off trips, on the traffic over the road network. Furthermore, the relationship established between road capacity and platoon characteristics is used to assess the impact of formed platoons on traffic conditions.

Fourth, an energy consumption model is linked with the mesoscopic traffic model to efficiently calculate the energy consumed by individual SAEVs for travelers' trips. It can also produce the energy estimate of intended trips, thus ensuring that the assigned SAEVs have sufficient power to complete their journeys.

The travel and energy potential of forming platoons under different formation policies and demand levels in AMoD systems is assessed using the urban road network of the case-study city, The Hague, the Netherlands, through a set of defined key performance indicators (KPIs).

4.3 Model Specifications

For building the ABM, we introduce the following main assumptions regarding the platoon formation of SAEVs in AMoD systems:

- All travel demand is produced and attracted between what have been designated as service points that are connected to the network nodes. Service points are thus locations where travelers can be picked up or dropped off by a vehicle. This is reasonable for the situation where many service points are designated in a service area.
- We assume that vehicles wait at service points to form platoons instead of using slow-down and catch-up strategies. The major drawbacks of slow-down and speed-up strategies are that urban traffic flow can be disrupted when driving slowly, and accelerating vehicles may violate urban road speed limits. Moreover, slow-down and speed-up strategies are very difficult for urban driving, which is characterized by one or two lanes for each direction and traffic congestion.
- We assume that there are enough parking places for SAEVs to form a platoon at the service points. SAEVs are purposely designed to be space-saving micro-vehicles (Renault Twizy for the reference model). Moreover, there are size restrictions on the platoon size.

The framework presented in Figure 4.1 includes a fleet management center and a traffic management center. The fleet management center mainly matches vehicles with travelers and coordinates the formation of platoons. The traffic management center primarily represents the network traffic dynamics and finds the time-dependent shortest routes for vehicles based on the current network traffic conditions. The fleet management and traffic management components capture different aspects of the system components' interactions. The modeling framework can evaluate system performance with regard to defined KPIs based on the realistic travel demand data and the existing road network.

The model assumes that OD trip demand and aggregated departure times are given. The demand generator in the simulation model will generate individual travel requests with an origin location, destination location, and request time according to the given OD matrix and departure time distribution. According to real-time information about the travel requests, the vehicle assignment component matches the available vehicles with incoming travel requests. Once the assignment has been done, the information on travelers' locations is sent to the assigned vehicles, and travelers are notified about the vehicle details. The assigned vehicle will be dispatched to pick up the traveler—the state of the assigned vehicle transition from idle to in-service state.

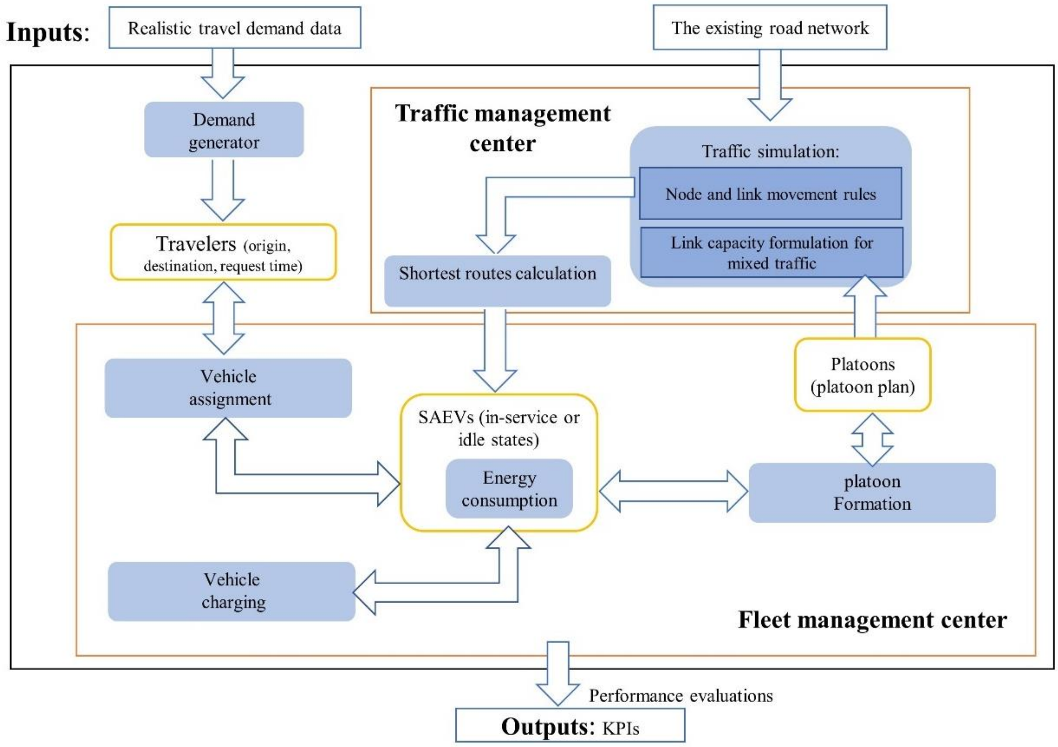

Figure 4.1 Platoon formation modeling framework

The traffic management center provides the time-varying traffic conditions, forming a basis for subsequent route calculations. A mesoscopic traffic simulation model is used to represent traffic patterns over the road network, which can be captured by simulating the movement of SAEVs along their routes as they carry out the travelers' journeys. The traffic simulation model manages static and dynamic information to determine the current network traffic conditions. The static inputs to the traffic simulation model are the traffic network representation, including links and nodes, traffic capacity, free-flow speed, and road length, while the dynamic information concerns the information about which road segments individual vehicles and/or platoon vehicles are traveling on. Based on the current network traffic conditions provided by the traffic simulation component, the time-dependent shortest routes between points are computed, which is a string of ordered road segments to be traversed.

The energy consumption model estimates the energy consumption of individual vehicles over the road network. The energy consumption of individual vehicles is computed as a function of the link travel speed. The charging component is responsible for finding charging points for low battery vehicles. Vehicles can be charged at every service point after completing the journey of a traveler. The time delay due to the charging operations is considered.

The platoon formation component in the fleet management center coordinates vehicles in an existing platoon at designated service points according to their destinations. Also, a new platoon can be initiated when one of the grouped vehicles arrives at the formation location. Once the platoon agent type is created, the platoon agents manage the information about the platoon plan, including platoon routes, the number of platoon vehicles, platoon speed, and the assigned leader and its followers with the determined vehicle sequence. The platoon followers adjust their shortest routes to the route of the platoon leader. The traffic simulation model in the traffic management center can account for the impact of the operations of formed platoons on traffic dynamics. Figure 4.2 illustrates the platoon formation and its potential. The detailed descriptions of the functionalities are explained in the following sections.

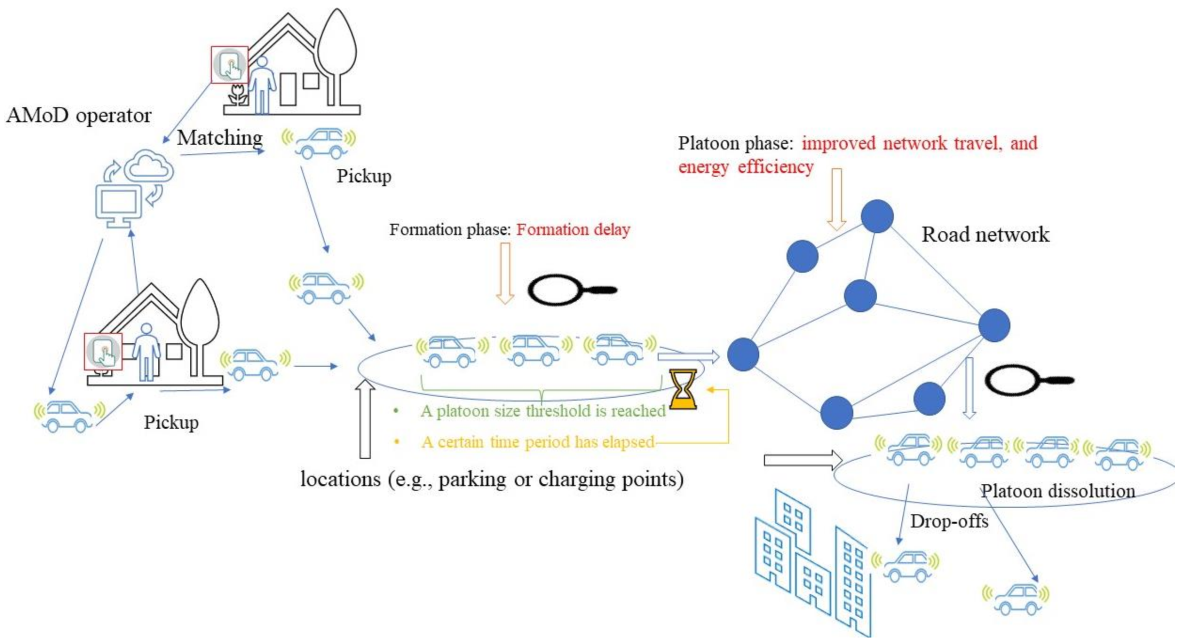

Figure 4.2 An illustration of the platoon formation and potential impacts

4.3.1 Energy consumption of the SAEVs

Existing studies (Bauer et al., 2018; Hu et al., 2019) estimate the energy consumption of electric vehicles on the network level as a function of travel distance, which means translating the kilometers driven into an estimate of energy consumed. However, the strong correlation between energy consumption and vehicle speed is not considered. We attempt to estimate the energy consumption of SAEVs and account for traffic congestion by making it a function of experienced travel speed. It is linked to a mesoscopic traffic simulation model in which the effect of forming platoons on traffic conditions is considered. The energy consumption model is thus capable of accounting for the effect of platoon driving.

The energy consumption model contains a set of regression models for different vehicle types. These regression models can be used to calculate the energy consumption associated with one vehicle traversing each road segment based on the speed of the vehicle and the length of the road segment. The calculation method is explained as follows.

First, the average speed for individual SAEVs traversing the corresponding road segment is calculated. Second, the energy consumed by the SAEVs per unit distance is estimated using the regression model in Equation 4.1, which describes the relationship between energy consumption and travel speed. Third, the total energy consumption on the route between the origin and destination is calculated as the sum of energy consumed by the individual SAEV in each road segment. The formula for calculating total energy consumption is shown in Equation 2.

$$E = \alpha + \beta * \mathrm{S_i} + \gamma * S_{\mathrm{i}}^{2} \tag{4.1}$$

Where:

α, β and γ are coefficients;

Si is the travel speed of an individual SAEV traversing road segment i;

E is the energy consumption per unit distance.

The total energy consumption of each SAEV to complete the pickup trip or drop-off trip can thus be calculated as:

$$\mathrm{E_t} = \sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{E_i} * \mathrm{L_i} \tag{4.2}$$

Where:

n is the total number of road segments between the locations (e.g., the locations of the assigned vehicle and the origin of the travelers, or the locations between the origin of the traveler and his/her destination;

L_i is the length of each road segment i.

E_t is the total energy consumption of an SAEV to complete the pickup trip or drop-off trip.

We estimate the energy consumption of different types of vehicles. Each vehicle type corresponds to a regression model derived from the laboratory dynamometer tests (Galvin, 2017). The coefficient for different vehicle types is given in Table 4.2 in Section 4, where the application of the model is presented.

4.3.2 Real-time vehicle assignment

The vehicle assignment component assigns available vehicles to serve travelers as travel requests come in, which are generated according to the aggregate travel demand (explained in Section 4.2). The vehicle assignment component will assign the nearest available SAEV with enough battery power to serve a traveler to his/her destination. For that to happen, there must be a real-time estimation of how much energy is needed if that traveler is satisfied, and this is estimated for each candidate vehicle based on its particular vehicle type.

The process of finding available vehicles for travel requests goes as follows. Firstly, the energy consumption of an individual vehicle to complete the intended trip is estimated based on the energy function. The estimate of energy spent on transporting the intended traveler can be calculated using Equation 4.3. Secondly, based on the estimated energy consumption of the intended traveler, available vehicles with sufficient remaining battery capacity that can undertake the traveler's journey are filtered from the group of idle vehicles; Finally, a vehicle located at the shortest Euclidean distance within the search radius is chosen from the filtered pool of available vehicles.

$$\mathrm{E}_e = \eta * \mathrm{E}_\mathrm{t} \tag{4.3}$$

Where:

η are coefficients; η is a safety coefficient used to ensure that the estimated energy for a traveler's intended trip is not less than the actual energy consumed by individual vehicles to complete the trip that might happen if traffic changes.

E_e is the estimated energy required by an individual vehicle to complete the trip of a traveler.

The function in Equation 4.3 estimates the energy needed to complete travelers' trips based on the link travel speeds the moment when a traveler calls the service, while the actual energy consumed uses the experienced speeds of vehicles in Equation 4.2 to calculate the energy spent after completing the traveler's trip. The proper estimate of energy spent to complete the trip of an intended traveler ensures that the assigned vehicle has sufficient battery capacity to reach the traveler's destination.

Once an available vehicle with sufficient remaining energy is assigned to a traveler, the time-dependent shortest route (lowest duration) from the current vehicle location to the traveler's location is computed. After the vehicle arrives at the pickup location, the time-dependent shortest route from the traveler's location to its destination will be determined. The computation of time-dependent shortest routes is based on the Dijkstra algorithm.

4.3.3 Mesoscopic traffic simulation

A mesoscopic traffic simulation model that includes link movement and node transfer is incorporated into the agent-based modeling framework. The mesoscopic traffic simulation model combines a microscopic level representation of individual vehicles with a macroscopic description of the traffic patterns (Mahmassani, 2001; Zhou & Taylor, 2014). In the link movement, vehicular movements are simulated. Vehicle speed on the road segments is updated according to the established macroscopic speed-density relationship. A modified Smulders speed-density relationship (Equation 4.4) is used to update the vehicle speed based on the link density.

$$v(k) = \begin{cases} v_0(1 - \frac{k}{k_j}), & k < k_c \\ \gamma(\frac{1}{k} - \frac{1}{k_j}), & k \geq k_c \end{cases} \tag{4.4}$$

Where:

k is the link traffic density.

$v(k)$ is the speed that is determined by the traffic density k; v_0 is the free-flow speed.

$\mathrm{k_c}$ is the link critical density; k_j is the link jam density.

γ is a parameter. The value of the parameter can be derived as $\gamma = \mathrm{v_0 k_c}$.

Node transfer means that vehicles transfer between adjacent road segments. A vehicle moving from an upstream link (road segment) to a downstream link will follow the defined rules:

- The vehicle is at the head of the upstream link queue. In other words, there are no preceding vehicles stacking in the waiting queue.
- The number of outflow vehicles has been checked to determine whether a vehicle can leave the road segment it is traversing.
- The number of storage vehicles has been checked to determine whether the downstream link has enough storage units to accommodate the upcoming vehicle.

The mesoscopic traffic simulation model, including link movement and node transfer, can provide the required level of detail in estimating the speeds of individual vehicles on the network while balancing the trade-off between computational cost and traffic model realism.

4.3.4 Traffic simulation for platoon vehicles

In the literature, strategic platoon formation was studied while ignoring the traffic. We fill this gap by developing a simulation component for mixed operations of platoon AVs and non-platoon AVs on top of a mesoscopic traffic simulation. The functional component for the mixed operation of platoon AVs and non-platoon AVs can capture the traffic impact of forming platoons across the road network. The relationship between road capacity and different proportions of platoon vehicles is established to assess the impact of platoon formation on traffic conditions. Chen et al. (2017) proposed a formulation to describe the correlation between platoon characteristics, including the proportion of platoon vehicles, inter-vehicle spacing levels, and macroscopic capacity. The formulation reveals how the single-lane capacity changes for different proportions of platoon vehicles. The derived macroscopic capacity formulation for mixed traffic solves the problem of determining the macroscopic traffic variables based on platoon characteristics. Therefore, it is very suitable to be combined in the mesoscopic traffic simulation that applies the macroscopic speed-density function to govern the movement of the vehicles that we use in the simulation methodology. The single-lane capacity is expressed as:

$$C_c = \frac{C_a}{1 - \frac{N}{M+N} * (1-\alpha)\left(1 - \frac{L}{N}\right)} \tag{4.5}$$

Where

C_a denotes the lane capacity for all vehicles traveling regularly.

L is the number of leaders.

N is the total number of platoon vehicles.

M is the total number of regular driving vehicles.

α is the ratio of platoon spacing to regular spacing.

As shown in Equation 4.5, the capacity C_c depends on the penetration rate of platoon vehicles $\varphi = \frac{N}{M+N}$ and the number of leaders (L). A smaller distance spacing between platoon vehicles allows an increase in lane capacity. The lane capacity increases as the penetration rate of platoon vehicles φ. Moreover, for the same number of platoon vehicles N, the more leaders L are created, the fewer capacity increases. We use the following definitions of different critical spacing types according to the operational characteristics of vehicle platooning. The critical spacing when vehicles travel regularly (e.g., AVs that are not in platoons) is defined as d_a. We define $d_p = \alpha d_a$, where $0 < \alpha < 1$. We assume that the critical spacing between a platoon vehicle and a regular driving vehicle that is not in a platoon is also d_a.

Notice that regular driving AVs that are not in platoons follow the regular driving distances of conventional vehicles, while platoon vehicles move at a reduced spacing.

The formulation of the capacity of one lane (for one direction) shows how it can be improved by increasing the penetration rate of platoon vehicles and the number of leaders or platoons (Each platoon has one leader). In order not to impede the narrative flow, the detailed derivations of Equation 4.5 can be given in Appendix A.

4.3.5 Platoon formation mechanism

Spontaneous or on-the-fly platoon formation without proper prior planning can cause a high frequency of joining and leaving operations by the vehicles, which might disrupt traffic and decrease safety (Gerrits, 2019). This type of platoon might not ensure a high rate of in-platoon driving. In AMoD systems, many SAEVs are assigned to take travelers from place to place in urban areas; therefore, they will be continuously routed to different destinations. The platoon formation for a fleet of vehicles that provide on-demand transport is more effective if done in a coordinated way. SAEVs can be coordinated in a platoon using the hold-on strategy while providing direct on-demand service between service points designated as the platoon formation locations over the AMoD network.

The formation behaviors of platoon participating vehicles are realistically represented. In relation to coordinating vehicles in the platoon formation, a vehicle can be assigned to an existing platoon as a follower vehicle. A vehicle can be connected to other vehicles to initiate a new platoon, either as a platoon leader or as a follower. In the first case, arriving vehicles at a service point are assigned to an existing platoon according to the destinations of travelers assigned to them.

There are no existing platoons at a service point in the second case, or the arriving vehicles cannot be assigned to an existing platoon. Arriving vehicles at the service point are divided into different groups. For vehicles in each group at a service point, the first vehicle to arrive is designated as the platoon leader. Once a platoon leader is assigned, the platoon is initiated.

Algorithm 4.1. Pseudocode for the formation of platoons

INPUT: information about a list of arriving vehicles A= $\{a_0, a_1, \dots, a_m\}$. The information Z_{a_i} for vehicle a_i can be represented by a set $\{a_i, r_i\ o_i, d_i\}$. Origin o_i is the service point that vehicle a_i is moving towards and destination d_i represents the next service point. r_i is the shortest route between o_i and d_i.

FOR each arriving vehicle a_i in the set A
Compare information $\{a_i, o_i, d_i\}$ $(i = 1,2,..,m)$ to the information $Z_{p_j} = \left\{p_j, r_{p_j}, o_{p_j}, d_{p_j}\right\}$ $(j = 1,2, \dots, n)$ of existing platoons' leaders $P = \{p_0, p_1, \dots, p_n\}$
IF ($Z_{a_i}(o_i, d_i) == Z_{p_j}(o_{p_j}, d_{p_j})$) AND platoon size s_j of the platoon p_j is not reached)
Add vehicles a_i to the platoon p_j as a follower;
Adjust the vehicle's shortest route r_i to the platoon shortest route r_{p_j};
Remove vehicle a_i from the set A;
ENDIF
Continue
FOR each arriving vehicle a_X in the set A
IF((a_i is not connected to a_X) AND $(a_i \neq a_X)AND(Z_{a_i}(o_i, d_i) == Z_{a_x}(o_x, d_x))AND$ (the number of connected vehicles for a_i < platoon size V))
a_i and a_X are paired, and the connection between a_i and a_X is established;
IF a_X is not in the destination group d of vehicle a_i
Let the vehicle a_X join the destination group d ;
ENDIF
ENDIF
ENDFOR
Remove vehicle a_i from the set A;
Vehicles that are not paired move as individual vehicles;
ENDFOR

OUTPUT: Platoons of vehicles and regular driving vehicles that are not in platoons

The hold-on strategy of the platoon leader is used to organize vehicles into platoons at a service point according to their destinations. The hold-on time of a platoon leader is the time from when the leader starts to wait for other vehicles until the moment the platoon is formed and starts to move. The release of a platoon (the moment when it departs) depends not only on the number of vehicles that it has (there is a maximum number of vehicles in a platoon) but also on the time that the platoon leader has been waiting. That is, the release of a platoon can be triggered by reaching the maximum vehicle size or the maximum hold-on (waiting) time of the platoon leader, as explained before. We denote the time threshold of platoon leaders as T and the maximum number of platoon vehicles as V. The physical constraints of road segments directly set a threshold for the number of vehicles in a platoon. Algorithm 4.1 explains the platoon formation mechanism.

The formation approach uses global knowledge about all arriving vehicles for each service point to assign them to an existing or newly created platoon. Vehicle sequence in a platoon is determined based on the arrival time of a vehicle at the platoon formation location. The platoon leader makes decisions on behalf of the followers to trigger the platoon release and split the platoon after arriving at the destinations of the travelers. Once the SAEVs are assigned to serve the travelers, their shortest routes are calculated using the Dijkstra algorithm. Platoon followers adjust their routes from their original shortest routes to the shortest route of the platoon leader. A plan is created for a formed platoon, including platoon ID, a leader and its followers, a platoon route, and the vehicle sequence in the formed platoon (see Algorithm 4.2).

Algorithm 4.2. Pseudocode for determining platoon plans

```
INPUT: Groups of vehicles
FOR grouped vehicles in each destination group D
    Determine the leader for the grouped vehicles d_k ∈ D;
    Initiate a platoon p_k according to the platoon leader's information (location and shortest route);
    Assign the other vehicles in the group into the new platoon as followers;
    Determine the vehicle sequence according to the arrival time;
    Adjust the shortest routes of the followers in p_k to the shortest route of the platoon leader r_{p_k};
ENDFOR
OUTPUT: Platoon plans, including platoon ID, a leader and its followers, a platoon route, the vehicle sequence
```

4.4 Model application to the city of The Hague

The detailed conceptual framework is implemented in the AnyLogic multimethod simulation modeling platform coded with Java programming language. The data used in the simulation experiment is explained below.

4.4.1 The topology of the road network in The Hague

Figure 4.3 displays the road network of the Zuidvleugel region (around Rotterdam and The Hague). The blue color indicates the part of the road network that is used for the simulation study, which includes eight districts of The Hague and the towns of Voorburg, Rijswijk, and Wateringen. The dots are the centroids of the Traffic Analysis Zones (TAZs), which are the origins and destinations of all travel requests. The data containing the aggregated OD Matrix, departure time distribution, and information about the study area centroids and the road network are exported from OmniTRANS transport planning software. The geospatial data in the Shapefiles are exported from OmniTRANS, a multimodal transport planning software package, in which road segments are polylines with many points.

Figure 4.3 Road network of The Hague in the Zuidvleugel Road network

We use the distance-based Douglas–Peucker algorithm to simplify each road curve (polyline) composed of lots of line segments into a similar road polyline with fewer points. A simplified polyline consists of a subset of the points defined in the original polyline. A polyline with fewer points represents a road with the same length, with higher resolutions than the straight line between nodes usually used in transport models of shared automated vehicles. Amersfoort/RD New (EPSG:28992) in the projected coordinate system is used for the map projection for locally optimized use. The coordinates in the Shapefiles must be transformed from Amersfoort / RD New in the projected coordinate system to WGS 84, one of the most widely used global geographic coordinate systems (e.g., it is standard for GPS).

4.4.2 Detailed travel demand

The OD trip table containing a total of 27,452 trips made by cars is used as input to generate time-dependent travel requests. The OD trip table specifies travel demand between TAZs in the AM peak hours over the study area. The departure time fractions shown in Figure 4.4 are used to calculate the number of trips between OD pairs per 15-minute time interval from 5:30 am to 10:00 am. A demand generator generates time-dependent travel requests based on the aggregate travel demand. Individual travel requests are characterized by the origin zone, destination zone, and time of the request. Demand generation requires two steps. The first step is to generate a certain number of time-dependent travel requests for each zone over each time interval (i.e.,15 minutes). The total production of demand in the morning peak hours for each zone is calculated based on the origin-destination (OD) matrix, and the demand per time interval is estimated using the departure time fractions. In each time interval, a number of travel requests are generated, which are then distributed according to a discrete uniform distribution within this time interval. The generated travel requests in each time interval are associated with a specified time of requesting the service. The second step is to determine a destination zone for each demand request. Observations of destinations for the generated trips

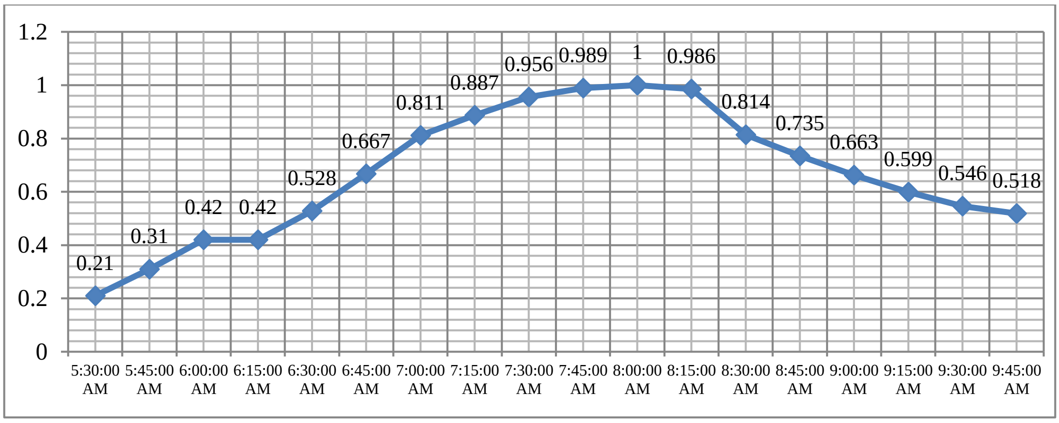

Figure 4.4 Departure time fractions for 18 time intervals from 5:30 am to 10:00 am

in each zone are naturally available in the OD matrix. That is, the number of trips ending in every other zone is known. For each zone, a custom distribution of demand destinations is constructed from the observations. A destination zone for each travel request can be chosen using the Monte Carlo simulation process based on the destination distribution.

4.4.3 Simulation parameters

The attributes of free-flow speed, the link travel speed at capacity, and the traffic capacity of different road types such as urban roads, rural roads, and local roads are read from an external dataset listed in Appendix B. The traffic parameters provide information about the traffic flow characteristic of the regular driving vehicles (that are not in platoons). In platoon driving, inter-vehicle distance (d_p) is determined based on field experiments (Browand et al., 2004; Lammert et al., 2014). We test different platoon formation strategies and compare their performance while treating the parameter d_p as fixed. The vehicle models used for the energy estimation are these commonly sold electric vehicles: Nissan Leaf SV 2013, Kia Soul Electric 2015, Nissan Leaf 2012, BMW i3 BEV 2014, Ford focus Electric 2013, Mitsubishi 1 MiEV 2012, Chevrolet Spark EV 2015, and Smart EV 2014. The coefficients used in Equation (4.1) are adopted from the work by (Galvin, 2017) (see Table 4.2).

Table 4.2 Coefficients in the regression model for different vehicle types

Coefficient	α	β	γ
NissanSV	479.1	-18.93	0.7876
Kia	468.6	-14.63	0.6834
Mitsubishi	840.4	-55.312	1.670
BMW	618.4	-31.09	0.9916
Ford	1110	-96.61	2.745
Chevrolet	701.2	-35.55	1.007
Smart	890.8	-43.12	1.273
Nissan2012	715.2	-38.10	1.271

We assume that SAEVs can be charged rapidly to 80% of the battery capacity in 30 minutes at every service point. All types of SAEVs initially have a battery level of 24 kWh. The value of η used in estimating the energy consumption in Equation (4.3) is determined based on a trial-and-error approach. It must be guaranteed that no travelers are stranded due to insufficient battery power of assigned vehicles. We repeatedly ran the simulation model by increasing the value of η until the estimated energy E_e is sufficient for each assigned vehicle to complete the intended trip. SAEVs are deployed over the designated service points in proportion to the amount of travel demand at the corresponding service point. 49 TAZs are connected to the road networks using zone centroids. The 49 locations of the centroids in the road network are designated as service points in the urban AMoD system. Table 4.3 gives a summary of the main model parameters.

Table 4.3 Summary of the main model parameters

Category	**Value**
The perimeter of the study area	46 km
The size of the study area	139 km^2
Time steps for speed update	6 seconds
Inter-vehicle distance (d_p) in platoons	6 meters
Avg. fleet size per service point (vehicles) for 100% demand	170
Service points (centroids of the zones)	49
Road segments	836
Road nodes	510
Total travel demand	27452 trips
Maximum number of platoon vehicles	{2,4,6,8} vehicles
Time threshold for platoon leaders	{2,4,6,8} minutes
Charging time	30 minutes
Coefficients η	3.05
Battery initial capacity	24 kWh
Average travel time under light traffic	18 minutes

4.5 Simulation results and discussion

In this study, several scenarios are simulated for the following purposes. First, scenarios for platoon formation policies are simulated to investigate how the formation of platoons affects the level of service provided to travelers. Second, simulation experiments are conducted to evaluate the impact of forming platoons on energy consumption for different car models. Table 4.4 gives detailed explanations of the main KPIs.

We analyze the system's performance with the platoon formation in terms of the platoon delays of travelers in the platoon vehicles at different demand levels. Demand for AMoD services (as input) is varied from 100% to 20% of the total private car trips in the study area. Fleet sizes at different demand levels in Table 4.5 are calculated based on the same scale factor as the decrease in travel demand. For every demand level, platoon formation policies (T, V) (T stands for the time threshold and V for the platoon size threshold)) are defined. We simulate the scenarios with platoon formation policies (T2, V2), (T4, V4), (T6, V6), and (T8, V8), where T2 means the maximum waiting time is 2 minutes and V2 represents the maximum platoon size equals 2.

Table 4.4 Description of the main KPIs

Key Performance Indicator	**Description**
Delay of travelers in platoon vehicles	The time delay of platoon vehicles is the average dwell time that platoon vehicles (platoon leaders and platoon followers) spend at formation points without moving.
Delay of travelers in platoon leaders (platoon delay for leaders)	The time delay of platoon leaders is the average dwell time that platoon leaders spend at formation locations without moving.
Network travel time	The network travel time is the in-vehicle time spent on average by all served travelers when vehicles are traveling from origin to destination. Platoon delays are not included in the network travel time for travelers in platoon vehicles.
Platoon travel time	The platoon travel time is calculated by the platoon delays plus the network travel time of travelers in platoon vehicles.
Congestion level	The congestion level describes how much longer, on average, vehicular trips take during the AM peak hours compared to the average travel time in light traffic conditions. The average travel time in light traffic in the case-study city is estimated based on the travel speed suggested by (Ligterink, 2016).
90% quantile travel time	The 90% quantile travel time indicates the travel time which is longer than 90% of the trips.
The percentage of energy savings	The percentage of the reduction in the energy consumption of all the vehicular trips in the platoon scenarios compared to the non-platoon baseline scenario.

Simulation results in Table 4.5 show that the increased values of two attributes ((from (T2, V2) to (T8, V8)) for the platoon formation lengthen the platoon delays of travelers in platoon vehicles. Under the platoon formation policies (T8, V8), the platoon delay of travelers inside platoon vehicles is about 3.67 minutes, which is more than five times the platoon delay of travelers under the policy (T2, V2). Results suggest that the formation of platoons can cause long unexpected delays of travelers in the platoon vehicles.

Table 4.5 Average delay of platoon vehicles for different demand levels

Demand levels	**100%**	**80%**	**60%**	**40%**	**20%**
The number of travel requests (trips)	27452	21962	16417	10980	5490
Avg. fleet size per service point	170	136	102	68	34
Platoon scenarios	Avg. delay of platoon vehicles (minutes)				
(T2, V2)	0.66	0.66	0.66	0.66	0.66
(T4, V4)	2.30	2.30	2.38	2.51	2.75
(T6, V6)	3.23	3.22	3.29	3.50	3.67
(T8, V8)	3.67	3.67	3.87	4.01	4.62

Moreover, results suggest that the delay of travelers in platoon vehicles tends to increase as the demand level decreases. For example, the delays of travelers in platoon vehicles increases by 25% when demand falls from 100% to 20% of the total private car trips under the formation policy (T8, V8). Few travelers requesting AMoD services cause more delays for the travelers in platoon vehicles, while a relatively large number of AMoD users lead to smaller platoon delays. There tends to be an inverse relationship between the demand level and platoon delays.

In order to look into the platoon delay encountered by travelers in more detail, delays of travelers in platoon leaders are presented in Table 4.6. Results indicate that the delays experienced by the travelers in platoon leaders are approximately twice that of other platoon vehicles with the formation policy (V8, T8). That is, travelers in platoon leaders have to wait longer than travelers in other vehicles of the platoon. The platoon formation has considerably more impact on the level of service provided to travelers in the platoon leaders. Since vehicles in the formed platoon are arranged in order of arrival, the platoon leader arrived early at the service point and waited the longest for the other vehicles to form a platoon. The platoon delays are getting smaller and smaller for the followers that arrive later.

Table 4.6 Platoon delays for platoon leaders and platoon vehicles under different operating policies

The time threshold (minutes) **The platoon size threshold (vehicles)**	**Non-platoon (0)** **Non-platoon (1)**	**2** **2**	**4** **4**	**6** **6**	**8** **8**
Platoon scenarios	No platoons	(T2, V2)	(T4, V4)	(T6, V6)	(T8, V8)
Avg. delay of platoon leaders (minutes)	0	0.69	3.49	5.67	7.02
Avg. delay of platoon vehicles (minutes)	0	0.66	2.30	3.23	3.67

4.5.1 Congestion levels and network travel times

We investigate the impact of forming platoons on network traffic performance. The indicator of the network congestion level (explained in Table 4.4) is defined to evaluate travel conditions under different platoon formation scenarios. The congestion levels in non-platoon scenarios are used as a baseline for comparison.

Moreover, we measure the network travel time of all travelers (in platoons and not in platoons) and platoon travel times of travelers in the platoon vehicles. Note that the platoon delay is not included in the network travel time, while the platoon travel time is calculated by the platoon delay plus the network travel time.

Results in Table 4.6 show that the platoon formation can reduce congestion levels and network travel times for all travelers. Compared to the non-platoon scenario, the formation policy (T2, V2) obtains a minimal reduction of 18% in the congestion level, resulting in a reduction in the network travel time of about 3 minutes. The formation policy (T8, V8) reduces the congestion level by up to 41.61%, which is equivalent to a reduction in the network travel time of about 7 minutes. This is because more vehicles are coordinated in platoons as the values of the two attributes (T, V) in the platoon formation policy are increased. As shown in Table 4.7, the total number of vehicular trips in platoons rises from 5564 to 8056 trips. Figure 4.5 shows that the number of platoon vehicles circulating in the transportation network increased (from the policy ((T2, V2) to the policy (T8, V8)). The more the vehicles travel in platoons, the more the road capacity is increased. The increased road capacity leads to an improvement in the network travel time. Furthermore, as shown in Figure 4.6, the number of vehicles circulating in the transportation network decreases as the number of vehicles traveling in platoons (see Figure 4.5) increases. The formation of platoons decreases the number of vehicles circulating in the transportation network. When the number of vehicles circulating in the transportation network decrease, travel conditions are improved. As a result, vehicles can travel faster through the road network.

As shown in Figure 4.6, the duration during which a high number of vehicles circulates in the transportation network is reduced in platoon scenarios compared to the scenario without forming platoons. The duration is shorter and shorter as more and more vehicles travel in platoons over the transportation network. The result suggests that the platoon formation could reduce the duration of urban road congestion.

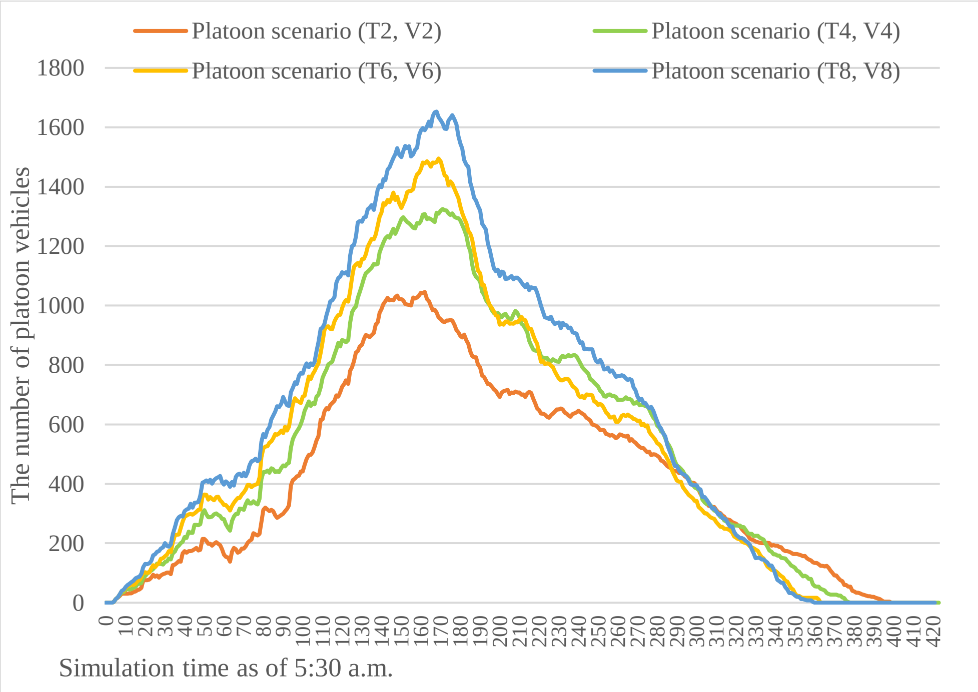

Figure 4.5 The number of vehicles traveling in platoons on the network over time

We compare the 90% quantile travel time in the platoon scenarios to the non-platoon scenario to take a closer look at how the formation of platoons affects network travel times. Shorter 90% quantile travel times imply reductions in network travel times. Results in Table 4.8 show that the formation of platoons can reduce the 90% quantile travel times. The 90% quantile travel times are about 44 minutes for the policies (T6, V6) and (T8, V8), which is 30 minutes less than that in the scenario without the formation of platoons. The results indicate that the network travel conditions are significantly improved by the formation of platoons.

Overall, the formation of platoons could reduce the road congestion level and shorten the congestion duration. On average, travelers can travel fasters across the urban road network. Moreover, the number of vehicles circulating in the transportation network affects the (network) reliability (Mahmassani et al., 2013). Therefore, platoon formation has the potential to improve travel time reliability.

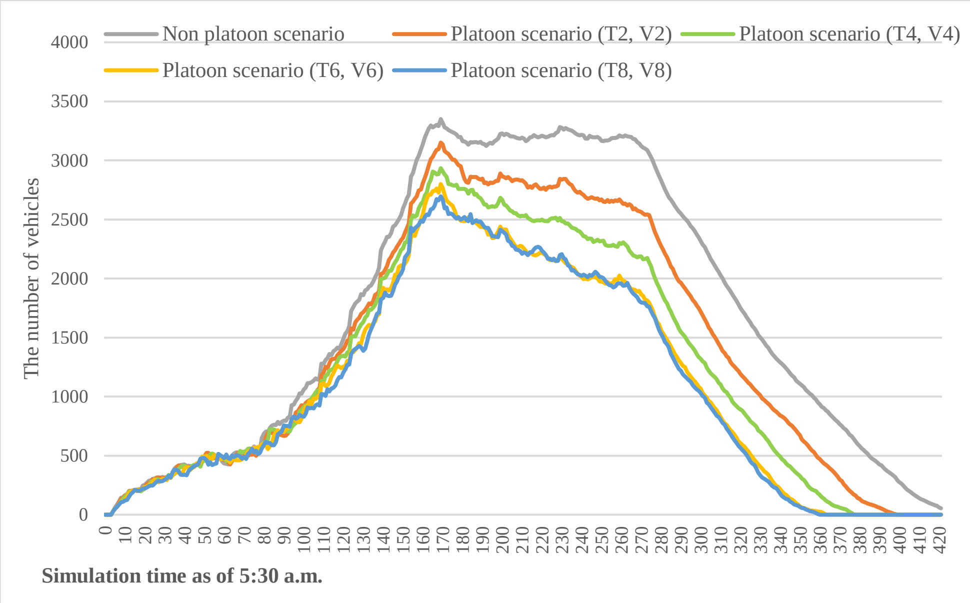

Figure 4.6 The number of all vehicles circulating in the network over time (in platoons and not in platoons)

Table 4.7 Congestion levels, network travel times, and platoon travel times at 100% demand level

Indicators	Congestion levels	Network travel time for all vehicles (minutes)	The total number of vehicular trips in platoons	90% quantile (network) travel times (minutes)	Platoon travel time of travelers in platoon vehicles (minutes)	Platoon travel time of travelers in platoon leaders (minutes)
Non-platoon scenario	53.28%	27.59	No	70.05	No	No
(T2, V2)	35.28%	24.35	5564	59.86	25.01	25.04
(T4, V4)	20.39%	21.67	6899	51.12	23.97	25.16
(T6, V6)	13.56%	20.44	7611	44.20	23.67	26.11
(T8, V8)	11.67%	20.10	8056	43.70	23.77	27.12

Table 4.8 The 90 % quantile (network) travel time at different demand levels

Demand levels	**100%**	**80%**	**60%**	**40%**
The number of travel requests (trips)	27452	21962	16417	10980
Avg. fleet size per service point	170	136	102	68
Indicator	The 90% quantile (network) travel times (minutes)			
Non-platoon scenario	70.05	31.52	15.13	13.49
(T2, V2)	59.86	28.34	14.10	13.50
(T4, V4)	51.12	26.37	13.95	13.17
(T6, V6)	44.20	20.71	13.81	13.38
(T8, V8)	43.70	19.67	13.89	13.41

4.5.2 Platoon travel times

The formation of platoons could cause platoon delays of travelers in the platoon vehicles while reducing network travel times. We found that the platoon travel time, including the platoon delay of travelers in platoons and network travel time, is shorter than the network travel time in the non-platoon scenario. Results of simulating a high-demand scenario where the AMoD system serves 100% of commuter trips made by private car show that formation policies (T6, V6) and (T8, V8) have more than 1 minute less in the platoon travel times than the in-vehicle travel time of travelers in the non-platoon scenario. The reason for this is that the reduction in the network travel times offset the platoon delays, leading to a shorter platoon travel time.

Although the platoon formation can reduce network travel times, travelers in the platoon leaders face longer unexpected delays. This led to a long platoon travel time (27 minutes) of travelers in the leaders, similar to non-platoon scenarios where high congestion is present.

Moreover, we found that the formation of platoons cannot improve network travel time in the low-demand scenario. For example, the 90% quantile (network) travel time is found at around 13 minutes and is not reduced by the formation of platoons when the demand level is below 60% (see Table 4.8). This suggests that platoon driving has no effect on traffic when demand is low, but only delays travelers in the platoon vehicles.

4.5.3 Energy consumption analysis with the platoon formation

We evaluate the impact of forming platoons on the system-wide energy consumption for different vehicle types. Results in indicate that the formation of platoons can reduce the total energy consumed by all vehicles in the AMoD system. The reduction of total energy consumption ranges from 0.42% for the Kia Soul Electric 2015 to 9.56% for the Ford Focus Electric 2013. Moreover, more savings are achieved when the time threshold (T) and the vehicle size threshold (V) for platoon release are increased. The reason is that more vehicles are coordinated in platoons, which results in more vehicles driving in platoons. Less congestion occurs when traversing the transportation network, indicating improvements in traffic efficiency. Therefore, more energy can be saved when platoons are formed.

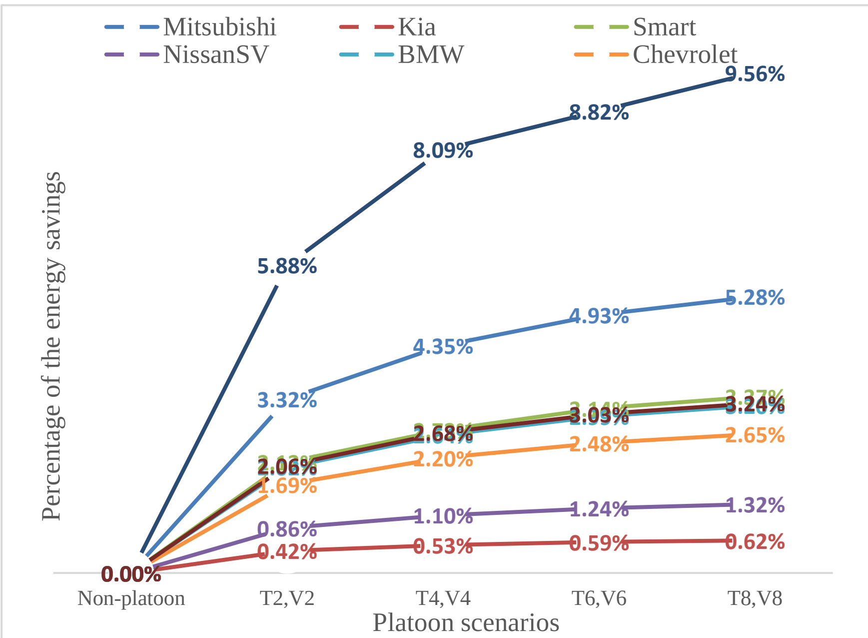

Figure 4.7 Total energy savings of AMoD systems for different types of electric vehicles
(T represents the time threshold of platoon leaders, and V is the maximum number of platoon vehicles.)

Results in Figure 4.7 show that energy savings are different from vehicle types when applying the same formation policy. The maximum saving of up to 9.56% is achieved for Ford Focus Electric 2013 in the (T8, V8) formation policy, while the Kia Soul Electric 2015 has the lowest energy saving of 0.62%. This is because the difference in vehicle characteristics for energy consumption leads to different energy savings. The energy consumption model contains a set of regression models corresponding to the different vehicle types. The regression model, derived from laboratory dynamometer tests, is used to calculate energy consumption as a function of travel speeds. In urban driving, the vehicles will consume more energy at lower speeds, while the energy consumption of individual vehicles will decline as the vehicle speed increases. Thus, vehicles will consume less energy per unit distance traveled with an increase in the travel speed. However, the modeled energy performance of different car types is different. The vehicle type with the sharpest gradient of modeled energy consumption-speed function will see the biggest reduction in energy consumption when having the same increase in the vehicles' speed. The Ford Focus Electric 2013 has the steepest decline in energy consumption-speed function; therefore, when the vehicle travel speeds increase, the Ford vehicle type has the most reduction in energy consumption. The energy-saving of the Kia Soul Electric 2015, which has the least steep gradient of the energy consumption function, ranks at the bottom.

We find that the degrees of energy savings strongly depend on the vehicle types as well as platoon formation policies. Coordinating more vehicles in platoons can significantly improve the energy efficiency for some vehicle types. However, the improvement in energy efficiency for certain vehicle types is relatively small because of the energy consumption characteristics.

4.6 General discussion and main conclusions

This chapter addresses the problem of studying the impacts of the strategic formation of platoons in urban AMoD systems by the development of an agent-based model. The formation of platoons in the urban AMoD system is more complicated because of the urban road network characteristics (narrow streets and multiple road segments between locations), platoon formation locations and policies, and the interaction between AMoD service users and SAEVs. The goal of this study is not to develop a very sophisticated method, but to show, through agent-based simulations, how the formation of platoons in AMoD systems affects people's travel and system-wide energy consumption.

Shared AVs could lead to more traffic and longer travel times due to the additional zero-occupancy movements. In the scenario where SAEVs replace all morning urban commuter trips (100% demand) made by private cars in the case-study city, without the formation of platoons, a high network congestion level of up to 53.28% is observed.

However, the network travel times and congestion levels are improved in the formation of platoons. For example, a congestion level of 11% can be achieved under the policy (V8, T8). That is, for 30 minutes of travel time, 3.3 minutes of additional time must be spent during rush hours. The extra time spent is far smaller than the time spent either in the non-platoon situation where SAEVs replace private car trips or in the current situation where private cars are used. In the first situation, travelers spent extra 15.98 minutes with a 53.28% congestion level. In the second situation, additional 10 minutes is spent in the case-study city (https://www.tomtom.com/en_gb/traffic-index/). In the formation of platoons, travelers are more likely to reach their destination on time or early with the improvement in the network travel times.

We also find that the 90% quantile travel times are significantly reduced in the formation of platoons. This suggests that the network travel times are improved without causing extremely long travel times when platoons are formed, even though additional (zero-occupancy) movements are generated in AMoD systems.

Simulation results demonstrate that the number of total vehicles circulating in the transportation network is reduced by the formation of platoons, which could lead to improved network travel time and reliability. Furthermore, the improved network travel time and reliability could improve the quality of time spent in the vehicles across the transportation network. In this respect, the platoon formation could improve the quality of services offered to all service users (in platoons and not in platoons) when they travel on the transportation network.

On average, the platoon travel time, including the platoon delay and the network travel time, is less than the network travel time in non-platoon scenarios where all morning commuters use AMoD service. That implies that travelers in the platoon vehicles could reach their destination faster even if they experience unexpected delays in the formation of platoons, suggesting improved service levels. In this respect, the benefits from network travel time savings may outweigh the cost associated with the platoon delays. Travelers may opt for the AMoD service in response to service improvements in the formation of platoons.

To be specific, we find that travelers in the platoon leaders experience longer platoon travel times due to longer unexpected platoon delays. In this regard, AMoD service users (morning commuters who were previously driving private cars) in the platoon leaders are provided with a low level of service. Travelers in the platoon leaders may be reluctant to use AMoD services.

We find the existence of an inverse relationship between platoon delays and demand levels. The platoon delays encountered by travelers in platoon vehicles are small in a high-demand scenario. This implies that forming platoons when the market penetration rate of AMoD services is high leads to lower platoon delays. In contrast, travelers face long unexpected platoon delays with fewer AMoD service users. In the former case, the network travel times can offset the platoon delays travelers encounter in the platoon vehicles. Consequently, travelers in platoon vehicles have shorter platoon travel times (total travel times of travelers in the platoon vehicles). In the latter case, no congestion occurs in the transportation network when few travelers request services (this may happen during off-peak hours); coordinating vehicles in platoons only causes unexpected delays for travelers in the platoon vehicles. Forming platoons when demand is low (e.g., below 60% demand) only causes delays for travelers in the platoon vehicles, suggesting a lower level of service. As a result, travelers may not be willing to use the AMoD service. Therefore, a high penetration rate of AMoD service is expected to coordinate vehicles in the formation of platoons to benefit the service users in such vehicles in future AMoD systems.

An important finding is that the improvement in traffic efficiency leads to system-wide energy savings. Forming platoons in AMoD systems can save about 9.56% of the system-wide energy consumption for the most efficient car model studied in urban areas. However, energy savings strongly depend on the vehicle characteristics for energy consumption and platoon formation policies used. Demand for AMoD services and operating policies for forming platoons are important variables of interest for obtaining travel and energy benefits from platoon driving. Effective platoon formation strategies need to be developed for different car models to obtain a favorable effect on system-wide energy consumption.

At the city scale, the formation of platoons enabled by vehicle automation could reduce travel times and unreliability in the modeled urban road network. This may influence their choices of residence with the improvement in travel times and the reliability of urban commuters. It can be inferred that automated mobility systems may have a detrimental impact on urban sprawl, leading to rapid urban expansions. Moreover, platoon operations effectively reduce energy computation in urban mobility systems. While energy consumption is reduced, emissions reductions could also be achieved in the formation of platoons. Thus, platoon operations could bring benefits to operators with regard to energy savings and to society in terms of emissions reductions.

The findings of this study contribute to the growing body of literature on the study of shared AV fleets by quantifying the impact of innovative platoon-formation operations on AV energy consumption as well as people's travel. We shed light on the energy aspect of platoons in urban AMoD systems to complement the existing studies on the fuel consumption of platoons on highways.

4.7 Recommendations for policy and future research

The findings of this chapter raise challenges for policy and for research. The findings suggest that the formation of platoons in AMoD systems can reduce system-wide energy consumptions. Platoon operations can be considered as an effective energy-saving and decarbonization strategy to achieve the government's energy and environmental goals. Moreover, it is recommended that policymakers and transport operators consider the vehicle characteristics for energy consumption in conjunction with platoon formation policies to develop effective energy-saving platoon strategies in future AMoD systems.

Developing platoon formation strategies over urban road networks is recommended aiming at improving traffic efficiency, leading to travel time reductions. However, we find that the magnitude of demand for AMoD services could influence the users' travel times and quality of time. Therefore, the magnitude of demand needs to be considered when deciding whether to coordinate vehicles in platoons. For example, forming platoons below 60% demand over the urban road network only causes unexpected delays. Travelers are reluctant to use the AMoD service due to the long unexpected platoon delays. In this regard, we recommend not forming platoons in the uncongested network with fewer road users (e.g., below 60% demand in the study area, which is the case during off-peak hours). At the same time, vehicles can be coordinated in platoons when congestion occurs to reap the benefits in improving travel times and energy efficiency.

Furthermore, travelers, especially those who travel in the platoon leaders, may not be willing to use AMoD service due to the long unexpected delay and long travel time. For policymakers and transport operators, careful consideration is required to reward the travelers who suffer long unexpected delays in the formation of platoons, which the system's benefit from energy savings can be distributed.

Further research efforts are required to develop mechanisms for distributing the energy benefits in order to incentivize engagement to make the system more sustainable, efficient, and equitable.

From the point where service users stand, the unexpected delay in the formation of platoons may reduce the quality of time spent in the platoon vehicles while increasing the travel times. Platoon driving reduces the network congestion level and improves network travel time and reliability, resulting in improved quality of network travel time spent. In addition to the changes in travel times, the valuation of travel time and valuation of travel time reliability, which are key variables to the appraisal of transport projects, may be influenced by platoon delays and reductions in network congestion levels. Therefore, research effort may be required to differentiate and estimate the new value of travel time and the value of reliability for different travel time components in the formation of platoons.

The modeling framework presented here still has some limitations that could be improved in future research. The traffic simulation model can estimate the traffic impact of forming platoons using mesoscopic operating characteristics. It can meet the design requirements of determining time-dependent link flows and route travel time according to the relationship established between road capacity and the formed platoons. Hence, the traffic simulation model allows testing different strategies in forming platoons on the network level. However, the mesoscopic model applied to single-lane urban scenarios cannot capture the microscopic traffic behavior such as accelerating, overtaking, lane-changing, and traffic behaviors at intersections. Moreover, the relationship established between formed platoons and road capacity is only meant for the capacity of a single lane for each direction according to the platoon characteristics. This is acceptable for urban driving conditions in most (European) cities with narrow streets (one lane for each direction). However, the traffic simulation component cannot model mixed traffic conditions under multiple-lane scenarios. Operational capacities in multilane scenarios depend on lane policies to distribute platoon vehicles. Modeling multiple-lane capacity with the formation of platoons remains an unsolved challenge in the literature.

Chapter 5

Modeling Multiple AMoD Operators with Exogenous Demand

The trend in industrial development shows that private companies of shared automated vehicles (SAV) are unlikely to disclose information about SAV fleets and service users because of their business objectives. This chapter investigates the operation of Automated Mobility-on-Demand (AMoD) Systems in which multiple independent companies operate their fleets to provide direct on-demand service to their registered clients in the same urban area. An agent-based model was developed to study the future scenarios of multiple-operator AMoD systems with different fleet sizes and relocation operations. We analyze how one company's operations affect the performance of its competitors, with a focus on the service quality offered to clients, operational efficiency (e.g., trips per car), and profit. Simulation results show that increasing the SAV fleet of a specific company affects the service quality of competing companies; this may lead to an increase in average waiting and (4-minute) travel times due to the added traffic. Nevertheless, SAV companies may be motivated to increase fleet sizes for higher profit. Regulation of fleet sizes is expected to avoid deteriorating social welfare (e.g., congestion). Moreover, findings suggest that relocations in anticipation of future demand could improve profit and service levels. For example, an operator providing relocations improves waiting times by about 11% compared to the competing operators without relocating vehicles. A nearly 16 % (more than 2000 euros in the morning hours) increase in profit can be achieved when relocations occur. The reason is that more trips are served with relocations while operating costs remain low. Developing a relocation capability is strongly recommended to gain an advantage in future urban mobility systems.[3]

5.1 Introduction

As we continue to witness the accelerating roll-out of AV, also known as self-driving vehicles, transportation is experiencing the fastest and most far-reaching disruption in the new era of automation.

There are uncertainties related to AV technology, regulation, and AV mobility service planning in the path to making commercial applications of the driverless future (Calabrò et al., 2022; Fan et al., 2022; T. Liu et al., 2020). Further development trends in the AV industry and academic literature show that combining AVs with the ride-hailing service is steering the paradigm shift of urban mobility systems. The transition toward AMoD systems is already underway for both people and goods (le Pira et al., 2021).

No companies in the emerging AV industry have yet developed the skills and resources to command a significant market share. Naturally, multiple technology companies in the AV industry will provide mobility solutions in the same urban areas, which may drive a new urban mobility system. The private AV companies are unlikely to share information about their clients (e.g., request time and locations) and the vehicle fleet (e.g., locations) because of their competing business development goals.

Previous research has investigated the pricing, relocation, fleet sizes, ridesharing strategies, and the strategic platoon formation either in single-operator AMoD systems or single-operator AMoD systems in the presence of public transportation options (Milakis et al., 2017; Narayanan et al., 2020; S. Wang et al., 2019). However, there is no managerial evidence to support the future development of urban AMoD systems in which AMoD services are operated by different operators.

The multiple-operator AMoD systems may be a system of multiple independent operators without sharing information or distributed systems with partly shared information in which a third party is involved. As expected, the dream version seems to be an integrated system with complete information sharing in relation to travelers, vehicle fleets, and transport modes. However, any form of urban mobility platform is full of uncertainty in technology, privacy, and security

This chapter examines the likely scenarios where multiple AMoD companies operate in the same urban areas without sharing information. We define and model multiple-operator AMoD

[3] *This chapter is an updated version of the manuscript that has been submitted to a journal: An Agent-Based Simulation Study of Shared Automated Vehicle Services of Multiple Companies without Information Sharing. The diagrams to present the demand data and road network are removed from this chapter. This is because they are also used and presented in Chapter 4.*

systems without information sharing as a substitute for private car use. We test future scenarios with different operating strategies (e.g., relocation strategy) and corporate profit to better gauge what to expect from multiple-operator AMoD systems (in which operators are unlikely to disclose customers' information). We thus contribute with an agent-based simulation study of future multiple-operator AMoD systems in response to technological disruptions.

The remainder of the chapter is organized as follows. Section 5.2 summarizes industry actions and development plans for future AMoD systems and discusses state-of-the-art literature. Section 5.3 presents the model specifications. Section 5.4 describes the application of the model to the case study city of The Hague, The Netherlands. Simulation results are analyzed in Section 5.5. Section 5.6 provides a discussion and recommendations. The final section presents the main conclusions and points out future research directions.

5.2 Background

5.2.1 Future development trends in the automotive industry around the globe

Despite the uncertainty and inspired by the vision of the disruptive transformation of the transportation system for people and goods, many car manufacturers and high-tech companies are investing in AV research and development. Successful field tests of operating AVs have been carried out in different application environments around the globe. Waymo, Google's original self-driving car project, announced that their self-driving cars had completed more than 20 million driven miles on public roads in cities across the United States by 2020 (VentureBeat, 2020). As an AV manufacturer, Cruise plans to commercialize AVs in partnership with Microsoft to provide riders with automated on-demand transportation options (Reuters, 2021b). In 2020, Amazon unveiled its fully self-driving vehicles designed to carry passengers and deliver goods in the already established logistics network (Bloomberg, 2020). Tesla's autopilot system is currently being developed for fully self-driving (Tesla, 2022). Apple plans to launch self-driving cars in 2024, aiming to build AVs to carry passengers for an automated ride-hailing service (The Guardian, 2020).

In Europe, Mercedes Benz is establishing a ride-hailing joint venture with BMW to compete with other mobility service providers. The joint-venture mobility portfolio will allow for the introduction of AVs in ride-hailing services (Forbes, 2019). In Asia, Toyota partnered with Uber to integrate Toyota AVs into Uber's ridesharing network since 2018 (TOYOTA, 2018). China's largest ridesharing company DiDi Chuxing has launched AV test projects for riders complementing the established ride-hailing network. Meituan, a food delivery giant, start driverless delivery services in Beijing, China (Reuters, 2021a). Baidu's AVs have already logged more than 1 million driven miles in urban environments. Baidu introduced Apollo AV services to the public in 2019 and has established a strategic partnership with Greely, which has considerable expertise in intelligent vehicle manufacturing (VentureBeat, 2019).

The commercial actions suggest that some AV technology companies are marketing AV fleets to provide an emerging alternative to existing urban transportation services; several AV technology companies are integrating AV fleets with a logistics network for goods delivery; others are providing automated driving systems for intelligent vehicles. Overall, different AV companies have their development goals and preferences. Companies are likely to manage AV services - in urban mobility systems or urban logistics systems - in a competitive market without sharing information so that they can keep their business undisclosed to competitors.

The actions in the automotive industry suggest that combining AVs with ride-hailing services is driving the paradigm shift of urban mobility systems. With the rapid entry of emerging AMoD systems, it will be natural to see fleets of shared AVs operated by various AV technology companies in the future mobility market.

5.2.2 Future multiple-operator AMoD systems in urban areas

According to the development trend in AV technology companies, a future AMoD system comprised of multiple operators is envisioned. With the shift from vehicle ownership to service usage, travelers in urban areas relinquish vehicle ownership and access the AMoD service upon request. Travelers choose the service provided by their favorable company and register for their services.

Operators manage their fleet to provide direct on-demand service to travelers between service points without sharing information about their clients and AVs. The fleet size is not very large in the early stage of trials, and the registered traveler may not be served by AMoD services.

On a typical working day, registered travelers (morning commuters) can summon AVs operated by a pre-registered company to their locations via a company's proprietary app without the intervention of human drivers. Decisions on assigning available vehicles to incoming requests are made on an operator’s platform with optimal assignments. While routing decisions will be provided by computing the shortest routes, vehicles move to pick up the travelers at the travelers' locations and take them to their destinations. Once travelers are dropped off, vehicles may get idled and be parked at service points, be relocated to service points in anticipation of future demand, or continue their journey to serve subsequent requests of registered travelers.

5.2.3 Existing literature

Given the great potential of AMoD systems and the expected disruptive transformations of the urban transport system, there has been significant interest in exploring the impacts of shared AV operations in urban passenger transport systems over the last few years. We review the existing literature with an emphasis on modeling AMoD scenarios and system functionalities.

Burns et al. (2013) examined the performance of AMoD services in different case-study cities regarding operating cost, service quality, and vehicle utilization. Fagnant and Kockelman (2014) investigated the travel and environmental implications of a single AMoD system in an Austin-sized city. Hörl et al. (2019) and Hyland & Mahmassani (2018) focused on deploying control or optimal strategies to manage AV-traveler assignments in a single AMoD system. Recent studies analyzed the routing and traffic assignment of shared AVs while considering traffic congestion (Levin, 2017; Liang et al., 2020). Wang et al. (2022) modeled the operations of coordinating AV into platoon formations and explored the travel and energy impact of forming platoons in an urban road network.

Studies were also conducted to integrate a future AMoD system into existing public transportation systems. On the one hand, an AMoD system can provide feeder services to complement the public transportation system (Huang et al., 2020; X. Liang et al., 2016b); on the other hand, door-to-door AMoD services are a competitive alternative to existing public transportation options (Hörl et al., 2021; Narayan et al., 2020). Notably, In modeling scenarios where AMoD systems are integrated into urban public transportation options, travelers can adjust their behaviors in response to the transport levels of service provided by public transit operators and a single AMoD operator- that are modeled as a two-sided transportation system. The creation of such mobility systems requires the integration of transport modes, user information, and payment methods (Hensher et al., 2021; Shaheen & Cohen, 2021). When private commercial AV companies (operators) enter the urban mobility market, the portfolio of multimodal mobility services with multiple AMoD operators may not be delivered. This is because operators may be reluctant to share information about AV fleets (e.g., locations) and service users with their business development goals and preferences. There is also a lack of collaborative mechanisms and entry regulations for emerging mobility services in the urban mobility system.

Inspired by the phenomena of multiple transportation network companies (e.g., Uber, DiDi Chuxing, Bolt) and carsharing companies in urban mobility systems, multiple AMoD operators may drive a new mobility ecosystem. To our best knowledge, the current studies in the literature only consider a mobility system with a single AMoD operator. We are aware of studies in the literature where competition either between multiple carsharing operators or multiple Mobility-on-Demand (MoD) operators is investigated (Balac et al., 2019; Kondor et al., 2022; Pandey et al., 2019a; Séjourné et al., 2018). However, AMoD systems differ from the other systems (i.e., MoD systems and carsharing systems). Vehicle automation in AMoD systems eliminates the interference and costs of human drivers required in MoD systems. In AMoD systems, the operating efficiency is improved with the fully controlled functioning of the automated driving systems; Vehicles can be assigned for customer use in a coordinated manner. Compared to carsharing systems, AMoD systems do not require relocation staff to perform relocation operations because of automated driving features. Thus, the relocation operations in AMoD systems eliminate the problems of distributing relocation staff and reduce the high cost of staff-based relocation. In addition, travelers can engage in productive activities when using AMoD services compared to using carsharing services.

5.2.4 Research challenges

In the literature, analogous but different multiple-operator MoD systems are studied using analytical methods. The analytical techniques can produce high-quality solutions while achieving the optimal value of the system objective. However, analytical methods have some weaknesses in modeling systems with multiple entities and interactions (e.g., AMoD systems).

Existing models and tools lag behind the rapid developments in urban multiple-operator AMoD systems. Therefore, there is an urgent need to develop an advanced modeling framework to simulate the emerging AMoD system with multiple operators and explore the potential of operations of AMoD operators in future cities.

5.2.5 Research contributions

The chapter aims to bridge that gap by developing an Agent-Based Model (ABM) for AMoD systems with multiple AV fleet operators to test different operating strategies. Agent-Based Modeling is well-suited to studying multiple-operator AMoD systems while tackling the limitations of analytical methods. The ABM is populated with realistic data. The interaction between vehicles and travel requests and between vehicles is realistically represented. The agent-based modeling technique can describe the system at different levels: the individual vehicle is simulated while capturing the traffic conditions; the behavior of individual vehicles in relocations is represented, while relocation decisions made by operators are modeled.

The main contributions of this chapter are the following:

We first define and model an urban AMoD system comprised of multiple competing operators, each of which manages the vehicle fleet to serve their clients (travelers) without information sharing.

We model the relocation operations in anticipation of future demand in the new multiple-operator AMoD systems. That is, we design a relocation mechanism in which the vehicle shortage service points are identified in anticipation of future demand to mitigate the imbalance between expected demand and supply of AVs. We test the effectiveness of proposed relocation strategies for an operator against its competitors in future scenarios.

In the agent-based modeling framework, an optimal assignment component, enabled by vehicle automation technology, is implemented and tested for the case-study city. At the aggregate level, the ABM in which the node and link movement rules are defined replicates traffic conditions resulting from the circulation of in-service vehicles (with passengers inside) and relocation of vehicles across the transportation network.

Fleet cost and fare structure for AMoD services are incorporated into the agent-based modeling framework to test how different operating strategies affect the profit of individual operators in the future multiple-operator AMoD system.

As a case study, we apply the urban multiple-operator AMoD systems to the city of The Hague, the Netherlands. We aim to understand how supply (vehicle fleet) changes affect the performance of operators coexisting in the same urban area. Therefore, supply-side simulation is performed to generate a spectrum of possible outcomes. Moreover, we design simulation experiments to explore the potential of relocation strategies in the multiple-operator AMoD systems.

The performance will be evaluated to gain useful insights into the competition by defining a set of key performance indicators (KPIs) in terms of service quality offered to travelers, system efficiency, and profit.

5.3 Model specifications

5.3.1 Model overview

The modeling framework includes five core functionality components (see Figure 5.1): a demand generator for individual fleet operators, a vehicle-to-passenger assignment component, a vehicle relocation component, a mesoscopic traffic simulation model, and the shortest route calculation component.

The demand generator generates time-dependent travel requests for each AMoD operator using the existing travel demand data. The demand generator also provides an estimate of the expected demand for relocation operations. Individual travel requests are not generated when estimating expected demand, but the expected number of travel requests is calculated.

Concerning fleet management of an independent AMoD operator, the optimal assignment component is responsible for matching available vehicles with their registered clients in real time. Moreover, we model the relocation operations of a specific operator. Relocation strategies are developed to address the imbalance between the supply of vehicles and expected demand.

A traffic simulation model that defines the link and node movement rules is incorporated to capture the traffic dynamics. We classify two information types: static and dynamic information. The road attributes (e.g., road capacity, speed limits, and road length) initiated using road network data are defined as static information, while dynamic information includes the instantaneous vehicle speed, link density, the number of vehicles on each road segment. The node and link mechanism for vehicle movements can reproduce road traffic to provide enough realism to the ABM in estimating the travel times of vehicles across the road network.

Based on traffic conditions determined by the traffic simulation component, the routing component is responsible for finding the time-dependent shortest routes between locations for vehicles. These routes are computed at three moments: toward picking up a client, traveling with a client to his/her destination, and relocating to areas with a shortage of vehicles.

The cost of operating three AV fleets is calculated using the simulation measurements (e.g., empty fleet distance and passenger travel distance and time, number of served trips, and fleet sizes). Profit also is estimated based on different fare structures and operating costs.

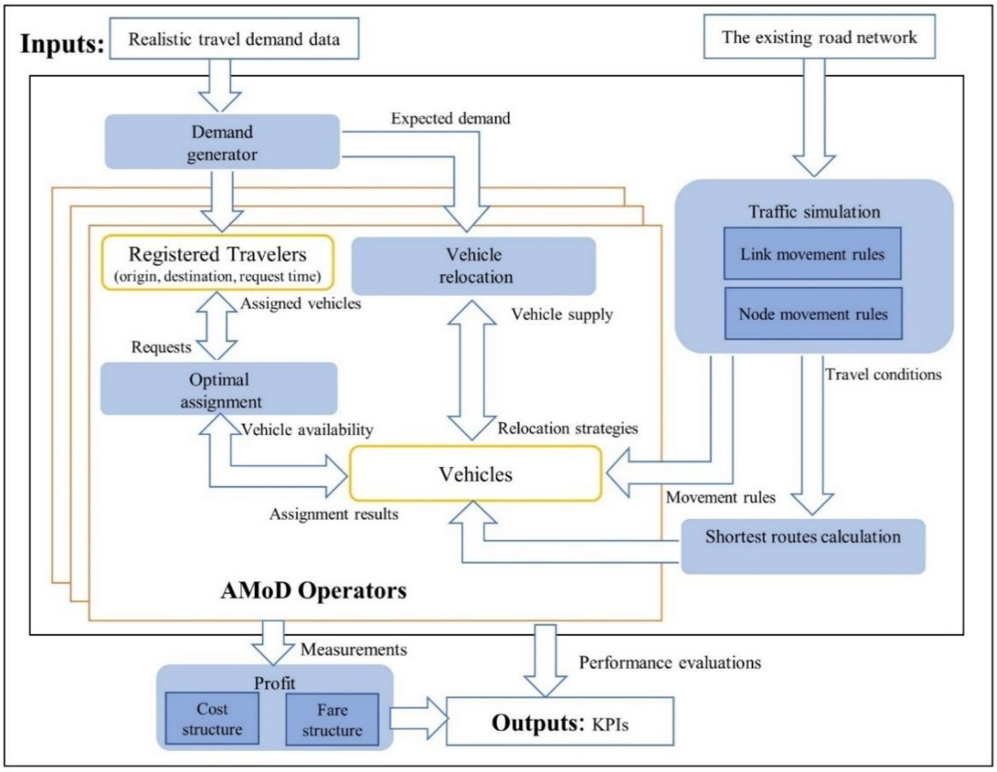

Figure 5.1 Overview of the model architecture

5.3.2 Behavior of clients and SAVs, and assignment Interactions

A vehicle-to-passenger assignment component is designed to match the available vehicles to the requests of registered travelers. Upon receiving requests, it determines which vehicles in the fleet could reach the travelers according to the operating rules for assigning available vehicles to requests.

Pre-assignment is done by searching the nearest available vehicles for requests, prioritizing earlier requests. Vehicle-to-request pairs are generated by assigning the nearest available vehicles. There are multiple vehicle-to-request pairs in a short time window in peak hours. Then, we can have the incoming requests set $R = \{r_0, r_1, \dots, r_n\}$ and nearest idle vehicles set $V = \{v_0, v_1, \dots, v_n\}$.

For each request r_i in set R, the nearest vehicles v_i in the Vehicle set V could be reassigned to any other request in the Request set R (see Figure 5.2). An optimal assignment can be obtained if it minimizes the sum of the cost of every assignment pair. The assignment problem can be solved using the Hungarian method (see Figure 5.3). In doing so, a bipartite graph is constructed whose vertices are two independent sets (i.e., set V and set R). The bipartite graph is represented by an adjacency matrix in which the horizontal row stands for vehicles in the set V and vertical columns for requests in the set R. Given $n \times n$ cost matrix, we define the entry as cost c_{ij} of assigning vehicle i to a request j. The cost c_{ij} can be measured for an assignment pair by the Euclidean distance between a vehicle i and a request j. In the Hungarian method, row reductions and column reductions for the cost matrix are performed once. Next, the solution is iteratively optimized until the minimum number of lines (rows or columns) covering all zeros in the matrix is equal to the dimension of the $n \times n$ cost matrix. The optimal assignment can be found for the original matrix based on the optimal assignment for the resulting cost matrix.

The optimal method which we propose can obtain an optimal vehicle-to-request pairs assignment for grouped requests. However, the assignment method does not provide the routes between locations. The routing component is responsible for computing the time-dependent shortest routes between any two given points using the Dijkstra algorithm.

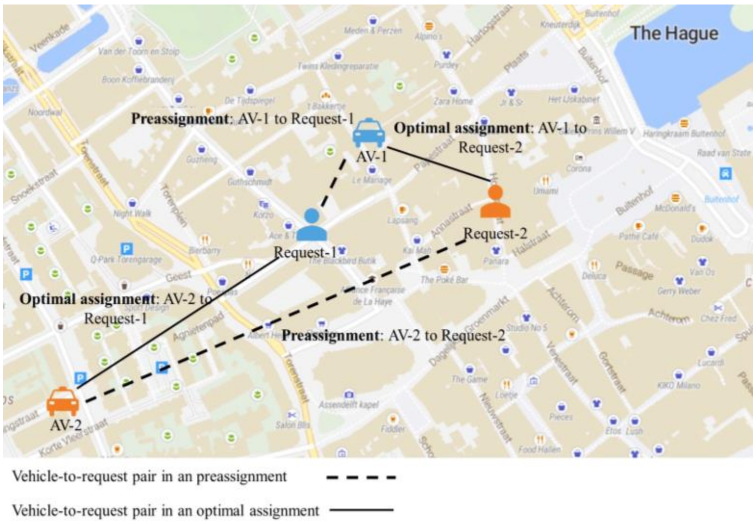

Figure 5.2 A real-world scenario for potential benefits of grouping requests

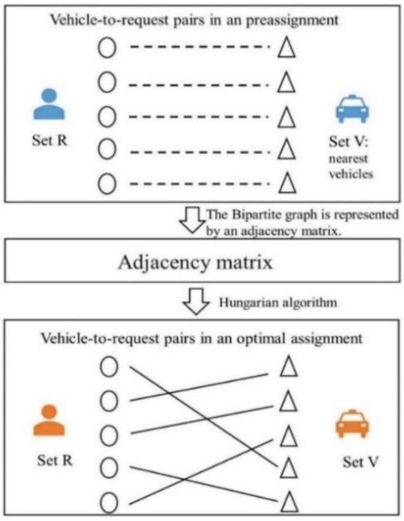

Figure 5.3 Schematic diagram of the pre-assignment and optimal assignment

5.3.3 Movement rules of in-service and relocation vehicles for reproducing traffic dynamics

Traffic conditions are considered by incorporating a mesoscopic traffic simulation model; a set of vehicle movement rules is defined to govern the movement of in-service vehicles and relocation vehicles.

In the link (road segment) movement, in-service vehicles and relocation vehicles experience a speed calculated by a macroscopic speed-density relationship. Travel speeds can be calculated based on the established relationship between speed and density. When the density d is less than the critical density d_c, the speed V can be calculated using Equation 5.1: $V = v_0\left(1 - \frac{d}{d_j}\right)$. Where v_0 is the maximum speed respecting the urban speed limit, and d_j is the jam density. When the density d exceeds the critical density d_c, the speed is calculated using Equation 5.2: $V = v_0 \times d_c\left(\frac{1}{d} - \frac{1}{d_j}\right)$. In modeling the movement of in-service and relocation vehicles, vehicles are stacked at accumulation areas (assumed places at nodes) for being transferred from an upstream road segment to a downstream road segment. Transferring rules for restricting the vehicle movement at nodes are defined (S. Wang et al., 2022a).

5.3.4 Vehicle relocation operations: basic definitions and relocation procedures

The AMoD system will provide on-demand services to travelers who request service at different locations and times in urban areas. The dynamic interaction between vehicles and travelers leads to an imbalance between available vehicles and future demand in some urban places. Relocation operations can mitigate the imbalance. We develop relocation strategies to distribute available vehicles (idle and not assigned to serve travelers) among different places in anticipation of future requests.

5.3.5.1 Basic definitions in relocation operations

An urban service area with high population and employment densities was divided into relatively smaller traffic analysis zones (TAZ). All TAZs, which correspond to origin and destination zones of demand, are defined as potential relocation zones from which relocation zones are determined. In relocation operations, expected demand is estimated using historical data in an O-D matrix and a departure time distribution of trips. The total number of trips between every pair of TAZs throughout the study period (i.e., the morning peak hours) is specified in the O-D matrix. The departure time distribution describes the number of trips per time interval (i.e., 15 minutes). We can calculate the number of trip requests for every time interval in advance using a fraction of the trips during that time interval.

To tackle the imbalance between the supply of vehicles and expected demand in TAZs, we classify relocation zones into two types: Supplier zones and Demander zones, depending on the available vehicles and expected demand. In Supplier zones, the number of available vehicles is much higher than the number of expected requests. In Demander zones, there is a significant shortage of vehicles in anticipation of future demand.

5.3.5.2 Relocation strategies

Vehicle relocation operations are scheduled cyclically. The relocation time interval for performing relocation operations is predetermined. At the beginning of each relocation time interval, Supplier and Demander zones are identified according to the number of available vehicles and the number of expected requests. Vehicles from the Supplier zones are relocated to the Demander zones. The specific relocation procedures (for an operator) are described below.

- The number of available vehicles and the number of expected requests in each zone are determined at the beginning of the relocation time interval.
- Relocation indices that are indexed to changes in the available vehicles and future demand (i.e., 15 minutes) in zones (TAZs) (S. Wang et al., 2022b). Accordingly, relocation indices are calculated using Equation 5.3 in the multiple-operator AMoD system.

$$R_i = V_t * \left(\frac{V_{ti}}{V_t} - \frac{R_{ti}}{R_t}\right) \tag{5.3}$$

  R_i is the relocation index for the zone i; V_t is the total number of available vehicles of an operator in the service area; V_{ti} is the number of available vehicles of an operator in zone i; R_t is the total number of expected requests for an operator' service in the service area; R_{ti} is the number of expected requests for an operator's service in the zone i.
- Measured by the relocation index, zones with a large surplus of available vehicles are classified as the Supplier zones, while Demander zones have a strong shortage of available vehicles.
- The vehicles in a Supplier zone will be relocated to the closest Demander zone. The number of vehicles for relocation in each zone is the additional number of available vehicles (those not needed to serve expected demand in the Supplier zone).
- The time-dependent shortest routes between the Supplier and Demander zones are computed using the Dijkstra algorithm for every relocation vehicle.

We model relocation operations between the Supplier and Demander zones while no relocation occurs in other zones. Compared to the Supplier and Demander zones, "no relocation zones" have a slight imbalance between the supply of vehicles and expected demand. In the AMoD system, vehicles in adjacent zones (TAZs) within the search distance will be assigned (dispatched) to serve clients upon requests; An additional number of available vehicles in a zone can be assigned to serve clients in adjacent zones. Relocation between zones with a slight imbalance could reduce vehicle availability to clients while increasing VKT (vehicle kilometer traveled) when relocation occurs. We develop relocation strategies to consider relocating vehicles from identified Supplier zones to identified Demander zones.

5.3.5 Fleet cost and fair structure

5.3.6.1 Fleet cost structure

We use a cost model based on the work by Hörl et al. (2021) to estimate the cost of AMoD fleets in which vehicles provide door-to-door service to single clients in urban areas. The total fleet cost was calculated based on the total distance traveled by the fleet (d_{fleet}), the number of served trips (n_{trips}) and the fleet size (n_{fleet}). The cost model (see Equation 5.4) is incorporated to estimate the operating cost of urban AMoD fleets.

$$C = c_d * d_{fleet} + c_t * n_{trips} + c_f * n_{fleet} \tag{5.4}$$

where,

c_d is the cost per vehicle kilometer; vehicle kilometers traveled include the trips with and without clients (the trips without clients include pickup trips and relocation trips).

c_t is the cost per trip (e.g., cleaning).

c_f is the cost per vehicle.

5.3.6.1 Fare structure

Fare is the out-of-pocket cost of a registered client. The fare p is structured by a base fare, a distance-based fare f_d and a time-based fare f_t for a single ride.

$$p_{dt} = -\eta * (f + f_d * d + f_t * t) \tag{5.5}$$

where,

η is the saving factor for AMoD services relative to an existing MoD service (we are using the UberX fare structure as a reference in the case study).

f is the base fare for MoD services.

d is the travel distance with a client.

t is the travel time with a client.

In Equation (5.5), the fare paid by clients is affected by the travel times. This may lead to increased profit in the congested network. We also test a pricing system in which the fare is formulated as a function of the distance traveled.

$$p_d = -\eta * (f + f_d * d) \tag{5.6}$$

5.4 Model Applications

The simulation model was developed in the Anylogic platform using Java programming language. The ABM is populated with existing travel demand data and road network data from the case-study city of The Hague, The Netherlands.

5.4.1 The road network and urban service area

The model contains a realistic representation of the road network and service area in the case study city. The road network that we have used, which covers the main districts around the city of The Hague. The 49 TAZs frame the urban service area. The locations of centroids of the TAZs are used as the points of travel requests injection in the road network; they are designated as travelers' origin and destination as well as service points for SAVs. Vehicles from different operators circulate over the road network of road segments and nodes when serving travelers. Road attributes are initialized based on the existing traffic data.

5.4.2 Travel demand data

Individual travelers are created to simulate the behavior of requesting AMoD services. 27,452 trips made by private car trips occur within the urban service area of The Hague. The temporal pattern of travel demand is shown for every 15 minutes in the morning peak period from 5:30 am to 10:00 am. The demand generator generates time-dependent travel requests using departure time fractions and an OD matrix data specifying demand between TAZs. The demand generator is designed to generate travel requests based on the aggregate travel demand available in the shape of an OD matrix. The requests on each OD pair can be split between operators using a custom input distribution. When the generated travel request cannot be satisfied, this is considered to be a rejected request, and this trip will be made with a private car.

5.4.3 AMoD service configurations

Regarding fleet deployment, we define N as the average number of vehicles deployed for all operators in each service point of the model. We denote the average fleet size of each operator at each service point as n_{o_i} where $\sum_{i \in \{1,2,3\}} n_{o_i} = N$. The fleet n_{o_i} is proportionally distributed as a function of demand for an operator's service in each service point. The fleet size n_{o_i} for AMoD operator o_i is treated as a parameter for which simulation is repeated for various values. We initiate smaller fleet sizes in the baseline scenarios as $n_{o_1} = n_{o_2} = n_{o_3} = \frac{N_0}{3} (N_0 = 51)$. N_0 is set to smaller values to explore the scenarios where an operator brings more vehicles to the service area. z_{o_i} will be used to denote the demand for operator o_i and Z as the total demand (27,452 trips) in the city for the AMoD services, thus $\sum_{i\in\{1,2,3\}} z_{o_i} = Z$. We model the 25,800 interzonal trips.

We are using the UberX fare structure that is active in 2022 in the Netherlands. We have $\eta = 0.6$ (60% of the existing MoD) $f = 1.4\, euro,\ f_d = 1.2\, euro\ per\ km, f_t = 0.26\, euro\ per\ min$ in Equation 5.5. We have $c_{d(2022)} = 0.098\frac{CHF}{vkm} = \frac{0.098CHF}{vkm} * \frac{0.97euro}{CHF} = 0.095\frac{euro}{vkm}$, $c_{t(2022)} =$0.375 CHF=0.364 euro. We model the AMoD service in the 4.5 morning peak hours (from 5:30 am to 10:00 am) and assume that the AMoD mobility service stay online from 5:30 am to 12: 00 midnight (maintenance is scheduled for the remaining hours). $c_{f(2022)}$ =33.30 CHF (per day) * $\frac{0.97euro}{CHF}$ $*$4.5/18.5=7.857 euro. Table 5.1 summarizes model parameters and case study characteristics for the baseline scenario.

Table 5.1 A Summary of the Model Parameters for the baseline scenario

Parameter/characteristics	Value
Travel demand (Z)	25,800 interzonal trips
Centroids (denoted by s)	49
The number of fleet operators i	3
Time steps for speed update	6 seconds
Vehicle assignment Time interval Δt	15 seconds
The search distance for vehicle assignment	5000 meters
Vehicle seat capacity	1 person
The average number of vehicles at the beginning of the simulation (N_0)	51 vehicles per service point
η saving factor for AMoD services relative to an existing MoD service	0.6
Cost per vehicle kilometer c_d	0.095 euro per vkt (vehicle kilometer traveled)
Cost per trip c_t	0.364 euro
Cost per vehicle c_f	7.857 euro
Base fare f	1.4 euro
distance-based fare f_d	1.2 euro per km
Time-based fare f_t	0.26 euro per min
Vehicles increment Δg per service point for sensitivity analysis	5 vehicles

5.5 Results and analysis

Simulation is performed to explore the implications of AMoD systems with multiple operators. A set of performance indicators is defined to reflect the different aspects of system performance in terms of system efficiency and service quality offered to travelers. The main performance indicator is summarized in Table 5.2 and described in detail.

Table 5.2 Key performance indicators for performance assessment

Indicator	Explanation
Waiting time	Waiting time is the out-of-vehicle time a traveler spends waiting for the assigned vehicle to reach his/her location.
Travel time	Travel time is the time a traveler spends in a vehicle moving from the origin location to the destination location.
Unserved trips	Unserved trips are the trips of registered travelers that the AMoD operator cannot serve. Unserved trips occur when there is no available found.
Total VKT	Total VKT is measured by multiplying the total number of vehicular trips by the length of these trips. The length of a vehicular trip includes the distance traveled with and without passengers.
Empty VKT	Empty VKT is the pickup distance traveled by unoccupied vehicles. The empty VKT is calculated by multiplying the total number of empty trips for pickups by the lengths of these trips.
Vehicle utilization	Vehicle utilization means that the average number of trips served per vehicle in the simulation time
Relocation trips	Relocation trips are the vehicular trips made by relocation vehicles.
Relocation VKT	Relocation VKT is calculated by multiplying the relocation trips by the distance traveled by the relocation vehicles.
Total Fleet profit 1	This total fleet profit is the total revenue from distance-based fares minus the total operating costs.
Total Fleet profit 2	This total fleet profit is the total revenue from distance-and time-based fares minus the total operating costs.

5.5.1 Simulation scenarios for evaluating changes in fleet sizes of an operator

This section evaluates strategies for increasing the vehicle fleet for a specific operator (e.g., operator 1) when attempting to improve the service offered to registered travelers. The objective is to assess the impact that changing the fleet of operator 1 has on the service level for all operators o_i (i =1,2,3).

The simulation results in scenario one and scenario two indicate that the increased fleet size could improve the service quality of operator 1 in terms of average waiting time compared with the other operators. Moreover, as expected, fewer empty VKT is generated in the system managed by operator 1; as the fleet size increases, the empty travel distance indicated by empty VKT reduces from 25.45% of total VKT in the baseline scenario to 20.35% of the total VKT in the scenario two with an increment of 10 vehicles per service point.

Intuitively, a larger fleet will reduce vehicle utilization. Results indicate that vehicle utilization decreases from 7.32 to 5.63 as the fleet size increases as measured by trips per car. That means that vehicle usage of an AMoD operator with the increase in the number of vehicles becomes lower in the morning hours compared to its competitor. Currently, commuters using privately-owned vehicles in our case study city may take 20-30 minutes to complete one trip. They are parked up to 90 percent of the time during the AM peak hours. Although vehicle usage of AMoD operators is reduced, they maintain higher usage rates compared to private vehicle use.

Table 5.3 shows the simulation results in the baseline scenario where the fleet is distributed equally ($n_{o_1} = n_{o_2} = n_{o_2}$). We increase the number of vehicles used by operator 1 by Δg (5 vehicles) (scenario 1) and $2 * \Delta g$ (10) (scenario 2) for the 100% demand scenario (Table 5.4).

The simulation results in scenario one and scenario two indicate that the increased fleet size could improve the service quality of operator 1 in terms of average waiting time compared with the other operators. Moreover, as expected, fewer empty VKT is generated in the system managed by operator 1; as the fleet size increases, the empty travel distance indicated by empty VKT reduces from 25.45% of total VKT in the baseline scenario to 20.35% of the total VKT in the scenario two with an increment of 10 vehicles per service point.

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Table 5.3 Key performance indicators in the baseline scenario where the fleet is distributed equally

Fleet operator	o_1	o_2	o_3
Demand		$z_{o_1} = z_{o_2} = z_{o_3}$	
Fleet size		n_{o_1}=n_{o_2}=n_{o_3}	
Avg. waiting time (minute)	9.09	9.06	9.11
Avg. travel time (minute)	20.30	20.58	20.60
Total VKT (km)	37906	38074	37317
Empty VKT (km)	9646	9792	9429
The percentage of empty VKT of the total VKT	25.45%	25.72%	25.27%
Vehicle usage (trips per car in morning hours)	7.32	7.30	7.24

Table 5.4 Key performance indicators with the increase in vehicle supply of Operator 1

Fleet operator	Multiple-operator systems (scenario one)			Multiple-operator systems (scenario two)		
	o_1	o_2	o_3	o_1	o_2	o_3
Demand		$z_{o_1} = z_{o_2} = z_{o_3}$			$z_{o_1} = z_{o_2} = z_{o_3}$	
Fleet size	$\boldsymbol{n_{o_1} + \Delta g}$	n_{o_2}	n_{o_3}	$\boldsymbol{n_{o_1} + 2\Delta g}$	n_{o_2}	n_{o_3}
Avg. waiting time (minute)	8.72	9.50	9.45	9.13	9.73	9.52
Avg. travel time (minute)	21.80	21.35	21.85	24.54	24.18	24.21
Total VKT (km)	40414	38116	37721	43530	37400	37019
Empty VKT (km)	8931	9563	9463	8857	9440	9293
The percentage of empty VKT of the total VKT	22.10%	25.09%	25.09%	20.35%	25.24%	25.10%
Vehicle usage (trips per car in morning hours)	6.34	7.45	7.36	5.63	7.36	7.31

Furthermore, simulation results in Figure 5.4 show that the increase in the fleet size of operator 1 can improve the percentage of served trips over time. The percentage of served trips of operator 1 is significantly higher than in the baseline scenario and the other operator without an increment of vehicles, particularly when the volume of travel requests is high from 6:30 am (simulation time 120 minutes). This means that more registered travelers of operator 1 are being transported during peak hours. In this regard, a larger fleet can help an operator to serve more clients and improve the service quality offered to them.

However, simulation results in Table 5.4 show the average waiting time of the other fleet operators (o_2 and o_3) and the average travel time of all operators is increased. For example, the average travel time increases from 20 minutes to 24 minutes. The reason is that increasing the fleet size of operator 1 leads to more requests being transported on the road network; operator 1 brings more vehicles to the roads (see Figure 5.5). It is demonstrated that the total number of busy vehicles operated by three operators circulating across the road network increased. The increasing number of vehicles circulating across the road network adds more traffic to the road network, increasing up to 4 minutes in average travel times. That means in the multiple-operator AMoD system, the growth of the fleet size of an operator brings an adverse effect on the road travel conditions, thereby degrading the service quality of its competitors.

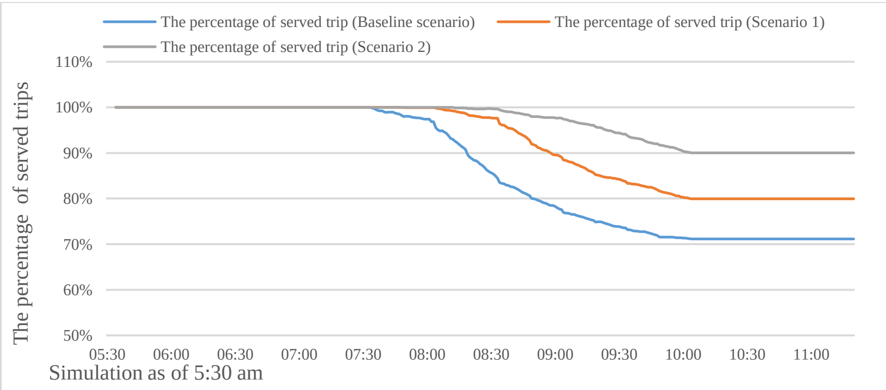
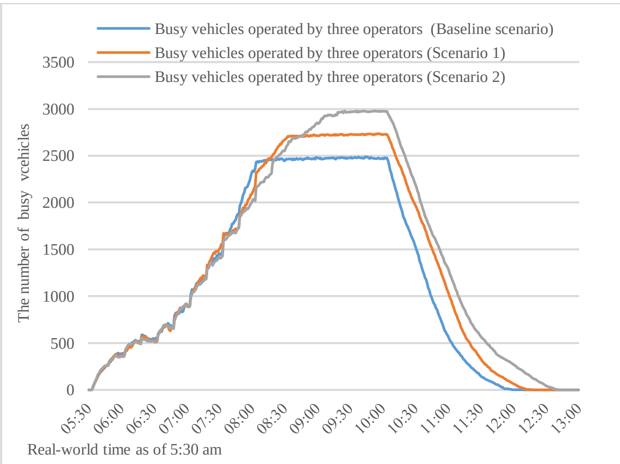
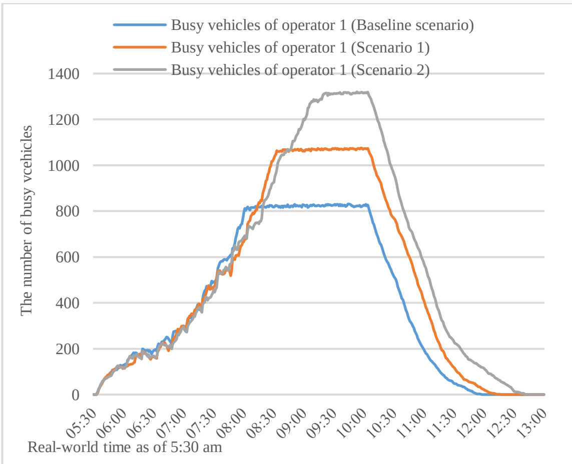


Figure 5.4 The percentage of served trips for AMoD operator 1 over simulation time (minute)



(a) The total number of busy vehicles circulating across the road network



(b) The number of busy vehicles of operator 1 in different scenarios

Figure 5.5 the number of vehicles circulating across the road network

We see (in Table 5.5) that when the fleet size of operator 1 increases, the total fleet profit of the operator reaches an increase of 5.87% in the total fleet profit 1 and 23.48% in the total profit 2 (in scenario 2). This suggests that an AMoD operator with a small fleet size in the early stage of the competitive market could achieve a higher profit if it increases its fleet size. In this respect, operators might decide to increase their fleet sizes to achieve a higher profit. Moreover, the fare structure significantly influences the profit of an operator. The distance- and time-based fare structure can produce a significant increase in the profit of an operator (operator 1). This is because the travel times included in the profit calculation (total fleet profit 2) contribute to an improvement in profit.

Table 5.5 The total fleet profits of operator 1 in different scenarios

Scenarios	Baseline scenarios	Scenario 1	Scenario 2
Fleet size	n_{o_1}	$n_{o_1} + \Delta g$	$n_{o_1} + 2\Delta g$
Total Fleet profit 1 (Euro)	13202	13611 (+3.10%)	13977 (+5.87%)
Total Fleet profit 2 (Euro)	34398	36852 (+7.13%)	42473 (23.48%)

Our main finding is that the growth of the fleet size of an operator leads to improvements in the average waiting times of its clients; however, it is at the cost of the loss of efficiency of its competitors in terms of average waiting and travel times. Increasing fleet size serves more trips with the increase in vehicle supply of an operator and brings more vehicles to roads. Hence, increasing fleet sizes add more traffic congestion on the roads.

Besides, more trips are served with the growth of the fleet size of an operator, resulting in a higher profit. This may motivate an operator to increase its fleet size to obtain a higher profit in the competitive mobility market.

5.5.2 Simulation scenarios for relocation operations

We design simulation experiments to examine how relocation operations affect the operators' performance in the competitive (AMoD) market. The performance of AMoD systems with multiple operators is assessed under the relocation operations of operator 1; In the system configuration of the baseline scenario, relocation operations are performed by operator 1. We compare the system performance of operator 1 that performs relocations with the system performance of other operators without relocating their vehicles.

Results in Table 5.6 show that relocations performed by operator 1 shorten the average travel times, leading to 1 minute less than that of operator 2 and 3. The reason is that vehicles are proactively relocated to the demanded area, and then the pickup distance is shortened. There is a significant reduction in empty VKT (the total pickup distance covered by vehicles) of operator 1 compared to the empty VKT generated by operator 2 or operator 3.

Table 5.6 Key performance indicators with relocation operations of Operator 1

Fleet operator	o_1	o_2	o_3
Relocation operation	Yes	No	No
Demand	$z_{o_1} = z_{o_2} = z_{o_3}$		
Fleet size	$n_{o_1} = n_{o_2} = n_{o_3}$		
Avg. waiting time (minute)	7.55	8.57	8.63
Avg. travel time (minute)	20.48	20.66	20.68
Total VKT (km)	39497	37679	37660
Empty VKT (km) (pickup trips)	8318	9482	9527
Empty VKT (km) (relocation trips)	1745	0	0
The percentage of empty VKT of the total VKT	25.47%	25.16%	25.30%
Vehicle usage (trips per car)	7.64	7.33	7.31
Served trips	6367	6106	6093
Operating costs (Euro)	12615	12347	12340
Total fleet profit 1 (Euro)	15182 (+2098 or +16.03% compared to operator 2; +2148 or +16.5% compared to operator 3)	13084	13034
Total fleet profit 2 (Euro)	35519 (+2758 or +8.4 % compared to operator 2; +2827 or +8.6% compared to operator 3)	32761	32692

We found that more registered travelers are served by the operator that performs relocation operations (see Table 5.6); operator 1 has a high percentage of served trips. That means relocating vehicles can mitigate the vehicle imbalances: Vehicles are relocated to the place (zones) where there is a shortage of vehicles, and the vehicle-to-traveler assignment component can find available vehicles for incoming requests in the demanded area. Furthermore, performing relocations can increase the profit of operator 1, up to 16% compared to the profit of other operators without relocations. The main reason for this is that relocating vehicles in anticipation of future demand can serve more trips. Although additional relocation VKT is generated, the operating cost per VKT for single-passenger AMoD vehicles remains low, with a slight increase of about 300 euro, while more than 2000-euro profit can be achieved.

Although vehicle relocation can shorten waiting times and serve more trips with a higher profit, additional VKT is generated in relocations. The relocation VKT might lead to more road congestion. To have a closer look at the relocation operations, Figure 5.6 demonstrates the vehicles in relocations over the morning hours (we are studying). Relocations occur in the very early morning and late morning hours. No relocation occurs in the time interval ([7:30 am, 10:00 am]) when a high volume of clients request services. The number of relocation vehicles between identified zones is given in Appendix C.

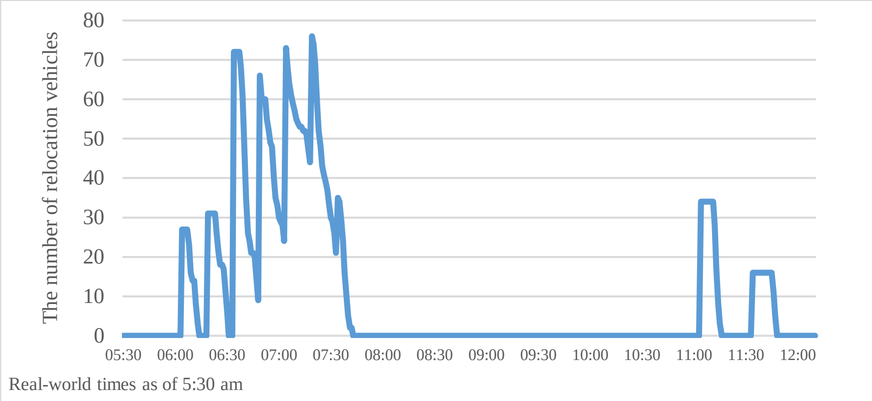


Figure 5.6 The number of vehicles in relocation states over simulation time

Figure 5.7 shows that performing relocation operations bring more vehicles to the roads in the very early morning hours and late morning hours when the road network is uncongested. Hence, relocating vehicles to a more advantageous position in anticipation of future demand does not cause more traffic congestion during peak hours. That means relocating vehicles in advance can avoid congestion while obtaining relocation benefits of improving waiting times, serving more trips, and achieving a higher profit.

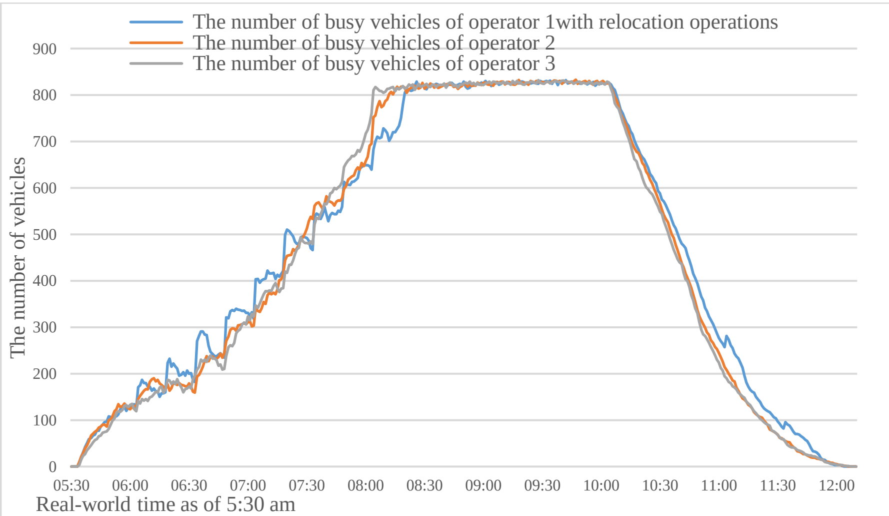


Figure 5.7 The number of busy vehicles for operators over simulation time (minutes)

Figure 5.8 shows vehicle shortages in Demander zones and vehicle surpluses in Supplier zones. Demand levels are shown as dots and are graduated by grey and black color. The red bar represents the vehicle shortage in a Demander zone, while the blue bar represents the vehicle surplus in Supplier zones. As expected, vehicle shortage occurs in places (TAZs) where the number of morning commuters is high. As pointed out in example 1, there are not enough available vehicles to serve the anticipated demand in the Demand zone (ZoneID 107 in Appendix C) and its adjacent zones where the demand is most concentrated. Simulation results show a total shortage of 160 vehicles in the morning hours ([5:30 am, 12:00 am]) in this Demander zone. Oppositely, In example 2, Two zones (zoneID 87 and zoneID 86 in Appendix C) have lower numbers of morning commuting requests, about 298 and 513 requests. Vehicles in these zones can be relocated to high-demand zones in advance to transport more morning commuters in an on-demand fashion.

Interestingly, in example 3, zone 89 (numbered in Appendix C) has a high number of 1310 morning commuters for AMoD services. However, there are still available vehicles (21vehicles) at a specific time for relocations (i.e., 06:33 am in Appendix C). This is because these zones are also destinations where SAVs drop off their customers for a short time. We found that vehicles in high-demand zones can be relocated to places where there is are shortage of vehicles on short notice (we generate time-dependent requests with a high spatial and temporal resolution and anticipate the demand in a 15-minute time interval). Notably, In the AMoD system, vehicles are fully controlled, so they can be relocated to serve more demand at short notice to mitigate the demand and supply imbalance. As a result, high profits and vehicle utilizations.

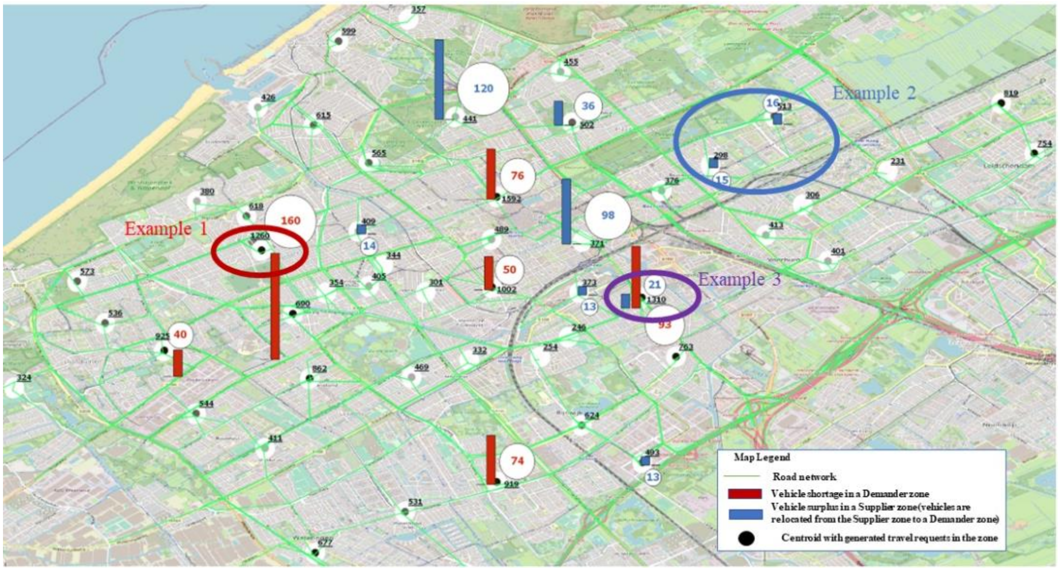


Figure 5.8 Vehicle shortages in Demander zones (red) and the number of relocation vehicles in Supplier zones (blue)

In the flow map (see Figure 5.9), the arrows show the relocation direction, and the width illustrates the number of relocation vehicles. Simulation results show that AMoD operators relocate idle vehicles from multiple Supplier zones to mitigate the vehicle shortage in a Demander zone. That is because in the early hours ([6:00 am,7:30 am]), travelers commute from home to work locations, then a number of requests for AMoD services increases. Few vehicles are available for performing relocation operations to serve the anticipated commuting demand. Moreover, we found that the relocation distance between a Demander zone and the Supplier zones is long. As a result, the relocation could generate a large percentage of empty VKT. Although additional VKT could lead to a higher operating cost, the AMoD operating cost is lower because of eliminating the relocation staff. Also, in future urban mobility systems, commercial AV companies are rolling out micro AMoD vehicles, further reducing operating costs. Therefore, applying relocation operation in AMoD systems is cost-effective while serving more demand. Moreover, relocation operations could improve service levels.

Thus, commuters could benefit from the convenience of the on-demand services and may be willing to use the AMoD services with a high service level.

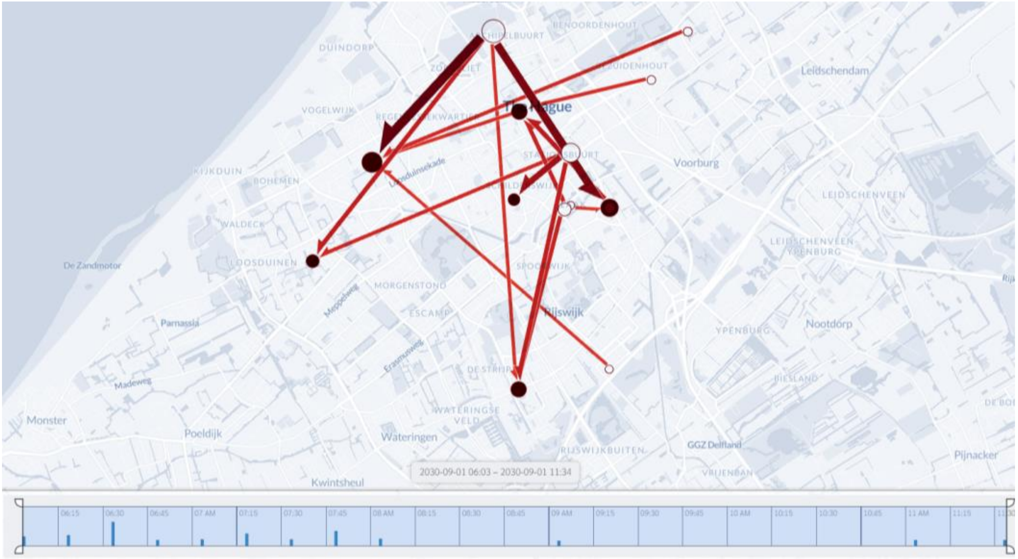


Figure 5.9 Flow maps of relocation vehicles between the Demander (grey) and Supplier (black) zones (in FlowblueMap)

5.6 General discussion and Recommendations

AMoD operators are introducing a smaller AV fleet in urban areas at the early stage of trials. Operators may increase the size of their vehicle fleet to improve the service quality (e.g., waiting times) and serve more trips with a greater profit. However, increasing fleet sizes result in more traffic on the road network and, therefore, deteriorate its competitors' service quality (average waiting and travel times). Hence, policymakers (e.g., city authorities) need to regulate the number of vehicles operated by AMoD operators in the competitive mobility market. Otherwise, the growth of fleet sizes will cause negative traffic externalities (e.g., congestion and pollution) and have an unfavorable impact on citizens' well-being.

Individual operators become efficient in dealing with demand when relocations occur. Relocations performed by an operator can increase operational efficiency (i.e., more trips are served for each vehicle) while providing a higher quality of service offered to travelers even if nothing on the supply side is done. Moreover, a higher profit can be achieved when vehicles are proactively relocated in anticipation of future demand. This is because vehicles are relocated toward a highly demanded area, resulting in more served trips. The operating costs for single-occupant AMoD vehicles are low compared to other systems (e.g., AMoD systems with large vehicles, carsharing systems, taxi systems). For example, AVs equipped with automated driving systems in AMoD systems eliminate the high cost of staff salary and staff relocation rides in carsharing systems. Compared with the relocation operations in competitive carsharing systems in which an unprofitable situation is estimated (Balac et al., 2019), performing relocations by operators in competitive AMoD systems shows an increase in profit. Our findings of the positive financial effect suggest fleet operators should perform relocations to provide better services and obtain a higher profit. It is recommended to develop the relocation capability for AMoD operators in their management systems.

We also found that fare structures can significantly influence an operator's profit. When congestion occurs during peak hours, distance- and time-based fare structures can help companies achieve a higher profit. Operators should carefully consider the fare structure to maximize profit. A relatively low fare in this study is assumed (60% of the existing MoD that is active in the case-study city) to calculate the profits of operators based on the works by Oh et al. (2020) and Spieser et al. (2014). An optimal pricing scheme is not derived and is beyond the scope of this study.

5.7 Conclusions and future directions

AMoD systems are considered an important form of urban mobility innovations. AMoD systems in the presence of public transportation systems are a promising pathway to transform the current transportation systems. At this stage, we address the need for modeling multiple AMoD operators and demonstrate the effectiveness of different strategies used by AMoD operators.

This chapter presented a framework for modeling the AMoD systems with multiple independent operators (which are entering urban mobility markets) to capture the interplay of operators. We model multiple independent operators coexisting in the same urban area to complement state-of-the-art literature relevant to a single urban AMoD operator. Notably, we have studied relocation operations and demonstrated the benefits of relocating vehicles, anticipating future demand in urban AMoD systems. We also contribute to a growing body of studies related to relocation operations in the multiple-operator carsharing system, which differs from multiple-operator AMoD systems in terms of the system operations (optimal assignment and relocation mechanism) and operating costs.

Through simulation experiments, application scenarios with different fleet sizes and relocation operations are tested to help decision-makers (e.g., city authority, fleet operators) identify multiple outcomes and impacts, leading to more effective strategic planning. Findings suggest that an improvement in profit and service levels can be obtained with a larger fleet of AVs and with relocations in the competitive market. However, unregulated AMoD services in terms of fleet sizes could deteriorate social welfare (e.g., more congestion). Hence, there is a need for policies to create a regulated environment where the number of vehicles operated by AMoD operators is limited. Commercial companies (operators) need to develop an effective relocation capability enabled by vehicle automated technologies to improve their competitive edge over their counterparts.

Introducing multiple operators into the AMoD systems makes the interactions and dynamism of system components more complicated. The developed ABM shows good promise as a virtual testbed for analyzing the performance of AMoD system operations with multiple players. This will be particularly useful for studying cooperative mechanisms between operators (e.g., cooperative vehicle assignments in the decentralized system).

We did not model the behavior of the travelers in response to service quality offered by different AMoD operators, either with or without consideration of public transportation options. Understanding why people choose a service offered by an operator over the service provided by another operator is crucial to making further conclusions about the performance of a future urban mobility system (e.g., multimodal transportation systems in which information is completely shared). In future studies, surveys can be done to investigate travelers' preferences towards emerging mobility services provided by different operators (e.g., Apple, Toyota, Mercedes Benz, and Waymo) since this is still difficult to find in the literature. Moreover, how the AMoD system is organized and operated in a multimodal transportation system (e.g., a centralized architecture or a distributed architecture) remains an interesting question for future research.

Chapter 6

Modeling Multiple AMoD Operators with Endogenous Demand

Motivated by the rapid development of AMoD services, an agent-based model (ABM) has been used to study the coexistence phenomena of multiple AMoD operators competing for customers. The ABM aims to investigate how pricing strategies, assignment methods, and fleet sizes affect travelers' choice of different AMoD services and the operating performance of competing operators in the case-study city of The Hague, in the Netherlands. Findings suggest that an optimal assignment algorithm can reduce the average waiting time by up to 24 % compared to a naïve heuristic algorithm. We also find that a larger fleet could increase demand but lead to higher waiting times for its users and higher travel times for competing operators' users due to the added congestion. Notably, pricing strategies can significantly affect travelers' choice of AMoD services, but the effect depends strongly on the time of the day. Low-priced AMoD services can provide high service levels and effectively attract more demand. For example, we found that up to 64.7% of customers choose the low-priced service in the very early morning [5:30 AM,7:20 AM]. In the subsequent morning hours, high-priced AMoD services are more competitive in attracting customers as more idle vehicles are available. Based on the quantitative analysis, policies are recommended for city authorities and service operators.[4]

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[4] *This chapter is an updated version of the published paper: Wang, S., Correia, G. H. de A., & Lin, H. X. (2022). Modeling the competition between multiple Automated Mobility on-Demand operators: An agent-based approach. Physica A: Statistical Mechanics and Its Applications, 128033. The diagrams to present the demand*

6.1 Introduction

The emerging AV industry can be described as a marketplace where no single organization has enough influence and resources to dominate the entire market. In a future urban mobility system, it will be natural that fleets of SAVs will be operated by different AMoD companies to meet mobility needs in urban areas. Existing research focuses on exploring the impact of AMoD services performed by a single operator and ignores the study of AMoD systems with multiple operators competing for customers in urban areas. This chapter aims to extend the agent-based model (ABM) to study the coexistence phenomena of multiple AMoD operators competing for customers. We explore the potential of operating strategies (e.g., fleet sizes, assignment strategies, pricing strategies) on travelers' choices through scenarios and a case study.

The remainder of the chapter is structured as follows. Section 6.2 provides the current state of research on modeling urban AMoD systems, emphasizing supply and demand interactions. Section 6.3 describes the model specifications. A detailed description of the model implementation and its application is presented in Section 6.4. Section 6.5 provides an analysis of the results of applying the model to the case study city of The Hague in The Netherlands. In Section 6.6, we discuss the main findings and provide recommendations for different stakeholders. The main conclusions are drawn in the final section, and future research directions are discussed.

6.2 Background

6.2.1 Modeling single-operator AMoD systems

Burns et al. (2013) examined the cost and operating performance of AMoD systems to serve the existing travel demand satisfied by private vehicles. They found that AMoD systems are compelling because they could provide mobility services with shorter waiting times and low operating costs. Fagnant and Kockelman (2014) investigated the travel and environmental implications of AMoD systems using exogenous demand. Their findings indicated that Shared Automated Vehicles (SAV) could improve vehicle utilization and reduce negative environmental impacts. Several works focused on the operational efficiency of AMoD systems and gave insights into the operational aspects of parking, relocation, charging, dispatching, and routing (Liang et al., 2020; T. Liu et al., 2020; Vilaça et al., 2022; Wang et al., 2019; Yang and Liu, 2022). Wang et al. (2022) investigated the travel and energy impacts of forming platoons in an urban AMoD system. Some studies have provided an assessment of operating AMoD systems when combining public transportation options (X. Liang et al., 2016a; Shen et al., 2018). Modeling frameworks in the above studies use either static demand

data and road network that were used in Chapter 4 is removed from this chapter. Model specifications in Section 6.3.3 are shortened since these building blocks are also used and explained in Section 5.3.3.

imposed for AMoD systems or exogenously determined modal share for the AMoD service and public transportation options. Therefore, the behavioral response to the level of AMoD services is usually not captured.

6.2.2 Modeling single-operator AMoD systems in the presence of public transportation options with endogenous demand

More recent research explicitly models the supply and demand interaction when studying AMoD systems in the presence of public transportation options. Attention is given to how travelers dynamically choose their transport mode in response to the performance of the different transport services.

Chen and Kockelman (2016) have incorporated different fare schemes in the mode choice model to examine the impact of electric AMoD service pricing strategies on mode share and fleet performance. Bösch et al. (2018) provided a cost-based analysis of AMoD services. The study by Bösch et al. (2018) considered user-case-specific preference for modes of transportation. The mode choice was determined according to the operating cost of the AMoD service. Pinto et al. (2019) formulated a modeling framework to solve the problem of redesigning a bus network while introducing an AMoD service. The modal share for the AMoD service and the bus service was determined endogenously based on the bus service's frequency and the AMoD fleet's performance. Wen et al. (2018) formulated a modeling framework to evaluate an integrated AMoD and public transportation system in which shared-use AVs provide a connection service to rail stations in low-density areas. The modeling framework captured the changes in travelers' behavior in response to the operating policies. Dandl et al. (2019) proposed a new simulation framework for AMoD systems that focuses on asynchronous approaches to computing decisions for a fleet operator in serving demand. The asynchronous framework is used to address the trade-off between computational complexity and the policy optimality of operators. Narayan et al. (2020) studied the problem of combining scheduled and fixed-route transit systems with AV fleets, where AVs provide either connection service to transit services or direct door-to-door services in a demand-responsive fashion. Using the MATSim framework, the demand for transit services, exclusive AV services, and integrated AV-transit systems was endogenously determined. Oh et al. (2020) examined the impact of introducing AMoD systems into the existing transportation system in Singapore through SimMobility, which was an integrated agent-based and activity-based simulation framework. The responsiveness of demand to the change in the fleet supply and operations was explicitly modeled. Hörl et al. (2021) simulated AMoD systems in a multimodal transportation system in Zurich using MATSim. The proposed modeling framework can model the customers' response to the level of service attributes (waiting time and price). In particular, their study proposed a cost-covering pricing scheme for the AMoD fleet. The relationship between AMoD demand (served requests) and fleet size was established under the constraint of providing a cost-covering AMoD service.

6.2.3 Modeling single-operator MoD and carsharing systems considering the supply-demand interaction

The works discussed above are directly related to the application of AMoD systems. Similar studies have been conducted to investigate the impacts of introducing mobility-on-demand (MoD) and carsharing systems in urban mobility systems while considering the supply-demand interaction.

Vasconcelos et al. (2017) presented a cost-benefit analysis method to analyze and compare the performance of one-way carsharing systems with and without vehicle relocation in the presence of private transport (private cars and motorcycles) and public transport. To simulate the behavioral response to the different transport modes, a discrete choice model was incorporated to allocate travelers to the transport modes in the city of Lisbon. One of the findings suggested that the use of electric vehicles in one-way carsharing systems can achieve environmental benefits, while vehicle relocations can counteract the environmental benefits due to the additional relocation kilometers. Lu et al. (2020) proposed an optimization model to examine the effect of pricing and vehicle relocation strategies on the performance of one-way carsharing systems, taking into account the competition with private cars. A logit model was incorporated into the optimization method to calculate the probability of the alternative choices. Findings suggested that combining a vehicle relocation strategy with a strategy of varying prices depending on vehicle stock can effectively balance the trade-off between the operator's profit and travelers' cost. Djavadian and Chow (2017) developed a modeling framework to incorporate an agent-based day-to-day adjustment process for both an MoD operator and travelers. In the modeled two-sided transportation market, travelers can adjust their behaviors of choosing a transport service, while the MoD operator can adjust the service offered using within-day operating policies and day-to-day fleet size policy. The modeling framework was applied to a first/last mile problem with an emphasis on testing the sensitivity of within-day operating policies and fare prices. Y. Liu et al. (2018) developed a framework to model the customers' choice for MoD systems in the multimodal transportation system aiming to optimize MoD fleet size and fare.

6.2.4 Research limitations in the literature

In all the above studies on AMoD, MoD, and carsharing systems, the services are assumed to be managed by a single operator. The phenomena associated with the competition between multiple AMoD operators for customers (e.g., morning commuters) are overlooked.

With the rapid growth of the ride-hailing market, multiple commercial MoD companies (e.g., Uber, Lyft, and Didi Chuxing) are operating their services simultaneously with other companies. Séjourné et al. (2018) studied the overall system's efficiency in a situation where multiple MoD platforms coexist and independently manage vehicles to meet a fixed demand. Pandey et al. (2019) presented an optimization-based approach to study cooperative and competitive assignments between multiple ridesharing operators. The proposed assignment method solved the coordinated assignment problems in multiple-operator situations without lowering the level of service compared to a fully centralized assignment. The modeling framework quantified the impact of customer preference on assignment results with varying percentages. Kondor et al. (2022) quantified the cost of adding more vehicles to serve demand when the market is segmented in the urban mobility system. They compared the cost of non-coordinated urban MoD systems with multiple operators to the cost of operating the vehicle fleet by a single operator for different cities. Their findings suggest that the total fleet needs to be increased by up to 67% to serve the given demand in non-coordinated urban MoD systems.

Despite the fact that AMoD systems are analogous to MoD systems, both of which rely on ride-hailing technology, underneath, the two systems differ because of the adoption of AV technology in AMoD systems. First, automation is expected to lengthen vehicle lifespan and lower maintenance requirements, leading to a reduction in operating costs (Bauer et al., 2018). The elimination of drivers can further reduce the operating cost in AMoD systems (Bösch et al., 2018a). Second, vehicles in AMoD systems can be fully controlled by the fleet management center and made to comply with the management's decisions. Therefore, efficient operations related to vehicle dispatching and routing can be performed without drivers interfering (Hörl et al., 2019; Hyland and Mahmassani, 2018).

6.2.5 Research contributions

We will examine the potential impacts of operating strategies under various competitive structures of application scenarios on the operating performance of individual operators and the entire AMoD system and how demand responds to changes in operating strategies. To achieve this, we present an agent-based modeling framework with a modular architecture consisting of a demand component, a fleet management component, and a traffic management component.

The main contributions of this chapter are summarized as follows:

The first is that an endogenous demand model is developed to represent the behavioral response of travelers to the level of service of AMoD operators. That is, a multinomial logit (MNL) model is used to calculate the choice probability in which utility is a function of service attributes. The MNL model is incorporated into the agent-based modeling framework to determine the AMoD service choices of travelers. The behavior of individual requests is simulated with high-level detail, leading to a high spatial and temporal model resolution.

The second is that in the AMoD service simulation, we explicitly model the interaction between vehicles operated by AMoD operators and their customers. An advanced vehicle-to-passenger assignment algorithm is implemented to match the available vehicles of an AMoD operator with incoming travel requests.

The third is that we implement a mesoscopic traffic simulation model, in which link and node movement rules are defined, into the multiple-operator AMoD modeling framework. In this respect, we do not contribute to the traffic models but formulate a framework that accounts for the network congestion effects of all SAVs operated by different AMoD operators. In this way, the levels of services provided by different operators to all the morning commuters can be measured while considering the impedance on the road network.

The last main contribution is that future service scenarios of multiple-operator AMoD systems are proposed and modeled for the case-study city of The Hague in The Netherlands. We perform simulation experiments for competition scenarios to study the impact of operating strategies (fleet sizes, assignment methods, and pricing schemes) on the behavioral response to AMoD services. Notably, we explore how behavioral choices affect the performance of competing AMoD operators.

6.3 Model specifications

We want to build a model for assessing the performance of a proposed AMoD system with several operators. The model should be able to capture the interaction between the clients (travelers) and SAVs, behavioral responses to services provided by AMoD operators, and the congestion effect. The model specifications and model assumptions for building the ABM are presented.

The following are the main ABM assumptions:

- The AMoD systems are studied for the morning peak commuting scenario in urban areas.
- There are three operators in the case study area. Vehicles managed by their respective operators provide on-demand mobility solutions between service points (centroids) over the network.
- In replacing all private car trips with SAVs, travelers can remain unserved when there are no vehicles available. We assume that the unserved clients will use private cars. These private cars are considered in road traffic but are not included in the mode choice model. This is because private car trips affect road traffic, which may contribute to road congestion. Moreover, the utility of the private car mode is assumed to be considerably lower when compared to the AMoD services which benefit from the elimination of the driver, improved operating efficiency with fully controlled movements, and lower parking costs because of continuous operation to serve subsequent trips.
- Travelers can not cancel services after they have been assigned vehicles.

6.3.1 Model Overview

The modeling framework with three main components is presented in Figure 6.1. The demand component includes a demand generator and a mode choice component. The demand generator is used to generate individual travelers with spatial and temporal attributes. The decision-making mechanism for travelers is considered by incorporating the mode choice component into the agent-based framework; the mode choice component allocates the time-dependent requests from the travelers to the different AMoD services according to the level of service attributes. Therefore, in reality, it is a service choice module since the mode is the same. Price with other choice attributes (i.e., out-of-vehicle waiting time and in-vehicle travel time) that can be measured in the simulation is incorporated into the discrete choice model in which travelers' preferences toward AMoD services are decided.

The traffic management center has full knowledge of the network and traffic conditions. Therefore, we envision a system whereby the traffic operator will provide the routing information to AVs in a centralized manner independently of how many companies are providing AMoD services. In the fleet management center, the vehicle-to-passenger assignment component is responsible for matching incoming requests of travelers with the available vehicles of an operator. The interaction between individual vehicles and individual travel requests for each operator is explicitly captured in the vehicle-to-request assignment process; thus, the model framework has the capability of evaluating the impact of SAVs which can be measured with different key performance indicators such as the empty movements to pickups clients in a multiple-operator AMoD system.

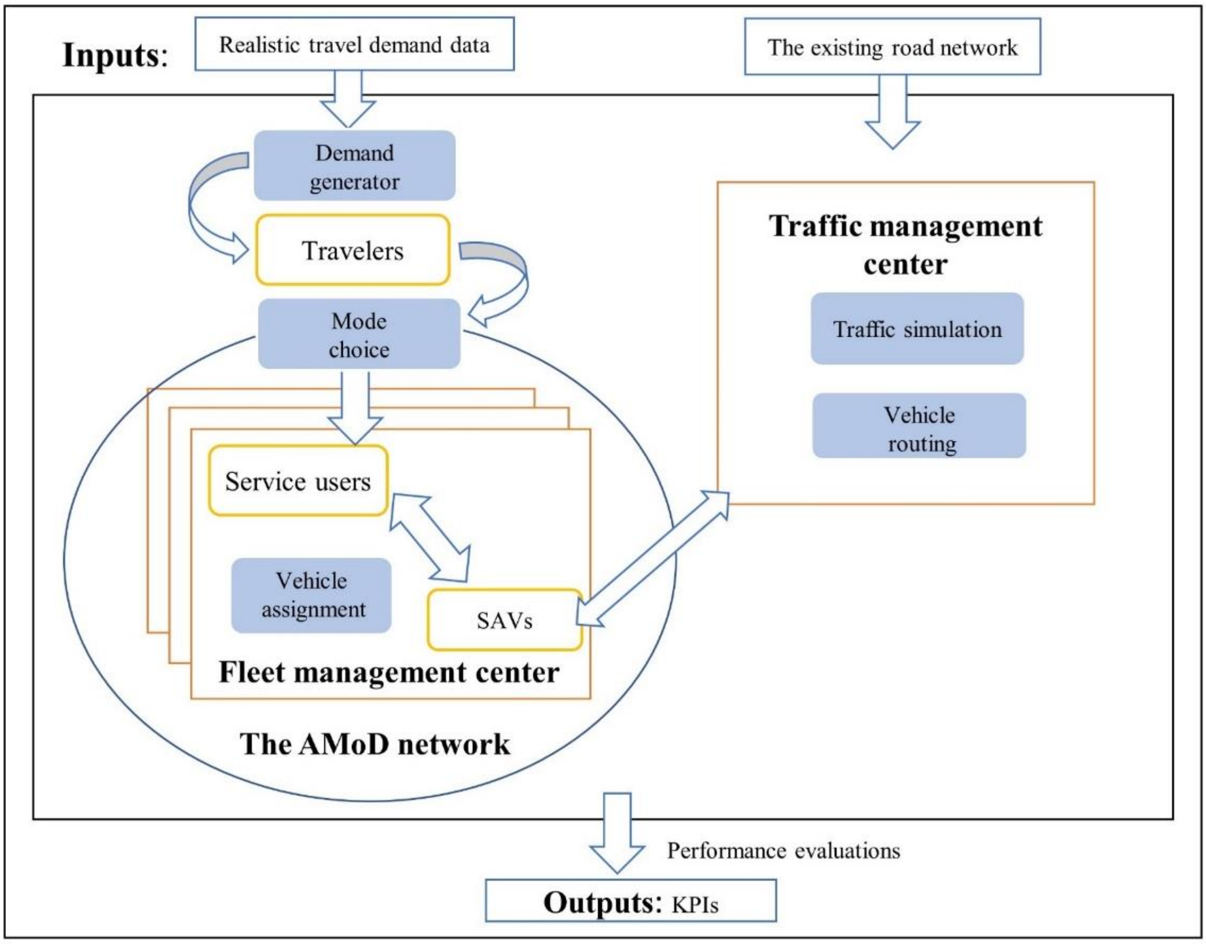


Figure 6.1 The conceptual simulation framework for multiple operators

6.3.2 Mode choice component

Demand (travel requests) is determined endogenously for competing AMoD operators. Requests of the travelers are allocated to different AMoD operators by the mode choice component. The AMoD system studied comprises three operators, each of which operates a fleet of SAVs. In this section, we will use this example to further explain the mode choice. The three AMoD operators provide direct door-to-door service to the public. That is, customers can access the service offered by any operator. Naturally, the choice sets of individuals have three alternatives. The probability of choosing a specific AMoD alternative is calculated based on an MNL model. In the MNL model, the probability of an individual k choosing an AMoD alternative i is assumed to increase monotonically with that alternative's systematic utility V_i.

Important alternative-specific attributes for AMoD services are waiting time, travel time, and fare, all reflecting the level of service offered by the AMoD operators. The systematic utility is expressed as a linear function of out-of-vehicle waiting time w_i, in-vehicle travel time (IVTT) t_i and out-of-pocket cost f_i associated with the service usage of operator i. The expected systematic utility V_i for the AMoD operator i can be formulated as follows:

$$V_i = V(w_i) + V(t_i) + V(f_i) \tag{6.1}$$

The alternative i with the highest utility will have the highest probability of being chosen by customer k relative to other travel options (the other two AMoD services in this case). The probability of choosing alternative i for an MNL is described by the logit expression:

$$Pr(i) = \frac{exp(V_i)}{\sum_{i=1}^{3}(exp\ (V_i))} \tag{6.2}$$

6.2.2.1 Discomfort of the out-of-vehicle waiting for the vehicle $V(w_i)$

The first component $V(w_i)$ of the utility describes discomfort of the out-of-vehicle waiting for the vehicle of the chosen operator i. The waiting time includes the time spent in the waiting queue where requests are waiting for being assigned a vehicle and the time spent waiting for the arrival of the pickup vehicle. The former is defined as the assignment time, while the latter refers to the expected pickup time. In this study, the expected assignment time w_a is formulated as a function of the number of requests on the waiting list to be assigned. The expected pickup time w_p is estimated based on the vehicles' availability.

$$w_a = \boldsymbol{\varphi} * \boldsymbol{m} \tag{6.3}$$

$$w_p = t_{max}\left(\frac{N_i - n_i}{N_i}\right) \tag{6.4}$$

$$\begin{aligned} V(w_i) &= -(\boldsymbol{\alpha} * VOTT_{AMoD}) * w_a - (\boldsymbol{\alpha} * VOTT_{AMoD}) * w_p \\ &= -(\boldsymbol{\alpha} * VOTT_{AMoD}) * (\boldsymbol{\varphi} * \boldsymbol{m}) - (\boldsymbol{\alpha} * VOTT_{AMoD}) * \left(\frac{N_i - n_i}{N_i}\right) * t_{max} \end{aligned} \tag{6.5}$$

Where,

w_a is the expected assignment time.

w_p is the expected pickup time.

$\boldsymbol{\varphi}$ is the average assignment time for individual requests. The average assignment time is computed through multiple simulation runs.

$\boldsymbol{m}$ is the number of requests on the waiting list.

t_{max} is the maximum pickup time, which is computed based on the maximum searching distance. Idle vehicles within a searching radius are considered to be available vehicles. The radius is defined as the maximum distance from a request to the available vehicles. We use the radius to estimate the maximum pickup time.

n_i is the number of idle vehicles of operator i. Note that travelers are allocated among operators based on the number of idle vehicles, while travelers are only served by available vehicles.

N_i is the total number of vehicles of operator i.

$\boldsymbol{\alpha}$ is the multiplier that reflects the inconvenience and discomfort of time spent outside a vehicle.

$VOTT_{AMoD}$is the monetary value of the travel time for AMoD mode. The monetary value of out-of-vehicle waiting time can be estimated using the multiplier α and the monetary value of travel time ($VOTT_{AMoD}$). This should typically be a value greater than 1.

6.2.2.2 Disutility of In-vehicle Travel Time $V(t_i)$

The second component $V(t_i)$ of this utility function models the cost of IVTT in AMoD vehicles. The cost of IVTT depends on the IVTT and VOTT in AMoD vehicles.

$$V(t_i) = -s_i * VOTT_{AMoD} \tag{6.6}$$

Where,

s_{ik} is the expected travel time for the OD of user k.

6.2.2.3 Disutility of fare $V(f_i)$

The third component $V(f_i)$ of this utility function regards the fare for the AMoD service. Fare is the out-of-pocket cost of a customer k of the chosen operator i. In this study, the fare is structured by a base fare, a distance-based fare, and a time-based fare for a single ride.

$$V(f_i) = -\ \varepsilon\ * \eta * (c + m * d_{ik} + n * s_{ik}) \tag{6.7}$$

where,

η is the saving factor for AMoD services relative to an existing MoD service (we are using the UberX fare structure as a reference in the case study).

c is the base fare for MoD services.

m is the distance-based fare for MoD services.

n is the time-based fare for MoD services.

ε is the controlling factor of a pricing strategy.

Regarding the pricing strategies, two different pricing schemes will be considered in the modeling framework to analyze the service uptake and operating performance of the AMoD fleets.

The first pricing strategy refers to a discount pricing strategy where users can access the service of a specific AMoD operator at a discounted rate. A percentage-based discount is implemented on the service offered by the operators. A 20% discount on the fares in relation to the baseline AMoD pricing is tested.

In the second pricing strategy, the fare of a specific operator is estimated according to the vehicle availability and future demand in an area (TAZ: Traffic Analysis Zone) where travelers request AMoD services. A rule-based supply-demand balancing pricing strategy aims to encourage travelers to use AMoD services when the vehicle supply is high and discourage travelers from using AMoD services when there is a vehicle shortage. The parameter ε follows the work suggested by Chen and Kockelman (2016).

$$\varepsilon = \begin{cases} 0.5, & p_{av} * p_{ad} < 0.1 \\ 1, & 0.1 < p_{av} * p_{ad} < 10 \\ 2, & 10 < p_{av} * p_{ad} \end{cases} \tag{6.8}$$

Where

p_{av} is the proportion of the total number of available vehicles in the study area to the number of available vehicles in the origin TAZ of the incoming travel request. A larger value of p_{av} suggests few available vehicles in the origin TAZ where a request is made compared to the other TAZs , while a smaller value means more vehicles available in the origin TAZ.

p_{ad} is the proportion of the anticipated demand that will be generated in a TAZ (origin) to the anticipated demand in the entire study area. A larger p_{ad} means a high volume of requests in a TAZ, while a smaller value indicates fewer requests are made in a TAZ compared to the other TAZs.

It is noted that the anticipated demand is the number of travel requests in the subsequent time interval. Individual travel requests in the subsequent time interval are not generated, but the anticipated number of travel requests is calculated.

6.3.3 Behaviors of vehicles and travelers, and their interactions

In AMoD systems, decisions on assigning vehicles to serve travel requests are made immediately. The behavior (states) of travelers and vehicles is further depicted in Figure 6.2. The assignment component knows the current vehicle locations and ascertains the states of all of them: upon receiving a trip request, it determines which vehicles in the fleet are able to reach the customer. Once the assignment has been done, the information on travelers' locations is sent to the assigned vehicles and the traveler is notified about the vehicle details. The assigned vehicle will transition from the idle to the in-service state when arriving at the traveler's origin location, while the state of a traveler will transition from "waiting for the vehicle arrival" to "traveling in the assigned vehicle". Once a traveler is assigned a vehicle, the AMoD service cannot be canceled. After reaching the destination location, the traveler switches to a served state. To avoid unrealistically long assignment times, travelers can remain unserved when there are no available vehicles and use a private car as referred to in model assumptions.

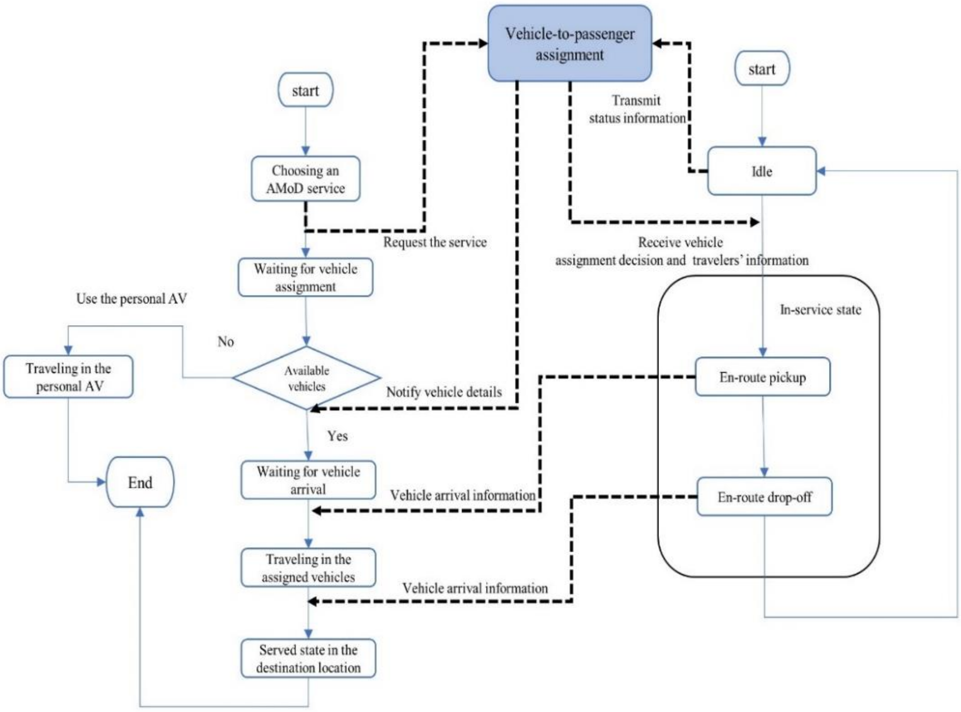


Figure 6.2 The interaction between individual vehicles and individual travelers

Vehicle-to-passenger assignment strategies could influence the AMoD system performance in terms of service levels (e.g., waiting and travel times), the number of served requests, and VKT. Therefore, we developed an optimal assignment algorithm and a simple heuristic algorithm and aimed to demonstrate the effectiveness of the two methods in the multiple-operator AMoD system.

An optimal assignment algorithm is implemented to assign available vehicles to incoming travel requests. The method can assign a group of available vehicles $V = \{v_0, v_1, \dots, v_n\}$ to bundled travel requests $R = \{r_0, r_1, \dots, r_n\}$. The Hungarian assignment is used to assign one vehicle in V to serve a travel request in R with the objective of minimizing the total cost (total distance between vehicles and requests) (Kuhn, 2010). Moreover, a naïve heuristic algorithm for the request-to-vehicle assignment is also implemented in the modeling framework. In the simple heuristic algorithm, each fleet operator assigns the closest available vehicles within a search distance to serve travel requests. The real-time SAV assignment decision of fleet operators is based on the Euclidian distance. Priority is given to trips that request the service earlier.

The vehicle-passenger assignment component that we have just explained assigns available vehicles to serve travel requests, but there is a need to compute routes between nodes in the network. The vehicle routing component is responsible for providing the shortest routes between two locations, such as the current vehicle location and pickup locations, the pickup location and the drop-off location.

The routing component can utilize the static and dynamic information relating to the road lengths and traffic conditions provided by the traffic simulation component to calculate the time-dependent shortest route between any two given points. Upon the assignment of an SAV to a traveler, the routing component will compute the time-dependent shortest route from the current location of the assigned vehicle to the location of the traveler using the Dijkstra algorithm. When the vehicle arrives at the pickup location, the time-dependent shortest route from the traveler's location to its destination will be obtained from the central traffic management system.

In the modeling framework, individual agents are being used to represent shared automated cars that are assigned to clients, but in order to provide realism to the travel times that they experience on the network, a traffic model is required. In the mesoscopic traffic simulation model, the rules of link movement and node transfer will govern the movement of individual vehicles owned by the different operators.

6.4 Model application to the case-study city of The Hague, the Netherlands

6.4.1 Urban Road network and demand data

A tailored road network in the case-study city is used for the study. The total private transport demand in the region of Zuidvleugel (285 TAZs) is 270,050 trips by car in the morning peak hours (5:30 AM to 10:00 AM). 27,452 trips happen within the boundaries of the selected study area of The Hague. However, intrazonal trips are not modeled. Therefore, the generated effective requests amount to approximately 25,800. The demand is distributed over 18 intervals in the morning peak period, each of which has a temporal step length of 15 minutes starting from 5:30 AM to 10:00 AM. The OD matrix contains 2401 non-zero pairs between 49

TAZs. A demand generator generates individual travel requests based on aggregate travel data (available in the form of an OD Matrix) and departure time. Individual requests are characterized by origin, destination, and request time. Requests for each OD pair can be allocated among operators using a mode choice component.

6.4.2 Mode choice parameters

Table 6.1 gives a summary of model parameters and case study characteristics for the base scenario. Regarding the values of parameters in the MNL, the monetary value of out-of-vehicle waiting time is larger than the monetary value of in-vehicle travel time. There is evidence that the out-of-vehicle waiting time multiplier is between 1.6 to 2.2 times the in-vehicle travel time in the Dutch context (Arentze & Molin, 2013; Yap et al., 2016). In this study, the multiplier $\boldsymbol{\alpha}$ is set to 2. That means the out-of-vehicle waiting time is valued twice as much as the VOTT of the AMoD mode.

The VOTT inside AMoD vehicles cannot be obtained from state-of-the-art due to the lack of relevant studies. In this study, the VOTT in AMoD vehicles is estimated based on VOTT in private cars and on the transit mode (bus, tram, and metro). In the Netherlands, the VOTT on private cars mode and transit mode is valued at 9.25 euros per hour and 7.75 euros per hour for commuting purposes (Kouwenhoven et al., 2014). Travelers in AVs can perform productive and leisure activities without having to drive in private cars and without standing on transit mode. VOTT in AMoD vehicles is supposed to be lower than those on private car mode and transit mode. The value of IVTT in AMoD vehicles is valued at a 35% reduction of VOTT in private cars (Chen & Kockelman, 2016). In this study, VOTT in AMoD vehicles is valued at 6.01 euros per hour. We are using the UberX fare structure that is active in the Netherlands. We consider a baseline pricing scenario, 60% of the existing MoD. Then, we have $\eta = 0.6\ \ c = 1.4\ euros,\ \ m = 1.2\ euros\ per\ km, n = 0.26\ euros\ per\ min$ in Equation 6.7.

Regarding the valuation of the controlling factor ε that is used in pricing strategies, we have $\varepsilon = 1.0$ in the baseline scenarios and $\varepsilon = 0.8$ when a 20% discount is tested. In the scenario where the supply-demand balancing pricing strategy is applied, the value of Epsilon is given through a step function in Equation 6.8.

6.4.3 AMoD fleet

In relation to the vehicle type used in this study, carmakers (Renault UK, Toyota) are producing and marketing small driving pods. The small vehicles can take up less road and parking space. Moreover, small-sized vehicles can save more energy with reduced weight (S. Wang et al., 2022a). Hence, we assume that purposely designed small SAVs are suitable for urban mobility applications and could be available and affordable for future large-scale deployment.

The simulation model is run with a growing fleet size and one operator to find the fleet that serves 80% of all the travel requests. This results in $N = 60$ vehicles as shown in Table 6.1. The model is also run for three operators where the fleet is distributed equally ($n\_(o\_1) = n\_(o\_2) = n\_(o\_3)$). Moreover, scenarios with vehicle increments for operator 1 are simulated, each of which has an increment of Δg (10 vehicles) per service point. In our results, we also show the average performance of the three-operator system (named overall performance - OP) so that this can be easily compared to the performance of a single operator. Ten simulation runs (replications) are performed for each scenario yielding average results.

In relation to the vehicle types used in this study, carmakers (Renault UK, Toyota) are producing and marketing small driving pods. The small vehicles can take up less road and parking space. Moreover, small-sized vehicles can save more energy with reduced weight. Hence, we assume that small-sized SAVs are purposely designed with one seat. Ten simulation runs are performed for each scenario yielding average results.

Table 6.1 A Summary of the Model Parameters for the base scenario

Parameter/characteristics	**Value**
The perimeter of the study area	46 km
The size of the study area	139 km^2
Road segments	836
Road nodes	510
Total travel requests (Z)	25,800 trips
Centroids (denoted by s)	49
Fleet operators I	{operator 1, operator 2, operator 3}
Time steps for speed update	6 seconds
Vehicle assignment Time interval Δt	20 seconds
The search distance for vehicle assignment	6000 meters
The VOTT inside AMoD vehicles	6.01 euros per hour
The multiplier $\boldsymbol{\alpha}$	2
The controlling factor ε used in pricing strategies in the baseline scenario	1
The controlling factor ε used in pricing strategies in the discount pricing scenario	0.8
η is the saving factor for AMoD services	0.6
c is the base fare for MoD services.	1.4 $euros$
m is the distance-based fare for MoD services.	1.2 $euros\ per\ km$
n is the time-based fare for MoD services.	0.26 $euros\ per\ min$
Vehicle seat capacity	1 person
The average number of vehicles per centroid at the beginning of the simulation (N)	60 vehicles
VOTT in AMoD vehicles	6.01 euros per hour
Vehicles increment of operator 1 per service point Δg for sensitivity analysis	10 vehicles (e.g., $2 * \Delta g$ =20 vehicles)

6.5 Results and discussion

The fleet sizes, pricing strategies, and assignment strategies are factors that influence the level of service offered by AMoD operators. The mode chosen by travelers is determined based on the levels of service, which in turn it affects the levels of service. Therefore, we examine how different strategies affect the demand as well as the operating performance.

6.5.1 Analysis of the effect of assignment strategies on operating performance

Two different methods of assigning vehicles to passengers (a simple heuristic algorithm and an optimal assignment algorithm) are implemented and compared for the base scenario. As shown in Table 6.2, compared to the simple heuristic algorithm, the optimal assignment algorithm can reduce the average waiting time by up to 2 minutes, which is a 24% reduction in the average waiting time of the overall AMoD system. The main reason is that the optimal assignment method can optimally match bundled requests with available vehicles to minimize the total pickup distance for bundled requests. Simulation results show that the optimal assignment algorithm generates fewer empty vehicle kilometers traveled (VKT), resulting in a significant reduction of 5511 km for the morning hours than the scenarios using the simple heuristic algorithm.

We also find that with the optimal assignment algorithm, the decline in the average waiting time leads to a reduction in the average in-service time, including average waiting and travel times. Simulation results show that the average in-service time is reduced by more than 1 minute, which is a 3% reduction. Results also show that the optimal assignment method slightly improves the system capacity in serving the demand (the number of served travel requests). There is a slight increase of 102 requests compared to the simple heuristic method. Therefore, the optimal assignment method is used in all scenarios in the following sections.

Table 6.2 Operating performance for different assignment strategies

Demand levels	100% (25,800)							
Systems	Multiple-operator AMoD system with the simple heuristic assignment				Multiple-operator AMoD system with the Hungarian assignment			
	Operator 1	Operator 2	Operator 3	Overall Performance (OP)	Operator 1	Operator 2	Operator 3	Overall Performance (OP)
Fleet size	$n_{o_1} = n_{o_2} = n_{o_3}$				$n_{o_1} = n_{o_2} = n_{o_3}$			
Demand share	8606	8519	8675	25800	8600	8580	8620	25800
Avg. waiting time (min)	8.11	8.32	8.45	8.29	6.29	6.23	6.37	6.30
Empty VKT (km)	11008	11216	11010	33234	9275	9244	9204	27723
Served requests	6897	6769	6957	20623	6874	6870	6981	20725
Unserved requests	1709	1750	1719	5177	1726	1710	1639	5075
Avg. travel time (min)	20.17	20.46	20.46	20.37	20.12	20.17	20.64	20.31
Average in-service time	28.28	28.78	28.91	28.66	26.71	26.40	27.01	26.71

6.5.2 Analysis of the competition scenarios: effect of fleet size

The simulation results in Table 6.3 show that travel requests shift drastically from operators o_2 and o_3 to operator o_1 when the number of vehicles of operator o_1 increases compared to the base scenario of equal fleet size among operators. The increases are done as referred to in Table 6.1 with a value of Δg of 10 vehicles. More demand chooses the operator o_1 in response to the added vehicle availability. It is suggested that demand for an operator can be significantly affected by the fleet size of competing operators. This is because a large fleet size increases the number of potentially available vehicles, that is a competitive factor in evaluating service levels and assigning vehicles to incoming travel requests.

Moreover, simulation results in Table 6.3 show that the total demand served by the urban multiple-operator systems rises as the fleet size of operator o_1 increases. This is due to the assumption that the urban private car demand is very high, and travelers can remain unserved when there are no available vehicles. A large fleet of operator 1 can increase the overall number of available vehicles; thus, more demand (attracted from competitors and not served without available vehicles) is served.

Table 6.3 Demand for different vehicle increments

Demand level	100% (25,800)						
Operators	o_1		o_2 ($n_{o_2} = 20$ $vehicles$)		o_3 ($n_{o_3} = 20$ $vehicles$)		OP
Vehicle increments of **operator o_1 per service point**	Requests for the operator	Served demand (requests)	Requests for the operator	Served demand (requests)	Requests for the operator	Served demand (requests)	Total served demand
Baseline: No vehicle increment ($n_{o_1} = n_{o_2} = n_{o_3} = 20$)	8565	6889	8553	6896	8682	6972	20757
$n_{o_1} + 2 * \Delta g$= 40	9759 (+13.94%)	8464 (+22.86%)	7990 (-6.58%)	6531 (-5.29%)	8051 (-7.27%)	6618 (-5.08%)	21613 (+4.12%)
$n_{o_1} + 4 * \Delta g$ =60	10859 (+26.78%)	9767 (+41.78%)	7546 (-11.77%)	6335 (-8.14%)	7395 (-14.82%)	6233 (-10.60%)	22335 (+7.60%)
$n_{o_1} + 6 * \Delta g$ =80	11845 (+38.30%)	11068 (+60.66%)	7031 (-17.79%)	6096 (-11.60%)	6924 (-20.25%)	5973 (-14.33%)	23137 (+11.47%)
$n_{o_1} + 8 * \Delta g$ =100	12841 (+49.92%)	12277 (+78.21%)	6420 (-24.94%)	5725 (-16.98%)	6539 (-24.68%)	5782 (-17.07%)	23784 (+14.58%)
$n_{o_1} + 10 * \Delta g = 120$	13707 (+60.04%)	13345 (+93.71%)	6058 (-29.17%)	5538 (-19.69%)	6035 (-30.49%)	5536 (-20.60%)	24419 (+17.64%)

When the total demand increases, more VKT will be needed to serve increased demand, resulting in a more congested road network. We introduce the indicator of congestion level to evaluate road traffic conditions. In the baseline scenario, a 45.97% congestion level represents the additional 45.97% time required on average to travel from origin to destination compared to the uncongested travel time. Figure 6.3 illustrates the established relationship between the total VKT and congestion levels. We find that the total VKT in AMoD with multiple operators is growing as the fleet of operator o_1 increases. Meanwhile, the congestion level is increasing with the rise in the total VKT. Compared to the baseline scenario, 17% more served demand (see Table 6.3) for the entire multiple-operator AMoD system leads to an 8.51% VKT increase, reaching 174626 km in the $10 * \Delta\text{g}$ scenario, and the congestion level soars from 45.97% to 88.84% (Figure 6.3).

Figure 6.4 shows the average waiting times, the 90% quantile of the distribution of the waiting times and the 96% quantile of the distribution of the waiting times of different scenarios. Take the 90% quantile of the waiting times as an example: it is a waiting time where 90% of the trips are lower than that.

Given the demand results (requests for the service of an operator) (in Table 6.3), more demand shifts to the operator o_1 when its number of vehicles increases, while the demand for the service of the other operators (operator o_2 and operator o_3) is reduced. Therefore, from the simulation results in Figure 6.4 (a), we can see that the average waiting times for travelers choosing the service offered by operator o_2 and operator o_3 fall as the demand shifts to operator o_1.

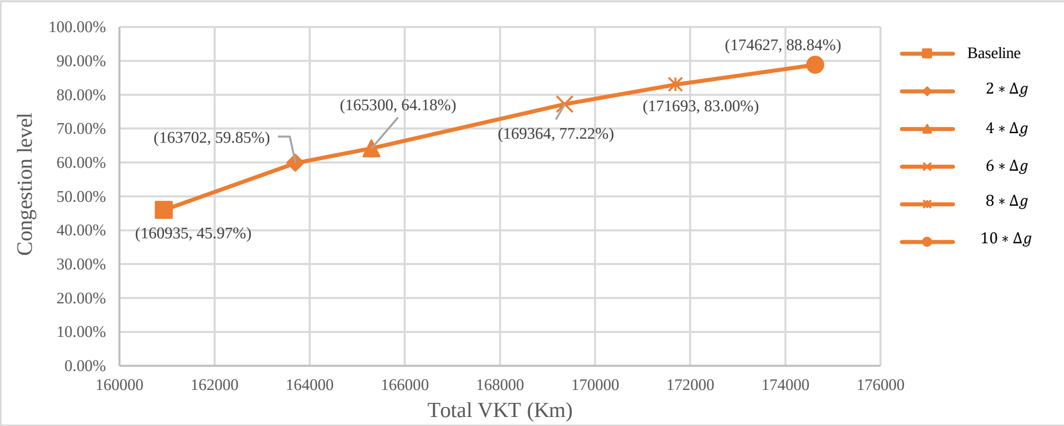
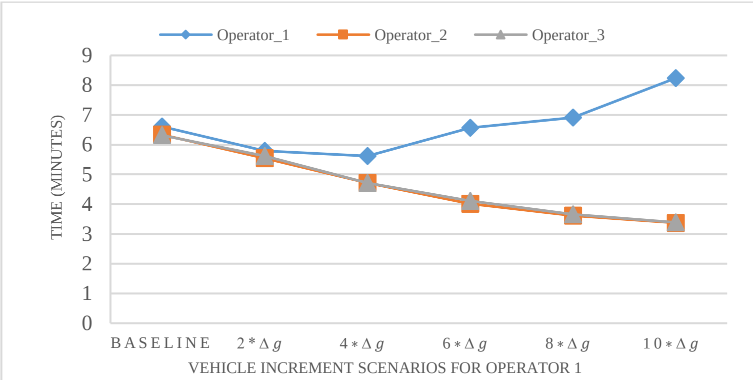


Figure 6.3 The relationship between total VKT and congestion levels

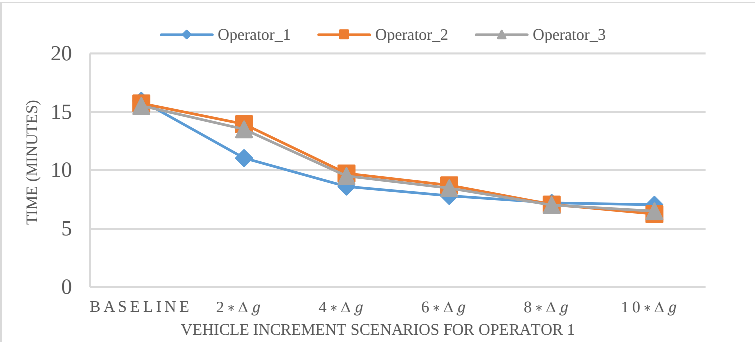
A large fleet size leads to low waiting times. The average waiting times of operator o_1 decline with the increase of the number of vehicles in its fleet; however, there is an increasing trend in average waiting times of all served requests when the vehicle increment is higher than $6 * \Delta g$ (60 vehicles per pickup point). Generally speaking, a larger fleet size could reduce the average waiting times in scenarios where AMoD systems replace conventional bus services in a regional area or provide feeder (first-mile or last-mile) services to complement public transit services. However, in a high-demand urban area, a large fleet size may increase the average waiting time, according to our results. This is because the added demand of operator 1 is not just brought from the other operators but also from the demand that was not being served before. We found that more VKT are needed to serve the increased demand, resulting in a more congested road network. When traffic moves at lower speeds on a congested urban road network, the travel and waiting times of served travelers increase. We found that some served requests experienced long waiting times as measured by an extreme value of 96% quantile waiting time in the waiting time distribution. Simulation results in Figure 6.4 (b) show that the 90% quantile of the waiting times of operator o_1 decline and then level off as the vehicle fleet increases, while the 90% quantile of the waiting times of operators o_2 and o_3 have a declining trend. Simulation results suggest that a few served travelers have long waiting times with a larger fleet size (i.e., for the vehicle increment scenarios of $10 * \Delta g$) compared to operator 2 and operator 3. Simulation results in Figure 6.4 (c) show that the 96% quantile of the waiting times of operator o_1 declines and then rises significantly as the number of vehicles increases. Surprisingly, the 96% quantile of the waiting times are found from simulation results at the level of 38.01 minutes, 74.30 minutes, and 96.65 minutes for the vehicle increment scenarios of $6 * \Delta g$, $8 * \Delta g$, and $10 * \Delta g$. Therefore, the larger fleet can serve more travel requests, but this leads to extremely long waiting times for just a few travelers.

In the model, we assume that travelers can not cancel their services after they are assigned vehicles. Based on this assumption, extremely long waiting times can be observed in the simulation results as congestion levels become higher for some travelers.

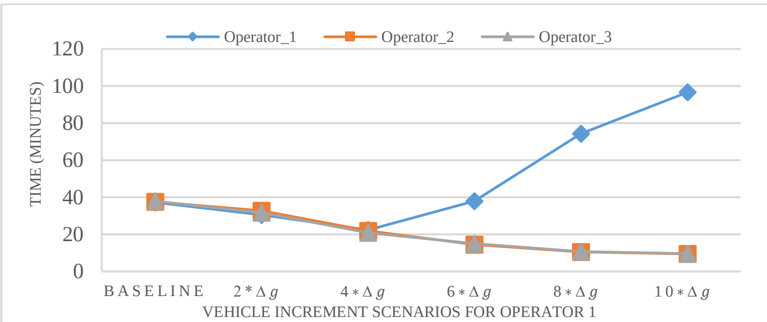
Moreover, simulation results show that operator 1 serves more than 2.4 times more requests than operator 2 and operator 3. Therefore, there are more requests served by operator 1 with long waiting times compared with operator 2 and operator 3. Average waiting times are easily affected by the extreme values of a few waiting times because they include all the waiting times of all served requests.



(a) Average waiting times for different scenarios



(b) 90 % quantile waiting times for different scenarios



(c) 96 % quantile waiting times for different scenarios

Figure 6.4 Waiting time analysis

Overall, one operator's myopic increase in vehicle supply degrades everyone's system performance due to added traffic congestion. We find that travel times for all travelers served by different AMoD operators increase significantly due to worsen congestion on the road network as the fleet of operator o_1 grows. The increase in travel times reflects the reduction in the quality of service across the entire AMoD system. Overall, the increase in the fleet size of an operator affects not only the choices available to the travelers and the operators' levels of service in terms of average waiting and travel times but also the levels of service offered by the competing operators. Nevertheless, one should have in mind that more requests have been satisfied with the increase in the vehicle fleet of one operator which is a positive outcome for the travelers.

6.5.3 Effect of pricing strategies on service uptake and operating performance

In this section, we analyze demand changes in response to price changes using the discount pricing strategy and the supply-demand balancing pricing strategy. In the context of multiple-operator AMoD systems, the two different pricing strategies are applied to operator o_1, while the other two operators (o_2, o_3) use the baseline pricing scheme where the fare is calculated based on travel time and distance.

6.5.3.1 Discount pricing strategy

We study the effect of the discount pricing strategy on attracting customers in the morning hours. A closer look at the chart in Figure 6.5 shows that the volume of requests for the different AMoD operators changes at different rates over time.

In the very early morning hours ([5:30 AM, 7:20 AM]), we find that the discount pricing strategy used by operator o_1 can significantly impact the choice made by travelers. Simulation results show that more travelers choose the low-price service of operator o_1, it's about triple the number of users of operator o_2 or operator o_3 at 7:20 AM.

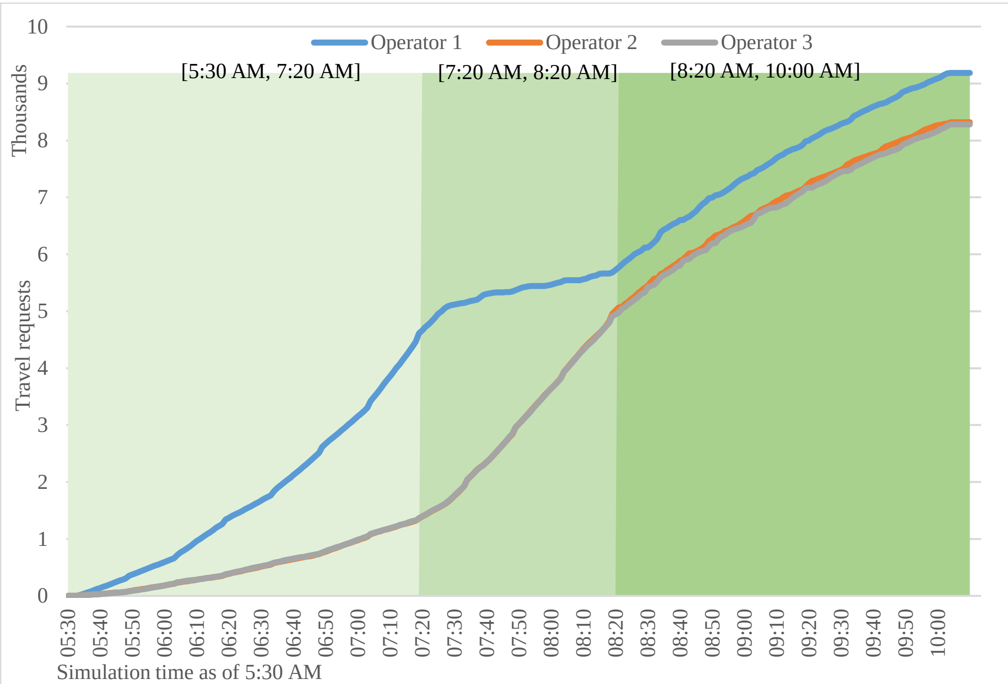


Figure 6.5 Demand share for different AMoD operators over time

Intuitively, a lower fare can attract more customers. However, in the morning period [7:20 AM, 8:20 AM], we see that the increase in the number of travelers choosing the service of operator o_1 slows down, while a large number of travelers choose the service of operator o_2 and operator o_3 who offer a regular price service. This is related to the volume of travel requests as well as the number of available vehicles. Because more travelers choose the low-price services offered by operator 1 in the very early morning [5:30 AM, 7:20 AM]. Hence, more vehicles are transporting travelers from place to place on the road network. As a result, fewer vehicles are available for subsequent travelers. A high volume of travel requests between 7:20 AM and 8:20 AM continue to request rides; accordingly, travelers choose the service of the competing operators (operator o_2 or operator o_3) in the early morning. Meanwhile, we see that the number of in-service vehicles of operator o_1 declines while the number of in-service vehicles of operator o_2 and operator o_3 rises sharply.

In the mid-morning period [8:20 AM, 10:00 AM], the same increasing rate of users is observed for all three operators, two of which are offering a regular-price service. Simulation results indicate that the number of users increases similarly for all operators, by about 3300. This suggests that the discount pricing strategy has no advantage in attracting more demand at this time of day, ceteris paribus. For the same time, simulation results in Figure 6.6 indicate that the total number of vehicles driving on the network is at the highest level, which could lead to bad traffic conditions.

By analyzing the demand for different AMoD operators as well as the in-service vehicles over time, we found that more requests are served in the very early morning when fewer vehicles are driving on the network, while the demand for operator o_2 and operator o_3 is high in the next period, when many vehicles are driving on the road network. Hence, we infer that the discount pricing strategy can strongly affect service levels related to waiting and travel times.

Regarding the service levels in terms of waiting time and travel times, the operator that offers the discount can provide a service with shorter waiting and travel times than the regular-price services of the other operators. The simulation results in Table 6.4 show that the average waiting and travel times of operator o_2 and the operator o_3 are more than double those of operator o_1. The 96% quantile waiting time of operator o_1 is located around 7.06 minutes, while operator o_2 and operator o_3 have a larger 96% quantile waiting time of about 11 minutes. The 96% quantile travel times of operator o_2 and operator o_3 are significantly larger than that of operator o_1. The reason for this is that up to 64.7% of the travel requests served by operator o_1 are in the very early morning [5:30 AM,7:20 AM] when fewer vehicles are driving on the network, as shown in Figure 6.6. We also see that the number of in-service vehicles from operator o_2 and operator o_3 is much higher than that of operator o_1 in the early morning [7:20 AM, 8:20 AM] and mid-morning hours [8:20 AM, 10:00 AM]. This indicates that the users of the services of operators o_2 and o_3 are transported at a time when the number of vehicles on the road is the highest. This leads to increased waiting and travel times of operator o_2 and operator o_3.

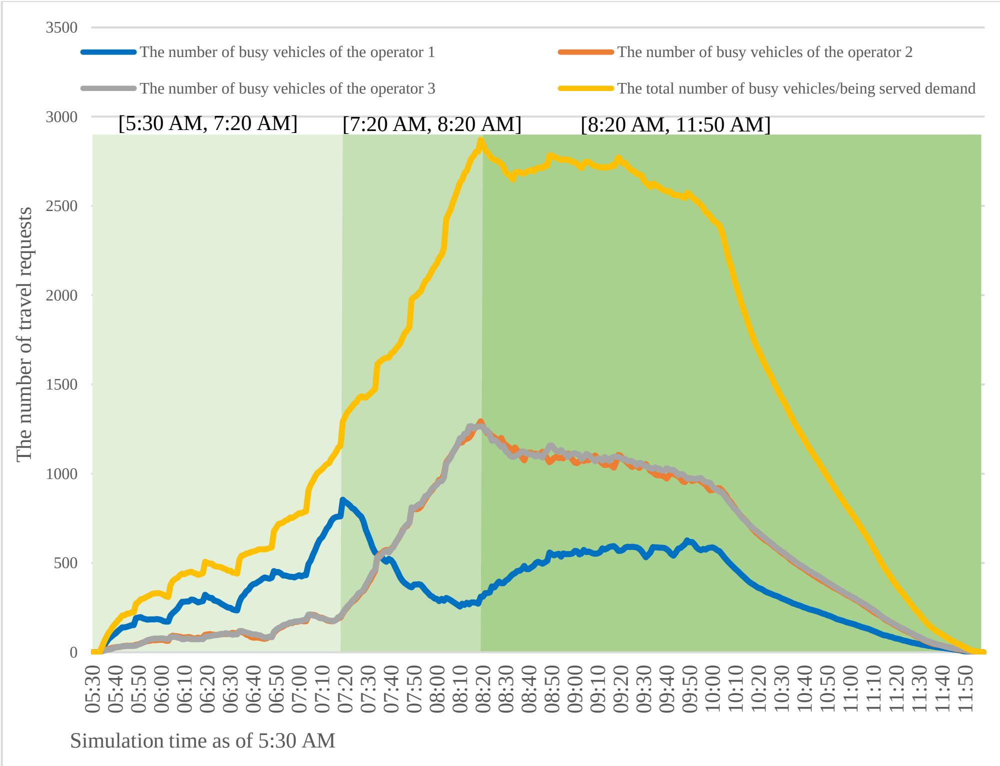


Figure 6.6 The number of busy (in-service) vehicles over time with discount pricing strategies

Table 6.4 Operating performance for the discount pricing strategy

Demand levels		25800 (100%)		
AMoD system		o_1	o_2	o_3
Fleet size		$n_{o_1} = n_{o_2} = n_{o_3}$		
Pricing strategies		Discount pricing strategy		
Served demand	The number of served requests in [5:30 AM, 10:00 AM]	7457	6769	6744
	The percentage of the number of served requests in [5:30 AM, 7:20 AM]	64.97%	21.08%	21.84%
Service quality	Avg. waiting times (min) of trips in [5:30 AM, 10:00 AM]	2.90	6.33	6.16
	The 96% quantile waiting times of trips in [5:30 AM, 10:00 AM]	7.06	11.01	11.57
	Average time of trips in [5:30 AM, 10:00 AM]	14.29	29.86	29.95
	The 96% quantile travel times of trips in [5:30 AM, 10:00 AM]	54.00	72.28	76.19
VKT	Empty VKT (km) per trip in [5:30 AM, 10:00 AM]	1.86	1.81	1.80
	Occupied VKT (km) per trip in [5:30 AM, 10:00 AM]	5.90	5.89	5.93

Given the simulation results, we can infer that the discount pricing strategies should be dynamically changed in multiple-operator AMoD systems. It is suggested that providing low-priced services becomes less effective in attracting more customers to use an operator's service when the demand is high and competing operators have fewer vehicles in use. Therefore, careful consideration is required when planning to apply flexible discount pricing strategies under certain demand scenarios.

6.5.3.2 Supply-demand balancing pricing strategy

Regarding the simulation scenario related to the supply-demand balancing pricing strategy, the simulation results in Figure 6.7 suggest different demand shares in AMoD services offered by the different operators, where one of them (operator o_1) applies the supply-demand balancing pricing strategy. Results show that the number of requests for the service provided by operator o_1 levels off in two periods, namely, [7:00 AM, 7:20 AM]) and [7:35 AM, 7:50 AM]. The supply-demand balancing pricing strategy can raise the price according to the relationship established between anticipated demand and available vehicles. In this situation, competing AMoD services become viable travel options. Instead of choosing the high-priced service, customers use the regular-priced service. Simulation results indicate that the number of travelers who use the services of another operator (o_2, o_3), instead of the service provided by operator o_1, increases rapidly. As shown in Figure 6.8, the number of in-service vehicles of operator o_1 falls rapidly, while the number of the other operators' vehicles engaged in transporting customers increases.

Subsequently, we find that more and more travelers choose operator o_1. Eventually, the number of customers choosing the services of any of the three operators is approximately the same. It is suggested that the high-priced service can be competitive in attracting travelers when a large number of subsequent travelers request rides. This is because more vehicles of operators o_2 and o_3 are in service to transport customers from place to place as the demand for their service grows. When more vehicles are in use, fewer vehicles of regular-priced service provided by operators o_2 and o_3 are available for subsequent trips. Therefore, travelers choose the high-priced service.

On the one hand, we find that the supply-demand balancing pricing strategy can influence the choice of travelers by raising the price of the service provided at certain times in the morning, leading to a reduction in demand. In that situation, the competing AMoD services can become the favored services. On the other hand, the service whose price is dynamically determined by the supply-demand balancing pricing strategy can be equally competitive at specific times when all operators are busy handling a large volume of requests.

We can also analyze the waiting times, the travel times, and the empty pickup VKT (in Table 6.5) to evaluate the impact of the supply-demand balancing strategy on service quality. The simulation results show that the supply-demand balancing pricing strategy leads to a reduction in the total number of served requests for the service provided by operator o_1. This is plausible because travelers opt for the alternative service with the regular price in the morning [7:00 AM, 7:50 AM] (as shown in Figure 6.7) rather than the high-priced service prompted by the supply-demand balancing strategy.

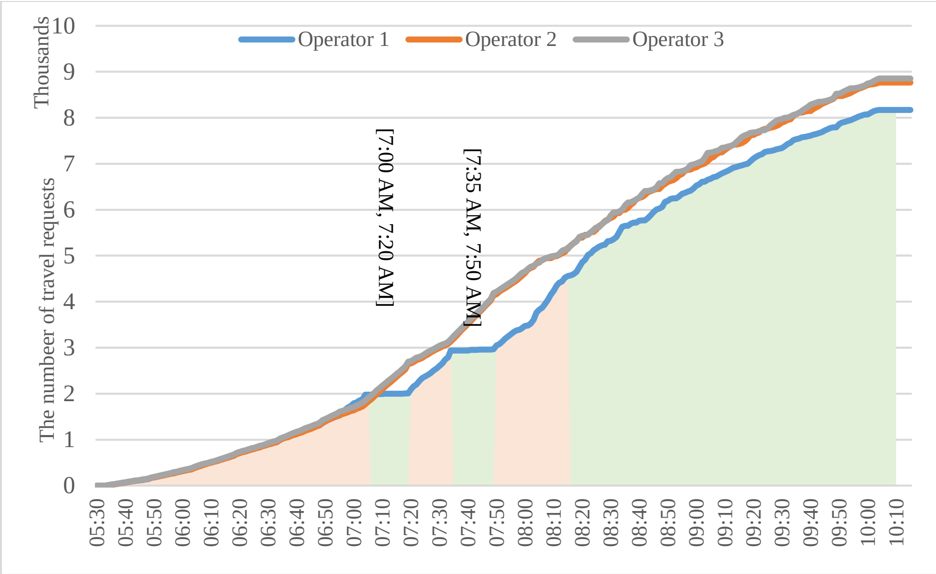


Figure 6.7 The number of travel requests over time for different AMoD operators

Moreover, we find that the empty pickup VKT of operator o_2 and operator o_3 is larger than that of operator o_1 when the supply-demand balancing pricing strategy is used. It is suggested that this pricing strategy can be effective in attracting travelers to use the service in locations where there is a surplus of idle vehicles, thereby reducing the pickup distances.

Although the pickup VKT is reduced and the number of requests for operator o_1 is lower than for the other operators, higher average waiting times and average travel times are found for the operator o_1. Similarly, the 96% quantile waiting time and the 96% quantile travel time are found slightly higher for operator o_1. This is because a high percentage (63.86%) of travel requests are served in the morning [7:50 AM, 10:00 AM] when the number of vehicles in use on the road network is the highest (shown in Figure 6.8).

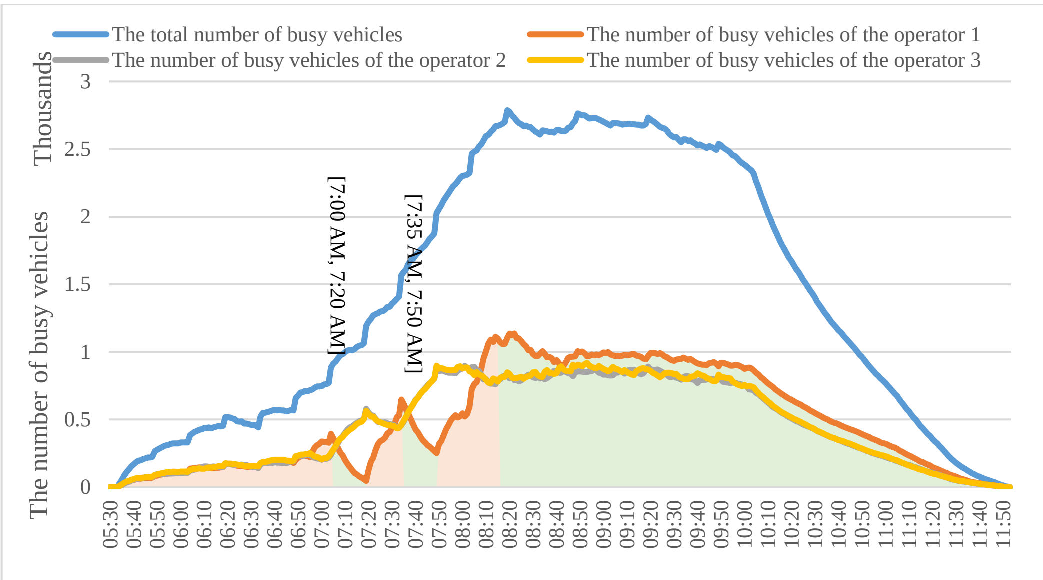


Figure 6.8 The number of busy vehicles over time with supply-demand balancing pricing strategies

Applying the supply-demand balancing pricing strategies can reduce empty pickup VKT, which is a key performance indicator in evaluating operating costs and environmental emissions. Detailed analysis of when travelers choose the operator shows that fewer travelers use the high-priced service in the early morning, while travelers prefer the high-priced service in peak hours. We found that the service levels, including waiting times and travel times, become slightly worse.

Table 6.5 Operating performance for the supply-demand balancing pricing strategy

Demand levels	25800 (100%)		
AMoD system	o_1	o_2	o_3
Fleet size	$n_{o_1} = n_{o_2} = n_{o_3}$		
Pricing strategies	Supply-demand balancing pricing strategy		
The number of served requests in [5:30 AM, 10:00 AM]	6711	7120	7118
The percentage of the number of served requests in [7:50 AM, 10:00 AM] ([140 minutes,280 minutes])	63.86%	52.92%	52.41%
Avg. waiting time (min) of trips in [5:30 AM, 10:00 AM]	6.26	4.76	4.61
96% quantile waiting time of trips in [5:30 AM, 10:00 AM]	14.32	13.51	13.85
Empty VKT (km) per trip in [5:30 AM, 10:00 AM]	1.63	1.86	1.85
Average travel time of trips in [5:30 AM, 10:00 AM]	22.45	20.54	20.70
Occupied VKT (km) per trip in [5:30 AM, 10:00 AM]	5.91	5.89	5.92
96% quantile travel time of trips in [5:30 AM, 10:00 AM]	73.26	71.37	71.40

6.6 General discussion and Recommendations

AMoD operators may apply different operating strategies to improve service levels and attract more customers in the future competitive AMoD market. Three operating strategies are tested through the agent-based modeling framework, demonstrating their potential effects on the operators, the clients, and the network.

We compared different vehicle-to-request assignment strategies and found that the optimal assignment method that matches bundled travel requests with a group of fully controlled AVs can improve the waiting times and allow operators to serve more requests. That means AV operators can take advantage of vehicle automation technology to develop an effective assignment to compete for customers.

Regarding fleet size, interesting findings are that a larger fleet size can attract more travelers to choose an operator's service in the scenario of multiple AMoD operators competing for customers; however, an operator's fleet size growth can lead to more congestion over the road network. As a result, the service levels are degraded in terms of waiting and travel times. It means that in the multiple-operator system, travelers faced long waiting and travel times. Because of the convenience and low price of AMoD services, travelers (commuters) are most likely to choose AMoD services provided by different operators. Similar to the evidence that the entrance of multiple transportation network companies into the existing urban mobility system can increase congestion (Diao et al., 2021), our results suggest that introducing multiple AMoD operators into the market without regulating fleet sizes can lead to degraded travel conditions. In this regard, future cities may experience severe congestion externalities (e.g., emissions and traffic accidents). The city authorities need, therefore, to develop regulations to avoid the negative impact of an unregulated market.

Concerning the pricing strategies, the supply-demand balancing pricing strategy incentivizes travelers to choose the services of the operator in the area where vehicles are oversupplied, and we found the empty VKT for users is reduced. However, service levels deteriorate when more travelers are served, and many busy vehicles in the road network are moving travelers from one location to another. A detailed analysis of when travelers choose operators shows that few travelers choose the high-priced service in the early morning; in conjunction with the reduction in the available vehicles from competing vehicles, a high percentage of travel requests are served by the operator during peak hours. This finding suggests that high-priced AMoD services could be more competitive than lower-priced AMoD services in attracting customers in the morning peak hours. AMoD operators could introduce high-priced services during very busy hours because of the potential benefits (e.g., more profit), while it is not recommended to promote a high-priced service in the early morning hours. Otherwise, travelers will opt for the competitor’s service.

Different from the supply-demand balancing pricing strategy, the discount pricing strategy attracts more travelers to use their services in the very early morning hours while providing a high level of service to users. We also find that low-priced service is not always effective in attracting demand in a situation when a high volume of travelers continue to request rides, and there are more idle vehicles from competing operators. Therefore, we strongly recommend that flexible discount pricing strategies must be considered in alignment with the demand temporal characteristics. The detailed demonstration of when travelers choose which services provided by different AMoD operators can help the operators better understand the pricing strategies. In future applications, operators should decide strategies that they will use to attract customers.

We consider multiple main aspects (waiting and travel time, pricing) in the utility evaluation for allocating travelers, which is very close to the reality of travelers in choosing transportation services. Notably, the utility evaluation accounts for the flexible changes in pricing schemes. In the absence of accurate behavioral models, transportation planners and platform developers could integrate the proposed mechanism into a platform where multiple AMoD operators coexist to deal with the problem of allocating requests with fast AMoD entries.

6.7 Conclusions and future directions

Introducing multiple operators into Automated Mobility-on-Demand (AMoD) systems makes the interactions and dynamics of system components more complex. Therefore, there is a need to create an Agent-Based Model (ABMs) that captures such complexity. This chapter has proposed such a framework, implemented it, and tested it for a real case-study city.

The ABM is used to understand how different operating strategies affect travelers' choices and what the resulting operating performance of competing AMoD operators is. Concerning travelers’ choices of operators under different operating strategies, we have implemented a choice model that allows estimating the relative share in the requests for each of the three operators in the case-study city of The Hague, The Netherlands. We provide a detailed analysis of the overall performance of AMoD systems with competing operators and the performance of individual operators as measured by waiting times, travel times, and empty pickup VKT. Fleet sizing, assignment methods, and pricing schemes as important decisions that any operator must take have been analyzed in detail.

In a multiple-operator AMoD system, a larger fleet allows one operator to attract more travelers. However, we find that the larger fleet size can degrade the level of service in terms of waiting times and travel times for the operator using this strategy and the travel times for the users of competing operators. Instead of increasing fleet sizes of competing operators since they all have to share the same road network, cooperative mechanisms between operators in mobility as a service platform, especially the cooperative assignment of the SAVs to clients to improve fleet utilization, could be an important research direction.

A shortcoming of this framework is that the socio-demographic attributes are not considered in the mode choice model. Attributes of decision-makers may create differences over different AMoD services in the dynamic pricing scenarios. In future research, surveys can be conducted to investigate travelers' preferences towards different emerging mobility service operators, as currently very little research can be found in the literature. Moreover, the developed agent-based modeling framework can be extended to consider the within-day or day-to-day adjustment of operating strategies in AMoD systems comprised of multiple fleet operators.

The mesoscopic traffic simulation model can provide an appropriate level of detail in estimating average speeds on the network, which is a requirement for modeling the pickups or drop-offs of SAVs on the road network in a realistic way. However, the more details the traffic model contains, the higher the resolution of the model. A microscopic traffic simulation can provide a detailed representation of every vehicle movement and interaction between vehicles. A possible extension of the framework is to implement a microscopic traffic simulation model or integrate a microscopic traffic simulation platform with the developed agent-based modeling framework in the future. Moreover, the modeling framework can be extended to consider different vehicle technologies (battery electric vehicles, hydrogen fuel cell vehicles) and different vehicle sizes (small, medium, and large vehicles).

Chapter 7

Conclusions and recommendations

This thesis aims to model the emerging AMoD systems to answer urgent questions in the planning and operations of such systems. Using the agent-based approach, a modeling framework has been developed to address the research questions introduced in **Chapter 1**. The detailed answers to these questions were provided in **Chapters 3 through 6**.

This chapter presents the conclusions of this thesis. Section 7.1 summarizes the main findings, followed by the overall conclusions in Section 7.2. Practical implications are discussed in Section 7.3. Section 7.4 provides recommendations for future research.

7.1 Main findings

A new agent-based modeling framework has been proposed, implemented, and tested in a case-study city for emerging services and innovative operations in different forms of AMoD systems. Through agent-based simulation of operating emerging AMoD services, the specific questions that arise in urban AMoD systems are addressed.

The research in this thesis has been divided into four parts, each of which answers an important research question introduced in Section 1.3 of **Chapter 1**.

Question 1: What are efficient ways of operating AMoD under different on-demand service schemes within the urban service area?

To answer this question, four different AMoD systems are modeled in **Chapter 3**. The modeling framework can simulate the operations of AMoD systems within a hypothetical urban area on a typical day. A preliminary study is presented for different AMoD services as defined: station-to-station services (SSS), door-to-door services (DDS), time-varying transit services (TVTS), and parallel transit services (PTS).

Sub-question 1: Which service schemes in terms of pickup points and doorstep service should be provided when serving demand in urban areas?

It is found that the DDS system has more VKT and energy consumption than other AMoD systems, while it brings great convenience of doorstep service for real-time requests. The time-varying transit service (TVTS) and parallel transit service (PTS) systems provide a significant gain in system capacity, waiting time, and additional trips by empty SAVs. AMoD systems that incorporate two services have the most significant improvements in system performance measured by the indicators above. We compare the TVTS system, which has inconvenient access during peak hours, with the PTS system where door-to-door services are available; we conclude that the latter could achieve a similar system performance as the former in terms of average waiting time and service time system capacity.

The question of what the best service scheme remains open. We examine the AMoD system performance with different service schemes from the operators' perspective. Through the agent-based simulation of different service schemes, the strengths and weaknesses of each service scheme are identified. AMoD operators should deploy their services into the urban mobility system depending on the application environments (e.g., demand levels and potential service locations).

Sub-question 2: How can available vehicles and passengers be effectively matched?

In **Chapter 3**, two assignment methods are proposed, implemented, and tested in a hypothetical urban area. According to the first-come, first-served principle, the first method assigns the nearest available vehicles to serve travel requests whilst in the second method, bundled travel requests are matched with a group of available vehicles to minimize the total travel (pickup) distance for the bundled requests. The optimal assignment method can significantly reduce the total empty VKT for all tested AMoD systems up to about 40% and improve the system capacity in relation to the number of served trips.

Sub-question 3: How do ridesharing operations affect the service offered to customers and fleet efficiency?

We find that AMoD systems with dynamic ridesharing operations can significantly reduce average waiting time, the VKT, and empty SAV trips. It can be inferred that ridesharing operations can be promoted to improve the service level and fleet efficiency. We did not design the optimal ride-sharing rules for travelers and have limited the maximum number of grouped travelers to two. We assumed the type of vehicles to be small-size vehicles with two seats. Small-size vehicles have a competitive advantage when operating in urban areas. The fact that we use a synthetic network can introduce some limitations to the study; however, by having created realistic trip requests and realistic vehicle movements, the small synthetic network serves well in comparing the different scenarios with the assumptions that were taken.

Question 2: What are the travel and energy impacts of forming platoons in AMoD systems?

To answer these questions, a novel modeling framework has been developed to assess the impact of forming platoons in future urban AMoD systems on people's travel and energy usage in **Chapter 4**. The travel and energy potential of forming platoons under different formation policies and demand levels in AMoD systems is assessed using the urban road network and travel demand data in the case-study city of The Hague, the Netherlands.

Sub-question 1: What are the impacts of the formation and operation of such urban platoons on the service quality offered to travelers and traffic efficiency related to road network travel times?

Findings suggest that the formation of platoons could cause platoon delays for travelers in the platoon vehicles while reducing network travel times in which platoon delays are not included. The platoon travel time, including the platoon delay of travelers in platoons and network travel time, is shorter than the network travel time in the scenario without forming platoons. That means that the reduction in the network travel times offsets the platoon delays, leading to a shorter platoon travel time. However, we found that platoon formation can increase the platoon travel time of travelers in platoon leader vehicles. The reason is that travelers in the platoon leaders face longer unexpected platoon delays. Interestingly, results indicate that although the travel time of travelers in the leaders is longer, this longer travel time is still similar to that in non-platoon scenarios where higher congestion is present.

Sub-question 2: How do changes in traffic conditions by platoon operations affect the travel-related energy consumption of traffic participants across the urban road network?

We evaluate the impact of forming platoons on the system-wide energy consumption for different vehicle types. We found that more energy can be saved when platoons are formed. We evaluate the impact of forming platoons on the system-wide energy consumption for different vehicle types. We found that more energy can be saved when more vehicles are coordinated in platoons formations. The reason is that forming platoons results in improvements in traffic efficiency. However, the degree of energy savings strongly depends on the vehicle types; improvements in energy efficiency for certain vehicle types are relatively small because of the energy consumption characteristics.

Question 3: What are effective operating strategies to gain a competitive edge for independent operators in a situation without information sharing?

To answer this question, **Chapter 5** investigates the operation of AMoD systems in which multiple independent companies operate their fleets to provide direct on-demand service to their registered clients in the same urban area. We study the future scenarios of multiple-operator AMoD systems with relocation operations and different fleet sizes.

Sub-question 1: How do changes in supply (vehicle fleet) affect the performance (service levels, fleet efficiency, and profit) of an operator and its competitors coexisting in the same urban area?

We found that the growth of the fleet size of an operator leads to improvements in the average waiting times of its clients. However, it degrades the levels of services offered by its competitors in terms of average waiting and travel times. Increasing fleet size (of an operator) can serve more trips for the operator while bringing more vehicles to the roads. The increasing number of vehicles circulating across the road network adds more traffic to the road network, increasing the average travel and waiting times of competing operators. In the multiple-operator AMoD system, the growth of the fleet size of an operator brings an adverse effect on road travel conditions.

Finding suggests that the vehicle usage of an AMoD operator with the increase in the number of vehicles decreases in the morning hours compared to its competitor. But they maintain higher usage rates than private vehicles, which take 20-30 minutes to complete a trip and are parked up to 90% of the morning hours.

Results show that the increase in the fleet size of an operator can improve the percentage of served trips over the other operators, particularly when the volume of travel requests is high. In this regard, a larger fleet can help an operator to serve more clients. Besides, more trips are served with the growth of the fleet size of an operator, resulting in a higher profit. This may motivate an operator to increase its fleet size to obtain a higher profit in the competitive mobility market.

Sub-question 2: What is the potential of relocation strategies performed by an operator in terms of service quality offered to travelers, fleet efficiency, and the operator's profit?

We design simulation experiments to examine how relocation operations affect the operators’ performance in the competitive market of AMoD systems. We found that the operator that performed relocations served more registered travelers. This is because vehicles are relocated to the place (zones) where there is a shortage of vehicles, and the vehicles are available for incoming requests.

An important finding is that relocation operations slightly increase operating costs due to the extra relocation VKT; however, a higher profit can be achieved with a higher number of trips served when relocations occur. For example, compared with the unprofitable relocation operations in multiple-operator carsharing systems, performing relocations by operators in multiple-operator AMoD systems show an increase in profit by up to 16% in the case-study city because of the lower operating cost of AMoD vehicles.

We also found that performing relocation operations brings more vehicles to the roads in the early morning hours and late morning hours when the road network is uncongested. Hence, relocating vehicles to a more advantageous position in anticipation of future demand does not cause more traffic congestion during peak hours. Relocating vehicles in advance can avoid congestion while obtaining relocation benefits of improving waiting times, serving more trips, and achieving a higher profit.

Question 4: How do operators compete for clients in multiple-operator AMoD systems where information (travel requests, vehicle fleet, prices) are completely shared within a platform?

To answer this question, the developed agent-based modeling framework in **Chapter 6** is used to investigate how changes in different strategies (e.g., pricing strategies, assignment methods, and fleet sizes) affect travelers' choice of AMoD services and the operating performance of competing operators. The model is applied to the case-study city of The Hague, the Netherlands.

Sub-question 1: How do changes in pricing strategies affect travelers' choice of AMoD services and the operating performance of competing operators?

We analyze demand changes in response to price changes using a discount pricing strategy and a supply-demand balancing pricing strategy. We find that the discount pricing strategy used by an operator can significantly impact the choice made by travelers. More travelers choose the low-price service of the operator. However, the low-priced services have the advantage of attracting travelers in the very early morning. However, as the volume of travel requests becomes high in peak hours (e.g., between 7:20 AM and 8:20 AM), demand for the services of the competing operators continues to increase due to the high vehicle availability.

Applying the supply-demand balancing pricing strategies can reduce empty pickup VKT, which is a key performance indicator in evaluating operating costs and environmental emissions. However, the supply-demand balancing pricing strategy leads to a reduction in the total number of served requests for the service provided by the operator. This is because travelers opt for the alternative service with the regular price in the morning rather than the high-priced service prompted by the supply-demand balancing strategy.

Moreover, a detailed analysis of when travelers choose the operator shows that fewer travelers use the high-priced service in the early morning, while travelers still choose the high-priced service in peak hours.

Sub-question 2: How do changes in assignment methods affect travelers' choice of AMoD services and the operating performance of competitors?

Two different methods of assigning vehicles to passengers: a simple heuristic algorithm and an optimal assignment algorithm (Hungarian algorithm), were implemented and tested in the case-study city that most closely matches real-world conditions. Findings suggest that the decline in the average waiting time with the Hungarian algorithm leads to a reduction in the average in-service time, including pickup and drop-off times. Also, we found that the Hungarian assignment method slightly improves the system capacity in serving the demand (the number of served travel requests) compared to the simple heuristic method. Operators in the competitive market need to develop the capability of optimal assignment to improve the service offered to travelers and increase the served trips.

Sub-question 3: How do changes in fleet sizes affect travelers' choice of AMoD services and the operating performance of competitors?

We use simulation to recreate the scene of varying fleet sizes by operators during morning rush hours in competition for customers. The finding suggests that demand is very sensitive to the changes in fleet size. More demand chooses the operator in response to fleet increases. However, as demand rises, the quality of service offered by the operator deteriorates. The relationship that is established between average waiting times and vehicle increment of an operator suggests that a larger fleet is not better for serving AMoD demand. Travelers are served with very long waiting times. The reason is that congestion occurs over the network with high traffic volumes due to SAV driving between served requests. The quality of service offered to the clients is reduced significantly as more vehicles circulate across the road network. As a result, the levels of service offered by the competing operators coexisting in the same urban area can be considerably affected.

7.2 Practical implications

This thesis has several important practical implications which are useful for future AMoD systems. The practical implications are discussed as follows.

System design related to the application scenarios is the key to the success of AMoD systems. The use of the developed simulation tools enables the stakeholders (mobility service providers, government, and OEMs) to better plan the AMoD fleet service and to be better prepared for the future. Simulations have the advantage of providing a virtual, risk-free, time- and cost-saving environment in which different forward-looking scenarios can be tested. Mobility service providers and public transport operators can take advantage of agent-based simulation to plan and operate AMoD services.

This thesis develops multiple functioning components in the simulated environment, such as the vehicle-to-passenger assignment, ridesharing component, relocation component, fare and cost component, and mode choice component. The effectiveness of different operating strategies has been demonstrated using the agent-based framework, which could be implemented in real-world systems (e.g., management systems).

In addition, policies and operating strategies are recommended for city authorities and transport operators to achieve operating efficiency, energy efficiency, and social welfare. *Important examples of policy recommendations are as follows:*

- AV companies may be motivated to increase fleet sizes to achieve a higher profit in the competitive market. The unlimited growth of fleet sizes will cause negative traffic externalities (e.g., congestion and pollution) and negatively impact citizens' well-being. Therefore, there is a need for policies to create a regulated environment where the number of vehicles operated by AMoD operators is limited.
- Platoon operations can be considered an effective energy-saving and decarbonization strategy to achieve energy efficiency improvement goals.
- Careful consideration is required to reward travelers who suffer long unexpected delays in the formation of platoons, which the system's benefit from energy savings can be redistributed.

Important examples of recommending operating strategies are as follows:

- Developing platoon formation strategies over urban road networks is recommended aiming at improving traffic efficiency and reducing travel times.
- It is recommended to consider the vehicle characteristics for energy consumption in conjunction with platoon formation policies to develop effective energy-saving platoon strategies in future AMoD systems.
- Developing a relocation capability is strongly recommended to gain a competitive advantage in the future competitive market of AMoD systems.
- Operators should carefully consider the fare structure when congestion occurs. Notably, distance- and time-based fare structures can help companies achieve a higher profit.
- Service schemes (e.g., defined SSS, DDS, TVTS, and PTS) must be decided according to the application of future scenarios.
- The discount pricing strategy attracts more travelers to use AMoD services in the very early morning hours while providing a high level of service to users. We also find that low-priced service is not always effective in attracting demand in a situation when a high volume of travelers continue to request rides and there are more idle vehicles from competing operators. Therefore, we strongly recommend that flexible discount pricing strategies must be considered in alignment with the demand temporal characteristics.

7.3 Recommendations for future research

This final section aims to provide several interesting but important aspects of future research directions.

Traffic assignment: platooning may lead to over synchronization of individual routes, creating new congestions, while system users (travelers) want to choose the shortest route. Therefore, the joint consideration of traffic assignment and coordinated platoon driving is required. The question of how to handle the trade-off between UE route assignment and route synchronization in platooning systems remains unsolved. That is an important challenge in platoon-enabled AMoD systems.

User preference and choice behavior: AMoD services could provide important transportation alternatives and have the potential to alter how people move around cities; therefore, the new transportation service introduced into a mobility ecosystem will impact the subsequent travel behavior of the users. One very important shortcoming of the modeling framework is that we did not investigate the choice behavior of the travelers toward AMoD systems based on data. In particular, the impacts of platoon-enabled AMoD systems on users' travel behavior and/or preferences are not studied. Given that SAVs equipped with platooning systems are not yet widely available, stated preference experiments can be designed to measure individuals' preferences. Moreover, in the multiple-operator setting (e.g., BMW, Mercedes-Benz, Waymo), understanding why people choose a service offered by an operator over the service offered by another operator is crucial to making further conclusions about system performance. In future studies, surveys can be done to investigate travelers' preferences towards different emerging mobility service operators since this is still difficult to find in the literature.

Cooperative mechanism: Chapter 5 investigated AMoD systems in which multiple technology companies coexist in the same urban area without sharing information. **Chapter 6** studied AMoD systems with completely shared information by incorporating a mode choice component to allocate travelers. However, the decentralized system with partial information sharing is also likely to exist in future cities because of improved privacy, safety, and robustness. The question that arises is how to develop cooperative operating strategies for competing operators. For example, independent operators can collaborate to effectively match supply and demand to improve the overall system performance. There is a lack of evidence to support the development of decentralized AMoD systems.

Energy consumption: In **Chapter 4**, we estimate the energy consumption of electric AVs and account for traffic congestion by making it a function of experienced travel speed. An interesting extension would be integrating a microscopic traffic flow that can provide second-by-second speed and acceleration measurements into an energy consumption model that produces a more accurate energy estimate.

Multilane mixed traffic simulation: the developed link and node movement rules can reproduce the traffic dynamics at a mesoscopic level while considering the effect of mixed traffic for a single lane in each direction. However, the microscopic traffic behavior is not modeled, such as accelerating, overtaking, lane-changing, and traffic behaviors at intersections. Moreover, the traffic simulation component cannot model mixed traffic under multiple-lane scenarios. Operational capacities in multilane scenarios depend on lane policies to distribute platoon vehicles. Modeling multiple-lane capacity with the formation of platoons remains an unsolved challenge in the literature.

A digital twin of an automated ride-hailing system: A digital twin refers to a real-time digital replica of a physical entity. A digital twin concept consists of the real-world system, the digital counterpart, and connections between the physical entity and the digital copy. The corresponding part of the physical world can be synchronized with its digital representation through the connection. In this thesis, an agent-based simulation model that is populated with real-world data has been developed for different operations. The developed ABM can capture the complicated interaction, simulate the operational process and represent the system entities in a high spatial and temporal resolution. The ABM, which allows experimentation with improvements, is key to developing a digital twin of automated ride-hailing or automated mobility-on-demand systems. This is because the insights uncovered from simulation experiments could be transferred to the physical world to manage the system efficiently. The development of the digital twin of AMoD systems can be investigated.

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Appendix

A. A single-lane capacity formulation for mixed traffic

We use the following definitions of different critical spacing types according to the operational characteristics of vehicle platooning. The critical spacing when vehicles travel regularly (e.g., AVs that are not in platoons) is defined as d_a. The critical spacing for platoon driving is defined as d_p. Except for the platoon leader, the platoon followers will follow the preceding platoon vehicles at a distance of d_p when capacity C is reached. Since platoon vehicles have a smaller following distance, then $d_a > d_p > 0$. We define $d_p = \alpha d_a$, where $0 < \alpha < 1$. We assume that the critical spacing between a platoon vehicle and a regular driving vehicle that is not in a platoon is also d_a. It means that the critical spacing between a platoon leader and any preceding vehicle traveling regularly (that is not in a platoon) is d_a. The platoon size n_i is the number of vehicles in platoon i. We denote the number of platoons as P and the number of regular driving vehicles in the traffic as M. The total number of vehicles in platoons N is $\sum_{i=0}^{p-1} n_i$. We define the total number of platoon leaders L, where $L = P$ (Each platoon has one leader).

According to the definitions and assumptions in this study, mean critical spacing in the work (D. Chen et al., 2017) is formulated as follows:

$$d_c = \frac{\left(\sum_{i=0}^{p-1} n_i - L\right)\alpha d_a + (M+L)d_a}{M+N} = \frac{(N-L)\alpha d_a + (M+L)d_a}{M+N} = \left(1 - \frac{N(1-\alpha)(1-\frac{L}{N})}{M+N}\right)d_a, \tag{A.1}$$

where $M > 0, N > 0$.

Denote $\varphi = \frac{N}{M+N}$ and $\omega = (1-\alpha)(1-\frac{L}{N})$, thus $0 < \varphi, \omega < 1$. Equation (A.1) can be rewritten as follows:

$$d_c = (1 - \varphi\omega)d_a \tag{A.2}$$

The single-lane capacity C_c is expressed as:

$$C_c = \frac{v_0}{d_c} = \frac{v_0}{(1-\varphi\omega)d_a} = \frac{C_a}{(1-\varphi\omega)} \tag{A.3}$$

Clearly, we have $C_c > C_a$ $(M > 0, N > 0)$. Where C_a denotes the lane capacity for all vehicles traveling regularly. The capacity C_c depends on the penetration rate of platoon vehicles φ and the number of leaders (L) $(\omega = (1-\alpha)(1-\frac{L}{N}))$. A smaller distance spacing between platoon vehicles allows an increase in the lane capacity—the lane capacity increases as the penetration rate of platoon vehicles φ. Moreover, for the same number of platoon vehicles N, the more leaders L are created, the less capacity increases. When all the vehicles (SAEVs) travel regularly $(N = 0)$, we have $d_c = d_a$, then $C_c = \frac{v_0}{d_c} = \frac{v_0}{d_a} = C_a$. Platooned vehicles can move with a reduced spacing d_p. If all vehicles are grouped into platoons $(M = 0)$, then $d_c = d_p$ and we have $C_c = \frac{v_0}{d_c} = \frac{v_0}{d_p} = C_p$. C_p denotes the lane capacity when all vehicles are driving in platoons. We get $d_p \leq d_c \leq d_a$, thus $C_a \leq C_c \leq C_P$.

B. Road attributes

The attributes of free-flow speed, the link travel speed at capacity, and the traffic capacity of different road types such as urban roads, rural roads, and local roads are read from an external dataset listed in Table B.

Table B. Summary of traffic-related parameter values for different road types

Road types	Capacity (Vehicles per hour per lane)	Free flow Speed (km/h)	Saturation flow (Vehicles per hour per lane)	Speed at capacity (km/h)	Jam density (Vehicles per km)
Urban road 1	1200	50	1200	35	120
Urban road 2	1200	50	1200	35	120
Urban road 3	1575	50	1575	35	120
Urban road 4	1600	50	1600	35	120
Urban road 5	1633	50	1633	35	120
Rural road	1350	50	1350	35	120
Local road	900	50	900	35	120
Local road	900	30	900	25	120

C. Demander and Supplier zones in relocations

Table C. Demander and Supplier zones with the number of vehicles in relocations at different times

Demander zone (zone ID)	Vehicle shortage (vehicles)	Supplier zone (zone ID)	The number of relocation vehicles	Relocation time (simulation time: minutes)
89	41	93	18	48
		101	13	
	52	90	15	108
		93	21	
92	56	87	15	63
		89	21	
	20	85	18	123
100	28	90	13	33
	22	90	16	63
107	21	93	14	33
	97	86	16	78
		93	17	
		97	14	
		123	13	
	42	90	18	333
		93	16	
112	20	93	20	63
	20	90	16	363
122	74	85	18	93
		90	20	
		93	14	
	Total Vehicle shortage: 493 vehicles		Total number of vehicles in relocations: 346 vehicles	

Note that AMoD systems have very high spatial and temporal dynamics of vehicle availability; as the travelers request services over time, available vehicles are dynamically assigned to serve requests from place to place. In the AMoD system, vehicles in adjacent zones (TAZs) within the search distance will be assigned (dispatched) to serve clients upon requests; We model relocation operations between Supplier and Demander zones while no relocation occurs in other zones. The vehicle shortage means the required number of vehicles, anticipating future demand in identified Demander zones.

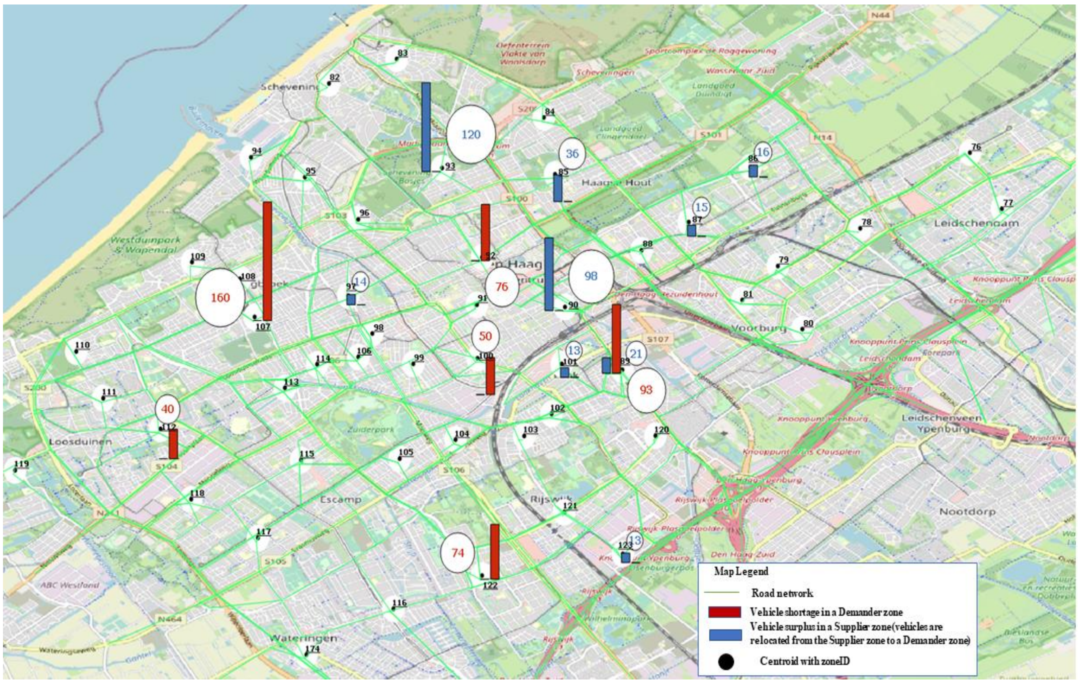

Fig. C. Vehicle shortage in the Demander zone and vehicle surplus in the Supplier zone with zoneID

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Senlei Wang was born in Pingdu, Shandong Province, China, in 1988.

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Journal papers

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Summary

Automated Mobility-on-Demand (AMoD) systems are expected to revolutionize urban mobility systems. However, there are uncertainties in the planning and operations of AMoD systems. We deem the agent-based approach as being well suited for modeling new phenomena in future AMoD systems and therefore shed some light on the uncertainties about the operation and the impacts of such systems. Recommendations to various stakeholders are provided through the different contributions.

About the Author

Senlei Wang received his MSc. Degree in System Engineering from the School of Traffic and Transportation, Beijing Jiaotong University. In September 2016, he started his Ph.D. research at Delft University of Technology on exploring the impacts of shared automated vehicle services using an agent-based approach.

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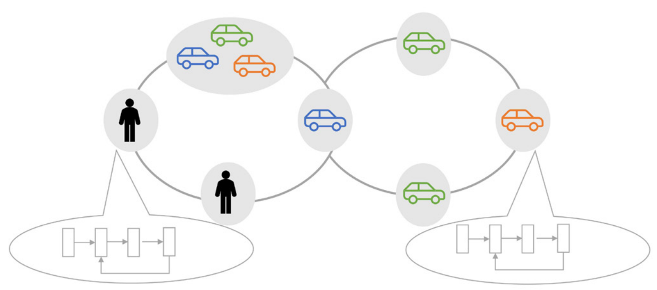

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