Autonomous Mobility on-Demand in urban areas

A Rotterdam-Zuid Case Study

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by

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Spatial and Transport Impacts of Automated Driving

Preface

This document is a master thesis which embodies a report of the research I did at the faculty of Civil Engineering and Geosciences at the Delft University of Technology for the master program Transport Planning of the MSc Civil Engineering in order to obtain the title Master of Science. This report describes a scientific research in which a societal issue has been addressed by a potential solution which involves an application of the knowledge that I have acquired during the courses as a part of the master program. The solution comprises a concept that integrates innovative autonomous vehicle technology with public transport systems, which is called the Autonomous Mobility on-Demand (AMoD) system. This research provides insight into the performance and the financial viability of the AMoD system applied as a solution for first- and last-mile transport for future public transport systems in urban areas using a newly developed agent-based simulation model that functions as an add-on module for an existing gravity-based travel demand estimation model.

For the past 8 months, I worked as a graduate intern at the public transport department of the Dutch mobility consultancy company Goudappel Coffeng B.V., at the office located in The Hague. During this period, I was supervised by Arthur Scheltes who works as a public transport & automated vehicle consultant. I would like to thank him for his guidance, support and ability to provide me with the helicopter-view at the moments when I lost the overview because of my tendency to zoom in rather quickly when my enthusiasm is fueled.

Moreover, I would like to thank Goncalo Correia, assistant professor at the Transport & Planning department at the TU Delft, for his effort, energy and enthusiasm during meetings, which were very helpful and interesting. Besides, thanks go out to Jan Anne Annema for helping me out with the financial- and policy-related aspects of my research and Bart van Arem for supervising the committee. Apart from the committee, I would like to thank Bastiaan Possel from the transport modeling department of Goudappel Coffeng B.V., who provided me with support in coding of the OmniTRANS demand model.

The facilities and colleagues at Goudappel Coffeng B.V. were tremendous and I am very thankful for the opportunity to get to know the company and its people so well. I would definitely recommend every student that is interested in mobility consultancy to consider Goudappel Coffeng B.V. as an opportunity to finish your master program at.

I would also like to thank my family for supporting me throughout my entire student life. Next to my family, I would like to thank the boys and girls from: De Raamstraat 47, B21, De Klittenband, JC Buurman and Dispuut Verkeer for providing me with happiness, at the moments I needed it. Last but not least, I would like to thank Fenna Saueressig for her endless support and love.

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Executive Summary

Urban mobility is under pressure, resulting from the still ongoing urbanization, urban densification, urban expansion, car-dominated cities and increasing mobility demand. In order to protect the accessibility, livability, safety, sustainability and efficiency of the cities of the future, transport policies focus on increasing the utilization rate of public transport and shared mobility as these are sustainable modes of transport in urban areas. This research is focused on a possible application of recent technological developments on Automated Vehicles (AVs) and shared mobility on urban mobility systems.

Public transport in urban areas suffers from disutility due to first and last-mile trip connectivity problems. In other words, improving the first- and last-mile trip leg of a public transport trip could lead to a modal shift from private to public transport. Recently, the application of vehicle automation and shared mobility concepts gains attention in scientific research and has resulted in the concept: Autonomous Mobility on-Demand (AMoD) systems, which is a demand responsive autonomous one-way carsharing service.

Multiple researches are published which aim at modeling the AMoD system for certain case studies in order to assess the impact of AMoD services on urban mobility. The far most popular transport modeling paradigm in doing this is agent-based modeling (ABM), in which the urban mobility system performance results from the interaction of agents according to their individual behavior.

However, there are certain shortcomings in research on AMoD systems. Firstly, these researches primarily focus on the supply-side of AMoD systems, often assuming certain extreme demand situations like a replacement of all taxi demand for AMoD demand. An alternative for assuming such demand situations is predicting the demand using existing travel demand estimation models. Secondly, the impact of operational variables on the financial viability of AMoD systems is not yet clear, while the financial viability plays an essential role in the implementation of automated vehicle applications. Therefore, the objective of this research is to develop an add-on agent-based supply module that is able to be connected with existing gravity-based demand estimation models and is able to account for the main costs and revenues for various operational scenarios of AMoD systems. As a result, the main research question that can be answered using the existing demand model and the agent-based add-on supply module is formulated as:

- ***What is the financial viability of Autonomous Mobility on-Demand operations as a first- and last-mile solution for public transport in urban areas?***.

In order to answer this research question, the AMoD concept is applied as a case study. Because this research is conducted at the mobility consultancy company Goudappel Coffeng B.V., the case study location follows from a recent project the company carried out, which was commissioned by the Municipality of Rotterdam. This project showed that although several measures will be implemented in the future to improve public transport, the job accessibility using public transport in the Rotterdam-Zuid area is predicted to lack behind compared to the remaining parts of the city. Therefore, opportunities for innovative mobility concepts like AMoD systems could be beneficial for this area. Within the area, two specific locations are chosen to function as a hub for AMoD operations based on the potential benefit it could lead to. From an operators perspective, Station Zuidplein and Station Lombardijen showed to be the preferred locations to function as an AMoD hub.

Modeling effort is required to add the AV as a mode for first- and last-mile transport to an existing travel demand estimation model. Goudappel Coffeng B.V. recently developed a new gravity-based transport model that covers the Metropolitan region of Rotterdam and The Hague, which is calibrated on recent data. To add the AV to this model, at first, the network must provide the opportunity for the AV to drive only within the study area. Moreover, all AV trips must be directed to Station Zuidplein and Station Lombardijen. Secondly, the new mode called AV is added to the set of initial alternatives for first- and last-mile transport: walking and bicycling. The mode choice is based on the AV speed, fare and waiting time. Eventually, the model is able to produce O/D-matrices for AV trips within the study area. The resulting spatial distribution of first-mile AV trips in the morning-peak is shown in Figure 1.

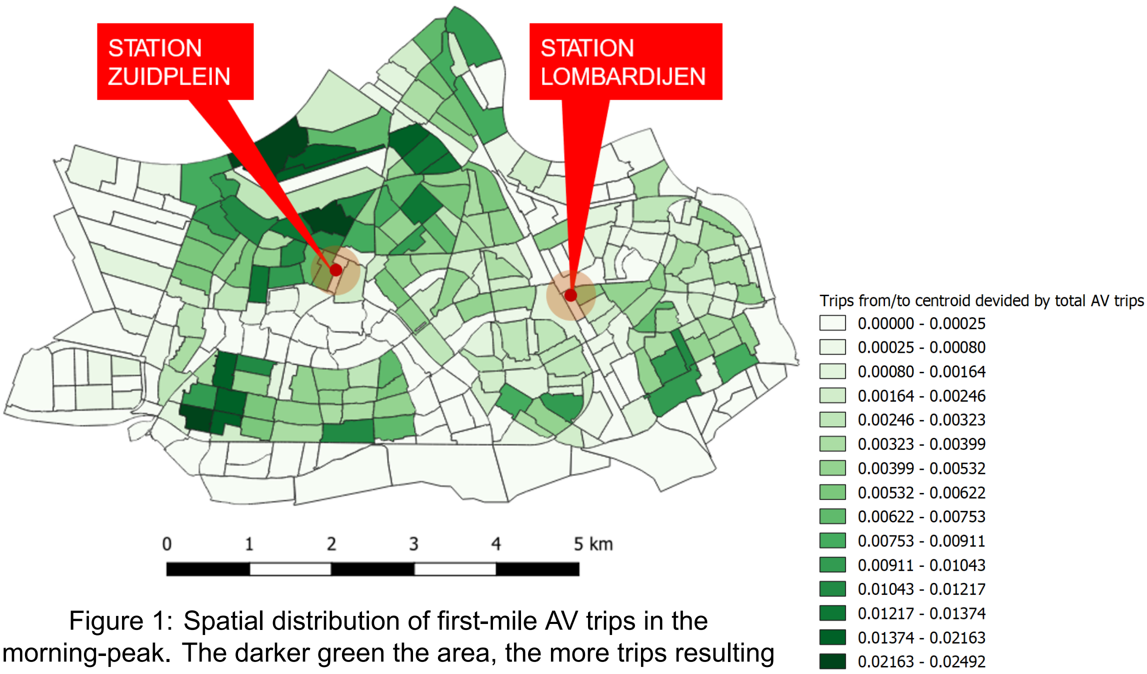

Figure 1: Spatial distribution of first-mile AV trips in the morning-peak. The darker green the area, the more trips resulting from the zone

The OD-matrices and network data that result from the existing MRDH demand model are fed into an agent-based supply model that is newly developed for this research. This model comprises the Rotterdam-Zuid area and is developed using the software Anylogic, which is based on the programming language Java. Within the model, the Travelers and AV's behave according to rules specified in statecharts as is shown in Figure 2. A statechart defines in which state the agents are and determine when the agents move to the next state based on predefined conditions. In yellow, the states are given and the black arrows represent the conditional transitions.

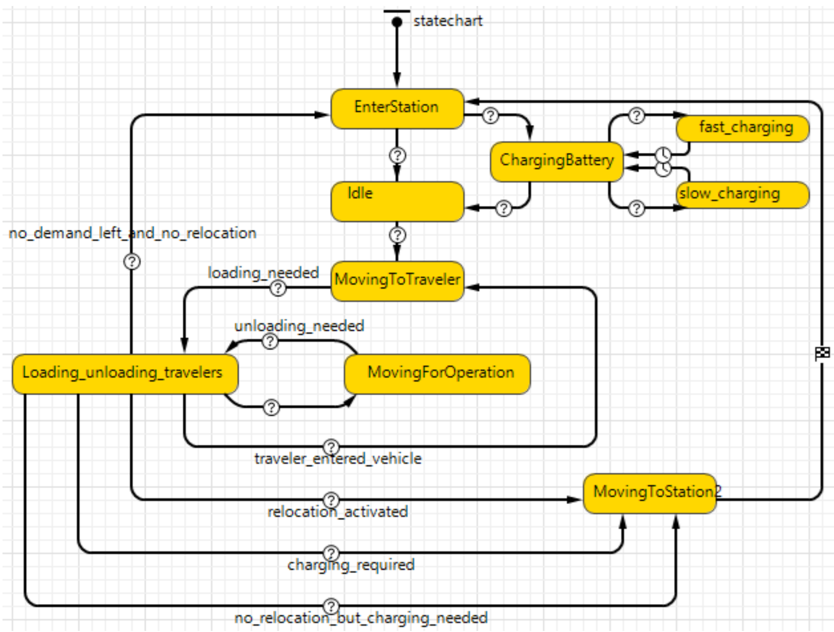

Figure 2: Statechart of the AV defining the behavior of the AV agent in the Anylogic model

Two AV operations are possible: first-mile and last-mile. A first-mile operation consists of a passenger trip from its Origin centroid in the study area to the nearest station. A last-mile operation consists of a passenger trip from one of the stations to its Destination centroid. Regarding the AVs, an operation consists of two parts. The first part consists of the movement from its current location to the Origin of the passenger, which is an empty vehicle trip. The second part consists of the movement from the Origin of the passenger to the Destination of the passenger, which is an occupied vehicle trip. Because the vehicle has a capacity larger than 1, rides can be shared dynamically, based on a maximum detour constraint. Ridesharing would lead to an additional trip part. For first-mile operations, this trip consists of the movement from the Origin of the first passenger to the Origin of the second passenger. For last-mile operations, this part consists of the movement from the first Destination to the second Destination.

Running the model in Anylogic with activated visualization results in a map on which the vehicles move between the station and the centroids. Figure 3 shows a snapshot of the Anylogic model during simulation. The circles indicate the vehicles. The color of the circle-cores indicates the occupancy of the vehicle and the color of the outer edge indicates the Battery state of the vehicle. The blue dots indicate the centroids that can function as an Origin or Destination. Moreover, both the stations are indicated.

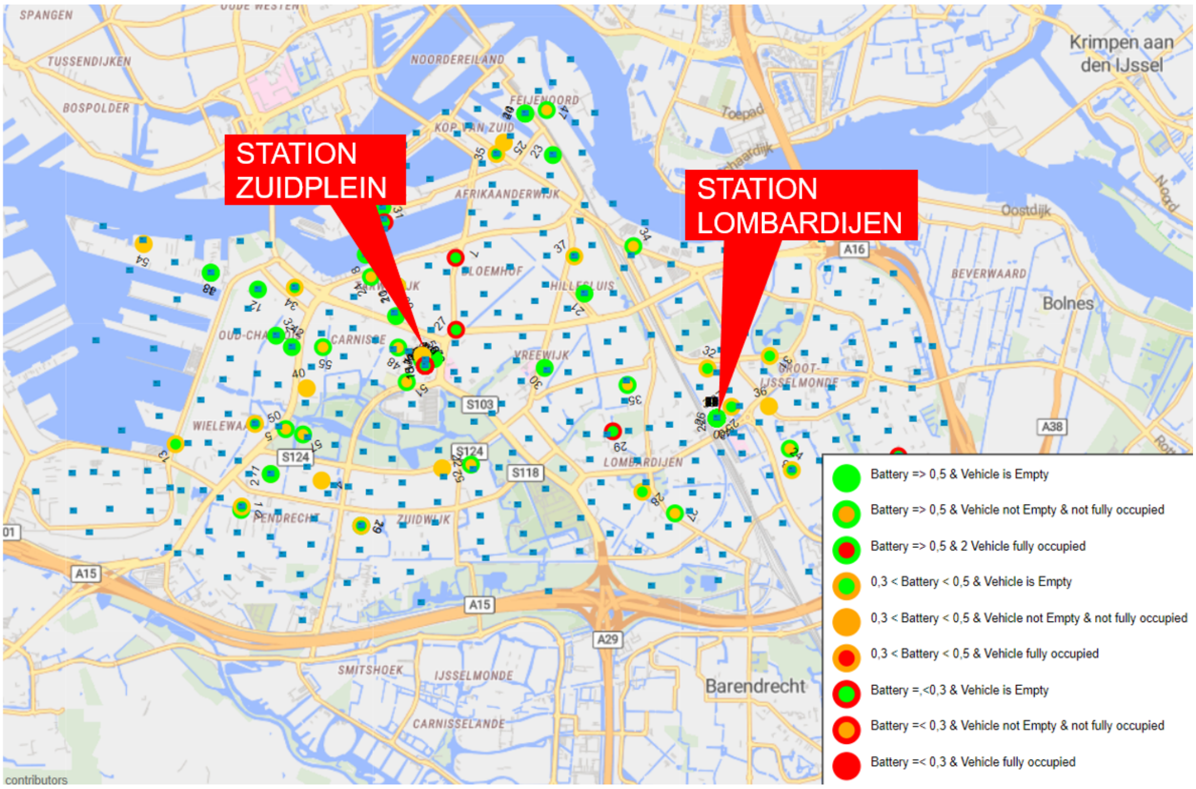

Figure 3: Snapshot of the Anylogic model with the circles representing the AVs in various states indicated by colour

To assess multiple AMoD operations, a simulation experiment is done. The first step of the simulation experiment is defining the simulation settings of the Base Scenario, which functions as a reference scenario in the evaluation of the impact of the other scenarios taken into account. Because this research is focused on the influence of the operational variables: relocation strategy, dynamic ridesharing strategy and charging strategy on the financial viability, at first the influence of the distinct operational variables on the finances of the AMoD operation is evaluated. In order to do this, in every scenario 1 operational variable differs from the Base Scenario.

The results of the simulation experiment are analyzed from an operators perspective in order to assess the financial viability of the AMoD operation, offering a certain level of service. The relative differences in % with respect to the base scenario of the transport system performance indicators for the scenarios varying in operational variables are shown in Figure 4 to 7.

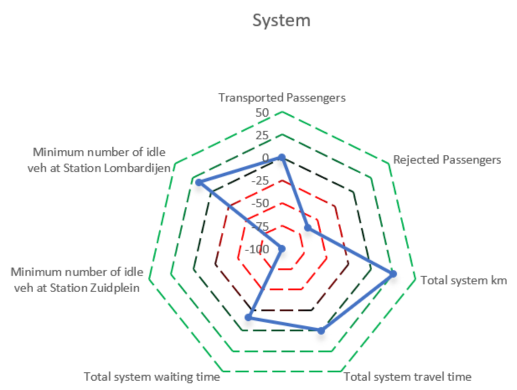

Figure 4: Spider plot for System related parameters of the Scenario with Relocation [%]

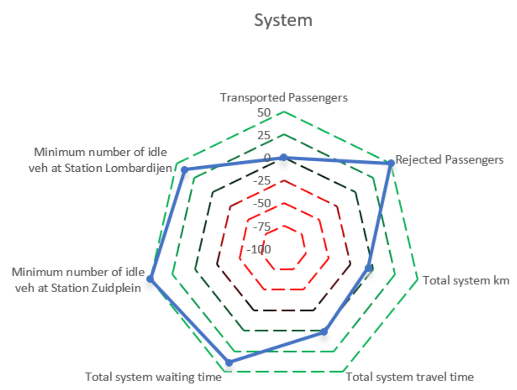

Figure 5: Spider plot for System related parameters of the Scenario with Ridesharing [%]

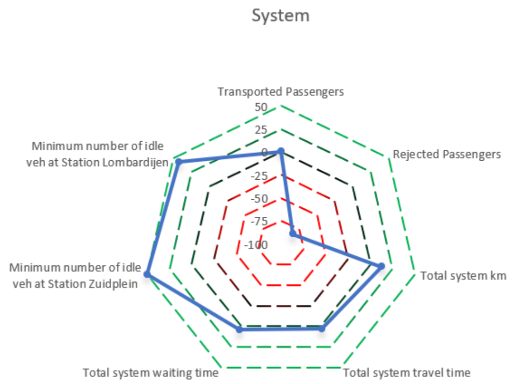

Figure 6: Spider plot for System related parameters of the Scenario with Ridesharing and Relocation [%]

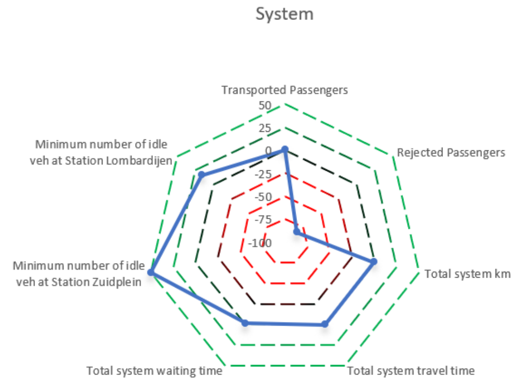

Figure 7: Spider plot for System related parameters of the Scenario using fast chargers [%]

As is shown in Figure 4, activating automatic relocation results in an increase of total system kilometers traveled due to additional empty vehicle relocation trips. This results in additional operational costs due to an increase in the required energy and maintenance. Moreover, as the total system waiting time and the number of rejected passengers have reduced, activating relocation increases the level of service from a passenger perspective. This has a positive influence on the revenues as more passengers can be transported.

Activating ridesharing has a negative influence on the system capacity as is shown in Figure 5, where an increase of the number of rejected passengers is visible. This resulted in reduced revenues. On the other hand, an increase of the total system travel time combined with a decrease in total system kilometers traveled is observed which has a profoundly positive influence on the financial viability as this increases the revenues and reduces the costs. However, the passengers experiencing a detour got discounted, which reduces the revenues.

Figure 6 shows that the number of rejected passengers has reduced and the minimum number of idle vehicles at the stations have increased. From this Figure, one can conclude that activating both automatic relocation and dynamic ridesharing has a positive impact on the system capacity. However, an increase in total system kilometers traveled is visible, which leads to additional energy and maintenance costs.

Using fast chargers instead of slow chargers leads to additional investment costs due to the higher purchase costs of fast chargers compared to slow chargers. However, the system capacity benefits from using fast chargers as the number of rejected passengers decreased and the number of minimum idle vehicles at the stations increased, as is shown in Figure 7.

Taking into account the knowledge gained from analyzing the results of the distinct scenarios as presented above, the preferred operational scenario from an operators perspective is simulated. The settings of the preferred scenario differ from the Base Scenario regarding the dynamic ridesharing strategy and the charging strategy. Dynamic ridesharing is activated and only fast chargers are used. Moreover, because the simulation experiment showed that a lower fleet size could be used when fast chargers are deployed, it is chosen to use a fleet size of 240 vehicles. The resulting influence on the financial viability is provided in Table 1. From this Table, one can conclude that the reduction of depreciation costs resulting from the fleet size reduction outweigh the increase of depreciation costs due to the use of fast chargers. Moreover, the energy costs and maintenance costs have reduced due to a reduced number of total system kilometers. The revenues have increased with respect to the Base Scenario as a result of the increased average travel time due to required detours. Eventually, operating the preferred scenario leads to a daily profit of € 2.002,-.

Table 1: Comparison of financial output parameters of the Preferred Scenario with respect to Base Scenario

Financial component	**Base Scenario**	**Preferred Scenario**	**Difference**
Costs			
Depreciation costs	€ 2.262,-	€ 1.957,-	- € 305,-
Energy costs	€ 601,-	€ 575,-	- € 26,-
Maintenance costs	€ 1.721,-	€ 1.673,-	- € 48,-
Wage expenses	€ 1.000,-	€ 1.000,-	0
Total costs	**€ 5.584,-**	**€ 5.205,-**	**- € 379,-**
Revenues	**€ 7.147,-**	**€ 7.207,-**	**+ € 60,-**
Daily Balance	**€ 1.564,-**	**€ 2.002,-**	**+ € 438,-**

The developed Anylogic model has a broad range of potential applications. This research showed that applying an add-on agent-based module on an existing gravity based travel demand estimation model is a feasible alternative for building an entirely new model which would imply substantial programming efforts.

From an operators perspective, the model could be used to evaluate many different AMoD operational strategies regarding relocation, dynamic ridesharing and charging. Moreover, the model can be applied to any other city, constrained by the network- and demand-data availability.

Next to operators, governmental authorities could use the model to evaluate the impact of the AMoD systems on the accessibility of the city by analyzing the key performance indicators from a passengers perspective.

Contents

Preface iii

Executive Summary v

List of Figures xiii

List of Tables xvii

Glossary xix

1 Introduction 1
1.1 Problem Definition . . . 1
1.2 Research-Objectives -and questions . . . 2
1.3 Scientific and Societal Relevance . . . 3
1.4 Scope . . . 6
1.5 Research Methodology. . . . 6
1.6 Thesis Reading Guide . . . 7

2 State of the Art 9
2.1 Public Transport in urban areas . . . 9
2.2 Carsharing . . . 10
2.3 Autonomous Vehicles and Carsharing . . . 11
2.4 Autonomous last-mile transport pilots . . . 12
2.5 Modeling autonomous carsharing . . . 13
2.6 Research Gap . . . 14

3 AMoD System & Conceptual Simulation Model 17
3.1 AMoD System Description . . . 18
3.2 Conceptual Model . . . 20
3.3 Model Requirements . . . 21
3.4 Conclusion . . . 23

4 Case-Study Rotterdam-Zuid 25
4.1 Current Situation at Case Study Area . . . 25
4.2 Future Situation at Case Study Area . . . 26
4.3 Station Selection . . . 26
4.4 Conclusion . . . 29

5 Applied Simulation Model 31
5.1 OmniTRANS MRDH model . . . 32
5.2 Anylogic simulation model . . . 38
5.3 Anylogic Model Input-Assumptions . . . 44
5.4 Experimental Variables. . . . 48
5.5 Simulation Output . . . 49
5.6 Model Verification. . . . 50

6 Results Analysis 53
6.1 Scenarios . . . 53
6.2 Relocation Strategy . . . 63
6.3 Ridesharing Strategy . . . 66
6.4 Charging Strategy . . . 70
6.5 Financial Viability overview . . . 73
6.6 Preferred Scenario . . . 76
6.7 Discussion . . . 77

7 Conclusions & Recommendations **83**
7.1 Conclusions 83
7.2 Recommendations 86

Bibliography **89**

List of Figures

1 Spatial distribution of first-mile AV trips in the morning-peak. The darker green the area, the more trips resulting from the zone . . . vi
2 Statechart of the AV defining the behavior of the AV agent in the Anylogic model . . . vi
3 Snapshot of the Anylogic model with the circles representing the AVs in various states indicated by colour . . . vii
4 Spider plot for System related parameters of the Scenario with Relocation [%] . . . viii
5 Spider plot for System related parameters of the Scenario with Ridesharing [%] . . . viii
6 Spider plot for System related parameters of the Scenario with Ridesharing and Relocation [%] . . . viii
7 Spider plot for System related parameters of the Scenario using fast chargers [%] . . . viii

1.1 5E's Framework. [2] . . . 4
1.2 Research Methodology Framework . . . 7

2.1 Schematic overview of possible future urban transport systems. . . . 10

3.1 Conceptual interaction between Transportation-demand and -supply . . . 17
3.2 Schematic overview of the AMoD vehicle behavior . . . 19
3.3 Schematic overview of the passenger behavior in the AMoD system . . . 20
3.4 Conceptual overview of a transport system . . . 21

4.1 Map of Rotterdam with the colour indicating the number of jobs in thousands that are accessible by public transport within 45 minutes. (Source: OV Visie 2040 [3]) . . . 26
4.2 Map of Rotterdam showing potential differences resulting from the proposed improvements in the number in thousands of jobs that is accessible by public transport within 60 minutes. by public transport. (Source: OV Visie 2040 [3]) . . . 27
4.3 Map of the public transport lines in Rotterdam-Zuid with red circles indicating the location of Station Zuidplein (left) and Station Rotterdam Lombardijen (right). (Source: RET[4]) . 28

5.1 Schematic overview of the composition of the overall case study simulation model . . . 31
5.2 Overview of the OmniTRANS network within the MRDH model . . . 34
5.3 . . . 35
5.4 . . . 35
5.5 . . . 35
5.6 First-mile demand distribution during morning-peak . . . 36
5.7 Last-mile demand distribution during morning-peak . . . 36
5.8 First-mile demand distribution during off-peak . . . 36
5.9 Last-mile demand distribution during off-peak . . . 36
5.10 First-mile demand distribution during evening-peak . . . 36
5.11 Last-mile demand distribution during evening-peak . . . 36
5.12 . . . 36
5.13 Network assignment plot for the mode AV. Link flows are indicated by the width and colour of the bars at the links. . . . 37
5.14 Link flows of the mode Bicycle at the location where the maximum AV flow is observed . 37
5.15 Link flows of the mode Walking at the location where the maximum AV flow is observed 37
5.16 Overview of the centroids within the study area, indicating the location of the stations. . 39
5.17 Statechart of the AV agent, which determines when conditional actions take place. . . . 41
5.18 Schematic overview of first-mile detour evaluation. . . . 42
5.19 Schematic overview of last-mile the detour evaluation. . . . 42
5.20 Statechart of the Traveler agent, which determines when conditional actions take place. 44

5.21 Distribution of demand for a typical day. Normal distribution for morning- and evening-peak and a uniform distribution between these peaks. 45
5.22 Snapshot of the study area in the simulation model after 360 min (12:00) 46
5.23 The number of rejected passengers as a function of the fleet size. 49
5.24 Average rejected passengers as function of replications #1 50
5.25 Average rejected passengers as function of replications #2 50
5.26 Average rejected passengers as function of replications #3 50
5.27 Average rejected passengers as function of replications #4 50
5.28 Average rejected passengers as function of replications #5 50
5.29 Average rejected passengers as function of replications #6 50

6.1 Stackchart indicating the states of the AV agents assigned to Station Zuidplein (seed 9) 55
6.2 Stackchart indicating the states of the AV agents assigned to Station Lombardijen (seed 9) 55
6.3 The total amount of energy used by the AV fleet while driving (seed 9) 56
6.4 The power required for charging as a function of time for both stations (seed 9) 56
6.5 Histogram showing the distribution of travel times of agents of type Traveler (seed 9) . . 57
6.6 Histogram showing the distribution of waiting times of agents of type Traveler (seed 9) . 57
6.7 Graph showing the Revenues and costs aspects of the Base Scenario as a function of time 58
6.8 Graph showing the costs and revenues components of the Base Scenario 58
6.9 Graph showing the number of rejected passengers as a function of the vehicle speed . 60
6.10 Graph showing average time related indicators as a function of the vehicle speed 60
6.11 Stacked chart showing the share of states of the AV agent as a function of time for 2 different vehicle speeds. (Seed 7) 60
6.12 Graph showing the impact of charging time variations on the number of rejected passengers 61
6.13 Graph showing the impact of battery capacity variations on the number of rejected passengers for three different fleet sizes 61
6.14 Graph showing the impact of fleet size variations on the daily costs and revenues 61
6.15 Graph showing the impact of price variations of energy and vehicle purchase on the total daily costs 61
6.16 Spider plot for System related parameters [%] 63
6.17 Spider plot for Energy related parameters [%] 63
6.18 Spider plot for Passenger related parameters [%] 63
6.19 Spider plot for Vehicle related parameters [%] 63
6.20 Stacked chart showing the share of states of the AV agent as a function of time for the Relocation Scenario (Seed 9) 64
6.21 Stacked chart showing the share of states of the Station Zuidplein AVs as a function of time for the Ridesharing Scenario (Seed 9) 66
6.22 Stacked chart showing the share of states of the Station Zuidplein AVs as a function of time for the Sharing & Relocating Scenario (Seed 9) 66
6.23 Spider plot for System related parameters of the Ridesharing Scenario [%] 67
6.24 Spider plot for System related parameters of the Sharing & Relocating Scenario [%] . . 67
6.25 Spider plot for Energy related parameters of Ridesharing Scenario [%] 67
6.26 Spider plot for Energy related parameters of the Sharing & Relocating Scenario [%] . . 67
6.27 Spider plot for Passenger related parameters of Ridesharing Scenario [%] 67
6.28 Spider plot for Passenger related parameters of the Sharing & Relocating Scenario [%] 67
6.29 Spider plot for Vehicle related parameters of Ridesharing Scenario [%] 68
6.30 Spider plot for Vehicle related parameters of the Sharing & Relocating Scenario [%] . . 68
6.31 Spider plot for System related parameters [%] 70
6.32 Spider plot for Energy related parameters [%] 70
6.33 Spider plot for Passenger related parameters [%] 70
6.34 Spider plot for Vehicle related parameters [%] 70
6.35 Stacked chart showing the share of states of the AV agent as a function of time for the Fast Charging Scenario (Seed 9) 71

6.36 Graph indicating the required energy for charging for both stations as a function of time for the Fast Charging Scenario (Seed 9) 71
6.37 Stacked barchart providing an overview of the composition of the costs for all scenarios 74
6.38 Barchart providing an overview of the total costs and revenues for all scenarios 74
6.39 Stacked barchart providing an overview of the composition of the costs for all AMoD operations including the non-automated operations 79

List of Tables

1 Comparison of financial output parameters of the Preferred Scenario with respect to Base Scenario ix

2.1 Types of Carsharing Systems. Source: [5] 11

4.1 Table which shows the scores of the possible station locations for the specified criteria and the total summed scores 28

5.1 Overview of the skim modification factors used in the OmniTRANS MRDH model 33
5.2 Pseudo code of the ControlScheme Algorithm showing its main statements 40
5.3 Overview of the possible values of variables taken into account in the simulation of scenarios 46
5.4 Calibration parameter values comparison between model and reality in order to verify the Anylogic model. 51

6.1 Overview of the scenarios simulated using the simulation model 54
6.2 Overview of the performance indicators of the Base Scenario 55
6.3 Comparison of financial output parameters of the Relocation Scenario with respect to Base Scenario 65
6.4 Comparison of financial output parameters of the Ridesharing Scenario and the Sharing & Relocating Scenario with respect to Base Scenario 69
6.5 Comparison of financial output parameters of the Fast Charging Scenario with respect to Base Scenario 72
6.6 Overview of the impacts of the Scenarios on the financial components with respect to the Base Scenario 73
6.7 Overview of the impacts of the Scenarios on the output indicators expressed in % difference with respect to the Base Scenario 75
6.8 Comparison of financial output parameters of the Preferred Scenario with respect to Base Scenario 76
6.9 Comparison of the resulting average waiting time with values found in literature 77
6.10 Comparison of the total daily costs with existing bus lines in the study area 78

Glossary

ABM	Agent-based Model
AMoD	Autonomous Mobility on-Demand
AV	Automated Vehicle
COS	Costs of Service
DRS	Dynamic Ride-sharing
DRT	Demand Responsive Transport
EV	Electric Vehicle
GDP	Gross Domestic Product
FIFO	First-in first-out
First- and Last-mile	The part of a public transport trip that completes the connection of the origin and destination with a public transport stop or station.
KiM	Kennisinstituut Mobiliteitsbeleid
KPI	Key Performance Indicator
MaaS	Mobility as a Service
MoD	Mobility on-Demand
PAV	Private Autonomous Vehicle
PHDV	Private Human-Driven Vehicle
PT	Public Transportation
SAV	Shared Autonomous Vehicle
SoC	State of Charge
TMC	Total Mobility Costs
VKT	Vehicle Kilometers Traveled
VoT	Value of Time
VTTS	Value of Travel Time Savings
WEVCS	Wireless Electric Vehicle Charging Systems
WPT	Wireless Power Transfer

1
Introduction

1.1. Problem Definition

Urban mobility is under pressure. The share of people living in urban areas is expected to grow from 54% to 66% of the total population in 2050 [6]. Due to the still ongoing urbanization, urban densification, urban expansion, car-dominated cities and increasing mobility demand, urban transportation systems suffer from congestion. In 2017, the increasing mobility demand led to an all-time high car-mileage of 188,5 billion kilometers in 2017 [7]. This is a threat to the accessibility, livability, safety, sustainability, and efficiency of cities, while cities are still the areas where the most economically important activities take place [8]. These negative external impacts of the utilization of motorized vehicles as the primary mode of transportation in urban areas leads to high both material- and human-costs [9]. Yearly 1% of the GDP is lost in external effects of urban transportation [10].

Due to limitations in public space, it is challenging to facilitate the increase in mobility demand in its current form. Therefore, urban transport policies focus on increasing the utilization rate of public transport, resulting in a shift from privately owned vehicles to shared or service-based mobility [11]. This modal shift to more sustainable modes of transport, which have a high capacity, flexibility and are increasingly deployed without using fossil fuels, is required to relieve the pressure on urban mobility [12]. To increase the attractiveness and accessibility of sustainable modes of transport in a multimodal network, a seamless connection between the new shared mobility concepts is required. Smartly integrating different mobility concepts could lead to an efficient service-based urban transport system where mobility is regarded as one integrated service, instead of a system where various modes are privately owned. The Mobility as a Service (MaaS) concept embodies this futuristic vision on urban mobility [13].

1.1.1. Vehicle Automation

A promising solution to urban mobility problems as described above which is currently getting much attention in research is the use of automated or autonomous (when SAE-level 4 and 5[14]) vehicles (AVs). The potential of AV-operations is regarded as an upgrade to conventional personal vehicles with the characteristics of demand responsiveness, fleet re-positioning and share-ability [15], [9], [16], [17]. It is expected that these vehicles will hit the streets in the nearby future. However, how long it will take for this to happen is highly uncertain, as the development is depending on many different factors. A gradual increase of the penetration rate of AVs will lead to a situation where conventional vehicles will share the infrastructure with AVs. How these two vehicle types will interact ensuring road safety, is one of the main challenges in the development of the AV technology. Other challenges in research regarding AVs are the choice behavior and the prediction of the impacts of AVs on transport systems.

Despite the uncertainty on the development of the penetration rate of AVs, the KiM Netherlands Institute for Transport Policy came up with specific development paths which provide a foundation for scenario-based predictions of the transition towards a future with AVs [18]. The publication of this document shows that the peak of the hype around AVs is already a few years behind us. Authorities, research institutions and market parties are focusing on the more practical realistic applications of the AV technology, and try to predict their impacts on transportation systems and spatial development.

Most of these researches show promising results, making these research institutions and market parties convinced of the potential benefits of this technology and aspired for getting a grip on the development and implementation of this technology. The benefits of the systems largely depend on the passenger's choice behavior regarding AVs, which is a new alternative playing a role in the passenger's mode choice. When AVs hit the streets, it is expected that a certain share of travelers will shift from their current mode of transport to a new mode of transport, because passengers have to make new choices. The resulting uncertainty about the choice behavior of passengers regarding automated vehicles is a big challenge in research on autonomous vehicles.

A few researches have been pointing to this challenge and were able to hypothetically determine the choice preferences of passengers regarding AVs [19], [20], [21], [22], [23]. However, new challenges arise in researches that focus on the application of these choice preferences in models regarding AV services, due to uncertainty about the long term impacts of AV applications on mobility systems. From a business perspective, these challenges comprise questions about the competitive position of AVs compared to existing modes of transport and public transport. Will the AVs compete or complement with public transport and when will AVs be attractive enough for passengers to cause a shift in mode choice in the direction of AVs. To answer these questions, knowledge about the cost structures is required, because price is the key attribute in the choice behavior of passengers [24].

Therefore, research is required that focuses on methods to address these uncertainties. To gain more insight into the impacts of AVs on transport systems, predictions must be made for various scenarios using models. There are various modeling paradigms available that are able to account for the implementation of AVs in transportation models. At first, studies developing random utility choice models implemented AVs as a mode of transport, predicting the share of passengers that chooses for the AV as a mode of transport. These are transport demand estimation models. Later on, as the ability to process large amounts of data, the activity-based multi-agent micro-simulation methods became much more popular. Currently, especially agent-based modeling (ABM), where the individual AVs are modeled being individual agents that interact within an environment according to specific behavioral rules, is getting much attention in literature [5].

1.1.2. Shared Mobility

Next to the developments in vehicle automation technology, the advancements in technology like social networking, GPS and the internet contributed to the spread of sharing economy concepts. PricewaterhouseCoopers estimated that the revenues in the sharing economy sector will grow substantially from US$15 billion in 2014 to US$335 billion in 2025 [25]. One of these growing concepts is the shared mobility concept. According to [26], this term includes the modes of carsharing, personal vehicle sharing, bike-sharing, scooter sharing, traditional ridesharing, ride-sourcing and e-taxis. Travelers can order a ride using Lyft or Uber and can rent a car, bicycle or scooter for a short trip (e.g., Zipcar, car2go, Greenwheels, Mobike, Felyx).

In urban contexts, shared mobility does not only have potential as an innovative transportation mode enhancing urban mobility but also as a solution for the first- and last-mile connection of public transport trips, increasing the connectivity of a multimodal network. It can provide a flexible option to access and egress trip-legs of public transport trips which can encourage travelers to use public transport. Combining this concept with the advancements in the autonomous vehicle technology, it is expected that the next generation carsharing vehicles will be autonomous [5].

The existing conventional Mobility on-Demand (MoD) systems cope with re-balancing problems when vehicles end up clustered at a certain location. Autonomous Mobility on-Demand (AMoD) systems address this issue because in AMoD systems vehicles are able to relocate themselves autonomously. Moreover, these AMoD vehicles are often electric and can monitor their batteries. However, the main benefit of implementing AMoD services in urban areas is the improvement of the attractiveness of public transport. This can cause a modal shift from privately owned vehicles to public transportation as the AMoD services could be a solution to "the last-mile problem" [27] in public transportation trips, which is currently causing a large part of the dis-utility in the choice behavior for public transport [11].

1.2. Research-Objectives -and questions

Although several companies already showed their interest in these AMoD operations acknowledging the potential benefits [28],[29], there exists uncertainty about the financial viability of these systems, as this is highly dependent on the operational characteristics. It is essential for the implementation of AMoD services in current urban transport systems that these services are proven to be financially viable because of required investments. The supply of the AMoD service determines the main cost aspects of AMoD operations: **(i)** investment costs, which is mainly dependent on the fleet size, **ii)** operation & maintenance costs, which include expenditure on assets due to operation, and **(iii)** fuel costs. In this research, it is assumed that the AVs can use existing infrastructure and are able to share this infrastructure with other modes. The revenues are resulting from fares, depending on the price and the demand for AMoD services. Therefore, the objective of this research is to assess the financial viability of such AMoD systems implemented at specific locations in urban areas, varying the operational characteristics in order to investigate which operation is the most financially viable for that location.

Because field tests are not yet possible for this research, models are required to be able to predict the demand for the AMoD service as well as the performance of the AMoD system itself. Assumptions based on the choice preferences of passengers regarding AMoD as a mode for first- and last-mile transportation in public transport need to be implemented in a demand estimation model. To be able to predict the financial viability of the AMoD system, also the supply-side determining the costs needs to be modeled. This can be done by using an ABM that is able to account for the operational characteristics of the AMoD. Defining relationships between the demand and supply component of the model and finding out how to efficiently link an agent-based model to an existing gravity model is essential for the functionality of the model. Because a financial viability study regards specific applications of transport systems, the conceptual AMoD service is applied to a specific case study location. Recent activities and collaborations of Goudappel Coffeng B.V. with the municipality of the city of Rotterdam, function as a foundation for the choice of the case study location, which therefore is chosen to be located in the city of Rotterdam.

The objective statement of this research is being supported by research questions that form the foundation of the steps required to fulfill the research objectives. The sub-questions are focused on the aspects of the main research question. The main research question is formulated as follows:

What is the financial viability of Autonomous Mobility on-Demand operations as a first- and last-mile solution for public transport in urban areas?

The sub-research questions are formulated as follows:

1. *What are the characteristics and model requirements of Autonomous Mobility on-Demand services applied as first- and last-mile transport in urban areas?*
2. *What specific locations in Rotterdam-Zuid are suitable to function as a hub for Autonomous Mobility on-Demand services?*
3. *What assumptions on the passenger choice behavior regarding automated vehicles are required in order to add the AV as a mode for first- and last-mile transport in the existing gravity-based travel demand estimation model in OmniTRANS?*
4. *What is the demand for Autonomous Mobility on-Demand services on the specific case study locations?*
5. *How can one ensure a consistent connection between an agent-based micro-simulation model and an existing gravity-based travel demand estimation model?*
6. *What is the influence of the operational variables: relocation strategy, dynamic ridesharing and charging strategy on the performance of Autonomous Mobility on-Demand systems?*

1.3. Scientific and Societal Relevance

This research can be regarded as an extension of the research that currently has been done on carsharing systems, autonomous vehicle services, passenger preferences on automated vehicles and especially the modeling of autonomous carsharing systems. Several researches aimed on developing choice models where automated vehicles are included in the set of alternatives [20], [22], [15], [21], [19]. As this research focuses on the modeling and financial viability of the AMoD system, the choice preferences resulting from researches mentioned above, will be implemented in an existing model in order to make a demand estimation for the AMoD services using a well calibrated and validated model. Using a model to determine the AMoD passenger demand fulfills one of the recommendations of the research Shen [30] carried out for a Singapore case study. Moreover, applying an agent-based simulation model as a complement to an existing aggregate gravity model for a specific case study location has not been done yet in The Netherlands, as agent-based modeling is still an innovative modeling paradigm. This combination of a gravity demand estimation model and an agent-based simulation model can provide a more efficient alternative of modeling AMoD services in urban areas compared to building a complete new micro-simulation model from scratch. Therefore, this research also contributes to the development of knowledge on combining various modeling methods that are existing [5].

Next to scientific relevance, this research is also relevant because of the interests of various stakeholders. The AV technology is widely known under market parties, which are generally aware of its potential. However, much uncertainty exists about the AV technology as well, which gives these market parties a restrained attitude against the AV technology as they hold back to take measures to realize the potential. Therefore it is essential to show and inform market parties actively to make them aware of the actual benefits. To learn more about the applications of the AV technology, the municipality of Rotterdam has shown its interest in the application of new modeling methods. Eventually, these modeling methods can help them to evaluate the application of innovative mobility solutions in the city of Rotterdam. Moreover, the AMoD services will require a third party that operates the services. This research could provide potential AMoD operators with guidelines on investments as it shows the main costs and benefits of the AMoD service.

The societal relevance can be clarified by looking at the promising large number of potential social benefits of AMoD services. These benefits often reduce human costs that are a consequence of externalities of urban transportation such as congestion, pollution and a low level of safety. As AMoD services are regarded as a mode of transport which will be integrated with public transport, the impacts can be described by the 5E framework, which is shown in Figure 1.1.: Efficient city, effective mobility, equity, economy, environment [2]. The potential benefits are categorized below per E of this framework.

Figure 1.1: 5E's Framework. [2]

- **Efficient City:**
  - Compared to contemporary carsharing services: autonomous vehicles have flexible stopping locations as they are able to return to their starting location or parking space without any intervention of drivers needed;
  - Different parking locations possible and no parking spaces in front of houses are required providing opportunities for a higher public space quality;
  - Opportunities for other land-use purposes at the current parking locations;

- **Effective Mobility:**
  - Higher efficiency due to demand-driven operations which can substitute unprofitable public transport services with low occupancy rate;
  - Flexibility in type and size of the car that matches the trip purpose;
  - No walking to stop required;
  - Better integration with public transport lines than private autonomous vehicles (PAV)'s as AMoD services can contribute to the MaaS concept;
  - More efficient traffic flow due to the absence of human reaction characteristics which currently result in latency and eventually in unstable traffic flows;
- **Equity:**
  - Less fixed traveling costs like taxes and maintenance, more variable and transparent costs per trip;
  - People without a driver's license are able to use autonomous vehicles [31];
  - Better connectivity of low density/demand areas;
- **Economy:**
  - Compared to Shared Autonomous Vehicles (SAVs), the number of kilometers Private Autonomous Vehicle (PAV) customers have to drive to reach the point where PAVs become beneficial is too high. Therefore, passengers reduce costs if they switch from PAVs to SAVs. [32];
  - More transparent costs structure than PAVs;
  - Human costs savings because of lower crash rates and increased safety;
  - Transport operators are involved which leads to employment opportunities;
  - The shared-mobility market will grow as new market parties will play a role;
  - Higher level urban mobility leads to less loss of production than in the current situation due to congestion.
- **Environment:**
  - The fleet of AMoD vehicles will consist of clean and light vehicles and are therefore more energy efficient;
  - Less pollution due to the ability to minimize pollution using mechanical optimization;
  - More space for urban green in the public space in the streets because less parking space is required inside an urban area.

Despite a large amount of potential benefits, there are as well potential disadvantages of autonomous carsharing services. For instance, it is uncertain how long passengers will have to wait till their AV will pick them up at their exact location of origin and is this service responding fast enough on passenger demand to be competitive to other modes. Long waiting times can lead to inconvenience which will affect the choice behavior of passengers. Besides, an important aspect where carsharing is not in favor of privately owned vehicles is prestige [32]. Owning a car can support somebody's prestigious image in some cultures. This image is often used in business. As autonomous carsharing services are potentially beneficial in business areas to transport commuters, this disadvantage has to be taken into account as it will affect the choice of potential users. Besides, it is uncertain if passengers will feel more comfortable and safe inside a vehicle without a driver because this depends on the way people trust the automated vehicle technology. A societal significant disadvantage is the adverse health effects due to the modal shift of passengers. The access- and egress-leg of a public transport trip consist mainly of active modes of transportation. When these trip legs are substituted by autonomous vehicles trips, people will have less daily physical exercise which might lead to additional human costs. Finally, there is an essential potential disadvantage of AMoD services looking at the total vehicle kilometers traveled (VKT). Due to unoccupied trips of autonomous vehicles, the VKT will increase for an equal demand. This might lead to additional costs as it can lead to congestion and furthermore to an increase in pollution. It is therefore vital that the SAV fleet is optimally assigned to a network to avoid additional congestion and pollution, which is the adverse of the intended impact.

1.4. Scope

The scope of this research is constrained by the operational aspects of the AMoD service. This research focuses on the implementation of one-way station-based autonomous mobility on-demand vehicle services as a solution to the “last-mile problem” [11] when integrating these services with existing public transport services in urban areas. The conceptual model, which is defined in Chapter 3, gives a generic framework of a transport system bordered by the case study area, which is the southern part of the city of Rotterdam and is further specified in Chapter 4. The motivation of the case study location choice has a strong relationship with recent activities of Goudappel Coffeng B.V.. The output of the project they carried out which was commissioned by the municipality of Rotterdam is the document called the OV Visie 2040 (Public Transport Vision 2040). Because of this project, a sufficient amount of data and knowledge is available within the company which increases the feasibility of this case study. On top of that, the city of Rotterdam is taking into account further development of automated passenger transportation in their future vision and policies (OV Visie 2040).

Because the AMoD services are especially beneficial in dense urban areas with high mobility demand, Rotterdam-Zuid is a suitable location. Moreover, implementing AMoD services in the Rotterdam-Zuid area requires less investment than alternatives like, e.g. additional light-rail lines. Finally, in this research, only automated vehicles with SAE international level of automation 4 will be considered, because at this level no human intervention is required and vehicles can drive fully autonomous in a specific geographical constrained area. Further technological aspects of the AV specifically are out of the scope of this research. Therefore, assumptions are made on the behavior of the AVs in Chapter 3. Moreover, assumptions are made about the passenger choice behavior regarding AVs, based on the existing literature. The eventual financial viability study comparing the various operational scenarios will be based on methods used in literature as well. The main challenge of this research is the model development, which includes both the building of the model components as well as the connection of these components.

1.5. Research Methodology

This research consists of 4 main parts. The first part of the research will be to gather knowledge about AVs, carsharing, AMoD, dynamic ridesharing, choice behavior regarding automated vehicles, financial viability analyses and the modeling of autonomous carsharing services using literature that is related to this topic. This knowledge, which describes the state of the art of this topic, has to be used in the second main part which is the development of the conceptual model as well as the applied case study model. The conceptual model has to be defined first, which includes the characteristics of the vehicles and passengers in the AMoD system. This conceptual model concludes with the model requirements which have to be met in the development of the simulation-model. In this simulation model, the conceptual model will be applied to an actual case study location to be able to analyze specifically applied AMoD services.

The choice of the specific case study location is based on criteria which are mostly related to the potential benefits of the AMoD services at this specific location. The main goal of the model development is applying the conceptual model to the case study location. As a side input, the choice preferences regarding AVs have to be incorporated into a demand estimation model. This demand estimation model results in an Origin-Destination matrix which includes the number of trips between specific locations using the AMoD system as a mode of transportation. The demand for the AMoD services is required in the eventual agent-based simulation model, which includes the behavior of the vehicles and passengers as defined in the conceptual model and uses the demand data as an input stream to produce key performance indicators (KPIs) for different operational scenarios. These KPIs will be used to analyze the system performance from three perspectives: passenger, system and business. The latter includes the financial viability analysis of these scenarios.

Furthermore, another data input stream which is used in the model development consists of the network data, GIS data and demographic data. Linking these model components to each other using the relationships and data streams as described will finalize the second main part of the research. A more elaborate explanation of the composition of the model can be found in Chapter 5. The third main part consists of running the simulation model which results in a component-based simulation process, consisting of a gravity-based demand estimation model producing the demand which is fed into the agend-based simulation model. In the last main part, the final results of the simulation will be used to analyze the AMoD system for various operational scenarios from a passenger perspective, a system perspective and a business perspective, of which the latter includes the financial viability study. In Figure 1.2, this research methodology is schematically shown.

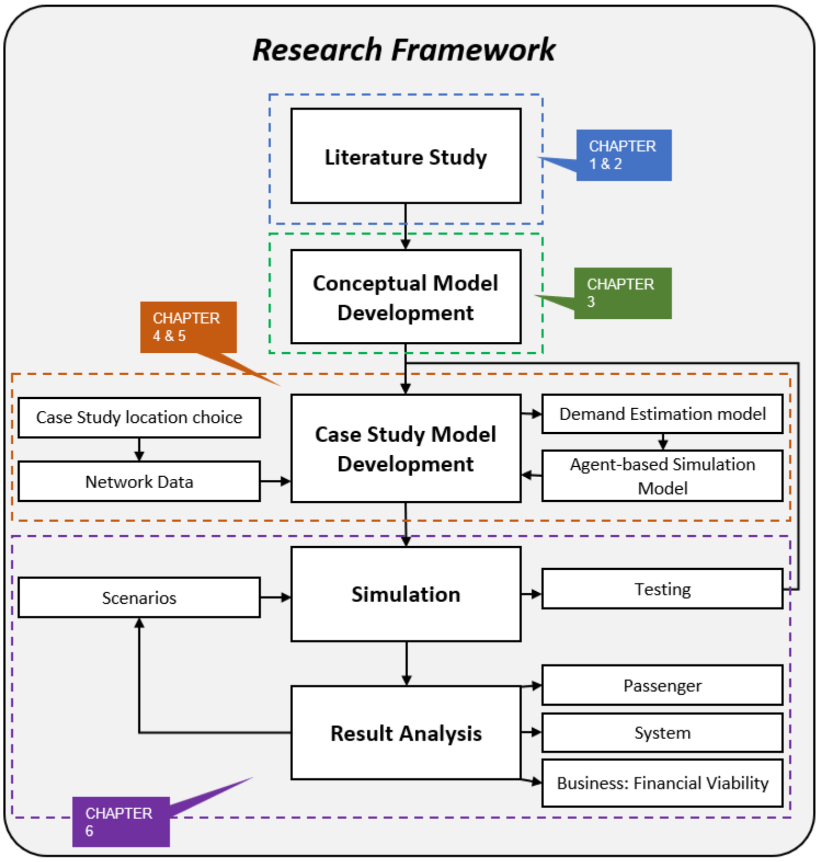

Figure 1.2: Research Methodology Framework

1.6. Thesis Reading Guide

The report furthermore consists of 6 Chapters. Chapter 2 describes the state of the art in the field of autonomous carsharing, carsharing modeling and financial viability analyses in order to conclude this Chapter with a research gap. This clarifies the recent related theoretical findings in literature, which are used further on in the research. Chapter 3 gives a description of the conceptual model. Both the urban transport system and the integration of the AMoD-service in this system is described including the behavior of the passengers and vehicles and how they interact within the transport system. Moreover, the model requirements are described which function as a framework that has to be filled by the eventual simulation model. Chapter 4 elaborates on the choice of the case study, where the conceptual model is applied to a real-life case. The specific case study characteristics including the current and future situation are described. Chapter 5 gives a detailed description of the development of the simulation model. The aim is to make the reader understand how the model is constructed and works. Chapter 6 shows the analysis of the results of the simulation from multiple perspectives: passenger, system, energy, vehicle and business. In this analysis, the scenarios are compared and assessed. Finally, a description of the preferred scenario from an operators perspective is given. Chapter 7 describes the discussion part, where the interpretation of the results and the eventual contribution is described in a broader context. The final part will contain recommendations for further research. So in the end, this report is a description of the theory, methods, results and conclusions that address the research questions presented in this Chapter.

2
State of the Art

As Chapter 1 showed that both vehicle automation and carsharing have much potential when implementing these innovative technologies to improve the first- and last-mile of public transport trips, it is important to gain enough knowledge and theoretical background on the introduced concepts to be able to answer the research questions. This Chapter will give an overview of the state of the art of the main aspects of this research and will be concluded with the main research gap which is about the analysis of the financial viability of autonomous carsharing services.

2.1. Public Transport in urban areas

Public transportation (PT) plays a major role in urban transportation because it has numerous potential benefits: it transports large numbers of passengers efficiently, it reduces the negative effects of transport in cities, it leads to business growth, it increases accessibility and it improves public health [2]. However, as most of the urban areas are dominated by privately owned vehicles, they suffer from congestion. To guarantee future urban mobility, a shift from privately owned vehicle dominated cities to cities dominated by public transport is needed. One of the concepts that currently gets a lot of attention in research is the Mobility as a Service (MaaS) concept, which aspires to integrate all modes of transportation to one mobility service where these modes are seamlessly connected in a multimodal network providing smooth door-to-door services [33]. Hietanen et al. describe MaaS as a mobility distribution model that delivers users' transport needs through a single interface of a service provider, where it combines modes of transport to a tailored mobility package, like a monthly paid mobile phone contract [34].

Automated vehicles can have various levels of automation, as is stated in the SAE levels introduced by the US National Highway Traffic Safety Administration (NHTSA) [14]. Level 4 and 5 automated vehicles are able to drive autonomously without the need for a fallback ready human driver. The difference between level 4 and level 5 is that vehicles of level 4 are geographically constrained to a particular area and level 5 vehicles are able to drive at every location. However, the developing process towards these high levels of automation implies significant developments and breakthroughs in software engineering and signal processing [35].

Zooming in on Maas, a lot of research is currently being done on automated vehicles and the application of these automated vehicles in future transportation systems. This is due to the promising potential benefits resulting from these researches. However, in most researches, the relationship between AV and PT has not been taken into account. A few studies offer limited insight into the relationship between AV and PT and mostly conclude that AV is a competitor to PT [36], [30]. Researches pointing at the complementary relation of AV with PT are scarce, as the AV services being researched mostly substitute another mode of transport. It is not the objective of these researches to gain insight into the complementary opportunities of AV regarding PT.

However, there is a substantial number of researches being carried out to investigate the impacts of AVs as first- and last-mile solution for public transport trips. Passengers in urban transport systems are choosing their destination, mode and route based on certain choice behavior. In the mode choice of passengers in urban transport systems, public transport is one of the options. To predict these choices, a lot of research aims at developing choice models. In these choice models, the probability that a passenger will choose for a certain mode is given by the utility. The higher the utility of an alternative, the higher the probability that a passenger will choose for this alternative. As for the alternative public transport, a substantial dis-utility is caused by the fact that there is a first- and last-mile trip is involved in a public transport trip[11], where passengers have to use a different mode to get to a certain stop or station to continue their trip or to go from a stop to their final destination. Figure 2.1 clarifies the choice alternatives a passenger can choose from when traveling in an urban transport system. When the dis-utility is decreased, the probability that passengers will choose public transport instead of private transport will increase. This increased attractiveness of public transport is one of the main goals of city councils that are facing urban mobility problems.

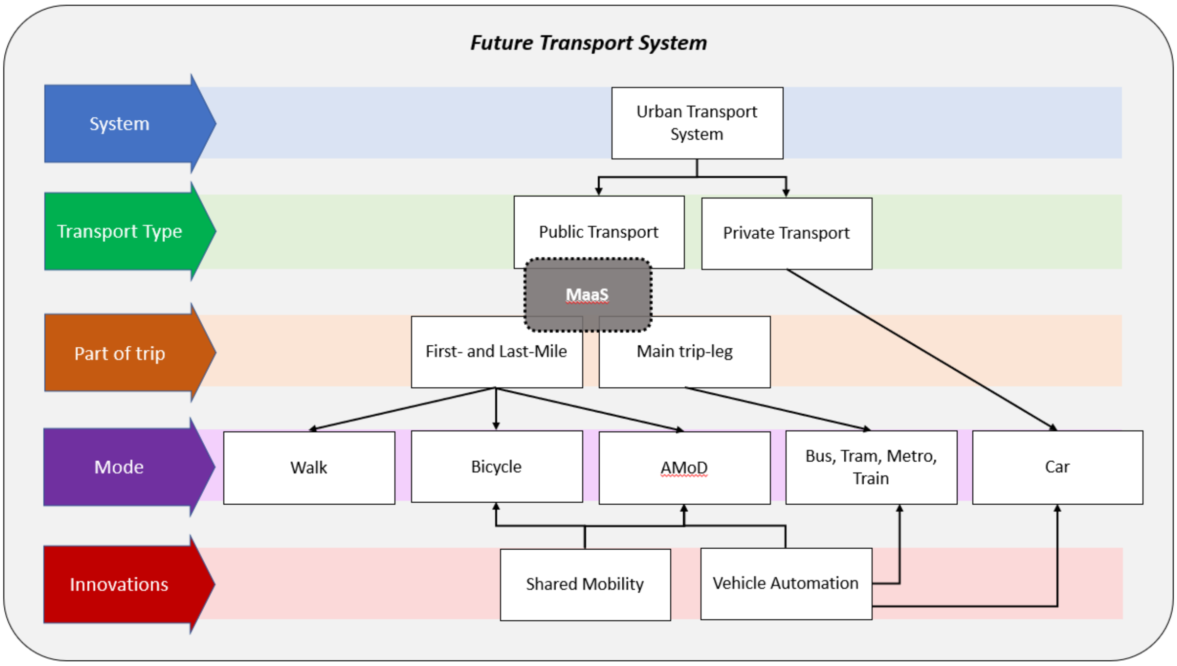

Figure 2.1: Schematic overview of possible future urban transport systems.

Next to city councils, there are more organizational actors involved [30]. The main actors are the AV operator, the PT operator, the public authority, the AV producer and the consumers or passengers. They all have a role in the performance of the system. The operators and producers function as the supply side, and the consumers or passengers function as the demand side of the system. It is yet uncertain if the AV operator will be a different authority than the PT operator or the same party. This depends on the competitive position of the AV system. Investigating the competitiveness and viability of AV services is a key to determine which actors will be attracted as an operator of the AV system.

2.2. Carsharing

In the transition from private mobility to shared service based mobility, a concept that next to automated driving is recently getting a growing attention in research is carsharing. Carsharing is the opposite of private ownership of a car. Through carsharing, individuals can gain the benefits of private vehicle use without the cost and burdens of ownership, e.g. fuel, maintenance and insurance [26]. Carsharing is developing in two main types: **(1)** round-trip carsharing in which users must return the car to the point of departure, and **(2)** one-way carsharing, where users are allowed to drop off the car at the point of destination, which is different from the point of departure [5], [37]. The one-way carsharing systems are categorized in station-based, free-floating and SAVs. In station-based carsharing systems, the car has to be picked up from the initial station and returned to a drop-off station. In Free-floating carsharing systems, pick-up and drop-off locations are not constrained by stations. SAV services hold the same regulations from drop-off and pick-up but are not constrained by availability because they can be ordered by using a mobile phone application connected to GPS and the internet. An overview of the types of carsharing systems is given in Table 2.1. When integrating the carsharing concepts with public transportation, the “last mile problem” [11] can be addressed. However, despite all the potential benefits of the Autonomous Mobility on-Demand (AMOD) systems, their impacts on travel demand on the short and long term are not yet certain.

Table 2.1: Types of Carsharing Systems. Source: [5]

	Carsharing types			
	Round-trip	***One-way***		
		Station-based	***Free-floating***	***SAVs***
Pick-up	Specified points	Any rental station	Anywhere available	Anywhere
Drop-off	Same point	Any station	Anywhere authorized	Anywhere
Park space problem	No	Yes	No/Yes	No
Rebalancing problem	No	Yes	Yes	No

2.2.1. Existing carsharing services

The first carsharing program can be traced back to 1948 in Zurich, Switzerland [38]. Later from 1980s on, more carsharing programs were launched in Europe. In the US, the concept of shared vehicles only started to become popular in the 1990s. Since then, the industry has grown worldwide to countries as Japan and Singapore. In October 2014, the total number of carsharing members worldwide was estimated to be around 4.8 million [26]. Carsharing services show to have a positive impact on urban mobility. Preliminary research [39] shows that in Northern America there is a substantial decrease of car-ownership in cities where carsharing is deployed. Moreover, a decrease of the VKT and emissions per vehicle is visible for these cases. This shows that cars are used more efficiently.

Carsharing services that are currently operational are operating following various pricing strategies. Most of the carsharing services handle fares per unit of time or unit of distance. Car2go in Amsterdam handles a price of € 0,31 per minute. Moreover, following the economies of scale theory, car2go offers discounted packages for longer distances or for a more extended period of time. A 2-hour package with a maximum of 50 km costs € 17,90 and a 24-hour package with a maximum of 90 km costs € 79,-. Another carsharing service provider is Zipcar, which has a different pricing strategy. Using a vehicle of Zipcar involves costs for application of $25 which results in a Zipcar-membership. Once approved, passengers receive a membership card (Zipcard) which they can use to unlock the car by tapping it on the windshield reader. Zipcar offers various packages which they call membership plans, varying in the type of user and the user pattern. The price of the most basic package which is called occasional driving plan is equal to $25 application fee and $70 annual fee with hourly rates depending on the type of car and city ranging from $8 to $12. During weekends, the hourly rate is lower and ranges between $7 and $11. It is also possible to rent a car for an entire day which involves costs between $60 to $90, which on an hourly basis is cheaper in the end following economies of scale. More elaborate strategic pricing schemes use pricing for managing vehicle stocks (Jorge et al., 2015), e.g. price incentives for grouping people if they are traveling from a station with a shortage of vehicles and ungrouping them otherwise.

2.3. Autonomous Vehicles and Carsharing

Currently, research on autonomous vehicles (AVs) is a very active field. Research that has been done often shows the promising opportunities of AVs in terms of their main benefits: **(i)** increased safety, **(ii)** increased convenience and productivity, **(iii)** increased traffic efficiency and less congestion, **(iv)** reduced environmental impact [40]. One other major benefit is that AVs can be used as an enabling technology for widespread carsharing. Autonomous vehicles are able to re-balance themselves, autonomously recharge their batteries and coordinate their actions system-wide to optimize throughput. These benefits solve current carsharing fleet balancing problems and provide a similar level of convenience as private cars.

2.3.1. Opportunities of autonomous carsharing

It is expected that the share of privately owned vehicles compared to shared vehicles will decrease gradually over time [18], although there exists large uncertainty on how rapidly this shift will take place. However, AMOD systems are regarded in literature as a promising solution to enhance urban accessibility, regarding the increasing problems related to congestion in urban areas [41], [42], [43], [5]. Milakis et al. [44] introduced the ripple model which describes these sequential implications over time of driving automation on its environment. Moreover, implementing SAV services as Demand Responsive Transport (DRT) in urban areas can provide future Mobility as a Service (MaaS) schemes with the collectiveness needed in urban networks [15].

2.3.2. Challenges regarding autonomous carsharing

As AV technology is still developing and no relevant comparable pilot version has been implemented and tested yet, various uncertainties temper the excitement about the possibilities that autonomous carsharing services entail. One of the uncertainties is what form of operation will attract the most passengers. First- and last mile operation where autonomous vehicles are involved show that they can be complementary to public transport, while SAV services in combination with Dynamic Ride Sharing form a competitor for public transport [45]. On top of that, private transportation is being challenged by SAV's as well [19] which might lead us from vehicles as an owned product to an on-demand service. Fagnant & Kockelman (2015) [16] concluded that 1 SAV would replace 12 conventional vehicles. However, previous research shows that the total amount of vehicle kilometers traveled (VKT) is likely to increase due to unoccupied trips of SAV's, although this is not appropriately modeled in the researches that emphasize the potential benefits. The increase of VKT could lead to congestion, which might negatively influence the environment because of pollution and the higher required amount of energy. Moreover, different carsharing systems have distinct impacts on parking. The one-way carsharing systems that are station based require parking places at stations while free-floating carsharing systems are more flexible in their choice of parking spot [5].

One other major challenge that arises when AMoD systems are implemented on a large scale is the logistics of the fleet to effectively manage the throughput of a large number of vehicles through an urban area [40]. Until now, simulation studies are often neglecting salient but fundamental features for the key performance metrics like, e.g. the interference of vehicles with humans, which might lead to a disruption of the conventional system.

Studies simulating SAV systems often allow for on-demand carpooling, which is called dynamic ridesharing (DRS). This concept allows travelers to share their ride when their travel paths show significant overlap or similarities, also when the passengers' origins or destinations are not exactly equal. This often involves inconvenience for passengers as there is a possibility for a detour or less privacy. The more DRS is used, the higher the efficiency of car use, but the higher is also the dis-utility to choose for the AMoD service [45]. This is a design trade-off where a certain threshold value must be used to account for the maximum detour a passenger will accept.

2.4. Autonomous last-mile transport pilots

Several pilots where autonomous vehicle technology is involved have been exploited in The Netherlands before to be able to evaluate the revealed practical experiences of these services. It is the objective to learn from these pilots and use this knowledge to apply to the implementation of self-driving services in the future. In [46], the 3 main pilot applications of self-driving vehicle services are being elaborated on and are named: Rivium Parkshuttle at Capelle aan den IJssel, WEpod at Ede-Wageningen and the Easymile at Appelscha. The WEpod and Easymile projects use existing infrastructure which is being shared with other modes while the Rivium Parkshuttle uses its own dedicated infrastructure. The WEpod uses public roads as infrastructure and shares infrastructure with other modes as, e.g. cars, bicycles and pedestrians. The Easymile uses bike lanes as infrastructure and therefore only interacts with bikes.

Because the Rivium Parkshuttle at this moment only drives at dedicated infrastructure, the flow of the vehicle is continuous and reliable. Moreover, the operator is able to control the vehicle from a distance by the use of cameras. The main disadvantage of the WEpod and the Easymile is that these vehicles have to come to a standstill because of detected objects on the road relatively often, which affects the level of service negatively. Moreover, these services still need a steward that takes place inside the vehicle during the trip. However, these challenges result in points of attention for further research and the ability to learn from these pilots is therefore higher than the Rivium Parkshuttle.

2.5. Modeling autonomous carsharing

Research on the impacts of autonomous carsharing systems often involves using a model, that is able to use scenarios as input and produces predicted results in order to compare these scenarios. There are various modeling paradigms available that can be applied to the modeling of one-way carsharing systems and AMoD systems. Per research, different research characteristics like data availability, expected accuracy and study scale form the basis of the model approach choice.

2.5.1. One-way carsharing systems

To estimate the travel demand for one-way carsharing systems, various approaches can be applied. Generally three categories of approaches can be recognized: **(i)** survey and analysis, **(ii)** discrete choice modeling, **(iii)** agent-based simulation [5]. The first category accounts for the least precise methods and is designed to produce rough demand estimations. The second category comprises choice behavior models which are widely used in travel demand models, determining most commonly the mode choice behavior of passengers. The more sophisticated with higher spatial resolution and accuracy are the agent-based microscopic simulation models in which travel demand emerges from the interaction of the agents: passenger, vehicle, arc and node. The behavior of each vehicle and passenger can be continuously modeled and the approach allows for including dynamic decision processing incorporating a dynamic mode-choice function of individual travelers [47]. To investigate the impacts of the interaction of agents requires a level of detail much greater than what is offered by the modeling tools of category 1 and 2. Therefore category 3 models are the most applicable ones considering carsharing systems.

Modeling one-way carsharing systems has to deal with three main challenges: **(i)** data availability, **(ii)** computation time, **(iii)** calibration and validation [5]. Most of the modeled systems are not yet used in practice, which requires issue-specific Stated Preference (SP) data. The effort to collect this data, which often is extremely fine-grained spatial information, is substantial when we want to model the mode choices of one individual for a short-distance trip. These fine-grained models with large choice sets, require a high computation time, depending on the traffic assignment method used. Because autonomous one-way carsharing is such an innovative concept, no real-life data or revealed preference data can be collected, which is makes it difficult to validate the model, which increases the uncertainty of these simulations. There is a clear predominance of studies about balancing vehicle stocks in one-way systems in the studies carried out after 2000, and the work on travel demand estimation is limited [37]. Including autonomous vehicles in these studies as AMoD systems, leads to a dominance of fleet size and financial viability related studies. These are described in Section 2.6.

2.5.2. AMoD

Regarding modeling of AMoD systems, the problem of fleet sizing is an actively researched topic [41]. In general, the fleet size of AMoD systems depends on six factors: **(i)** the size and configuration of operating network, **(ii)** the demand for the service, **(iii)** the level of service that a service provider wants to achieve, **(iv)** the routing policy, **(v)** the rebalancing policy and **(vi)** the parking facility dimensions. Most of the factors are being optimized in research. However, in real life applications, additional boundary conditions play a role which makes systems unable to be optimized. The most common approaches for facility location optimization are: minimizing travel costs and maximizing coverage. In the paper of Marczuk et al. (2015) [41], it is shown that the maximizing coverage approach results in better performance in terms of minimizing the waiting time of passengers.

Pavone et al. (2015) [48] addressed AMoD systems along three dimensions: modeling, control and economic. In the modeling dimension he applied the spatial queueing model to AMoD systems and compared the lumped control approach and the distributed control approach. The lumped approach assumed that passengers arrive at a fixed set of locations within a given environment and in the distributed approach the number of station represents a continuum, which results in the fact that passengers can stop at any location along a route [49]. Consequently, these approaches are applied at the case studies New York City and Singapore. For these case studies, a general financial analysis is carried out which for both cases concluded that it is much more affordable to access mobility in AMoD systems compared to traditional privately owned vehicle-based mobility systems.

As was mentioned earlier, the third category of modeling approaches applied to carsharing systems consists of agent-based modeling. In the paper of Dia 2017 [47], an agent-based simulation tool is used called the Commuter-model and is applied to the city of Melbourne. The results of this research show that incorporating shared driverless-cars can significantly reduce the total number of vehicles required to meet the transport demand. However, the VKT is likely to increase. A shortcoming of this research is the demand forecasting. The demand used in this study is based on SP surveys that are calibrated and validated to a limited extent.

Shen et al. [30] developed an agent-based simulation model of autonomous first- and last-mile mobility on-demand service for public transport. However, in this model, a fixed modal split was assumed and the choice behavior of passengers was not modeled. Therefore, this model is called a supply-side model. Also, the model does not take into account a scenario where there is no automatic relocation when there is no demand. Moreover, this paper regards the AMoD service as a competitor for only existing bus services. To investigate the impacts on the use of bus services in Singapore, extreme scenarios that determine the demand are used, either everyone shares their vehicle or nobody shares their vehicle. These demand scenarios are somewhat unrealistic, but do exploratory show the effects of large scale radical change of urban mobility systems. Logically, one of the recommendations for further research is to use a multimodal demand model based on consumer preferences of the population where the case study is conducted. This would lead to a model that is capable of predicting the relationship between demand and supply for a mobility system where AMoD services are implemented.

2.6. Research Gap

The main research gap resulting from the state of the art research on autonomous first- and last-mile carsharing services is the financial viability of these services. As the autonomous carsharing services are likely to be operated by a third party regarding the integration with public transport, it is important to attract the industry to innovative concepts like AMoD services. However, as the investment in these innovative services involves risks, transportation service operators only invest when the operations are financially viable. At first, this Section provides comprehensive insight into the scientific background of the financial aspects of carsharing services and consecutively it will describe the financial viability of AMoD services specifically from an operators perspective.

2.6.1. Financial aspects of carsharing services

There are a few studies that estimated the costs of AMoD services, but only focused on limited operational scenarios and did not incorporate a demand estimation model that produces the demand data used in an agent-based simulation model. Moreover, there is no research yet that analyzed the financial viability of AMoD services as a first-and last-mile solution for public transport with this demand- and supply-side modeling approach. To represent the competitiveness of a service, various indicators regarding costs and revenues can be used. Recent financial viability studies of mobility services [24], [40], [49] show different approaches. In the research of [24], the costs of production are the sum of costs aspects, which consist of fixed costs, variable costs, overhead costs, operations costs and fares. Moreover, the total vehicle- and passenger kilometers are used in combination with the costs aspects to express the financial viability in several indicators, e.g. costs per vehicle kilometer and price per passenger kilometer.

In the paper of Spieser, 2014 [40] a minimum fleet size optimization problem for an AMoD system applied as a case study for Singapore was used to compute estimates of the fleet sizes required to reach a certain performance level. The performance level was determined by the waiting times of the passengers. As for Singapore, Spieser estimated a minimum fleet size which came down to one shared car for every 12,3 households, given the assumption that the total current taxi demand shifts to AMoD demand. Moreover, the results clearly show that the vehicle availability increases and the waiting time decreases for an increasing fleet size. The interesting thing is that these effects are different for different demand patterns. During peak hours, increasing the fleet size has less effect than during an average demand period. During fleet sizing, the operator has to take into consideration that there is a point where investment costs made by increasing the fleet size, do not anymore outweigh the benefits resulting from that increasing fleet size.

The financial analysis in the paper of Spieser, 2014 [40] makes a comparison between a system that includes human-driven vehicles and a system that includes autonomously driven vehicles. The total costs of mobility (TMC) are defined as the sum of the cost of service (COS) and the value of time (VOT). The COS is defined as the sum of all explicit costs associated with accessing mobility and includes aspects like purchase, service, parking, insurance and fuel. The VOT is the monetary valuation of the total time invested in mobility-related activities 2.1.

$$TMC = COS + VOT \tag{2.1}$$

The VOT for the autonomous system is found to be significantly lower than the VOT of the non-autonomous system. This is mainly a result of the fact that passengers do not have to search for a parking spot an do not have to walk far to the vehicle. Moreover, during the trip, they can conduct secondary activities like working or leisure activities. According to recent research, the decrease in value of time is the largest for commuter trips because passengers are more willing to substitute their traveling time for working time than substituting traveling time for leisure time [50].

In the paper of Zhang [49], a case study has been performed for the cities of New York (Manhattan) and Singapore. Congestion effects are not being taken into account. The evaluation of case these case studies compares the costs of mobility (TMC) of an AMoD system with a traditional model based on private vehicle ownership. A similar approach is used in the financial analysis as earlier presented by Spieser 2014 [40].

As for the Manhattan case study, 3 demand scenarios are considered: peak-demand (7-8 pm), low demand (4-5am), average demand (4-5pm). For each demand scenario, the vehicle availability is calculated by solving the linear program presented earlier in the paper. Vehicle availability is related to fleet size. A larger fleet results in a more considerable vehicle availability and a lower average waiting time. Three sets of simulations are performed for the pre-specified fleet sizes: 8000, 7000 and 6000. The output shows the average customer waiting time over the course of the day for all the 3 fleet sizes.

The Singapore case study has been performed as a thought experiment to investigate the potential benefits of an AMoD solution replacing the entire transportation infrastructure and addresses three main problems: minimum fleet size estimation, fleet size to reach an acceptable quality level of service and the financial assessment of the AMoD service. Again, just like the research done by Spieser [40], an estimated number of 12,3 households per shared car is found. Zhang emphasizes the fact that this is a lower bound since the waiting times would be unacceptably high for this fleet size. So to solve the second main problem, the fleet size needed to be increased. This case study considers 2 demand scenarios: peak demand (7-8am) and average demand (2-3pm). Again the fleet sizes have been determined using a certain level of availability, followed by an estimation of the waiting times for these fleet sizes.

The financial analysis of the AMoD system results in the cost of service (COS) and the cost of time (COT), which is related to VoT, for a reference situation with private human-driven vehicles (PHDV) and for a future situation which includes a fleet of AMoD vehicles. This involves several assumptions. The COS of the AMoD situation is being assumed lower than for the PHDV situation which makes mobility more affordable in the AMoD situation than the PHDV situation. Using the appropriate Value of Travel Time Savings (VTTS) based on actual driving patterns gives a COT for the PHDV situation which is almost three times as high as the COT in the AMoD situation. This is mainly due to the pricing and the quality of service of the AMoD. The AMoD service provides the opportunity for passengers to sit comfortably while being able to do perform working- or relaxing-activities and due to less walking time from vehicle to origin and destination and no time is spend searching for a parking spot. The result of the financial analysis shows that the AMoD system leads to a TMC which is almost half of the TMC of traditional transportation systems.

2.6.2. Financial viability from Operator's perspective

In the paper of Zhang [49] and Spieser [40], costs related to the VoT are taken into account. These costs are relevant from a passenger perspective, but are no direct costs for the operator. As this research is about the operational aspects of AMoD systems, the financial viability analysis will only take into account the costs from an operator perspective, which are the direct costs of service (COS). The costs will be estimated for a typical day, where the vehicle purchase costs and the charging infrastructure purchase costs are taken into account by discounting the total investment costs as depreciation costs assuming a certain lifespan. Within this estimation of investments costs, a distinction is made between multiple types of chargers which have been used before in financial analyses of electric vehicle (EV) systems [51]. The costs of charging facilities are assumed to be accounted for by the AMoD operator, which is in line with examples from previous research where charging facilities of electric buses are being financed by the bus service operators [52]. The other daily costs aspects are energy costs and maintenance costs, which are directly proportional to the number of kilometers a vehicle drives. Moreover, wage expenses are taken into account by assuming a certain team of people that operates the system and provides additional service when required.

Next to the costs, the revenues of the AMoD system have to be estimated, in order to assess the financial viability of the AMoD system. These revenues consist of passenger revenues due to fares, which are directly proportional to the passenger demand because the fare is a fixed amount per time unit. Subsidies are not taken into account, because it is highly uncertain if the future political situation is able and willing to facilitate certain subsidies.

3
AMoD System & Conceptual Simulation Model

Concluding from Chapter 2, automated carsharing services could improve the attractiveness of public transport when used as an alternative for first- and last-mile transport in urban areas. To be able to investigate the impacts of such systems, one can develop a model. This model represents a system in which an interaction takes place between the transportation-demand and -supply. In order to model this interaction of the not yet existing AMoD services inside an existing urban transport system, we have to understand how the urban transport system works. Therefore, this Chapter describes the characteristics and requirements of the conceptual model that represents an urban transportation system. Section 3.2 describes multimodal urban transport systems, including AMoD services, where passengers interact with the network and AMoD services according to certain choice behavior. This Section also includes a description of the AMoD vehicle behavior. In Section 3.1, the conceptual model is described, including a more detailed description of the content of the model. This includes a description of the demand-side and the supply-side of the model. The Chapter ends with Section 3.3 where the model requirements are described, which functions as a framework for the case study simulation-model development.

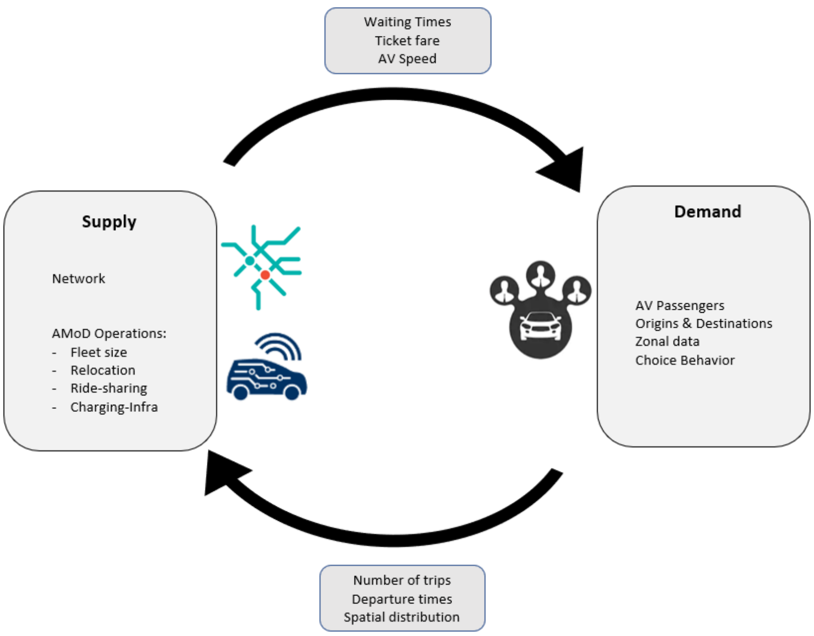

Figure 3.1: Conceptual interaction between Transportation-demand and -supply

3.1. AMoD System Description

In this Section, the urban transport system will be described for the situation in which AMoD services are functioning as a first- and last-mile mode for public transport. First, a description will be given of the vehicle specific characteristics and afterwards, the vehicle behavior will be described based on Figure 3.2. Finally, the passenger behavior will be described based on Figure 3.3.

3.1.1. Vehicle Characteristics

The vehicles that will be used for the AMoD service in this conceptual model will have similar characteristics as the Twizy of Renault [53]. The Twizy is an electric car which has a capacity equal to 2 passengers, which are seated behind each other. The vehicle is part of Renault's Zero Emission Program [54] and is therefore fully electric with a maximum range of around 100 km. Because of its compact design with a width of 1,19 m and a length of 2,32 m and its relatively short range, the vehicle is ideally designed for usage in urban areas. Combining this with the recent carsharing initiatives and contributions to the development of autonomous vehicles of Renault, the Twizy is appropriate for the AMoD service. As this research will not focus on the vehicle technology itself but only on the operation of the service, only the characteristics required in the AMoD model will be described here.

The speed of the vehicle has a maximum of 45 km/h. However, in dense urban areas, the eventual average speed of cars within this area will be around 30 km/h. Therefore, an average effective speed of 30 km/h will be assumed in this model. Moreover, because the Twizy is fully electric, assumptions on the battery capacity and power consumption are important to mention. The Renault Twizy contains a Lithium-Ion battery which has a battery storage capacity of 6.1 kWh. The range of the vehicle lies around 100 km. The time required to charge the battery takes up to 3.0 hours, depending on the type of charger used. [53].

The level of automation of the vehicles that will be used in the AMoD system can be characterized as SAE level 4 [14], because the vehicles are fully autonomous and the driver does not need to be fallback-ready. Moreover, the Operational Design Domain (ODD) of the vehicle is bounded geographically because the vehicles can only operate within the service area.

3.1.2. Vehicle Behavior

The station-based one-way AMoD services that will be implemented in the existing urban transport system are used to function as first- and last-mile public transport trip leg solution. The vehicles are part of the fleet and are based in a depot which is located at a station. This is where all the vehicles start their operation. There are two operations possible: first-mile operation and last-mile operation. The first-mile operation transports passengers from their origin to a station where they will transfer to a different mode. The last-mile operation transports passengers from the station they arrived at, using a different mode, to their final destination. The service area is equal to a circle with a radius of 3 km which has the station as the center point. So the service runs between origins/destinations and stations. These stations consequently will function as a hub which function as centers for the operational area.

The AMoD vehicles will drive on existing infrastructure where they share the road with several other existing modes of traffic: cars, buses, motorbikes and scooters. The advantage of this is that the infrastructure and network adaptations required are minimized which result in lower investment costs. However, the interaction of autonomous vehicles with other modes of traffic includes uncertainties regarding technology and safety, because these vehicles are not yet widely deployed. Because the autonomous vehicles have similar characteristics as cars, the interaction of autonomous vehicles with other modes will also be assumed similar to cars in this model.

For the first-mile operation, after unloading the passenger(s), the vehicle will automatically be ready to serve the next demanding passenger at the station. The vehicle will serve the demanding passengers based on the First In First Out (FIFO) principle. If the embarking passenger is willing to share his ride with another passenger and they do not have an equal destination location, the ride will only be shared if and only if the detour resulting from the destination difference is smaller than the maximum detour value. The first requesting passenger sets the primary origin where the vehicle will move to first. After the passenger embarked the vehicle, the vehicle moves to either the destination of the passenger inside the vehicle or the origin of a second passenger, depending on the detour that is required to pick-up this second passenger. When the number of passengers inside the vehicle is equal to the capacity and the vehicle is therefore fully occupied, or there is no demand left to serve within the maximum detour boundaries, the vehicle will move to the destination, which is the station.

For the last-mile operation holds that when the final destination is reached and the passenger has left the vehicle, this vehicle can find its way back to the station autonomously if there is no demand left to serve. This involves an unoccupied trip. However, if at the final destination location a first-mile operation request is received by the vehicle which origin lies within the service area, then the vehicle will pick-up the demanding passenger. In case of no demand left, the vehicle will become available for requests and moves to the station. If after some time, a last-mile request is received by the vehicle, the first passenger enters the vehicle. If there is a second requesting passenger, which has a destination that leads to a detour that is within the detour boundaries, the second passenger enters the vehicle as well. Consequently, the vehicle will move to the nearest destination first, in order to minimize the detour. After the first destination is reached, the vehicle moves to the second destination. In Chapter 5, there will be elaborated more on the specific numbers of the detour constraints.

Because the vehicle will be electrically driven, when dropping a passenger at its destination, the vehicle will always check if the battery is still sufficiently loaded to perform the required trips for the consecutive operation. If the battery is lower than a particular threshold value, the vehicle needs to return to the depot as charging of the vehicles only happens at the depot. When the battery of the vehicle is fully charged, it will become available for a request again.

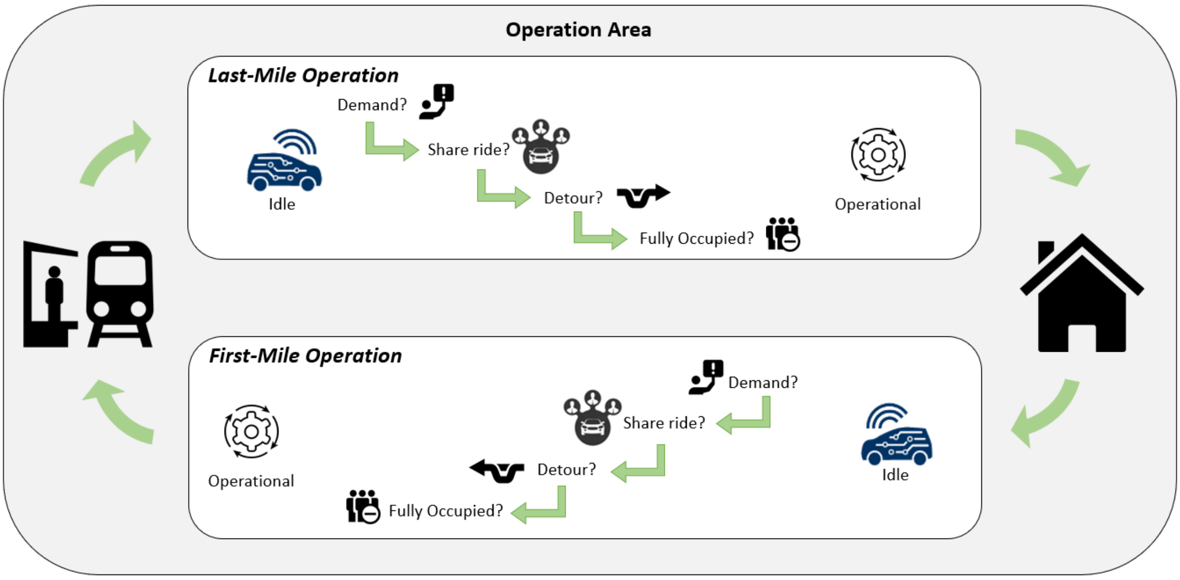

Figure 3.2: Schematic overview of the AMoD vehicle behavior

If the additional travel time or distance due to the detour is exceeding the maximum detour boundaries, the ride will not be shared and only 1 passenger will be transported. A schematic overview of the first- and last-mile operations of the AMoD vehicle is shown in Figure 3.2. In this Figure, the main sequential checks are shown: checking for demand within the service area, checking the willingness to share a ride, checking the possibility for ridesharing using the maximum detour, checking if the vehicle is fully occupied. After these checks, the vehicle will start moving to its primary destination, followed by its secondary destination.

3.1.3. Passenger Behavior

A vital characteristic of the AMoD system is that it is a demand driven system and therefore is only operational if triggered by demand from passengers. This makes the system more efficient than existing public transport lines which run according to a fixed schedule or frequency. At the start time of the model, the passenger arrives at its origin location. At the departure time of the passenger, it requests a vehicle by using a mobile phone application, which is connected to the AMoD system. The request is sent to the vehicle by this application. The time a request from a passenger is received by the vehicle, the system will feedback the information of the assigned vehicle to the passenger. If there is a vehicle available, the closest vehicle available will be assigned to the requesting passenger. If there is no vehicle found, the passenger will retry. After the maximum number of retry attempts, the passenger will give up and leave the system, choosing for a different mode of transport. In case when there is a vehicle found, the passenger waits for the assigned vehicle to arrive at its origin. When the vehicle arrives, the passenger will embark the vehicle and will be transported to its destination, depending on the remaining demand and the detours required to serve this demand.

Looking at Figure 3.3, for last-mile demand, when the passenger arrives at the station, it follows the consequential steps. First, it requests a vehicle and then it waits and depending on the waiting time it embarks the vehicle and is being transported to its final destination. As for the first-mile demand, the passenger will terminate its activity and requests a vehicle, waits and will be moved to the station.

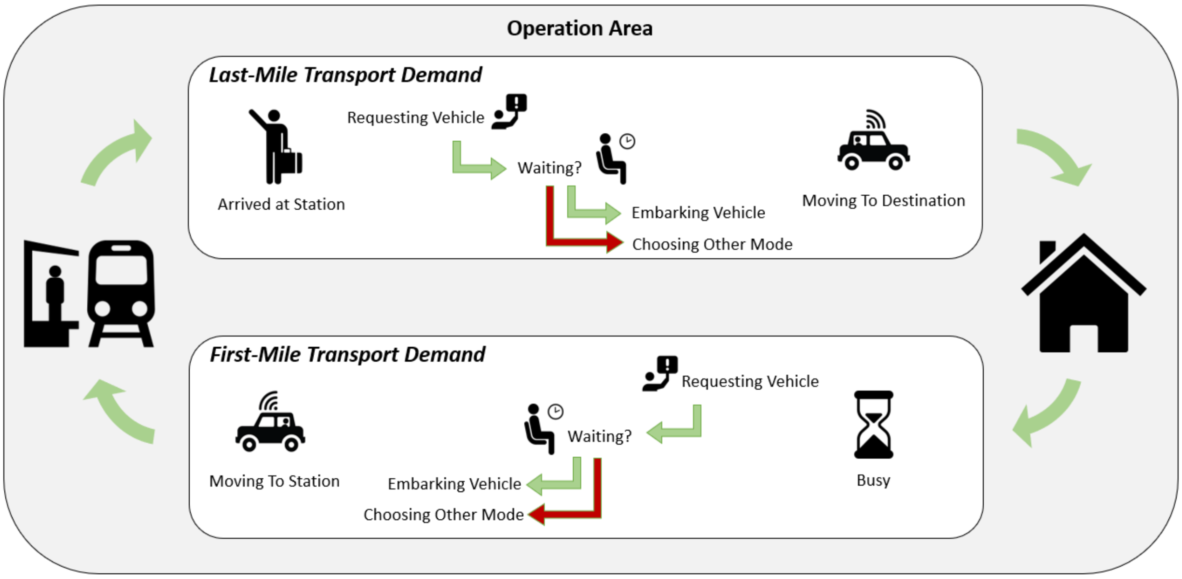

Figure 3.3: Schematic overview of the passenger behavior in the AMoD system

3.2. Conceptual Model

This section describes the concept of the simulation model of the AMoD system described in Section 3.1 and will include the general modeling approach and the model requirements. This description functions as the basis for the further development of the simulation model, which is more elaborated on in Chapter 5.

3.2.1. Transport system: 4-step model approach

The behavior of urban transportation systems can be described by a transportation model. A conceptual version of this model would be a system, where the relationship between passengers, infrastructure and modes of transport forms the center part, including assumptions and simplifications. Input variables feed the system, and its performance can be evaluated using the output variables when these are being related to the objective. In Figure 3.4, a schematic overview of this conceptual model is given. The conceptual model consists of the interaction of the passengers and the vehicles and describes the assignment of vehicles to passengers as well as the routing of the vehicles according to the behavior of both populations.

The transportation system is usually described by the 4-steps model which consists of the following sequential choices a traveler makes: (1) Trip Generation, (2) Trip Distribution, (3) Mode choice and (4) Network Assignment. During the Trip Generation step, the zonal input data generates trip productions and attractions per location, which are departures and arrivals. The network data is used to generate skim matrices which provide travel distances, times or costs between zones. Both the production and attraction as well as the skim matrices are input for the trip distribution model, which estimates an Origin-Destination (OD) matrix containing the number of trips between specified locations. In the third step, these numbers are distributed over the possible modes of transport based on passenger choice behavior. This results in mode-specific OD-matrices. As for the AMoD service, this determines the distribution of the demand. Eventually, these trip numbers are assigned to a network, which results in certain traffic loads on road stretches.

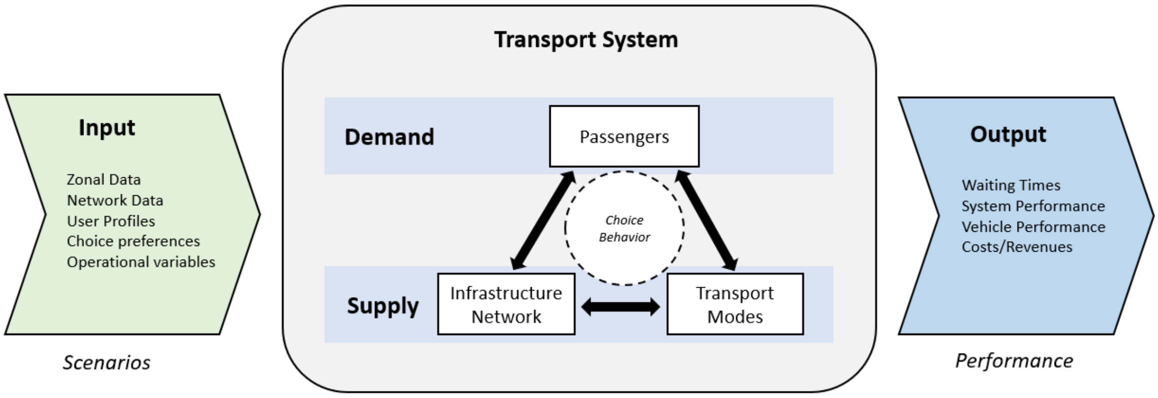

Figure 3.4: Conceptual overview of a transport system

3.2.2. Choice Behavior

According to Figure 3.4, the choice behavior of passengers is a crucial element in the estimation of the mode-specific OD-matrices. Therefore one needs to understand how the choice behavior can be defined and which main factors play a role. Because the mode-specific demand for AMoD is required, particularly mode choice is essential to highlight. In a multimodal transport system, a passenger has different choice alternatives in its mode choice for a trip from a certain origin to a destination. Each alternative can be characterized by attributes. For the AMoD service, attributes that play an essential role in the mode choice are: travel time, which is determined by the vehicle speed and the distance to travel, fares, which is determined by the operator and waiting time, which is determined by the level of service. The probability of an alternative to be chosen by a passenger is defined as the utility, determined by its utility function. The travel time, fare and waiting time are negatively influencing the utility of the AMoD system as an increase of these values will reduce the attractiveness of the AMoD system.

3.3. Model Requirements

In this Section, the conceptual model is described more in detail and focuses on the relationships of the inputs and outputs, which can be defined as the model requirements. This includes a further description of the Demand- and Supply-side of the conceptual model. Finally, the Control Interface which links these two sides will be described.

3.3.1. Objectives

The objective of the conceptual model is to define the interaction between the demand and the supply, which is determined by the interaction between the passengers and the vehicles in the AMoD system. This interaction, which is mainly based on the behavior of the passengers and vehicles as is described in Section 3.1, will eventually play a large role in the system performance. Moreover, the conceptual model requires the ability to allow variations in input variables and has to show the impact of these variations on the system performance according to the behavioral rules of the agents.

3.3.2. Inputs

Network Data

One of the inputs that is required in order to facilitate for the interaction between passengers and vehicles in the conceptual model is the network data, which consists of the coordinates of centroids which are connected by links. The centroids are the center points of the zones involved. The resulting conceptual network is given by a set of centroids, which are all individually connected with the hub at the station by links. Moreover, every centroid is connected to all other centroids directly. This is a virtual network, which uses straight lines between nodes. These lines can be traveled on in both directions in order to facilitate for first- and last-mile transport.

Demand: OD-matrix
According to the passenger behavior, the demand will be determined by the OD-matrix which contains the total number of trips for OD-pairs, which distributes the demand over the centroids of the network. To distribute these trips over the day, a daily distribution will have to be assumed. The demand pattern is important as it determines the performance of the AMoD system. Moreover, passenger related constraints like the maximum waiting time and maximum detour are important inputs, because exceeding these maximums will lead to a lower level of service.

Supply: AV Operator
The vehicle input data determines to a large extent how the vehicles behave within the system. Next to the vehicle specific technological characteristics, also operational variables determine the final system performance. The 3 operational variables determining the AMoD operation characteristics are: relocation strategy, ridesharing strategy and the charging strategy. A large fleet size will lead to a higher level of service, but also to higher costs. Besides, the autonomous relocation of the vehicles will solve the vehicle fleet balancing problems that is experienced by current non-automated carsharing systems. However, this will require a larger depot at the station as the vehicles are clustered and not spread over the operational area. Moreover, this requires empty vehicle kilometers if there is no demand left to serve. Finally, the ability to share a ride will increase the system efficiency, as more passengers can be transported per kilometer and less empty vehicle kilometers are required. However, this requires a higher level of acceptance of passengers as they have to accept a longer travel time due to a detour.

3.3.3. Outputs
Based on the inputs, the model will produce certain outputs. Figure 3.4 shows the main set of output parameters. The parameters can be categorized by 4 perspectives: Passenger, System, Vehicle and Business. The average waiting time and the number of satisfied/unsatisfied passengers determine the level of service from a passenger perspective. The total number of transported passengers and the energy usage determine the system performance. The operational time, vehicle occupancy and the vehicle kilometers traveled determine the performance of the system from a vehicle perspective. The costs and revenues of the AMoD operations, depending on the operational variable inputs, determine the system performance from a business perspective which can be defined as the financial viability of the AMoD services.

3.3.4. Control Interface
The connection of the passengers with the vehicles is facilitated by the control interface. This interface is activated by the passenger demand at the time a passenger sends a request. The control interface checks if there is a vehicle available by checking the control conditions. If the control conditions are satisfied, it searches for the nearest available vehicle. The control conditions consist of the following checks:

- The number of passengers inside the vehicle is lower than the Capacity
- The battery of the vehicle is sufficient to perform the requested trip
- The detour is within margins
- The waiting time of the passenger to be picked up is not exceeded

If all conditions are found to be sufficient, this vehicle will be assigned to the requesting passenger. The vehicle will be triggered by the control interface and moves to the origin of the passenger and afterwards transports the passenger to its destination. The control interface also accounts for the communication between the passenger and the vehicle, in order to provide information to the passenger about the assigned vehicle. Then the passenger knows it has to wait for the vehicle to arrive and also how long it has to wait. Moreover, the control interface also sends information to the passenger if there is no vehicle available found.

3.4. Conclusion

By describing the behavior of the vehicles and passengers, the main characteristics of the AMoD system are defined. Besides, the main inputs needed to eventually obtain the outputs required to be able to assess the AMoD operations from the operator and passenger perspective. Using the network data and the OD-matrices, the Supply model can be developed. The operational variables relocation strategy, ridesharing strategy and charging strategy are the inputs required for the supply-model that produces the outputs that can be used to assess the financial viability of the AMoD operations.

4

Case-Study Rotterdam-Zuid

To evaluate the concepts presented in Chapter 3, a case study can be carried out where the conceptual model can be translated into a real-life case, which involves model development effort. However, before starting with the model development, attention has to be paid to the selection of the case study to show the relevance of the choice of the specific location where the AMoD service will be applied. This is important because the relevance of the case study location determines the value of the assessment of the financial viability of the AMoD service. It is crucial that the case study location meets the requirements of AMoD operations. The eventually chosen case study area must be a dense urban area with a high mobility demand which contains public transport hubs that are able to function as a station for AMoD services. Below, a description of both the current and the future situation will be given of the proposed case study location which clarifies the case study location choice. Afterwards, the choice of the specific station locations within the case study area will be described, based on certain criteria.

4.1. Current Situation at Case Study Area

The case study area where AMoD services will be applied to in the simulation model is chosen based on the report OV Visie 2040 [3]. In this report, produced by the transport authority of the metropolitan region of Rotterdam and The Hague (MRDH) together with the municipality of Rotterdam, a description is given of the intended specific measures regarding public transport to achieve objectives stated in document Stedelijk Verkeersplan Rotterdam (SVPR) [55]. The SVPR document contains the general vision of the municipality of Rotterdam regarding urban mobility. Goudappel Coffeng B.V. played an advisory role in the production of these documents.

The OV Visie 2040 contains a description of the way the city of Rotterdam is able to cope with the urbanization. Rotterdam is planning to densify the city with a number of additional houses equal to 50.000 and aims to realize this ambition before 2040. The municipality of Rotterdam is convinced that a structural improvement of the public transport accessibility in certain areas will result in opportunities for urban densification. This is a result of the interaction between accessibility and land-use. The first- and last-mile improvements in these areas are expected to contribute to this improvement of the public transport accessibility.

An important indicator used in the OV Visie 2040 [3] and in literature [56] is the job accessibility. As the OV Visie 2040 focuses on public transport, the job accessibility by public transport is used. To calculate the job accessibility by public transport of the city of Rotterdam, a transport model developed by Goudappel Coffeng B.V. is used. Figure 4.1 shows a map with the job accessibility indicated by the color blue, according to the legend. From this Figure, it becomes clear that in the areas south of the river Maas, the job accessibility by public transport is limited. The red rectangle indicates these areas. Several neighborhoods within this area are connected by tram and still show a low job accessibility. This could be a result of the relatively low operational speed of trams in this area. A faster connection of these neighborhoods to metro stations could improve the job accessibility by public transport of these areas.

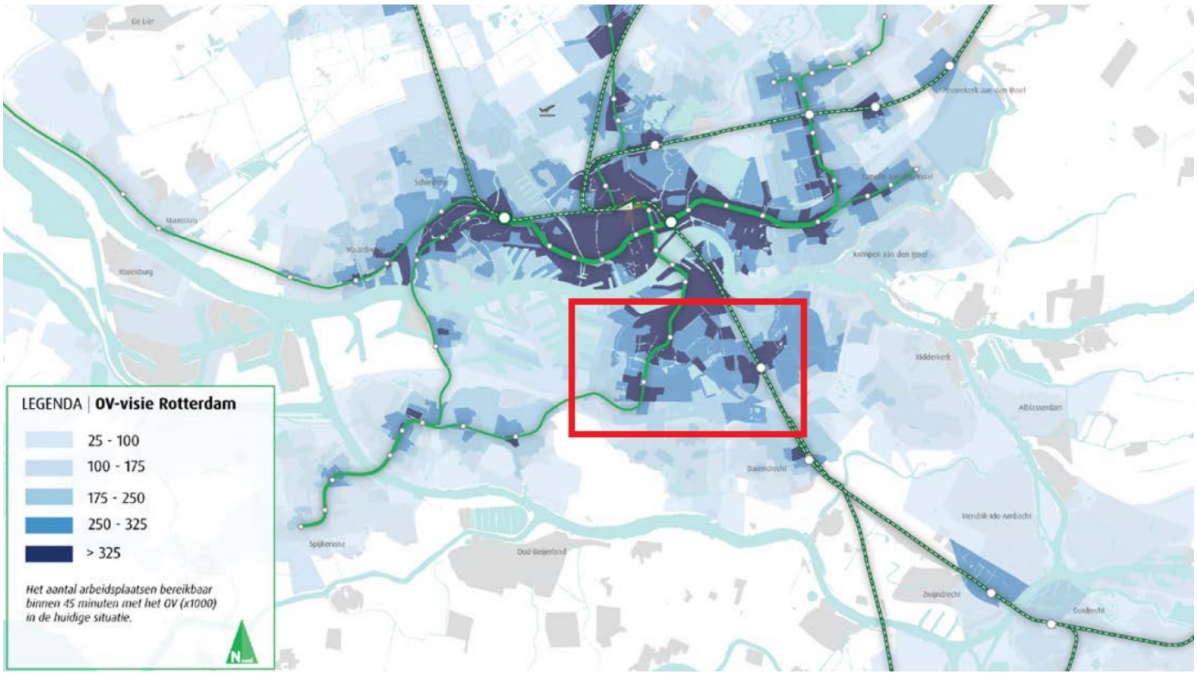

Figure 4.1: Map of Rotterdam with the colour indicating the number of jobs in thousands that are accessible by public transport within 45 minutes. (Source: OV Visie 2040 [3])

4.2. Future Situation at Case Study Area

The document OV Visie 2040 [3] contains a prediction of the situation in 2040, where the specific measures to improve public transport are incorporated. The predicted impact of these measures on the job accessibility by public transport in Figure 4.2 shows that despite the public transport enhancements, the southern part of Rotterdam (Rotterdam-Zuid) still copes with a level of accessibility that is significantly lower than the remaining parts of Rotterdam. Around metro stations, the accessibility levels show improvements, but areas solely connected by bus and tram show still show a limited accessibility.

So despite public transport improvements that have been described and assessed in this document, there exists an accessibility challenge in Rotterdam-Zuid. The connectivity of the metro stations to the areas in the rest of Rotterdam-Zuid is weak because bus services and tram lines are on average mostly too slow in these areas. Therefore, there is room for improvement in the first- and last-mile connectivity of public transport trips, making these metro-stations more attractive and accessible and eventually increasing the job accessibility in the Rotterdam-Zuid area. Moreover, better job accessibility will also increase economic prosperity in this area which improves the socio-economic situation in Rotterdam-Zuid. This makes Rotterdam-Zuid a suitable location for the deployment of AMoD services.

4.3. Station Selection

Specific public transport stations that can function as an AMoD-hub have to be selected because the AMoD service is station-based. Within the red rectangle in Figure 4.2 indicating the case study area, 3 metro-stations can be identified, which are located along 2 main transportation axes: Metro-line D/E and the main railway track. As it is assumed no stations will be added along these links up to the year of 2040, these stations will be the possible locations to deploy the AMoD vehicles at:

- Along Metro-line D/E:
  - Zuidplein
  - Slinge
- Along main railway track:
  - Lombardijen
  - Feyenoord City

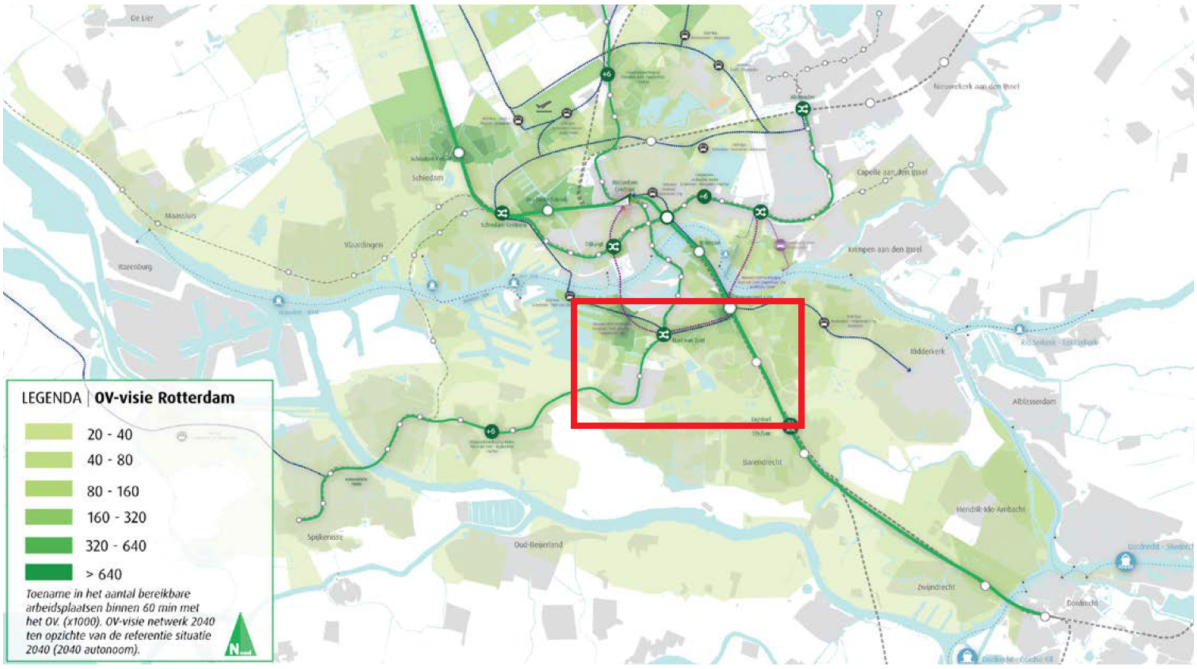

Figure 4.2: Map of Rotterdam showing potential differences resulting from the proposed improvements in the number in thousands of jobs that is accessible by public transport within 60 minutes. by public transport. (Source: OV Visie 2040 [3])

The station that is the most suitable for AMoD services is chosen based on criteria which originate from literature. Below at first, the determination of the criteria will be described and afterwards, the analysis of the criteria will be described followed by the station selection conclusion.

4.3.1. Criteria determination

In optimization research, the station location problem is categorized as being NP-hard, which makes it a computationally complex problem. Most existing work on the station location optimization relies on approximation algorithms [57]. However, in recent research, stations are optimally located based on the expected demand for the service [41]. The objectives of this optimization are minimizing the travel times and maximizing the spatial coverage. In this research, it is on top of that important that certain specific areas benefit from the AMoD service. Solving the station location problem as an optimization problem is out of scope of this research. Therefore, a simplified station-location selection is performed where the optimization objectives of Marczuk et al. (2015) are used as selection criteria.

From the above, it can be concluded that the following criteria are appropriate:

1. minimization travel times
2. maximization spatial coverage
3. maximization of expected benefit for low accessible areas
4. maximization of public transport connectivity

The first criterion will allocate the stations such that the sum of all of the weighted costs between demand points and stations is minimized. The second criterion allocates stations such that the number of demand points within reach from the stations is as high as possible. The third criterion allocates the stations such that as many as possible low accessible areas will be within reach of the station. The fourth criterion allocates the station based on the number of options passengers have to transfer to a different mode of public transport because AMoD is especially beneficial as a complement to public transport.

4.3.2. Criteria Analysis

As optimization of the station location is out of the scope of this research, a criteria analysis will be carried out for the criteria used in previous research [41]. All the 4 possible locations will be scored for all criteria. In Table 4.1, the scores of the locations are given for all criteria. At the bottom row, the summed total of the given scores is shown for all locations.

Table 4.1: Table which shows the scores of the possible station locations for the specified criteria and the total summed scores

	Zuidplein	**Slinge**	**Lombardijen**	**Feyenoord City**
Minimization of Travel Times	++	+	+	+
Maximization of Spatial Coverage	+	-	++	-
Maximization of Expected Benefit for low accessible areas	+	++	++	-
Maximization of Public Transport Connectivity	++	+	+	++
Total	**+6**	**+3**	**+6**	**+1**

The total scores show that station Zuidplein and station Lombardijen are potentially the most beneficial station locations. Therefore, both station locations will be chosen to function as hubs for AMoD services. In Figure 4.3, the location of the stations is indicated using a red circle. Moreover, this Figure shows the existing public transport lines within the case study area. The blue line intersecting Station Zuidplein represents the metro-line and the black and white dashed line intersecting Station Lombardijen represents the railway line between Rotterdam-Zuid and Barendrecht.

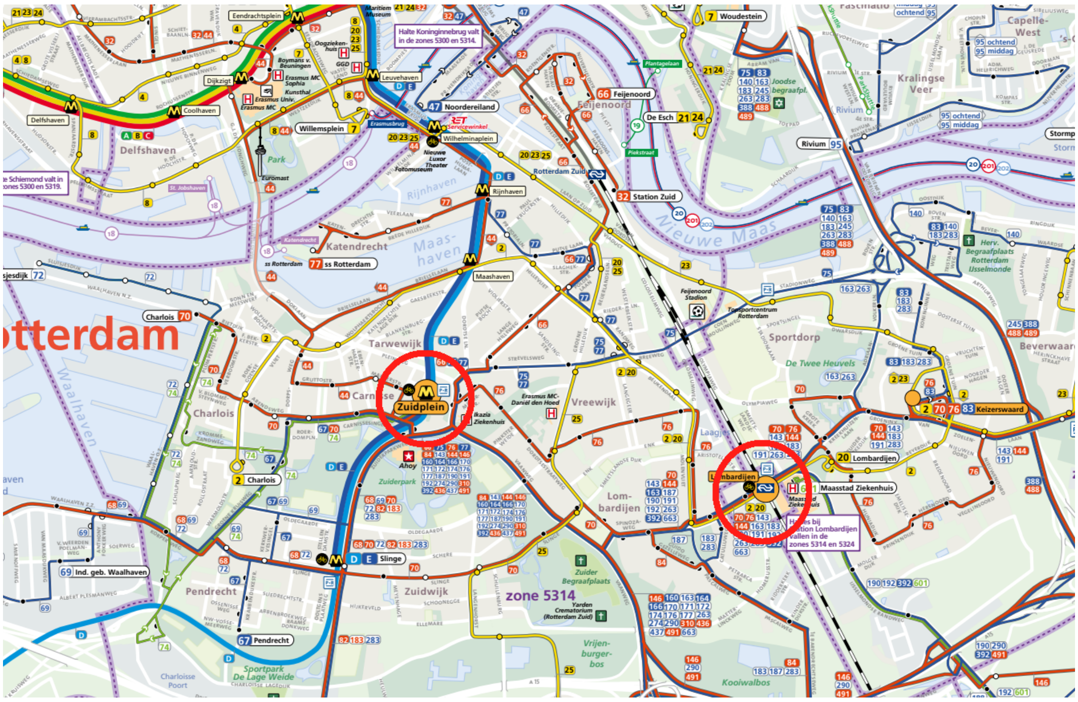

Figure 4.3: Map of the public transport lines in Rotterdam-Zuid with red circles indicating the location of Station Zuidplein (left) and Station Rotterdam Lombardijen (right). (Source: RET[4])

4.3.3. Station Zuidplein

Currently, Station Zuidplein is an important node in the south of Rotterdam. It connects a shopping mall, metro station and a bus-station with each other and plays an important role in the urban- and regional public transport network because the bus services connect the outskirts at the south of Rotterdam with the city center. The metro services using this node are line D and E, operated by the RET, and connect the areas at the North of the river the Maas to the south with an average operational speed of 35 km/h. Line E even connects The Hague Central Station with Rotterdam up to Slinge. Next to the metro-lines, multiple bus-lines use this station which are currently operated by the following operators: RET, Arriva, Connexxion, Qbuzz. Station Zuidplein is the second largest bus-station of The Netherlands after Utrecht Central Station regarding the number of passengers.

4.3.4. Station Rotterdam Lombardijen

Station Rotterdam Lombardijen is a railway station which is located in between the neighborhoods Lombardijen and Groot-IJsselmonde. The station facilitates for the Sprinter services between The Hague Central Station and Dordrecht, operated by the NS (Dutch railway operator). The station functions as a gateway to the regional train network for people originating from Rotterdam and using the tram-lines 2 or 20. Moreover, it guarantees the accessibility of the Maasstad Hospital and the Albeda School, which are located near the station. The station can also be accessed by the regional buses and city buses, operated by the RET and Connexxion.

4.4. Conclusion

Chapter 4 describes the current and future situation in Rotterdam-Zuid regarding public transport and described the choice of specific stations that will function as an AMoD hub. Given these locations, there is data required to be able to model these case study locations. This data consists of demand data and network data.

The number of passengers that use first- and last-mile connections to get to station Zuidplein and station Lombardijen is not explicitly known and no passenger survey data on the willingness to use AMoD services at these locations is available. Therefore, the demand data results from the demand estimation model which is described in Chapter 5. This number is required to be able to evaluate the scenarios for this case study. The departure times of the passengers will determine when an AV has to start moving across the network. Network data required to build the model for this case study location also originates from the demand estimation model.

5

Applied Simulation Model

To be able to assess the conceptual model, it will be applied to a real-life system. The applied model is called the case study simulation model. The choice of the location where this case study will be conducted at has been described in Chapter 4. The way the model has been set up including an elaboration on the various components software packages that are used in the model development will be described in this Chapter. The goal is to clarify the outline of the model, which is schematically shown in Figure 5.1, and to justify essential modeling choices and assumptions made in the development of the model.

The simulation model is composed of 2 main components: **(1)** OmniTRANS MRDH Model, which functions as the demand generation & distribution model and **(2)** Anylogic agent-based simulation model, which functions as the supply model and produces the results required to answer the research questions. The rectangles inside the grey areas in Figure 5.1 are called model aspects. The rectangles on the blue arrows are inputs and outputs of both model components. From literature, values for the transport fare, waiting time and AV travel speed are obtained which function as input for the OmniTRANS MRDH model. This model produces AV O/D-matrices and Network Data, which is fed into the Anylogic simulation model. This model produces the costs/revenues, system KPIs and Passenger KPIs that will be analyzed in Chapter 6 based on the operational variables: relocation strategy, ridesharing strategy and charging strategy.

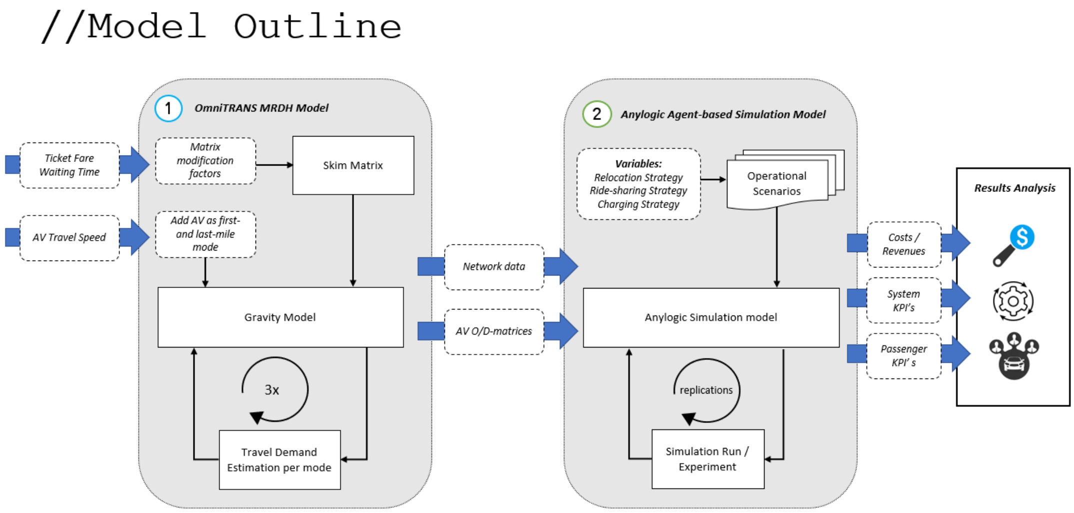

Figure 5.1: Schematic overview of the composition of the overall case study simulation model

In the following sections, a description of the development of the model components is given, including the substantiation of essential modeling choices. In this description, the relationship between model aspects and the way they produce the simulation outputs is clarified.

5.1. OmniTRANS MRDH model

In order to produce the OV Visie 2040 document [3], a transport model of the city of Rotterdam was used, which was developed using the software called OmniTRANS. This model, which was called the Regionale Verkeers- en Milieukaart (RVMK) model, was used to analyze the impacts of public transport measures on the accessibility and economic prosperity throughout the city of Rotterdam. The RVMK model is an aggregated gravity-based travel demand estimation model that is mainly used to evaluate the intensities on roads for different mobility measures. This software is developed by DAT Mobility which is likewise Goudappel Coffeng B.V. a part of the umbrella organization Goudappel Groep. Therefore, the knowledge required for this software is amply available within the company.

However, the RVMK model has been substituted for most of the current applications by a newer model which is called the Metropoolregio Rotterdam Den Haag (MRDH) model, which contains the network of the case-study area. This model incorporates extensive possibilities in modeling first- and last-mile transport in public transport trips. As this research focuses on AVs as a mode for first- and last-mile transport, the possible applications of the MRDH model match the requirement of this research. Therefore the MRDH model is used as travel demand estimation model in this research. Moreover, the MRDH model has been calibrated using more recent data than the RVMK model, which makes the forecasts more accurate. The MRDH model has been widely used in consultancy activities of Goudappel Coffeng B.V..

5.1.1. Skim-Matrix

In OmniTRANS, traffic is being distributed over networks based on a gravity model, which is based on the impedance or resistance of routes between O/D-pairs. These resistances can be expressed in multiple quantities like: time, distance and costs. The generation of the skim matrices is being done using classes. A class is a tool that generates shortest paths for all O/D-pairs and stores the impedance of these paths in a skim-matrix. As for public transport, the class that can be used to generate skim-matrices is called OtTransit, while OtTraffic is used for private transport. Usually, during the simulation these skims are being modified by various successive jobs that include scripts defining which matrices are being modified in what way. These matrix modifications make it possible to account for other choice behavior factors that play a role in choosing a certain mode, e.g. waiting time, transport fare and number of transfers. Expressing these factors or attributes in costs according to a certain weight parameter β can result in a generalized costs skim-matrix. The class in which the AMoD system is included as a choice alternative is the OtTransit class, which accounts for all public transport and first- and last-mile transport. The existing alternatives for first- and last-mile transport that are used in previous studies done with the MRDH model are walking and bicycling. In this research, the AV is added, so three alternatives are included for first- and last-mile transport. The skims for walking and bicycling are extensively estimated, and show detailed variations over the network. Because for AV, there is no data available to base the network speeds on, a single assumed speed will be assigned to all AVs. The assumed speed is equal to 30 km/h, which is based on the speed of AVs as used in previous modeling studies [19]. Using this speed, the travel time skims of the AV are generated.

5.1.2. Skim-Matrix modifications

To account for choice parameters, skim modifications can be added. To guarantee consistency between the demand and the supply model, the choice parameters taken into account are waiting time and fare. The fare, which will be elaborated on more in Section 5.3, is a price a passenger has to pay per min of travel time inside the AV. In the MRDH model, the fare is taken into account by using a multiplication factor which increases the travel time skim for the AV alternative. This factor is calculated using the value of time (VoT). In the research of Yap et al. [20], a VoT of AV users is used varying between €2,00 and €2,10 per 10 minutes. Taking the average of these values and multiplying it by 6 results in a VoT of 2,05 * 6 = € 12,30 per hour. This price is equal to the price an average passenger is willing to pay to reduce its travel time by 1 hour. Dividing the fare equal to € 0,31 per min by the VoT using consistent units results in a fare expressed in time units: $0{,}31/\frac{12{,}30}{60}$ = 1,51 min. The effective speed of the AV therefore is equal to $\frac{30}{1{,}51}$ = 19,9 km/h.

Next to the fare, the waiting time is an important choice parameter according to Yap et al. [20]. The waiting time is assumed to be 3 minutes on average, which lies within the maximum waiting time for shared taxi systems according to [58]. Taking this into account using a skim modification, would not lead to a multiplication factor for the AV skim just like is used for the fare. However, the waiting time leads to a summation factor of 3 minutes for every trip. This results in an offset of the trip time of a passenger of 3 min. Comparing this to the modes bicycling and walking, applying the factor leads to dis-utility for the AV alternative, making the AV slightly less attractive. Especially short distance trips will become less attractive as the waiting time factor is equal for all trips and therefore has a higher relative influence for short distance trips than for long distance trips. The resulting skim-modification factors are summarized in Table 5.1

Table 5.1: Overview of the skim modification factors used in the OmniTRANS MRDH model

Choice Parameter	Absolute Value	Skim Modification factor
Speed	30 km/h	-
Fare	0,31 €/min	* 1,51
Waiting Time	3 min	+ 3

5.1.3. Travel Demand estimation per mode

Because the MRDH model is a multimodal model, mode- and destination-choice are highly interdependent. The gravity model used here is called a simultaneous gravity model because not only trips are being distributed over destinations but as well over different modes. The relative attractiveness of modes is determined by the deterrence function which describes the incentive of traveling for a certain travel impedance. The OtGravity class is used in multimodal models to generate an OD matrix for each mode following Equation 5.1.

$$T_{ijm} = a_i b_j P_i A_j f_m(c_{ijm}) \tag{5.1}$$

where

T_{ijm} = number of trips from zone i to zone j using mode m,
a_i, b_j = scaling factors,
P_i = trip production of zone i,
A_j = trip attraction of zone j,
$f_m(\cdot)$ = deterrence function describing the incentive of travelling to zone j from zone i by mode m, and
c_{ijm} = travel impedance (e.g. distance, travel time) from zone i to zone j using mode m.

5.1.4. Autonomous Vehicles as additional first- and last-mile mode

In order to implement AV as an alternative for first-and last-mile transport, several modelling steps are required. At first, the AV has to be added as a mode in the project setup, where all the modalities used in the model are listed, and there speeds are defined. The maximum speed of the Twizy is 45 km/h, but due to varying traffic flows over the day, congestion and traffic management & control measures as traffic lights, the average speed of the AV in the case study area has been used and assumed to be 30 km/h initially. However, the effective speed is slightly lower due to skim-matrix modification factors described in Section 5.1.2.

Next to adding the AV as a mode in the project setup, the AV has to be added in the codes that determine the structure and eventual behavior of the simulation model. Within OmniTRANS, the codes are called jobs. In the jobs where the first- and last-mile alternatives are defined, the AV has to be added.

5.1.5. Network Assumptions

After adding the AV as a mode, it is important to make sure the AV is can drive on the network. Therefore, a new road type, called AV-road, has been added that functions as infrastructure that facilitates for AVs. The AV characteristics are in line with SAE level 4 of automation. Therefore, it is assumed that no adjustments to the existing physical infrastructure are required. Moreover, it is assumed that the AV shares the existing infrastructure with other modes as car, bus and bicycle. After defining the new road type, it needs to be assigned to the network. First, a selection of links in the network is made, which is equal to the links within the case study area. Afterwards, the road type of these links is set to AV-road. As a result, a geographical constrained operational area is modeled because the AV can only be used within the case study area. The AV network is indicated in Figure 5.2 by the pink links.

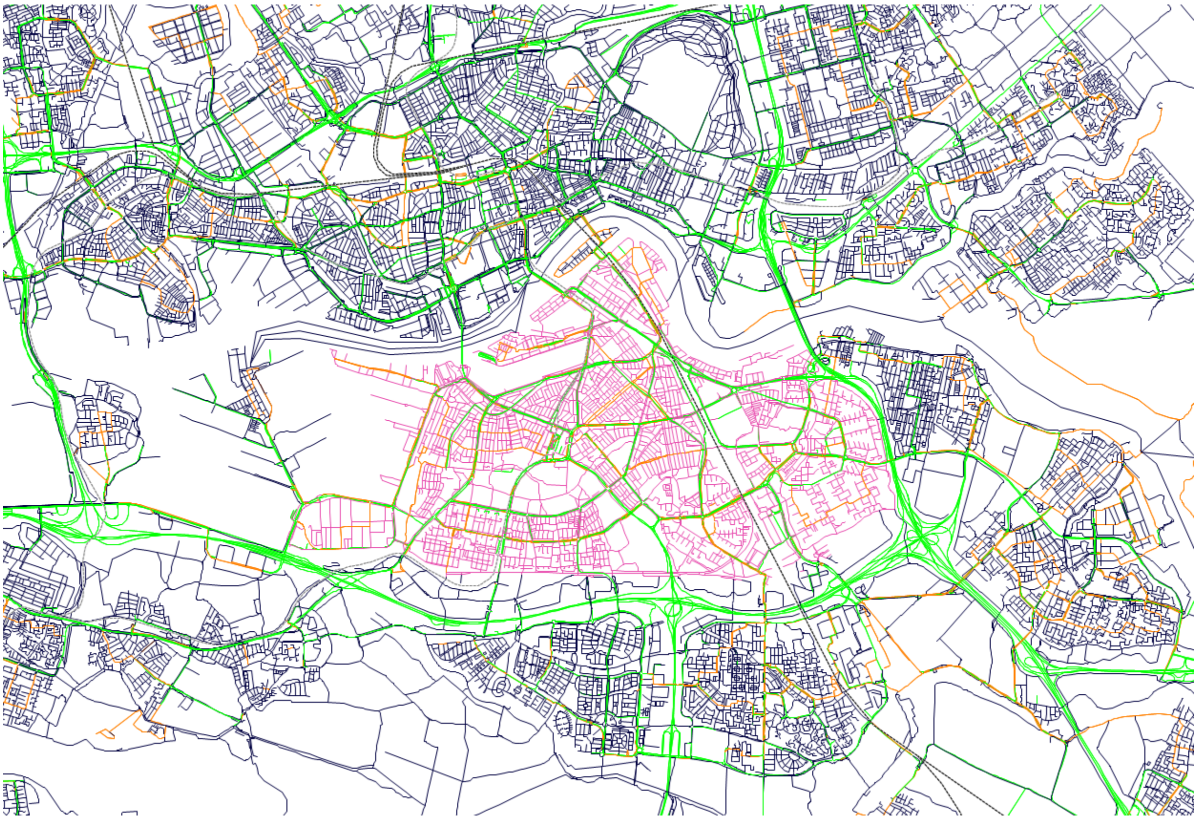

Figure 5.2: Overview of the OmniTRANS network within the MRDH model

Within the case study area, certain zones are located which have centroids as center points. The centroids can function as an Origin or a Destination of a trip. When the AV is chosen by a passenger originating from a centroid within the case study area that is not the station, it is vital that the AV always transports this passenger to the station. This is a first-mile operation. In the Transit network of the MRDH model, the stations and stops are assigned to a specified location. The stations that are important in particular are Station Zuidplein and Station Lombardijen. To avoid trips between two centroids that both are not a station, high penalties are given to the public transport stops that are not Station Zuidplein or Station Lombardijen.

5.1.6. MRDH Model Output

After 43 hours of simulation time, the model performed one total run. This comprises a simulation run for all three times of day: morning-peak (07:00-09:00), evening-peak (16:00-18:00) and off-peak (all other times of day). Moreover, for the morning- and evening-peak, 3 iterations are performed. The model run results in O/D-matrices and network assignments according to the travel demand estimation theory described in Section 5.1.3. In total, regarding AVs as a first- and last-mile transport mode, 6 O/D-matrices have been produced by the model:

1. Morning-peak first-mile
2. Morning-peak last-mile
3. Off-peak first-mile
4. Off-peak last-mile
5. Evening-peak first-mile
6. Evening-peak last-mile

The matrices include trips between all zones that are incorporated in the model, which leads to matrices with a size of nearly 8000 rows by 8000 columns, making them computationally challenging to handle. Further elaboration on the required analysis to process these datasets is described in Section 5.3. The circle diagrams in Figures 5.3, 5.4 and 5.5 show the resulting distribution of AV trips in the study area. The mode with the highest share is walking, which accounts for 57% of the first- and last-mile trips in the study area. Figure 5.3 shows that the mode AV accounts for 6% of the first- and last-mile trips in the study area. Zooming in on the distribution of AV trips, Figure 5.4 shows that 54% of the AV trips are last-mile trips and are therefore made from the station to final destinations. For both first- and last-mile trips, Figure 5.5 shows the distribution of the number of AV trips over the 3 times of day distinguished by the MRDH model: morning-peak from 07:00 till 09:00, evening-peak from 16:00 till 18:00 and the off-peak for the remaining times of day. From Figure 5.5, it becomes clear that only small differences exist between the time of day distribution of first-mile and last-mile trips.

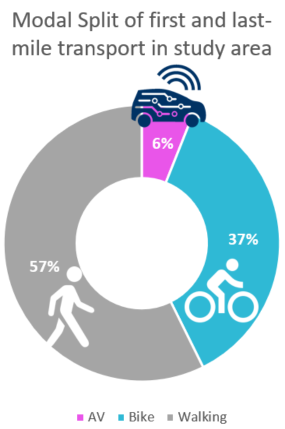

Figure 5.3

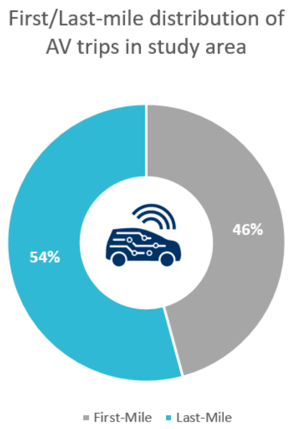

Figure 5.4

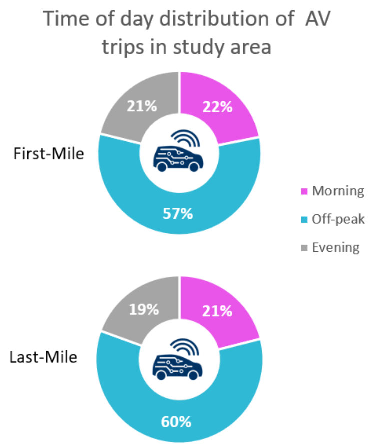

Figure 5.5

Next to the distributions of AV trips as shown in Figures 5.3, 5.4 and 5.5, the spatial distributions are essential for the AMoD system performance. In the density plots in Figure 5.6 up to 5.11 show the distribution over the study-area of the demand for all 6 matrices enumerated on the previous page. The number of trips originating (first-mile) and destining (last-mile) from the zones is indicated by the colour green according to legend in 5.12.

The density plots clearly show similarities when comparing the first-mile morning-peak demand spatial distribution in Figure 5.6 with the plot last-mile evening-peak in Figure 5.11. These plots show high densities in the residential areas because first-mile operations in the morning transport passengers to stations originating from residential areas, and last-mile operations in the evening transport passengers to their destination which often is again a residential area. A similar pattern is visible when comparing Figure 5.7 with Figure 5.10. The areas with high densities are the industrial areas where passengers work. The Figures for the off-peak time of day show a mixture between the 2 observed patterns.

5.1.7. Demand model Validation

As the output of the demand model is essential for the performance of the supply model, it is important that the output is valid. An overestimation of the demand for the AV would not lead to realistic results in the eventual supply model and therefore has to be avoided. In order to check whether the number of trips found for the travelers using the AV as first- and last-mile transport results in an overestimation, a comparison of the maximum links flow resulting from the network assignment is made with the link flows on the exact same location of the other alternatives: bicycle and walking. The maximum link flow of the AV is shown in Figure 5.13 and is equal to 402 vehicles.

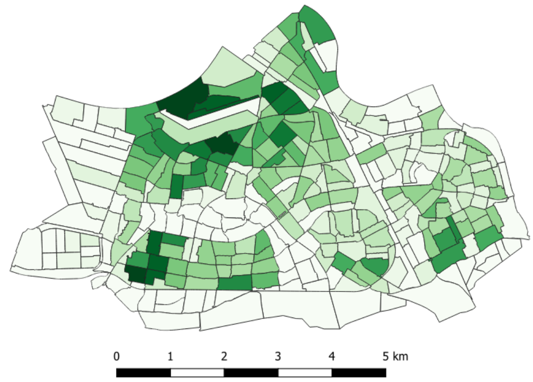

Figure 5.6: First-mile demand distribution during morning-peak

Figure 5.7: Last-mile demand distribution during morning-peak

Figure 5.8: First-mile demand distribution during off-peak

Figure 5.9: Last-mile demand distribution during off-peak

Figure 5.10: First-mile demand distribution during evening-peak

Figure 5.11: Last-mile demand distribution during evening-peak

Trips from/to centroid devided by total AV trips

- 0.00000 - 0.00025
- 0.00025 - 0.00080
- 0.00080 - 0.00164
- 0.00164 - 0.00246
- 0.00246 - 0.00323
- 0.00323 - 0.00399
- 0.00399 - 0.00532
- 0.00532 - 0.00622
- 0.00622 - 0.00753
- 0.00753 - 0.00911
- 0.00911 - 0.01043
- 0.01043 - 0.01217
- 0.01217 - 0.01374
- 0.01374 - 0.02163
- 0.02163 - 0.02492

Figure 5.12

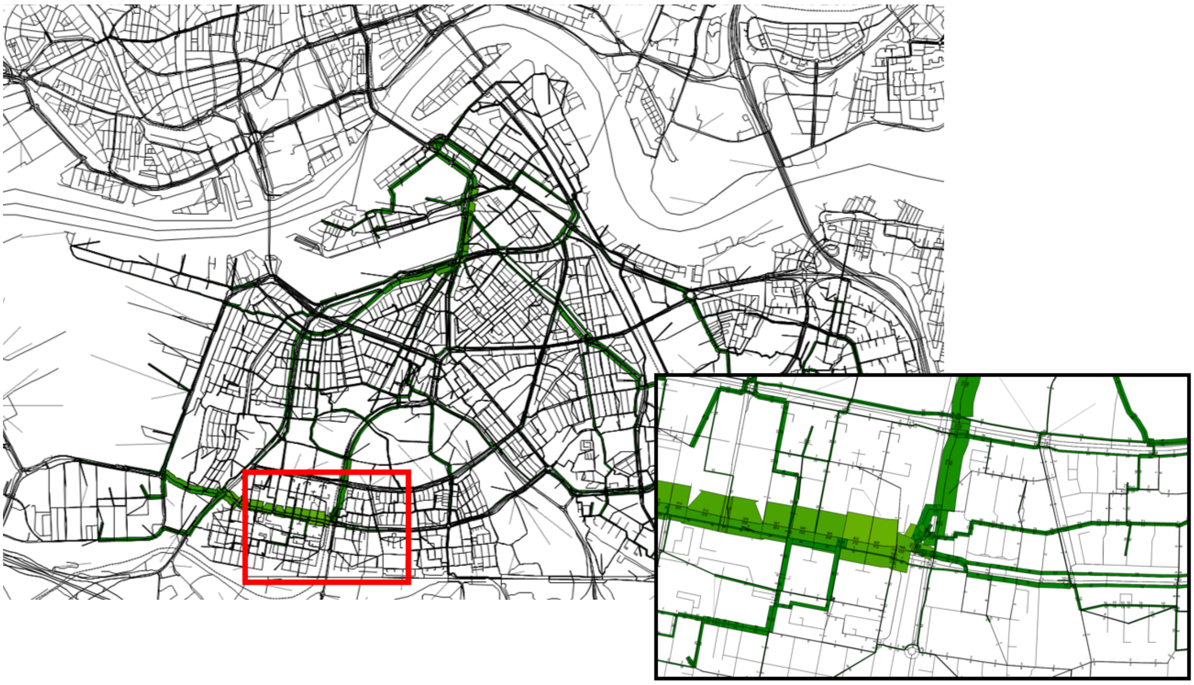

Figure 5.13: Network assignment plot for the mode AV. Link flows are indicated by the width and colour of the bars at the links.

The number of bicycles on the link where the maximum AV flow is observed is equal to 197 bicycles according to Figure 5.14, which is nearly half of the number of AVs found on this link. Therefore, the number of AVs seems rather high. However, regarding the remainder of the network, this is only a local phenomenon. Comparing the number of AVs with the numbers of passengers that use walking as first- and last-mile mode in Figure 5.15, shows that the link flows are more centralized around public transport stops, resulting from shorter distances of walking trips than bicycle trips. The number of passenger walking at the link where the maximum AV flow is observed is equal to 2033 which is way higher than the maximum AV flow. However, as this is close to a bus stop and the mode walking is only used for short trips, this is a local phenomenon.

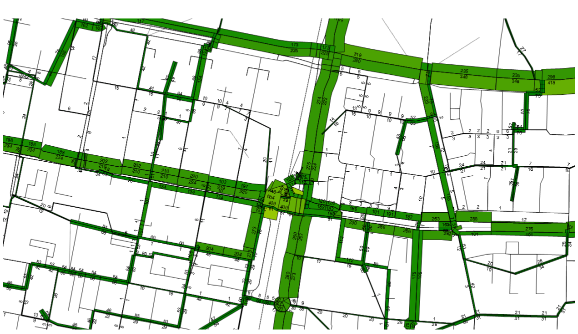

Figure 5.14: Link flows of the mode Bicycle at the location where the maximum AV flow is observed

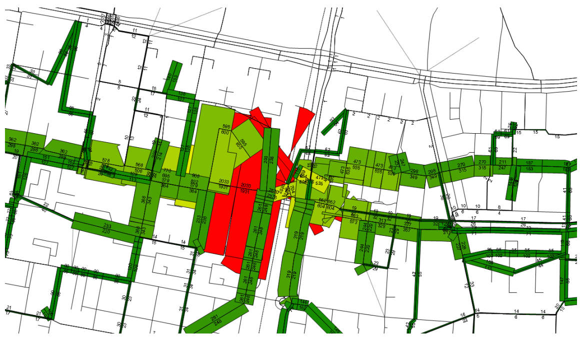

Figure 5.15: Link flows of the mode Walking at the location where the maximum AV flow is observed

5.2. Anylogic simulation model

Research on modeling carsharing systems in multi-agent based models currently gets growing attention in literature [5]. Agent-based microscopic simulation models are especially useful to model carsharing because it entails the possibility to include the individual characteristics and behavior of autonomous vehicles and passengers. Compared to aggregated gravity demand estimation models as OmniTRANS, agent-based simulation better matches the requirements of shared autonomous transport services.

Various software packages are available that are able to facilitate agent-based modeling. It is important that the chosen software matches the requirements of the conceptual model in order to apply the conceptual model to the case study area. An inventory of the software used to model carsharing that is encountered during the literature study is made. Based on the following criteria, a software assessment has been done to evaluate which software has to be used in this research:

- Possibility to implement a new mode of transport
- Possibility to import network data
- Possibility to import demand data
- Complexity of modeling
- Availability of Knowledge
- Satisfactory spatial resolution
- Case study opportunities
- Data availability to build the model

Based on these criteria, the chosen software package is Anylogic, which is written in the widely used programming language Java. This software is able to combine several simulation paradigms like discrete event, system dynamics and agent-based simulation into one simulation model. Moreover, Anylogic has the ability to translate data from an external source into the model. Because in this research the demand and supply models need to be connected, this option is especially useful to import the network data and demand data.

Moreover, Anylogic provides the ability to specify the individual behavior of agents that play a role in the model. In Chapter 3, it became clear that the individual behavior of the agents AV and Traveler are essential for the AMoD system performance. The way they interact with each other determines the output statistics of the simulation including the aspects that determine the financial viability. In Anylogic, it is possible to let the agents interact using a GIS environment that is linked to Open Street Map (OSM) data. Using this environment results in a model background that matches the latitude and longitude coordinates of the centroids resulting from QGIS. This makes it possible to use the case study location in the supply model.

The abilities of Anylogic make it feasible to use the MRDH model as a basis and add the AMoD services at specific locations using the agent-based supply model. The simulation model consists of the following agents: **(i)** Main, **(ii)** AV, **(iii)** Traveler and **(iv)** Centroid, which are hierarchically connected. The Main agent functions as the environment in which the other agents behave. The Centroid agents consist of static points that function as Origin, Destination or Station. The AV and Traveler agents interact with each other within the Main. In the following subsections, the behavioral rules and characteristics of the agents are described.

5.2.1. Main

The Main agent functions as the main environment of the model and is responsible for the interaction between the agents: AV and Traveler, and distributes them over the network based on the network- and demand-data. At the model start-up, the model is initialized in the Main. This involves the allocation of the centroids on the GIS map according to the latitude and longitude coordinates. To obtain these coordinates, several steps are needed. At first, the shapefiles of the network data are exported from OmniTRANS. Afterwards, the latitude and longitude data of the centroids are obtained. Finally, this data is fed into the Anylogic model.

Centroid-Network data

To guarantee consistency, equal networks have to be used in both the demand and supply model. The MRDH model contains a function that is able to export the shapefiles from the network used. A shapefile is a data format that contains geospatial information that can be used in geographical information system (GIS) software. A shapefile consists of three files: nodes, links and areas representing centroids, roads and zones that are used in the OmniTRANS model. Each of the files has attributes that describe the objects in the network. The attributes that are particularly important for this research are the coordinates of the centroids because they are used in both models. In order to process the shapefiles, a GIS software package called QGIS is used. QGIS is an open source GIS software application that is able to convert the centroid coordinates to the latitude and longitude expressed in degrees and eventually export the centroid attribute table to an Excel spreadsheet file. Plotting these coordinates leads to the overview of the centroids within the study area including Station Zuidplein and Station Lombardijen as shown in Figure 5.16. The network used in the Anylogic model consists of virtual straight connection links between the centroids.

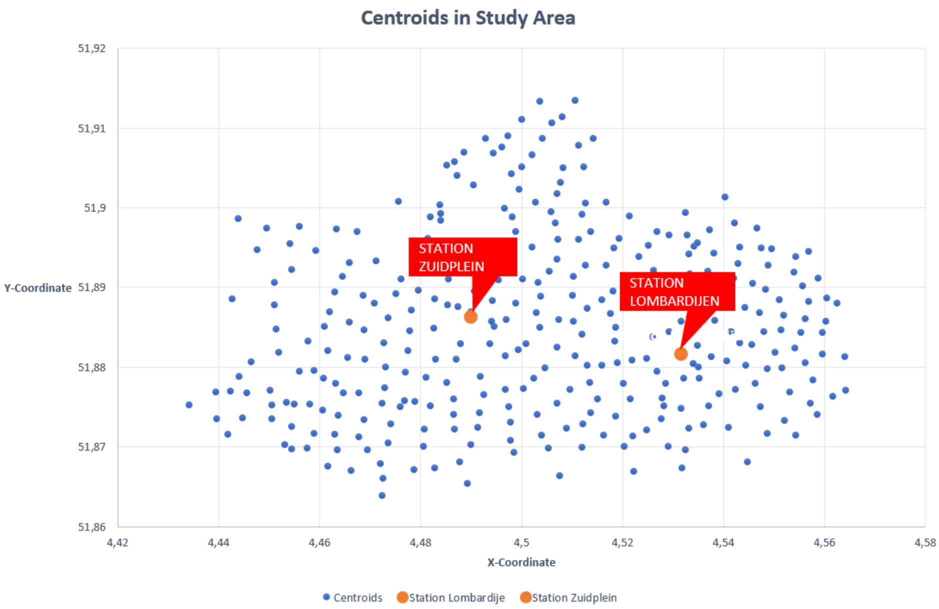

Figure 5.16: Overview of the centroids within the study area, indicating the location of the stations.

Main functions

Moreover, the passenger properties function is being activated at start-up, which determines the departure time of the travelers, based on the demand data. The essential functions that determine the interaction between the agents are also defined in the main. The ControlScheme function is the most important function and consists of an algorithm that receives a request from a Traveler and searches for the closest available vehicle. The availability of an AV is determined by the ControlConditions function. This function checks for all vehicles if it is available to serve the request, based on the following control conditions:

- There are seats available in the vehicle, which means that the number of passengers inside the vehicle has to be lower than the capacity;
- The vehicle battery is loaded sufficiently to be able to carry out the operation;
- The maximum waiting time of the passenger to be picked up is not exceeded;
- When there is already a traveler inside the vehicle, the ride can be shared only if the detour required to share the ride does not exceed the maximum acceptable detour.

If the vehicle satisfies all control conditions, the ControlScheme will check whether more vehicles satisfy the conditions. After all the vehicles are checked, the closest available vehicle will be assigned to the requesting traveler. When this happens, the traveler knows which vehicle will pick-up the traveler and knows the time it needs to wait for the vehicle to arrive. Table 5.2 gives an overview of the ControlScheme Algorithm using a pseudo code.

Table 5.2: Pseudo code of the ControlScheme Algorithm showing its main statements

ControlScheme Algorithm pseudo code

```
if Traveler is assigned to Zuidplein or Lombardijen then
    for all AVs in assigned station:
        Check if Traveler requests a First or Last-mile operation
        getEuclideanDistance from vehicle location to Origin
        return EuclideanDistances
        if AV matches ControlConditions then
            getNearestAV
            return ID of nearest AV
        end if
    end for
    Assign ID to requesting Traveler
    Add requesting Traveler to AV collection travelers_to_be_picked_up
    Remove requesting Traveler from collection travelers_to_be_served
end if
```

Next to the essential AMoD system function, also the output statistics are calculated in the Main agent. These include statistics from the different perspectives: system, energy, passenger, vehicle and business. Moreover, the costs and revenues determining the financial viability are calculated in the Main. The Main also determines the model display, which is visible during the simulation model runtime. This display predominantly consists of a GIS map, where the centroids are allocated and indicated by small blue houses. Later on in Figure 5.22, a snapshot of this display is given. Between these centroids, movement of vehicles can be observed during runtime.

5.2.2. Autonomous Vehicles Agent Behavior

The behavior of the individual AVs is defined in the AV agent type following a statechart, which is shown in Figure 5.17. A statechart shows in what consequential states the vehicles can be. The black transition arrows between the yellow states determine the condition for which the vehicle is allowed to move to the next state. Both the transitions as well as the states can contain conditions and actions that are coded using Java. These codes can refer to other agents creating certain relationships. E.g., a request from the traveler agent can lead to an action of the autonomous vehicle. The statechart of the AV agent is shown in Figure 5.17.

The statechart starts at the top, where the AV enters its initial location in the state EnterStation. The total fleet size of AVs is being distributed over the stations according to the ratio of centroids that have this station as the nearest station. This leads to 58% of the fleet size assigned to Station Zuidplein and 42% of the fleet size assigned to Station Lombardijen. When the AV enter the station, the battery is checked. When the SoC is lower than 25%, the AV moves to the state ChargingBattery. When the SoC is higher than 25%, the AV moves to Idle and becomes available for a request. When a request is communicated to the AV via the ControlScheme in the Main, the AV moves to the state MovingToTraveler, which accounts for the movement of the vehicle to the Origin of the Traveler it is assigned to. When arrived at the Origin of the Traveler, the AV goes to the state Loading_unloading_travelers in which the embarking and disembarking takes place. When the Traveler entered the AV, the AV starts moving to the Destination of the Traveler following the state MovingForOperation or starts moving to the Origin of the second Traveler that has to be picked up following the state MovingToTraveler. When the AV arrives at the Destination of the Traveler, it will unload the Travelers untill it is empty. If the automatic relocation is activated, then the vehicle will move back to the station after an operation in case there is no demand left following the actions defined in the MovingToStation2 state. If relocation is not activated, the AV will remain parked at the final Destination of the Travelers it has transported.

5.2.3. Routing of Vehicles

The routing of the vehicles consists of movement between a station and a centroid, as the small movements inside the station and parking area are neglected. In Anylogic, a built-in functionality offers the opportunity to let the AVs use the roads of the GIS map because the map is linked to Open Street Map data. However, as this functionality drastically increases the computational time, it is chosen to use straight routes between centroids and stations. Moreover, because of the scale of the project, using the real road network instead of straight line routes would only lead to minor differences in travel times between nodes.

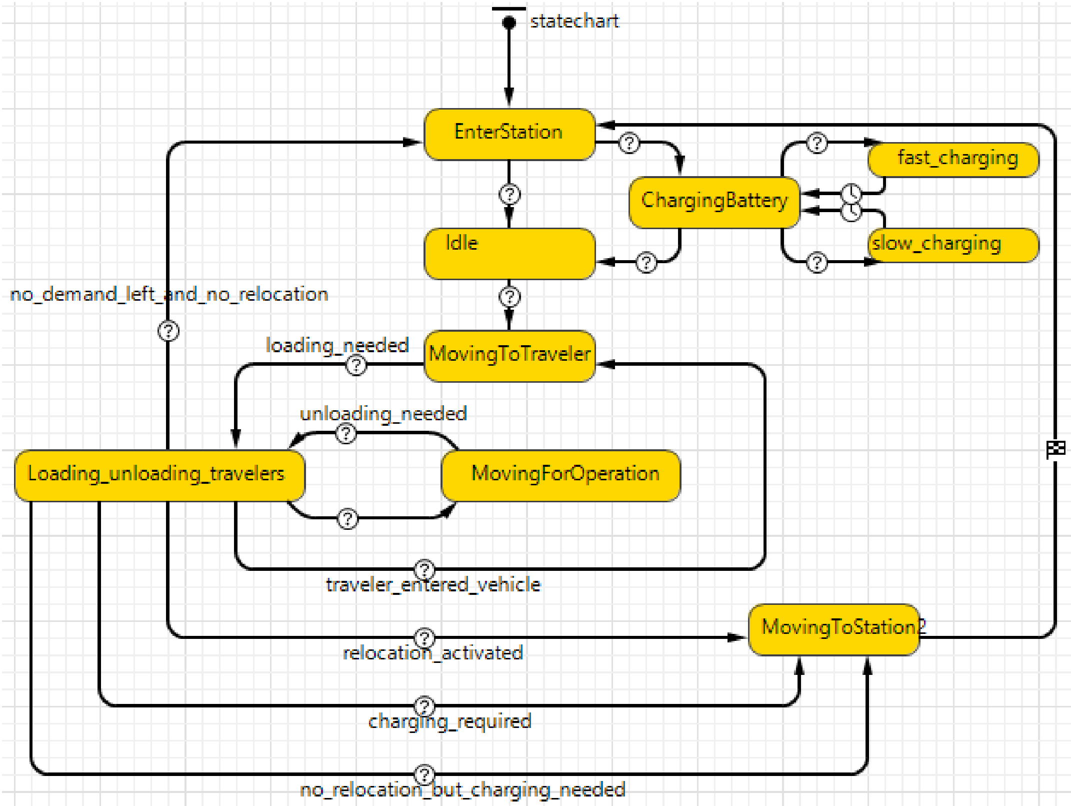

Figure 5.17: Statechart of the AV agent, which determines when conditional actions take place.

When dynamic ridesharing is activated, two travelers with distinct Origins (first-mile) or distinct Destinations (last-mile) can share their ride, when the detour required to pick up the second passenger is smaller than 25% of the direct travel time. It is assumed that first-mile travelers can only share their ride with first-mile travelers and last-mile only with last-mile travelers.

For a first-mile operation, the first requesting traveler experiences the detour because the first requesting traveler will be picked up first according to the first come first serve principle. The direct route travel time is determined by the travel time of the direct route of the first requesting passenger. If the resulting additional travel time including the detour to pick up the second requesting traveler is lower than 25% of the direct travel time, the second passenger will be picked up and the ride will be shared. This constraint equal to 25% is called the global detour constraint [30], and is based on previous research [59]. Figure 5.18 schematically shows the direct and detour route evaluation for first-mile operations.

For a last-mile operation, all travelers have an equal Origin which is one of stations. According to the first-in-first-out (FIFO) principle, the AV firstly moves to the Destination of the first requesting traveler. The direct travel time which is being evaluated by the detour constraint function is determined by the travel time from the station to the destination of the second requesting traveler. Again, the detour constraint of 25% of additional travel time will be used to check if the second passenger can be picked up. So for a last-mile operation, the detour is experienced by the second requesting traveler. Figure 5.19 schematically shows the direct and detour route evaluation for last-mile operations.

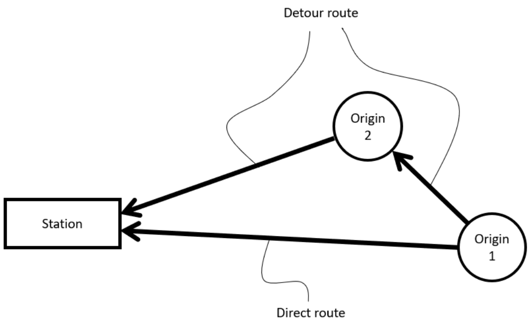

Figure 5.18: Schematic overview of first-mile detour evaluation.

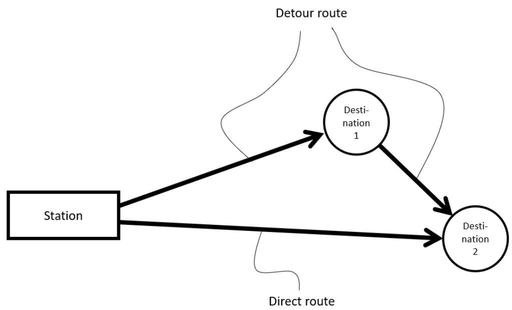

Figure 5.19: Schematic overview of last-mile the detour evaluation.

5.2.4. Energy Usage

The energy use of the vehicle determines the rate at which the battery of the vehicle loses energy. Mathematically, this can be described by a differential equation. The energy use is equal to the kinematic energy which is required to let the vehicle roll at a certain speed. This kinematic energy is equal to the longitudinal Force F multiplied by the speed of the vehicle. The Force F is given by the vehicle's longitudinal dynamic equation [60], which is a summation of the rolling resistance force F_r, the air dynamic drag force F_{air}, the gravity force F_g and the acceleration force F_i caused by vehicle inertia. In the equation 5.2 below, the longitudinal dynamic equation is given, including the parameters, variables and constants required.

$$\begin{aligned} \frac{d(Battery)}{dt} &= -Energy\_use \\ Energy\_use &= F \cdot v \\ F &= F_r + F_{air} + F_g + F_i \\ &= C_{rr}mg + \frac{1}{2}\rho C_d A v^2 + mgsin(\theta) + ma \end{aligned} \tag{5.2}$$

Where

$Battery$	= battery capacity of the vehicle [Wh];
$Energy\_use$	= the rate at which the battery loses energy [Nm/s];
F	= force required to make the vehicle roll longitudinally [N];
v	= speed of the vehicle [m/s];
C_{rr}	= rolling resistance coefficient [-];
m	= mass of the vehicle [kg];
g	= gravitational constant [m/s^2];
ρ	= air density [kg/m^3];
C_d	= aerodynamic drag coefficient [-];
A	= vehicle frontal area [m^2];
θ	= slope of the road [rad];
a	= acceleration [m/s^2].

The speed of the vehicle is constant and equal to 30 km/h. This means that acceleration and deceleration is not taken into account. The mass of the vehicle varies depending on the number of passengers inside the vehicle. A person is assumed to have a weight of 75 kg. The slope of the road is assumed to be equal to zero as no vertical alignment of roads is modeled. Consequently, the terms F_g and F_i are zero. This leads to a slightly underestimated energy use of the vehicle. However, the slope does not play a prominent role in areas in the study area due to the absence of hills and mountains. On top of that, the acceleration term is assumed to play a minor role in the total energy use because of the optimized driving style of the AVs.

5.2.5. Battery Charging

The charging possibilities of the AVs are limited because there is no driver available to plug the power connector in a socket to charge the battery. Although the AV might be able to plug itself in the future, a more suitable alternative for autonomous vehicles is Wireless Power Transfer (WPT)[51]. WPT uses magnetic resonance that results in inductive power transfer. This charging method is especially suitable for electric vehicles (EV) because it would take away the troublesome currently encountered during vehicle charging. The only thing that is required is that the AV has to be parked at a specific point where the WPT technology is applied[61]. Charging systems that use WPT technology are called Wireless Electric Vehicle Charging Systems (WEVCS) [62]. SAE defined levels for WEVCS according to their power. Level 1 provides 3.3 kW and level 2 provides 7.7 kW [63]. It is chosen to apply both fast chargers of level 2 and slow chargers of level 1 to the stations in order to evaluate the impact of different types of chargers.

As for Li-ion batteries, like the Renault Twizy has, it is not desirable to be fully charged because high voltages can stress the battery and affect the quality [64]. Choosing a lower voltage threshold or eliminating the saturation charge, prolongs battery life but this reduces the range, as not the full capacity of the battery is used. Therefore, it is chosen to charge only up to 80% of the State-of-charge (SoC), which is a percentage equal to what extent the battery is charged relative to the total battery capacity. When a vehicle has a battery with an SoC lower than 25%, the vehicle has to charge. For a level 1 charger, this results in a charging time of $\frac{6{,}1\cdot(0{,}80-0{,}25)}{3{,}3}$ = 1,02 h = 61 min and for a level 2 charger to $\frac{6{,}1\cdot(0{,}80-0{,}25)}{7{,}7}$ = 0,44 h = 26 min. In this calculation, a linear charging relationship is assumed between the Battery and the time during charging from a lower bound of 25% and an upper bound of 80%. The saturation of the Battery is not reached and therefore non-linearity during charging is not taken into account. Moreover, influences like temperature and the durability of the battery are not taken into account.

5.2.6. Traveler Agent Behavior

Likewise the AV agent, the Traveler agent contains the definition of the behavior of travelers using a statechart. The statechart is shown in Figure 5.20. The statechart starts at the top at the departure time of the travelers. The passenger_properties function generates the departure times, the Origin and the Destination of the travelers. Firstly, this function distributes the total number of travelers over the day according to the pre-specified demand distribution as shown in Figure 5.21. This distribution shows a normally distributed morning-peak around 08:15 with a standard deviation of 42 min and a normal distributed evening-peak demand around 17:30 with a standard deviation of 49 min and is based on [65]. In between the peaks, the demand is distributed uniformly with a probability-density function (pdf) value of 0,02.

Afterwards, for each time of day period and for first- and last-mile operations, a distribution over the centroids is specified by table functions. These functions determine how much percent of the total number of travelers originates or has its destination at which centroid. In the end, this distributes the demand over time and allocates them on the network. In Section 5.3, there will further be elaborated on the analysis carried out on the demand data.

The first state that is encountered is the state Busy, where the travelers are busy with a certain activity which does not require transport. At the departure time of the traveler, their traveling request is sent to the ControlScheme in the Main. Note that the Origin and Destination of the traveler locations are simplified to be at the exact location of the centroids. Walking time is not included to guarantee consistency with the MRDH model. If an available vehicle is found, the vehicle_id is communicated to the traveler and the traveler moves to the state called Waiting, where it waits for the vehicle to arrive at the Origin, with a maximum waiting time of 5 minutes [58]. If no available vehicle is found, the traveler will move to the state WaitingTilAvailable, where it considers a retry. After 3 retries, the traveler will no longer request a vehicle and moves to the state Give-up, where the traveling ends. This leads to an unsatisfied traveler which negatively affects the level of service.

If the traveler requests a last-mile operation, then the traveler moves to the state called timeout. This state produces a small additional waiting time of 1 second in order to avoid the vehicle to be assigned to a first-mile and a last-mile passenger at the same time. The next state encountered is called the Traveling state. In this state, the traveler moves along with the vehicle to the Destination. The travel_time_traveler loop calculates the travel time of the traveler. When the location of the traveler is equal to the Destination, the traveling ends.

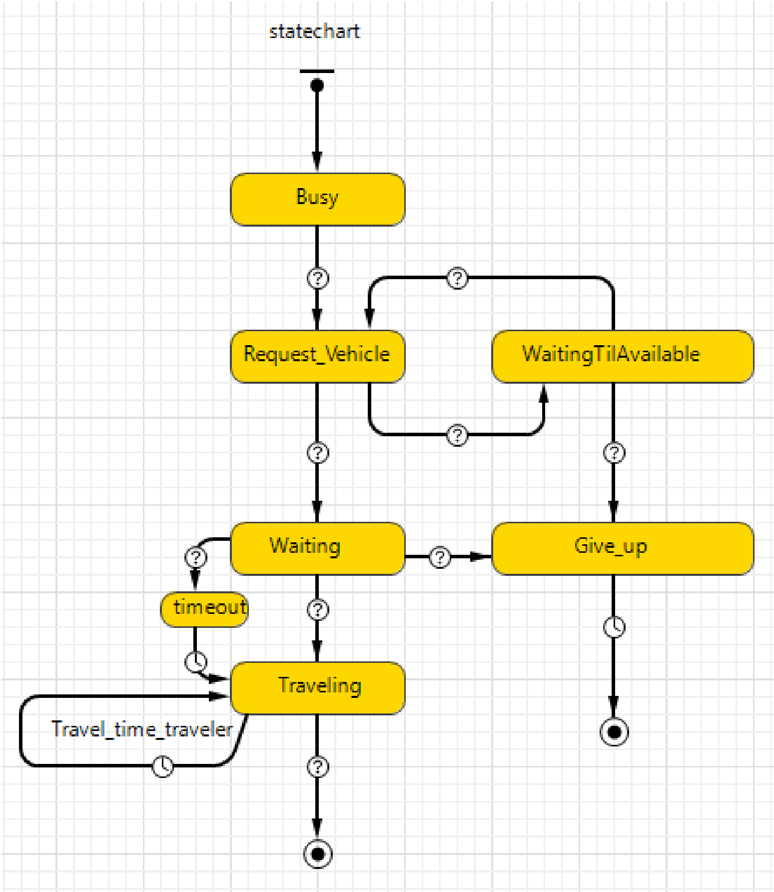

Figure 5.20: Statechart of the Traveler agent, which determines when conditional actions take place.

5.2.7. Centroids

The coordinates of the centroids are imported from the Excel spreadsheet obtained from QGIS. In Anylogic, the centroids are modeled as a static agent type as it remains at the same location and has no statechart. The data consists of latitude and longitude coordinates of centroids which will place the centroids on a GIS display using Open Street Map data. Connecting all centroids with straight lines results in the virtual network.

The virtual network does not include a dynamic traffic model because the traffic impact of the AMoD service is not the main focus of this research. Also, the interaction of the AVs with other road users has not been taken into account due to the lack of research that has been done on this topic. Therefore, the traffic model is static [66], assuming that the traffic flow of AVs on the network does not significantly change the travel times on the links connecting the centroids.

All of the centroids can be fuction as an Origin, Destination or Station. This is a simplification because in reality, a passenger must have the ability to request a vehicle at any location within the operational area. However, using the centroid locations as imported in Anylogic, makes the connection with the OmniTRANS model more accurate.

5.3. Anylogic Model Input-Assumptions

Developing the Anylogic model involves several assumptions on input parameters. Regarding the vehicle, the characteristics are based on the vehicle specifications of the Renault Twizy are used [53]. The used average speed shows similarities with the speed of currently operational bus lines in the study area [3].

5.3.1. OD-matrices input

Another essential model input is the OD-data resulting from the MRDH model in OmniTRANS. This model produces a matrix for first-mile operations and last-mile operations for each time of day: morning-peak, evening-peak and off-peak. In total, this results in 6 matrices, which includes a total number of trips for all OD-pairs included in the MRDH model. Because nearly 8000 zones are incorporated in the MRDH model, these matrices are computationally challenging to handle by Excel software. Therefore, a data analysis python-script is programmed to account for the following data analysis needed.

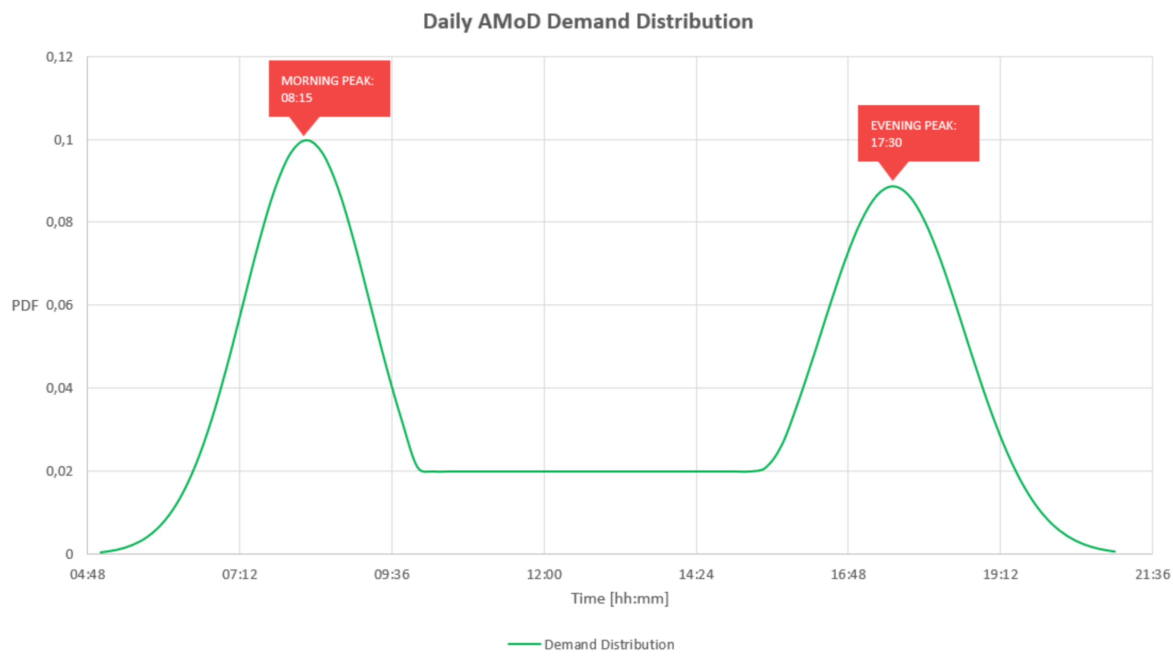

Figure 5.21: Distribution of demand for a typical day. Normal distribution for morning- and evening-peak and a uniform distribution between these peaks.

For first-mile OD-matrices, a selection of rows was made which includes the Origins within the study area. For last-mile OD-matrices, a selection of columns has made because only the Destination of Public Transport trips located within the study area are required. The number of trips in these matrices represents the movement from an Origin to the stations for first-mile operations and movement from the stations to the Destinations for last-mile operations. For both the selections, the totals are calculated. The row totals for first-mile trips and column totals for last-mile trips are used to calculate the % of trips per centroid. These spatial distributions over the centroids are imported in Anylogic using table functions. A summation of the totals of the 6 OD-matrices results in a daily total number of passengers choosing for AV equal to 7009 passengers.

5.3.2. Model Simplifications

Model simplifications can be applied to avoid the requirement of extensive computational resources. The spatial simplification used in this model results from taking into account only discretized centroid locations, being points with exact specific coordinates. Next to spatial simplifications, abstracting groups of agents into meta-agents is a suitable approach [67]. According to model testing, the computational time of a simulation run for 1 typical day for an input of 7009 agents of the type Traveler is equal to 135 minutes. Regarding the fact that multiple simulation-runs, using different random seeds, per scenario are required in order to obtain robust results, this simulation run-time would result in an unfeasible experiment.

Taking this into account and for the sake of computational feasibility of the simulation experiment, it is chosen to let 1 meta-agent represent 10 agents in reality for both the Traveler and the AV agent type. This phenomenon is called abstraction [67] and is suitable because all Traveler agents and all AV agents show equal behavioral rules and can be therefore regarded as homogeneous populations. The Traveler agents only differ in simulation input parameters: Origin, Destination and departure time. Therefore a number of $7009/10 = 701$ passengers is used as total daily passenger demand. According to model testing, the computational time of a simulation run of the abstracted model for 1 typical day takes slightly less than 1 min. Therefore, the decrease in computational time resulting from the abstraction is substantial.

However, the validity of the outputs of the abstracted simulation model has to be verified. In order to do so, a comparison has been made between the outputs of the abstracted model and the model with the original scale. The averaged outputs of 30 runs with randomly chosen random seeds of the abstracted simulation model are compared to the averaged outputs of 6 runs with randomly chosen random seeds of the original scale model. The differences between the outputs are given in Table 5.3. Only the relative differences larger then 10% are included in this Table, because minor differences may be the result of stochastic effects.

Table 5.3: Overview of the possible values of variables taken into account in the simulation of scenarios

Output parameter	**Relative difference [%]**
Number of slow-chargers	+ 15,8
Investment costs of charging facilties	+ 15,8
Residual value of charging facilities	+ 15,8
Average VKT	- 11,7
Average operational time with 1 passenger	- 14,6
Maximum energy required at Station Zuidplein	+ 15,0
Maximum energy required at Station Lombardijen	+ 18,0

Analyzing the performance of the AMoD system in the original fine-grained model shows that for the base scenario, vehicles end up in an imbalanced way at locations which are relatively far away from the station. This is the result of the control algorithm which does not assign these vehicles to passenger demand because there are vehicles available that more close-by.

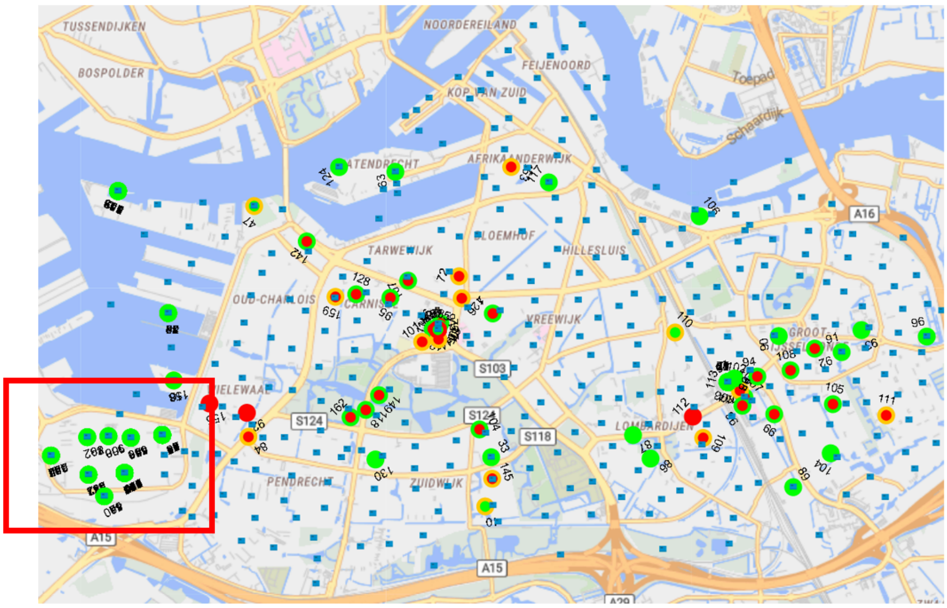

Figure 5.22: Snapshot of the study area in the simulation model after 360 min (12:00)

In Figure 5.22, the area within the red rectangle indicates the location at which a large number of vehicles end up after a last-mile operation to this area. Therefore, the batteries of these vehicles are nearly fully charged. The other vehicles which are not parked in this area are still moving most of the time, satisfying demand. This results in the fact that at a certain moment all of the other vehicles have to charge and the vehicle parked in this area far away become responsible for satisfying the demand, although this demand might originate from centroids relatively far away. Therefore, the traveled distance per vehicle is higher for the original fine-grained model.

However, this situation has advantages for the system capacity, as the peak in required charging of the vehicles is lower, because the parked vehicles still have enough battery to serve the demand. At the time their battery is empty, the other vehicles are again fully charged.

The differences found between the abstracted simulation model and the original individual level simulation model do not outweigh the decrease of required computational resources. Therefore it is chosen to use the abstracted model for further simulation experiments in this research. Consequently, the number of passengers used in the model is equal to 701. This number is used as a stable input variable and is being distributed over time and over the centroids by the Passenger_Properties function.

5.3.3. Costs & Revenues parameters

The calculation of financial related statistics requires several input parameters. The energy costs per kWh are based on the number found on the website of the Dutch automobile association called the ANWB [68], where a built-in functionality makes it possible to calculate the direct and indirect cost aspects of specific vehicle types. This source is especially suitable for this case study research because the costs are based on the Dutch market prices. The purchase costs of a new Renault Twizy is equal to € 13490,-. It is expected that automating this vehicle would lead to an increase in the purchase costs, due to advanced and innovative technologies that have to be installed. However, the average price of autonomous Renault Twizy vehicles will again decrease due to economies of scale as a bigger fleet of vehicles is required for AMoD operations. Moreover, the price of automated vehicles is expected to decrease over time as the technology required for automating a vehicle will become more widely available and therefore less expensive. Taking these price reducing factors into account, a purchase cost of € 13490,- per vehicle is used as an input parameter.

The expected residual value of the vehicle is € 4800,- after 3 years [68], which is equal to 36% of the new purchase price. The empty effective mass of the vehicle is 474 kg. The usage of energy is around 7,2 kWh/100 km which comes down to a range of 85 km for the total battery capacity of 6.1 kWh. The energy costs are assumed to be equal to € 0,23 /kWh, based on previous research [51], [69]. Expected maintenance costs are around € 823,- for a lifespan of 3 years. The maintenance costs parameter value used in this study is equal to € 0,07 per km, which is higher than the value of the maintenance costs of € 0,06 per km for the highest costs scenarios found in previous studies [51], [69]. However, the difference can be explained by the maintenance of the charging facilities which are also taken into account in this research.

In the Dutch public transport stakeholder system, the operator currently is accountable for investments on charging infrastructure. As the financial viability is analyzed from an operators perspective in this research, the costs of the required charging infrastructure have to be taken into account as well. The costs of an induction charging facility are assumed to be €1950,- and are based on the price the company Plugless Power uses to sell rather simple to install inductive systems [70]. These systems charge the vehicle batteries with 3.3 kW. The fast chargers of 7.7 kW are assumed to cost twice as much as the slow charger, so €3900,-. The assumed lifespan of wireless chargers is equal to 10 years, with a residual value of 20% of the investment costs after 10 years. Note that the installation costs are not taken into account, because installation requires minor effort for these types of chargers. However, the maintenance costs of the wireless charging systems are taken into account in the total maintenance costs of the AMoD system.

The number of chargers installed at the stations in total is equal to the maximum number of chargers required to avoid charging capacity problems and to remain consistent with the demand model. So the peak in the number of vehicles charging over time determines the number of chargers required. The maximum number of vehicles charging at both stations is determined by the statistics calculation function in the Main agent. Using the number of chargers required and the AV fleet size, the depreciation costs can be calculated using Equation 5.3.

$$
\begin{aligned}
Cd_{total} &= Cd_{AV} + Cd_{charger} \\
Cd_{AV} &= fleet\_size \cdot \frac{C_{AV} - RV_{AV}}{Ls_{AV} * 365,25} \\
Cd_{charger} &= N^{y}_{chargers} \cdot \frac{C^{y}_{charger} - RV^{y}_{charger}}{Ls^{y}_{charger} * 365,25}
\end{aligned}
\tag{5.3}
$$

Where

Cd_{AV} = Total Depreciation costs by AVs [€];
$fleet\_size$ = Fleet Size [vehicles];
C_{AV} = Purchase costs of 1 AV [€];
RV_{AV} = Residual value of 1 AV [€];
Ls_{AV} = Lifespan of an AV [days];
$Cd_{charger}$ = Total Depreciation costs by chargers [€];
$N_{chargers}$ = Number of chargers of type y required [chargers];
$C_{chargers}$ = Purchase costs of 1 charger of type y [€];
$RV_{charger}$ = Residual value of 1 charger of type y [€];
$Ls_{charger}$ = Lifespan of a charger of type y [days];
Cd_{total} = Total Depreciation costs [€];

The revenues consist of the revenues due to the use of the service which is equal to the total travel time of all passenger multiplied by the fare per minute of € 0,31. The fare per minute used in the model is based on the price of Car2go, a carsharing company [71], [37]. Additional revenue streams like, e.g. subsidies and vehicle advertisement revenues are not taken into account, because of the high uncertainty of political interest in AMoD systems and the limited space for advertisement on a vehicle like the Renault Twizy.

The passengers that experience a detour due to dynamic ridesharing would be charged with an additional fare following this pricing strategy because the duration of their detoured trip is higher than their direct trip. From a passenger perspective, this additional fare makes it very unattractive to share a ride. In order to compensate for this, a discount of 50% on the fare charged for the entire trip is given to the passengers that experience a detour. This discount is taken into account in the calculation of the revenues.

5.4. Experimental Variables

The experimental variables that determine the operational scenario that will be simulated consist of 3 operational variables: (1) ridesharing strategy, (2) relocation strategy and (3) vehicle charging strategy. Number 1 and 2 are binary variables, which can be equal to ”ON” or ”OFF”. Number 3 can result in a high number of scenarios as there is a high number of vehicle charging strategies possible when varying over types of chargers and applying these different types at different moments in time. To guarantee the computational feasibility of the simulation study, 2 possible charging strategies have been chosen. The first consists of only slow chargers with a power of 3.3 kW, the second of only fast chargers with a power of 7.7 kW. This has an influence on the financial viability as fast chargers are more expensive. On the contrary, it also has an influence on the level of service since fast charging will lead to more vehicle availability. Moreover, fast chargers will are expected to result in higher peaks in energy demand. Peaks in required energy for charging are especially important because it is normative in the determination of the required charging facilities.

5.4.1. Base scenario

To be able to compare the outputs of different scenarios, a base scenario is required which functions as a reference for comparison. The base scenario consists of a unique set of input variables which is most straight forward and is the least complex:

- Fleet size enough to satisfy all demand, so waiting times are minimized;
- Relocation turned to ”OFF”;

- Ridesharing turned to ”OFF”;
- Loading strategy with only slow chargers used.

The fleet size required to satisfy all demand is determined by model testing, using the base scenario parameter settings as introduced above. For 6 different random seeds, simulation runs have been carried out varying in fleet size, in order to determine the exact fleet size for which all demand is served. This fleet size is found by searching the number of vehicles for which the number of rejected passengers is 0. In order to find this, firstly the outcomes of the 6 iterations have been averaged to filter out the outliers in simulation outcomes. Below, the results of these iterations are given in Figure 5.23.

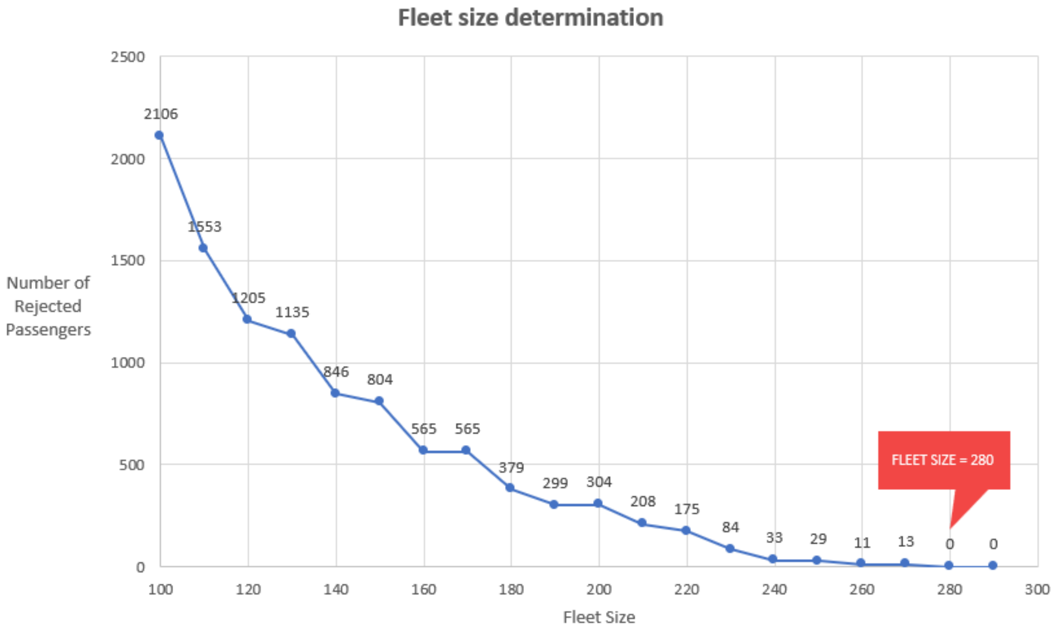

Figure 5.23: The number of rejected passengers as a function of the fleet size.

The graph in Figure 5.23 shows a decreasing number of rejected passengers for an increasing fleet size. From this Figure, one can conclude that the fleet size for which the number of rejected passengers is 0 is equal to 280 vehicles. However, a constant fleet size of 280/10 = 28 vehicles is used in further simulation runs because 1 agent represents 10 vehicles in reality.

5.5. Simulation Output

Randomness in the simulation output is generated using a random seed. Varying these random seeds leads to variability in the outputs. When the model completed a full simulation experiment run, the AMoD system is simulated for 1 typical day for a particular number of replications using randomly chosen seeds. The number of replications is determined based on a model experiment where the simulation has been run 6 times with 30 replications for each run. For each of the 30 replications, a different random seed is used which is randomly chosen. Stochasticity in the model has a large influence on the passenger departure times since these are generated using a random seed. Therefore, for each run, the number of rejected passengers has been calculated. Plotting the cumulative averages of the number of rejected passengers shows that the average is stable after 30 replications. The slope of the curve gives the variability of the average. The average is stable when the variability of the average is low. Following from the graphs in Figures 5.24 up to 5.29, the robustness of the results is guaranteed after 30 replications. Although there is some variability visible for a number of replications just below 30, large oscillations are not visible anymore. Moreover, for the sake of computational time, it is chosen to simulate each scenario for 30 replications.

When the model simulation run is completed, it automatically produces an Excel file which contains the KPIs of all the 30 replications that are required in the results analysis. These KPIs are calculated by the 'Statistics_Calculation' function in the Main agent. The output Excel file contains statistics on 4 categories: System outputs, Time outputs, Vehicle outputs and Financial outputs. These statistics are used to evaluate the scenarios in the results analysis in Chapter 6.

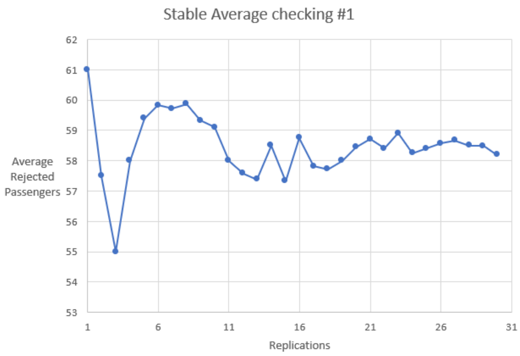

Figure 5.24: Average rejected passengers as function of replications #1

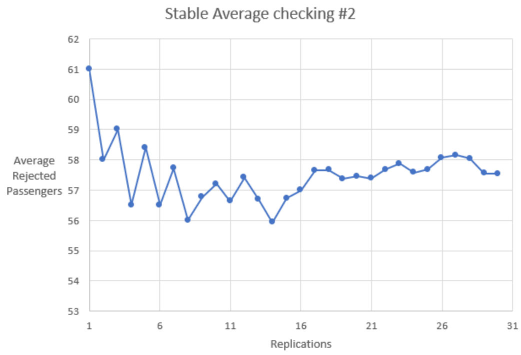

Figure 5.25: Average rejected passengers as function of replications #2

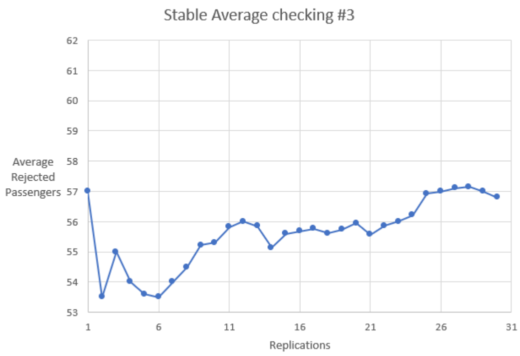

Figure 5.26: Average rejected passengers as function of replications #3

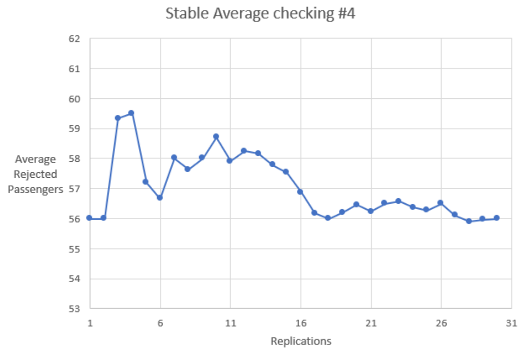

Figure 5.27: Average rejected passengers as function of replications #4

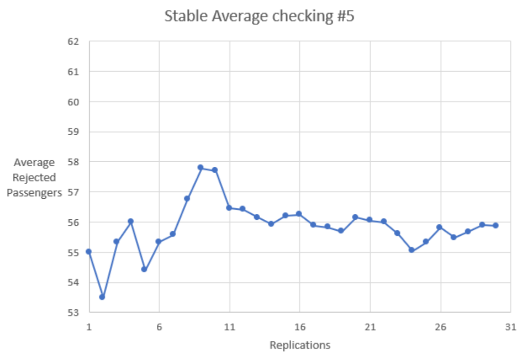

Figure 5.28: Average rejected passengers as function of replications #5

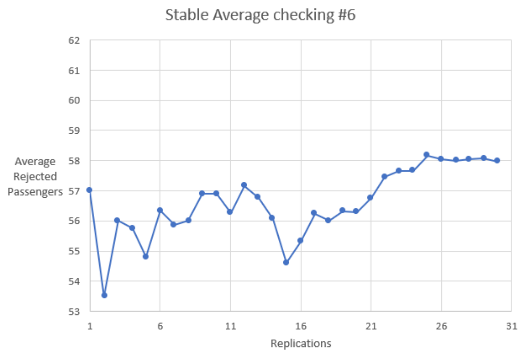

Figure 5.29: Average rejected passengers as function of replications #6

5.6. Model Verification

To check whether the simulation model produces outcomes that are realistic and therefore do not show significant differences from reality, the model has been verified using calibration parameters. Table 5.4 shows the values for the model calibration parameters produced by the model and compares them with values taken from reality. For both the essential model aspects: network and the vehicle, two calibration parameters have been checked.

Table 5.4: Calibration parameter values comparison between model and reality in order to verify the Anylogic model.

Calibration Parameter	Model	Reality	Difference
Direct Distance from Plein 1953 to Station-Zuidplein	2,2 km	2,0 km	0,2 km
Direct travel time from Plein 1953 to Station-Zuidplein	6,7 min	7 min	0,3 min
Charging time of slow chargers	61 min	74 min	13 min
Range of AV	73 km	+- 80 km	7 km

The direct distance from Plein 1953, which is used in the model as centroid_id 243, to the Station-Zuidplein, which is represented in the model as centroid_id 235, is used as a calibration parameter to verify the network. This O/D pair is used because its impedance is around average. This avoids the comparison of extreme values, which might lead to large differences. The distance in the model is calculated by the ControlScheme function and equals 2,2 km. The distance in reality is measured by using the Google Maps distance measuring function, which results in a distance of 2,0 km. The difference is relatively small. The travel time for this O/D pair for the model is calculated by dividing the distance over the speed, which is 30 km/h. For the travel time in reality, the travel time of the car using the Google Maps navigation function is used. Again the difference is relatively small. In conclusion, no significant differences have been observed in the network calibration parameter.

The charging time of the slow chargers, which is the type of chargers most often used, and the Renault Twizy vehicle range are the parameters chosen to verify the AV vehicle characteristics. The charging time of slow chargers is based on the time that is required to charge a vehicle from 25% up to 80% of the total battery capacity using a charger with a power of 3,3 kW, which results in a charging time of $((0,8 - 0,25) * 6,1/3,3) * 60 = 61$ min. In reality, the efficiency of the wireless charging systems used is not 100%. Based on recent research [61], an efficiency of 90% is more realistic. This results in a charger with a power of $3,3 * 0,9 = 2,97$ kW. This results in a charging time of $((0,8 - 0,25) * 6,1/2,97) * 60 = 74$ min. The difference between the model and reality is equal to 13 min, which leads to an underestimation of the charging time in the model. However, as wireless charging technology is developing, it is expected that at the time AMoD systems will be deployed, this underestimation will be compensated and might even be an overestimation.

The range of the Renault Twizy used in the model can be calculated using Equation 5.2. The resulting range, again using a speed of 30 km/h, results in a value of 73 km in the model. In reality, the range depends on multiple factors like, e.g. temperature, driving style, road type and slopes. According to tests [72], the average range of the Renault Twizy is around 80 km. The resulting difference is 7 km. However, as variations of the range might occur in reality, this difference is not regarded as significant. Moreover, a value of 73 km avoids an overestimation of the vehicle range in the model.

6 Results Analysis

In order to assess the modeled AMoD services in the described case study simulation model, certain operational scenarios are simulated using the Anylogic model. In this Chapter, at first, the description of the Base Scenario performance is given including a sensitivity analysis of certain essential model input parameters. Consecutively, the simulation outputs of the scenarios required to answer the research questions are compared to the base scenario in order to evaluate the direct influence of the three main operational variables: ridesharing strategy, relocation strategy and vehicle charging strategy. The impact of each operational variable is described from multiple perspectives: System perspective, Energy perspective, Passenger perspective, Vehicle perspective and Business perspective, of which the latter includes the financial viability analysis. In Section 6.5, the overview of the impact of the scenarios on the output indicators is given. With the knowledge on the impact of the operational variables taken into account, Section 6.6 aims to simulate a most profitable scenario from an operators perspective. In Section 6.7, a discussion is described which includes a comparison of the results with results found in similar scientific studies. Moreover, a comparison of the AMoD operational finances is made with existing bus-lines and non-automated mobility services. Finally, a description of the limitations of both the demand- and the supply-model is given.

6.1. Scenarios

Each scenario that will be considered consists of a unique set of variable settings. An overview of the scenarios is shown in Table 6.1. The influence of the variables on the financial viability is determined with respect to the base scenario. In the base scenario, the vehicles do not automatically relocate themselves after an operation, and only 1 passenger can be transported per operation. The charging strategy in the base scenario contains only slow chargers. In the other scenarios, for every distinct scenario 1 variable is changed. This provides the opportunity to show the direct impact of a change of a variable with respect to the base scenario. The Relocation Scenario shows the impact of the automatic relocation of the AVs. The Ridesharing Scenario shows the impact of activating dynamic ridesharing. The Sharing & Relocating Scenario shows the impact of the combined activation of relocation and dynamic ridesharing. The Fast Charging Scenario shows the impact of using fast chargers instead of slow chargers. A further description of the simulated scenarios is given in Sections 6.2, 6.3 and 6.4.

Anylogic contains various possible simulation experiment types. The experiment type that is used in this research is called the parameter variation experiment, which offers the opportunity to run the model multiple times consequentially for varying parameter values. Because various scenarios are evaluated in this research, this simulation experiment option is highly suitable for running the scenarios. The only intervention required is to tick the boxes for the scenario settings and press the ”run”-button, which will result in 30 replications with randomly chosen seeds. The total simulation run-time per scenario consists of around 30 minutes using a computer with extensive computational resources. Ending a simulation run automatically writes the values for the KPIs to an Excel file, which facilitates the processing and analysis of the results.

Table 6.1: Overview of the scenarios simulated using the simulation model

Scenario	Relocation	Dynamic Ridesharing	Charging Strategy
0. Base Scenario	OFF	OFF	slow
1. Relocation Scenario	ON	OFF	slow
2. Ridesharing Scenario	OFF	ON	slow
3. Sharing & Relocating Scenario	ON	ON	slow
4. Fast Charging Scenario	OFF	OFF	fast

6.1.1. Base Scenario Performance

The fleet size of the base scenario is chosen to be equal to the minimum fleet size for which all demand is satisfied. Ideally, a slightly lower fleet size would be more appropriate to evaluate the system performance, because the resulting number of rejected passengers would not be zero for a smaller fleet size and the number of rejected passenger is a useful indicator for the system performance. However, as the demand model does not incorporate a fleet size and it is important to achieve maximum consistency between the demand and the supply model, the fleet size to satisfy all demand is used. Using this fleet size, the system performance is evaluated in an alternative way. For scenarios that result in an improved system performance, the number of available vehicles that are not used during peak-hours is used. For scenarios that result in a deteriorated system performance, the number of rejected passengers is used.

Because relocation is not activated, the vehicles will remain parked at the Destination point of their operation. In this situation, it is assumed that there are enough parking facilities available at the destination points as no time penalty is incorporated for searching a parking spot. Table 6.2 gives an overview of the output indicator values of the base scenario. In the following subsections, the performance indicators will be analyzed for all perspectives.

System Perspective

The output parameters that belong to the system category are especially interesting from an operators point of view. The operator tries to maximize the total system travel time as the revenues are directly proportional to the total travel time. However, operators also strive for minimizing operational costs and maximize costs effectiveness. As expected, using a fleet size of 280 vehicles results in a low number of rejected passengers. Due to the stochastic impact of using randomly chosen random seeds, this number is not exactly equal to 0, but approximately it is. However, there is a space for optimizing the fleet size for this scenario as the number of unused vehicles is not equal to zero. For Station Zuidplein, this number is equal to 3 and for Station Lombardijen this is 35. From an operators point of view, to maximize the efficiency of the operation, the number of unused vehicles must be equal to zero to avoid unnecessary investment costs.

In Figure 6.1 and 6.2, the stacked statecharts of the AV agents are given for the base scenario using random seed 9, which resulted in results closest to average. The figures show the share of the total number of vehicles for all the states earlier presented in Figure 5.17. Each state is indicated by a distinct color. The model outputs the minimum number of Idle vehicles for both stations. For Station Zuidplein, this point is found just over 600 min, which is equal to the time 16:00. The graph shows that at this point in time, a peak is found for the number of vehicles that are charging and a peak of found in the MovingForOperation state and the MovingToTraveler state. A combination of high demand and low batteries at the same moment in time, results in the point where the minimum number of Idle vehicles is found. As for the vehicles assigned to Station Lombardijen, the minimum number of Idle vehicles is higher. The graph shows that this minimum is almost equal to 50% of the total number of AVs assigned to Station Lombardijen. Note that Figure 6.1 and 6.2 are only shown here for visualization purposes and do only account for a simulation run of the base scenario for random seed 9. Therefore, conclusions on the base scenario results should only be drawn from values shown in Table 6.2.

Table 6.2: Overview of the performance indicators of the Base Scenario

Perspective	Indicator						
System	Transported passengers	Rejected passengers	Total system distance [km]	Total system traveltime [min]	Total system waiting time [min]	Minimum idle vehicles	
						Station Zuidplein	Station Lombardijen
	7001	8	24582	23056	12605	3	35
Energy	Total system energy use [kWh]	Maximum power required [kW]					
		Station Zuidplein	Station Lombardijen				
	1503	242	79				
Passenger	Waiting time for vehicle arrival [min]		Waiting time for vehicle assignment [min]		Travel time [min]		Trip distance [km]
	Average	Maximum	Average	Maximum	Average	Maximum	Average
	1,83	9,14	0,79	1,44	3,30	8,03	2,47
Vehicle	Average traveled distance [km]	Average transported passengers	% of total operational time occupied	Average empty operational time [min]	Average operational time with 1 passenger [min]	Average operational time with 2 passengers [min]	
	106	30,3	47,8	83,5	76,6	0	
Business	Depreciation costs vehicles + charging facilities [EUR]	Energy costs [EUR]	Maintenance costs [EUR]	Management costs [EUR]	Revenues [EUR]		
	2262	601	1720	1000	7147		

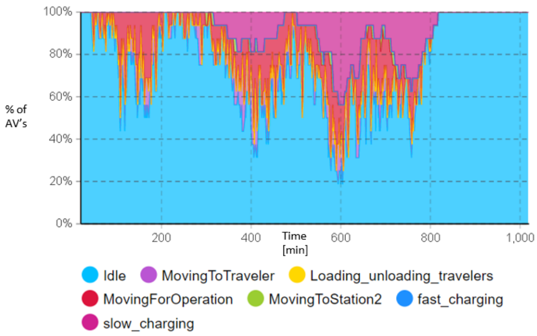

Figure 6.1: Stackchart indicating the states of the AV agents assigned to Station Zuidplein (seed 9)

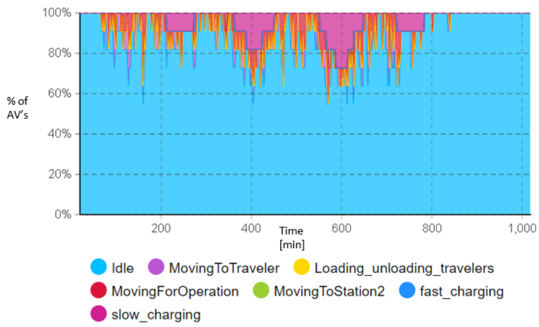

Figure 6.2: Stackchart indicating the states of the AV agents assigned to Station Lombardijen (seed 9)

Energy perspective

The output statistics regarding energy consist of the total system energy use, which is calculated by applying Equation 5.2, and the required power for charging for both stations, which is calculated by the number of vehicles charging multiplied by the power required for charging 1 vehicle. The total system energy is an important indicator as it determines the Energy costs. Figure 6.3 shows the used energy by the driving AV fleet over time. The morning peak is clearly visible in this graph, where the maximum used energy is found after 181 min and is equal to 5,84 kW.

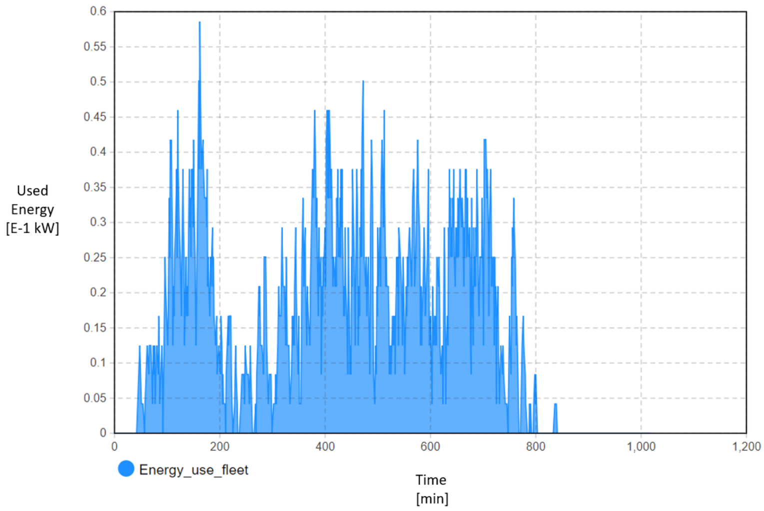

Figure 6.3: The total amount of energy used by the AV fleet while driving (seed 9)

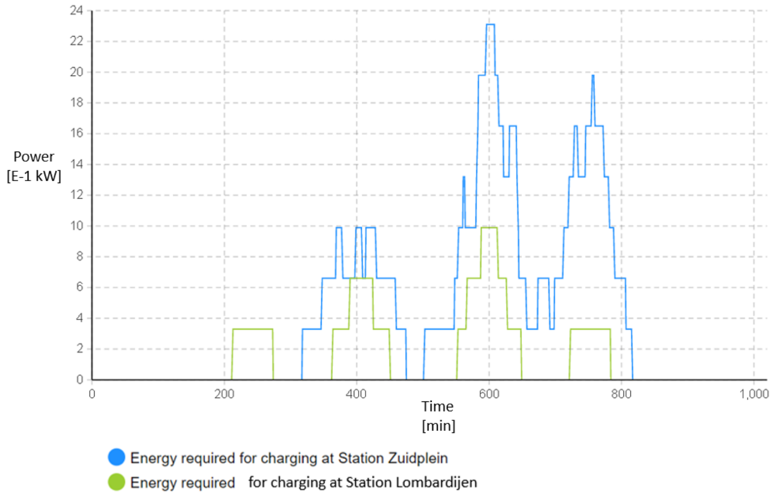

Figure 6.4: The power required for charging as a function of time for both stations (seed 9)

Besides, the maximum power required for both stations is shown in Table 6.2, which is an essential indicator for energy suppliers and the governmental agency responsible for the policy-making regarding charging infrastructure. The maximum power required is normative in the determination of the electricity transformer size required and is in this situation equal to 242 kW, although the graph in Figure 6.4 shows a slightly lower value. This is due to the fact that this graph only represents a simulation run of random seed 9. The graph shows the required energy for charging over time for both stations. The peaks in the graph in Figure 6.4 show the maximum required power for charging. From an operators perspective, high peaks in the required power for charging is undesired since this would mean that a large part of the total fleet will have to charge at the same time, which will have a negative impact on the system performance since fewer passengers can be transported at this period. This will have a negative impact on the revenues.

Passenger perspective

The histograms of the travel time and the waiting time show different distributions. The travel time histogram in Figure 6.5 shows a clear mean value of 3,43 min with a more or less evenly spread of values around the mean, which can be considered as being normally distributed. The maximum travel time is 8,1 min. Using the speed of 30 km/h, this results in a distance of $\frac{30}{3,6} \cdot 8,1 \cdot 60 = 4,05km$. This is exactly equal to the maximum direct distance found between a centroid and a station in the model.

The waiting time histogram in Figure 6.6 shows a broad peak for lower level values, due to the surplus of vehicles chosen in order to let the number of rejected passengers approximate 0. This is not a normal distribution, because the distribution is not centered around the mean of 1,54 min. Nevertheless, the value of 2,52 min shows similarities with the demand model input value for the waiting time penalty which was equal to 3 min per trip. The maximum waiting time shown in the graph is 9,81 min which is higher than the maximum waiting time for vehicle constraint of 5 minutes. This can be explained by the fact that the total waiting time consists of a combination of waiting time for vehicle assignment and waiting time for vehicle arrival, which can exceed the boundary value of 5 minutes.

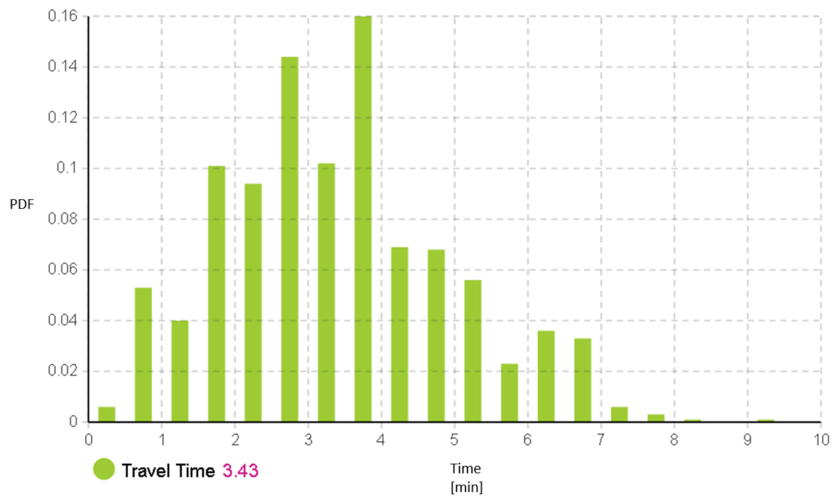

Figure 6.5: Histogram showing the distribution of travel times of agents of type Traveler (seed 9)

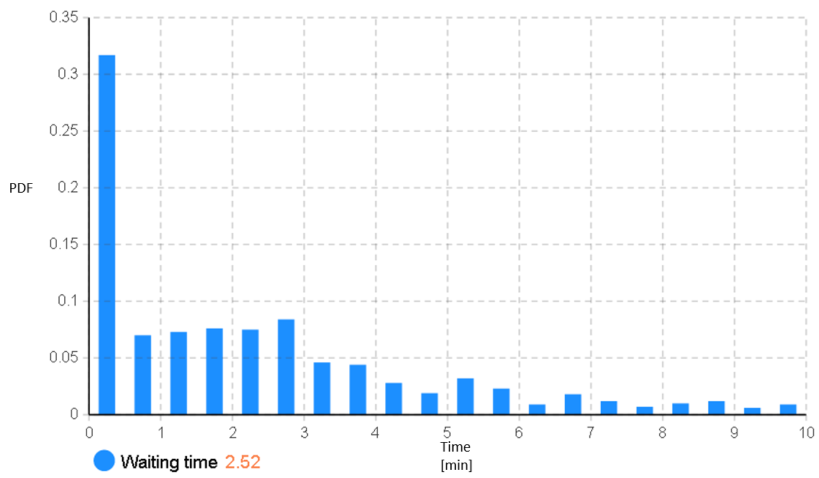

Figure 6.6: Histogram showing the distribution of waiting times of agents of type Traveler (seed 9)

Vehicle perspective

Table 6.2 shows that the average traveled distance per vehicle is 106,1 km. Calculating the average operational time using the speed of 30 km/h results in $\frac{106{,}1}{30} \cdot 60 = 212,2$ min. Comparing this value with the average empty operational time and average operational time with 1 passenger found in Table 6.2, the value does not equal the sum of these two values, which is equal to $83,5 + 76,6 = 159,1$ min. This can be explained by the fact that in the calculation of the average traveled distance, only the vehicles which are used are taken into account. In the calculation of the average operational times, the entire vehicle fleet is taken into account.

The percentage of operational time a passenger on average occupies a vehicle is equal to 47,8 %, which can be explained by the empty trips made to the Origin of the Travelers to pick one up and by the empty trips to the station when charging is required. Because ridesharing is turned off in the base scenario, the average operational time with 2 passengers is equal to 0. The number of transported passengers per vehicle is 30,3 on average. This number is rather low because of the vehicle capacity is turned to 1. Therefore, every operational trip of a vehicle counts only 1 transported passenger.

Business perspective

In order to analyze the financial viability of the AMoD operations, several financial output parameters can be used. Figure 6.7 shows the cash flow as a function of time for the financial aspects: Depreciation_costs, Wage_expenses, Maintenance_costs, Energy_costs and Revenues. Moreover, the Total_costs value, which is equal to the sum of all costs aspects, is given as a function of time. The graph shows that the initial total daily costs, which are determined by the fixed costs aspects for a typical day: depreciation costs and wage expenses, are equal to $€2262,15 + €1000 = €3262,15$. The depreciation costs consist of the depreciation of the vehicles and the charging facilities, based on the assumed lifespan and residual value described in Section 5.3.3. The variable costs aspects are the maintenance costs and the energy costs, which both are proportional to the total VKT of the system.

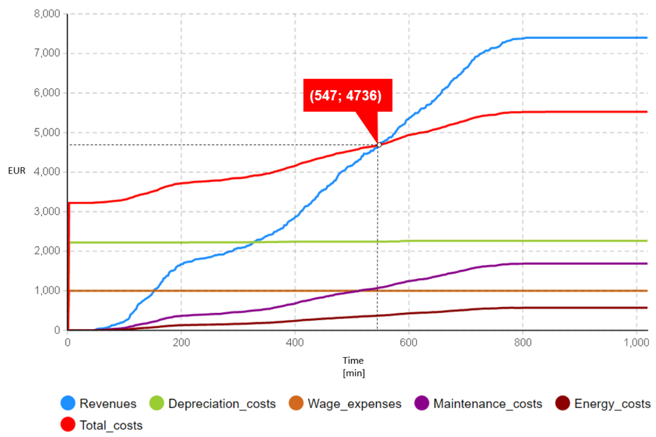

Figure 6.7: Graph showing the Revenues and costs aspects of the Base Scenario as a function of time

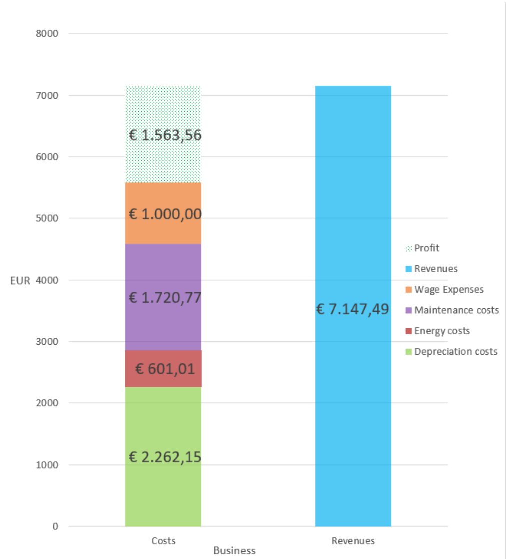

Figure 6.8: Graph showing the costs and revenues components of the Base Scenario

Next to the total costs which increase proportionally to the total number of system kilometers, the total revenues are increasing proportionally to the total system travel time. Therefore, the morning peak shows a steep slope, which is being followed by a less steep period just after the morning peak. After 310 minutes of model time, the slope of the total revenues graph is again increasing. Eventually, the slope of the revenues line grows to a value for which it will intersect with the total costs graph. After 547 minutes, which is equal to the daytime of 15:07, the revenues exceed the total costs for the first time. From this point in time, the AMoD system becomes profitable. So only operating as a morning peak service will not lead to a financially viable system.

Alongside the graph, Figure 6.8 shows the values of the costs aspects and revenues at the end of the day. Subtracting the total costs from the total revenues results in the daily balance for an AMoD operation of 1 typical day, which is indicated as profit in Figure 6.8. In order to show how the total costs are composed, Figure 6.8 shows the stacked costs components in a bar-chart. From Figure 6.8, one can conclude that the depreciation costs account for the highest share of the total costs. The depreciation costs are calculated by Equation 5.3. For the AVs and charger, this Equation assumes a simplified linearly decreasing relationship between the value and the time, which in reality might follow an exponentially decreasing relationship. Following Equation 5.3, the depreciation costs for the AVs Cd_AV are equal to €2220,58 and the depreciation costs for charging facilities Cd_charger are equal to €41,57 for the base scenario per day. So the AV is a far more essential aspect in the determination of the depreciation costs. Therfore, from a business point of view, it is more important to focus on optimizing the fleet size instead of focusing on the charging facilities.

6.1.2. Sensitivity analysis

In order to determine the sensitivity of the supply-model for certain essential input parameters, the impact of parameter variations is analyzed. The sensitivities of the input parameters of the demand-model are not taken into account resulting from the extensive computational resources required, making the analysis unfeasible. At first, the sensitivities of system related input parameters: vehicle speed, charging speed and battery capacity are determined by analyzing the impact of parameter variations on the number of rejected passengers since this is an indicator of the system capacity. These three input parameters are chosen to analyze because they are expected to have a decisive influence on the system capacity.

Consecutively, the sensitivities of financial input parameters: energy price and vehicle purchase price are determined by analyzing the impact of parameter variations on the total operational costs. These two parameters are chosen because in reality, the prices are not stable, depending mainly on market circumstances. Moreover, the impact these parameters play an essential role in the calculation of the total operational costs, based on the financial analysis of the Base Scenario.

Finally, the impact of fleet size variations on the costs and revenues is analyzed in order to show the operators trade-off when sizing the fleet. The simulation results are averages of 10 runs with randomly chosen random seeds, instead of 30 used for the simulation of the Scenarios. This is done to save computational time and is appropriate because the sensitivity analysis focuses on relationships rather than specific indicator values. During the variation of a specific parameter, the values of the other parameters remain constant.

Vehicle Speed

The impact of the vehicle speed variation on the number of rejected passengers is given in Figure 6.9. This graph shows that for low vehicle speeds, the number of rejected passengers is very high, which is logical since low speeds result in a low system capacity. However, for high vehicle speeds, a high number of rejected passengers is found as well. This can be explained by the fact that the speed has a considerable influence on the power consumption of the vehicle following Equation 5.2. Therefore, higher charging peaks and thus a lower system capacity in the evening peak are the result. The impact of the vehicle speed variations on the required vehicle charging is shown in the stacked statechart-graphs given in Figure 6.11. The graph for an assumed vehicle speed of 40 km/h on the right shows that the number of idle vehicles becomes 0 after 630 min, while this is not the case in the graph for the 30 km/h situation on the left. A number of idle vehicles equal to zero results in unsatisfied passenger demand, which reduces the system capacity.

From a system perspective and resulting from Figure 6.9, a speed of 30 km/h is close to the most preferred speed, as the number of rejected passengers is almost equal to 0. Investing in dedicated infrastructure to increase the operational vehicle speed, assuming equal charging facilities, would therefore not be desirable for operators as it reduces the system capacity.

Figure 6.10 shows that the average travel time and the average waiting time for vehicle arrival curves have a similar shape and decrease for increasing vehicle speed. The average waiting time for assignment decreases for speeds lower than 28 km/h but increases for speeds higher than 28 km/h. This can be explained by the impact of the speed on the system capacity shown in Figure 6.9 and 6.11. If the number of idle vehicles is equal to zero, which happens after 630 min for a vehicle speed of 40 km/h, all vehicles are already assigned to a passenger. This leads to an increase in the vehicle assignment time.

Charging Time

The impact of increasing charging time is shown in Figure 6.12. The range of the variations of the charging time values is based on the fast chargers used in the supply-model and traditional slow chargers. According to Renault [53], the time it takes to charge the Twizy from 25% of the battery capacity to 85% of the battery capacity using traditional slow chargers is equal to 155 min. From Figure 6.12, one can conclude that the number of rejected passengers increase for increasing charging time. This means that an increased charging time has a negative influence on the system capacity. Moreover, the graph also shows that the charging time variations have a smaller impact on the system capacity for low charging times than for high charging times.

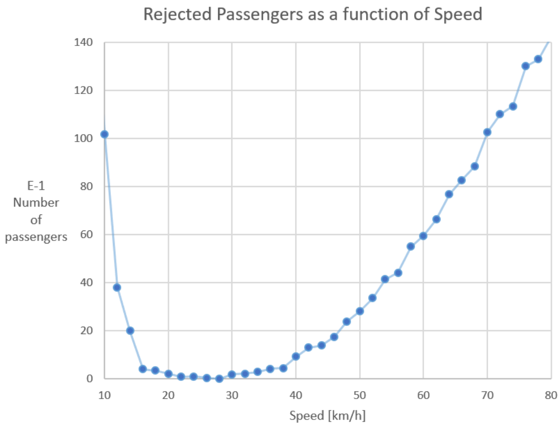

Figure 6.9: Graph showing the number of rejected passengers as a function of the vehicle speed

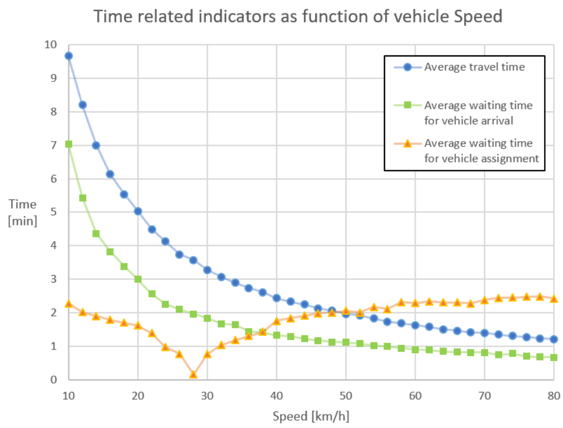

Figure 6.10: Graph showing average time related indicators as a function of the vehicle speed

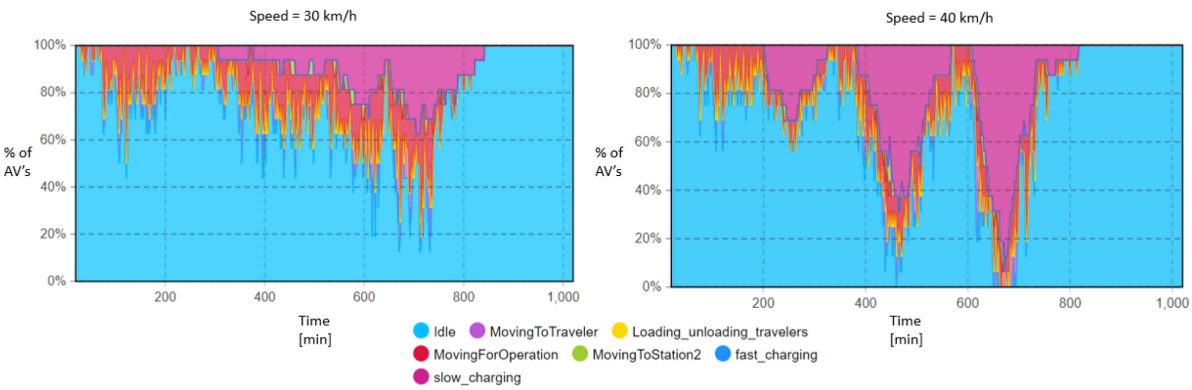

Figure 6.11: Stacked chart showing the share of states of the AV agent as a function of time for 2 different vehicle speeds. (Seed 7)

Battery Capacity

From Figure 6.13, it becomes clear that the impact of an increased battery capacity results in a decreasing number of rejected passengers approaching 0. When a number of rejected passengers equal to 0 is reached, the system capacity is as high as possible. Concluding from the shape of the graphs, increasing the battery capacity has a positive influence on the system capacity. Moreover, Figure 6.13 shows the graph for 4 different fleet sizes. From these graphs, one can conclude that reducing the fleet size results in a higher battery capacity required for a maximized system capacity. Using a fleet size of 200 vehicles will require a large battery capacity to reach the maximum system capacity, while a fleet size of 280 requires a battery capacity with only 5 kWh to reach the maximum system capacity.

Fleet size

Fleet size variations have an impact on both the costs and revenues. A higher fleet size will result in higher investment costs due to vehicle purchase costs. On the other hand, a high fleet size could lead to more revenues, since more passengers can be transported, depending on the passenger demand. In Figure 6.14, these impacts are given, assuming a stable demand which is not influenced by the fleet size. It is shown in the graph that an optimal fleet size value can be found at the point where the profit is maximized, indicated by the orange arrow. Therefore, from an operators perspective, the preferred fleet size for the Base Scenario would be close to 200 vehicles, determined from Figure 6.15. However, when a fleet size close to 200 is used, not all passenger demand can be satisfied. The fleet size will consequently function as a demand constraining factor, which is not taken into account in the demand-model. To avoid inconsistency between the demand and supply-model, a fleet size of 200 can not be used.

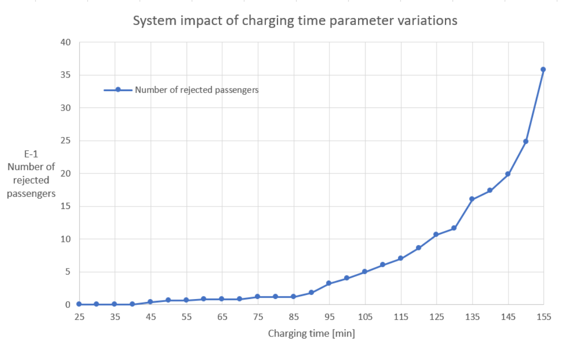

Figure 6.12: Graph showing the impact of charging time variations on the number of rejected passengers

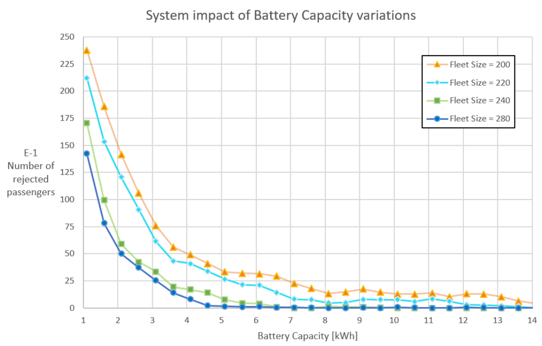

Figure 6.13: Graph showing the impact of battery capacity variations on the number of rejected passengers for three different fleet sizes

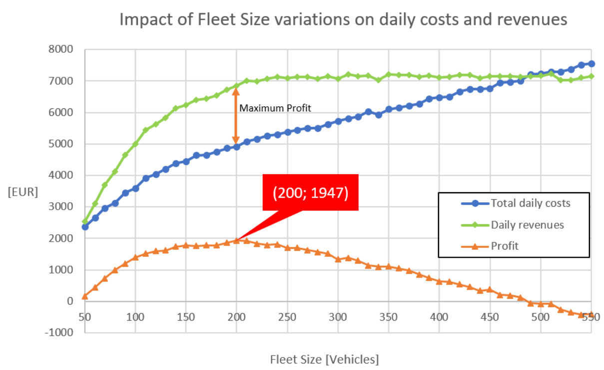

Figure 6.14: Graph showing the impact of fleet size variations on the daily costs and revenues

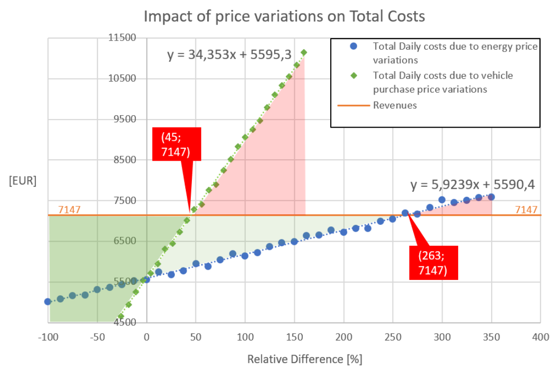

Figure 6.15: Graph showing the impact of price variations of energy and vehicle purchase on the total daily costs

Energy price & Vehicle purchase price

In Figure 6.15, the graphs of the total daily costs are given as a function of the relative differences with respect to the Base Scenario of energy price variations and vehicle purchase price variations. Moreover, the orange horizontal line indicates the revenues. Since the energy price and vehicle purchase price have a directly proportional relationship with the total costs, linear graphs are visible. The costs sensitivity of the vehicle purchase price shows to be higher than the costs sensitivity found for the energy price because of the steeper slope of the graph. The sensitivities of the energy price and vehicle purchase price are especially interesting because the prices could increase in the future because of economic circumstances. The red rectangles indicate the coordinates of the intersection points of the green- and blue-line with the revenues. Assuming all other input parameters remain equal, one can conclude from this that if the energy price increases by 45 %, which results in a price of € 1,45 per kWh, the AMoD system will not be profitable. Moreover, if the vehicle purchase price increases by 263 %, which results in a vehicle price of € 19600,- per vehicle, the AMoD system will not be profitable as well. The green areas indicate the potential profit and the red areas indicate the potential losses.

Conclusion

From the sensitivity analysis, it can be concluded that the system capacity is moderately sensitive to variations within a close range around the actual used value of the input parameters: vehicle speed, charging time and battery capacity. Similar observations can be made for the energy- and vehicle purchase price variations. However, the total daily operational costs show to be more sensitive to the vehicle purchase price than to the energy price. Therefore, it is important that AMoD operators pay attention to the vehicle price and the fleet size in order to retain a profitable operation.

6.2. Relocation Strategy

Chapter 2 showed that the main problem in current carsharing systems is the fact that the shared vehicles end up accumulated at certain locations, causing vehicle imbalance. To address this problem, relocation of vehicles is required. Chapter 2 showed that one of the main benefits of the automation of shared vehicles is the automatic relocation of vehicles, because no driver is needed and the vehicles can be relocated to a location which is most strategically advantageous at a time of day which causes the least problems. However, relocation trips are empty vehicle trips which lead to more system kilometers and a lower average occupancy. This leads to additional energy costs and maintenance costs.

To show the influence of the relocation strategy on the AMoD performance with respect to the Base Scenario, the Relocation input parameter is activated. This means that a vehicle will automatically move back to the station it is assigned to after it finished an operation and there is no demand left to serve. The Relocation Scenario will show the direct impact of activating relocation since this is the only simulation input that differs from the Base Scenario simulation input. The objective of this scenario is to reduce the waiting times for passengers waiting for a vehicle to arrive. It is expected, that due to additional empty trips, the number of traveled kilometers and the operational time will increase. This will have a negative influence on the total costs of the operation.

After the simulation run, which consists of 30 replications with a randomly chosen random seed, the output parameters have been averaged and compared with the output parameters of the Base Scenario given in Table 6.2. The impact of relocation is given by the relative differences expressed in percentages with respect to the base scenario. The spider plots in Figures 6.16 up to 6.19 give an overview of the relative differences of Scenario 2 with respect to the Base Scenario. Note that the output parameters from a passenger perspective are negative when the difference is positive, because a positive difference would mean an increase of travel time and waiting time which is a negative influence from a passenger point of view.

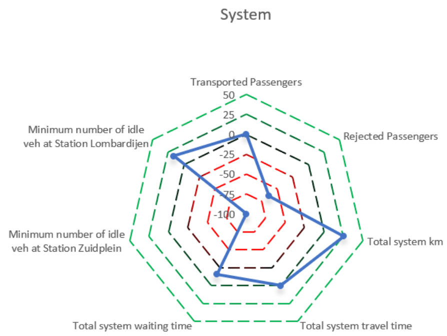

Figure 6.16: Spider plot for System related parameters [%]

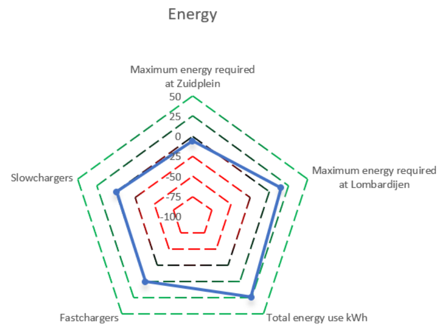

Figure 6.17: Spider plot for Energy related parameters [%]

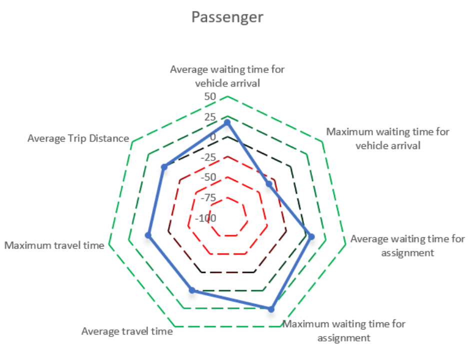

Figure 6.18: Spider plot for Passenger related parameters [%]

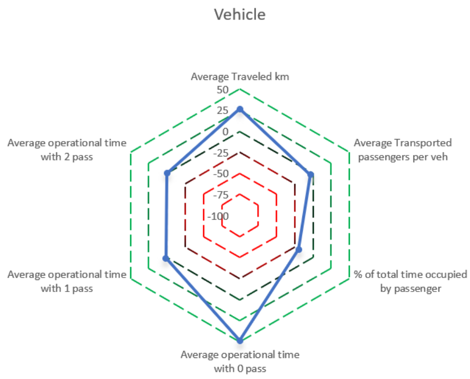

Figure 6.19: Spider plot for Vehicle related parameters [%]

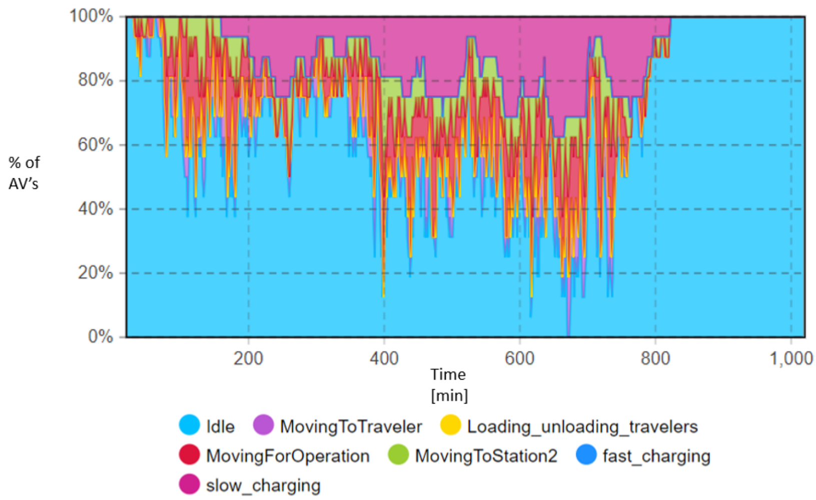

Figure 6.20: Stacked chart showing the share of states of the AV agent as a function of time for the Relocation Scenario (Seed 9)

System Perspective

The main impact of relocation on the system output parameters shown in Figure 6.16 is observed looking at the total system kilometers traveled. Due to the increase of empty relocation trips after vehicle operation, the total number of system kilometers has increased by 26%. The number of rejected passengers has decreased by 63 %, but as the number of rejected passengers found for the Base Scenario is equal to 10, this decrease is equal to 6 passengers which is a relatively small number. The total system waiting time is reduced by 16 %, which is the result of the fact that the waiting time for last-mile operations is 0 if enough vehicles are available because the vehicles always move back to the station, which is the Origin of last-mile trips. However, during peak hours, some waiting time can be experienced by last-mile travelers originating from Station Zuidplein because all vehicles will be operational according to Figure 6.20, where the minimum number of idle vehicles at Station Zuidplein which is equal to 0 at t = 650 min. This implies a reduction of minimum idle vehicles at Station Zuidplein of 100%. However, in absolute numbers, this reduction is only equal to 3 vehicles.

Energy Perspective

Resulting from the increased number of total system kilometers traveled, the energy output parameters in Figure 6.17 show an increase in the total energy use of 24 %. Accordingly, it is expected that this will lead to an increase in charging facilities. For Station Lombardijen this is indeed observed as the maximum required power has increased by 15 %. However, at Station Zuidplein a decrease in maximum power required of 6% is observed. This can be explained by the moment of charging of the vehicles which has resulted in a more evenly distributed demand for charging over time. Due to the additional kilometers traveled by the vehicles, the rate at which the vehicle battery decreases is higher for the Relocation Scenario than for the Base Scenario. Therefore, before the evening peak where the maximum required power for charging is found, almost all vehicles are already fully charged and do not have to charge at this moment in time. This results in a lower peak in the demand for charging-power at Station Zuidplein.

Passenger perspective

Figure 6.18 shows that from a passenger perspective, enabling relocation generally results in an improved level of service. The average waiting time for vehicle arrival is reduced by 17% and the average waiting time for vehicle assignment is decreased by 6 %. Looking at the maximum values for these waiting times, the maximum waiting time for assignment is reduced by 26%, which is a substantial reduction. However, the maximum waiting time for vehicle arrival has increased substantially by 34%. This can be explained by the result of the increase of total kilometers traveled due to empty trips. At peak hours, when all vehicles are operational and there is a high number of passenger requests.

Therefore, a high maximum waiting times can be observed incidentally.

Vehicle

Due to the additional vehicle kilometers resulting from empty vehicle relocation trips, the averaged traveled kilometers of the vehicles has increased by 26 %. This is equal to the increase in total system vehicle kilometers. Accordingly, the average occupancy of the vehicles is decreased by 19 %. Therefore, the use of the material resources is less efficient in the Relocation Scenario than in the Base Scenario.

Business perspective

In general, the Relocation Scenario shows an increase in the level of service, but an increase of vehicle kilometers and a decrease in vehicle occupancy. Looking at Table 6.3, this has a negative impact on the financial viability of the AMoD system. The main differences are found looking at the Energy costs and the maintenance costs, which both have increased due to the increased number of vehicle kilometers traveled. Eventually, the Relocation Scenario is still a financially viable option since the daily balance shows a positive value. However, the daily balance has been reduced by € 586,- which is equal to 37 %.

Table 6.3: Comparison of financial output parameters of the Relocation Scenario with respect to Base Scenario

Financial component	**Base Scenario**	**Relocation Scenario**	**Difference**
Costs			
Depreciation costs	€ 2.262,-	€ 2.262,-	0
Energy costs	€ 601,-	€ 744,-	+ € 143,-
Maintenance costs	€ 1.721,-	€ 2.157,-	+ € 436,-
Wage expenses	€ 1.000,-	€ 1.000,-	0
Total costs	**€ 5.584,-**	**€ 6.162,-**	**+ € 578,-**
Revenues	**€ 7.147,-**	**€ 7.140,-**	**- € 7,-**
Daily Balance	**€ 1.564,-**	**€ 978,-**	**- € 586,-**

6.3. Ridesharing Strategy

In order to increase the efficiency of vehicle operations within the AMoD system, dynamic ridesharing can be enabled when the vehicle capacity is larger than 1. In this research, the vehicle characteristics provide the opportunity for ridesharing since the capacity of the Renault Twizy is 2. The main challenge in dynamic ridesharing is the uncertainty of the willingness for passengers to share a ride since often a detour is required to pick up the second passenger because its location is not exactly on the direct route of the first requesting passenger. This might negatively influence the level of service, because of increased average travel time.

The Ridesharing Scenario will show the direct impact of enabling ridesharing since the ridesharing simulation input parameter is the only difference with respect to the Base Scenario. Moreover, the Sharing & Relocating Scenario shows the impact on the performance and the finances when both relocation and ridesharing are activated. In the calculation of revenues, a discount is taken into account. This discount is given to the passengers that experience a detour due to ridesharing and is equal to 50% of the total fare for there entire trip.

It is expected that for both scenarios, the number of transported passengers per vehicle increases for a limited additional traveled kilometers. Moreover, it is expected that the average travel time will show a slight increase resulting from the detours required. The resulting spider plots indicating the differences of the performance indicators with respect to the Base Scenario are given in Figure 6.23 up to 6.30 and the stacked statechart graphs are shown in Figure 6.21 and 6.22.

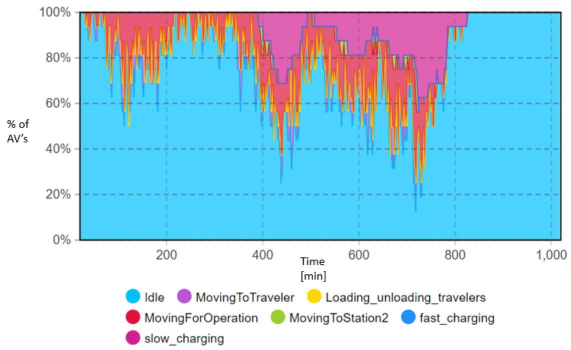

Figure 6.21: Stacked chart showing the share of states of the Station Zuidplein AVs as a function of time for the Ridesharing Scenario (Seed 9)

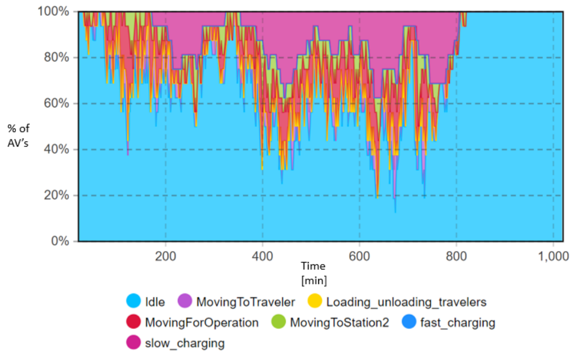

Figure 6.22: Stacked chart showing the share of states of the Station Zuidplein AVs as a function of time for the Sharing & Relocating Scenario (Seed 9)

Figure 6.21 shows that for a simulation of the Ridesharing Scenario using random seed 9, the minimum of idle vehicles at Station Zuidplein has not been equal to zero during simulation time, as the peak does not touch the line that indicates 0%. Similar peaks are visible in Figure 6.22 for the Sharing & Relocating Scenario. However, a large difference is found in the time of day the vehicles have to charge. In the Ridesharing Scenario, where relocation is not activated, the first moment vehicles have to charge is at 395 min, while in the Sharing & Relocating Scenario, this moment is found at 171 min. This can be explained by the fact that when relocation is activated, the usage of the vehicles is less distributed over the entire vehicle fleet because when a vehicle arrives back at the station, it will be the first one to receive a passenger request and become operational again, resulting in imbalanced vehicle- and battery-usage. In the Ridesharing Scenario, the vehicles will remain idle at the destination for a certain period of time if no requests are received. The vehicle use is more evenly distributed over the entire fleet, and therefore the vehicles will have to charge at a moment in time later on.

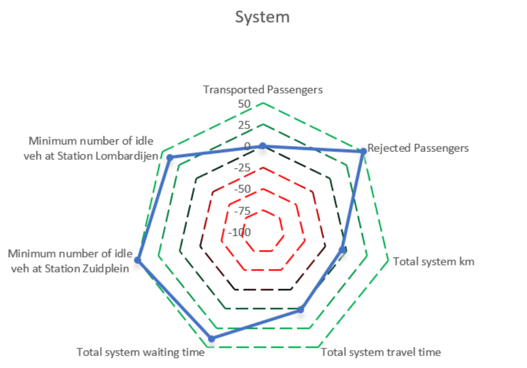

Figure 6.23: Spider plot for System related parameters of the Ridesharing Scenario [%]

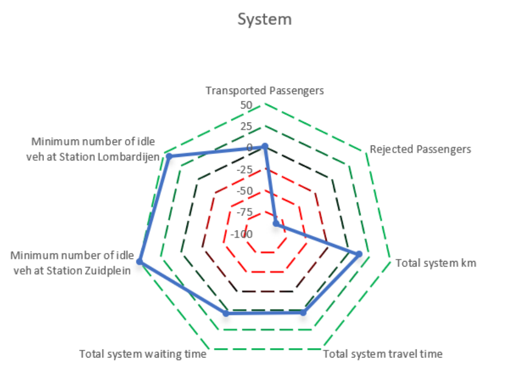

Figure 6.24: Spider plot for System related parameters of the Sharing & Relocating Scenario [%]

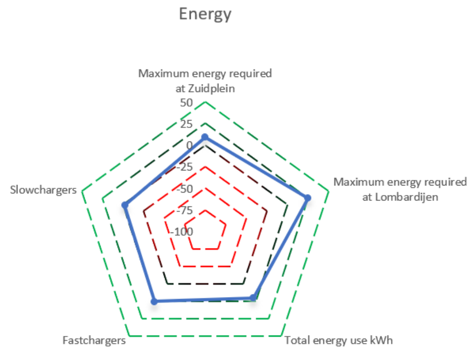

Figure 6.25: Spider plot for Energy related parameters of Ridesharing Scenario [%]

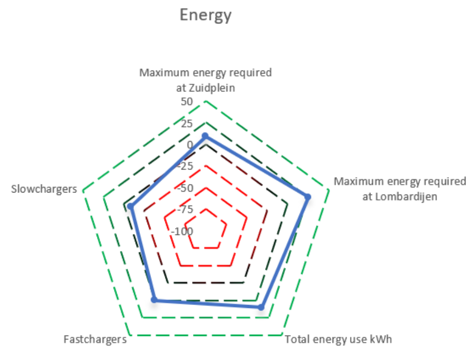

Figure 6.26: Spider plot for Energy related parameters of the Sharing & Relocating Scenario [%]

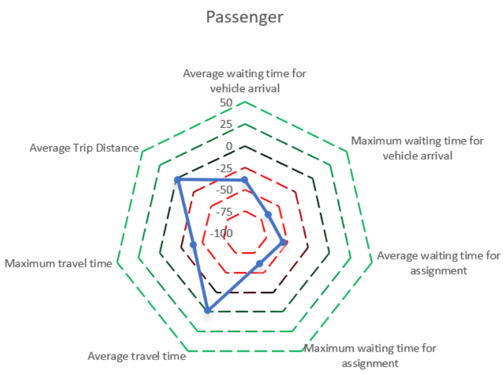

Figure 6.27: Spider plot for Passenger related parameters of Ridesharing Scenario [%]

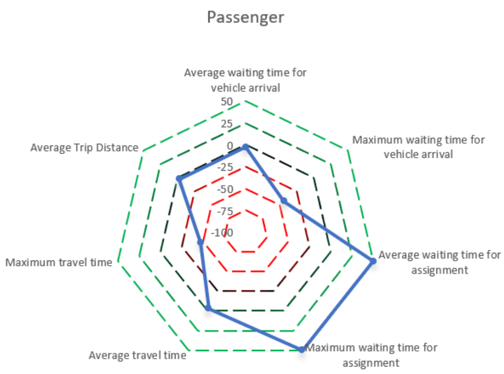

Figure 6.28: Spider plot for Passenger related parameters of the Sharing & Relocating Scenario [%]

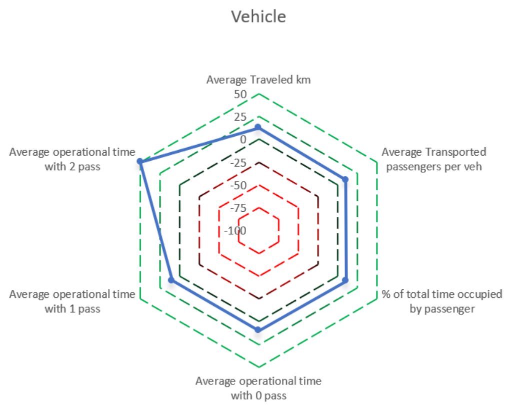

Figure 6.29: Spider plot for Vehicle related parameters of Ridesharing Scenario [%]

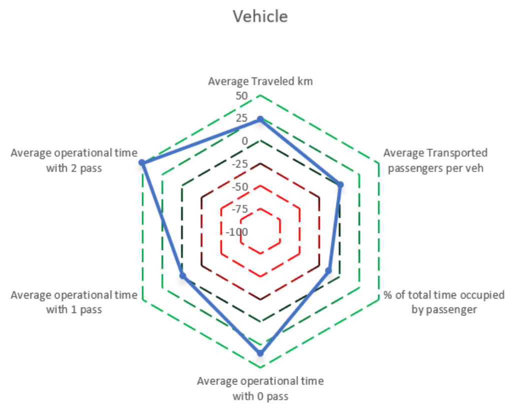

Figure 6.30: Spider plot for Vehicle related parameters of the Sharing & Relocating Scenario [%]

System Perspective

Figure 6.23 shows that activating ridesharing has a negative influence on the system capacity since the number of rejected passengers has increased from 10 to 15 passengers. The number of total system kilometers has decreased by 5% while the total system travel time has increased by 1,4%. This can be explained by the more efficient use of the vehicle kilometers by the trips occupied by 2 passengers where 1 of the 2 passengers experiences a detour. Moreover, the total system waiting time has increased by 39% due to ridesharing. This is the result of the AMoD system that forces the passengers to share a ride, regardless of the additional waiting time. In the Base Scenario, every requesting passenger is served by a vehicle that is only operational for that passenger and therefore only direct routes to the Origin of the passenger are made. However, with ridesharing activated, the passenger has to wait longer for operation because at first, the first requesting passenger has to be picked up. From an operators perspective, ridesharing results in more total system travel time with less vehicle kilometers, which is a highly beneficial combination of indicators since this would mean more revenues with less costs.

Comparing the Sharing & Relocating Scenario with the Base Scenario, a substantial decrease of rejected passengers of 83% is visible in Figure 6.24, which accounts for 8 passengers. In combination with the increased number of minimum idle vehicles at both stations, one can conclude that the combination of relocation and ridesharing has a positive influence on the system capacity. Compared with the Ridesharing Scenario, the most considerable difference is visible regarding the total system kilometers, which are increased by 13% with respect to the Base Scenario. This is the result of the additional vehicle kilometers required for the empty relocation trips. The total system travel time has increased by 3% and the waiting time has increased by 4%. From an operators perspective, the increase in the total system travel time will lead to higher revenues. However, the increased total system kilometers will lead to higher energy and maintenance costs.

Energy Perspective

The energy required for charging for both the Ridesharing Scenario and Sharing & Relocating Scenario show a similar increase by 9% at Station Zuidplein and 25% at Station Lombardijen according to Figures 6.25 and 6.26. For the Ridesharing Scenario, this can be explained by the relatively long period of time where no charging is required, resulting in a substantial number of vehicles that has to charge at the same moment in time. However, for the Sharing & Relocating Scenario, this can be explained by the substantial increase of the total system kilometers which lead to more energy use and eventually to more required energy for charging. This is supported by the 10% increased energy use.

Passenger perspective

From a passenger perspective, the Ridesharing Scenario is disadvantageous because Figure 6.27 shows a negative influence of ridesharing on all of the passenger-related indicators. The average waiting time for vehicle arrival has increased by 39% and the average waiting time for vehicle assignment has increased by 55%. Therefore, the level of service decreased drastically. It is remarkable that ridesharing has a larger influence on the waiting times than on the travel times, which on average only increased by 1,5 %. For the Sharing & Relocating Scenario, less drastic impacts are visible in Figure 6.28. The average waiting time for assignment even decreased substantially by more than 50%. For the sake of visualization, the Figure shows a decrease of 50%. However, the average waiting time for vehicle arrival and the average travel time have increased, but only by 2,6 % and 3 % respectively. Therefore, activating relocation shows a positive impact on the waiting times from a passenger perspective.

Vehicle

Because ridesharing is activated, the average operational time with 2 passengers will increase by 100%. Again, for visualization purposes, this increase is set to 50% in the Figures 6.29 and 6.30. Both Scenarios show an increase in average traveled kilometers. For the Ridesharing Scenario, this is unexpected, as the same amount of passengers will be transported with passenger sharing their ride will lead to more transported passengers per traveled kilometer. The increase of average traveled kilometers in this scenario can be explained by the fact that there is an increased value of unused vehicles, which do not take part in the calculation of the average. As a consequence, when the denominator of a fraction decreases and the numerator remains equal, the eventual value increases. For the Sharing & Relocating Scenario, the increase is due to the additional relocation trips. Moreover, due to these empty trips, the average transported passengers per vehicle is lower for this scenario than for the Ridesharing Scenario.

Business perspective

Resulting from the observed reduction of the number of total system kilometers and the increase of total travel time in the Ridesharing Scenario, the energy and maintenance costs have reduced while the revenues have increased. In Table 6.4, it is shown that this results in a reduction of the total costs by € 84,- and an increase in the total revenues by € 33,-. The daily balance results therefore in a profit which is € 117,- higher than the Base Scenario profit. In the Sharing & Relocating Scenario, the total revenues are even larger than the revenues of the Ridesharing Scenario and are equal to € 7.270,-. However, this required a lot more kilometers which resulted in increased energy costs and maintenance costs. Eventually, the daily profit of the Sharing & Relocating Scenario is € 156,- lower than the Base Scenario.

Table 6.4: Comparison of financial output parameters of the Ridesharing Scenario and the Sharing & Relocating Scenario with respect to Base Scenario

Financial component	**Base Scenario**	**Ridesharing Scenario**	**Difference**	**Sharing & Relocating Scenario**	**Difference**
Costs					
Depreciation costs	€ 2.262,-	€ 2.261,-	- € 1,-	€ 2.258,-	- € 4,-
Energy costs	€ 601,-	€ 571,-	- € 30,-	€ 663,-	+ € 62,-
Maintenance costs	€ 1.721,-	€ 1.668,-	- € 53,-	€ 1.941,-	+ € 221,-
Wage expenses	€ 1.000,-	€ 1.000,-	0	€ 1.000,-	0
Total costs	**€ 5.584,-**	**€ 5.500,-**	**- € 84,-**	**€ 5.863,-**	**+ € 279,-**
Revenues	**€ 7.147,-**	**€ 7.180,-**	**+ € 33,-**	**€ 7.270,-**	**+ € 123,-**
Daily Balance	**€ 1.564,-**	**€ 1.680,-**	**+ € 117,-**	**€ 1.408,-**	**- € 156,-**

6.4. Charging Strategy

To evaluate the impact of the charging strategy on the AMoD output indicators, the Fast Charging Scenario uses fast chargers instead of the slow chargers used in the Base Scenario. Using Fast chargers results in a charging time of 26 minutes, which is 35 minutes faster than the charging time of the conventional slow chargers. It is expected that this reduction of charging time has a positive influence on the system capacity because more vehicles are available to transport passengers. However, this entails two big disadvantages. First, the costs of charging facilities will be higher, due to the purchase price of the fast chargers which is twice as high as the slow chargers. Second, from an energy perspective, because the fast chargers required twice as much energy as the slow chargers, the peaks in the required energy for charging graph will be likely to be higher.

The only simulation setting of Fast Charging Scenario that is different from the Base Scenario settings is the charging strategy used. The charging strategy is set to ”fast”, which means that the charging time required for charging the battery from 25% to 80% is reduced from 61 min to 26 min. The resulting output parameters are given in the Figures 6.31 up to 6.34. The stacked statechart graph in Figure 6.35 shows relatively small shares of vehicles charging of the day, indicated by the dark blue color at the top of the graph. This results in a surplus of vehicles, as the minimum share of idle vehicles is equal to only 20%.

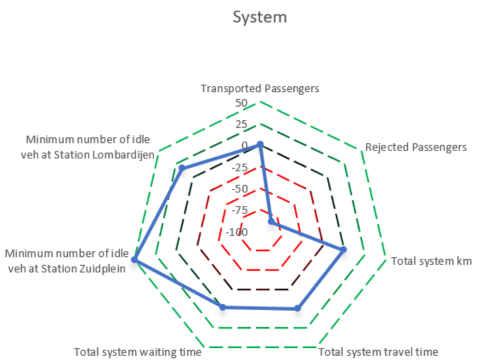

Figure 6.31: Spider plot for System related parameters [%]

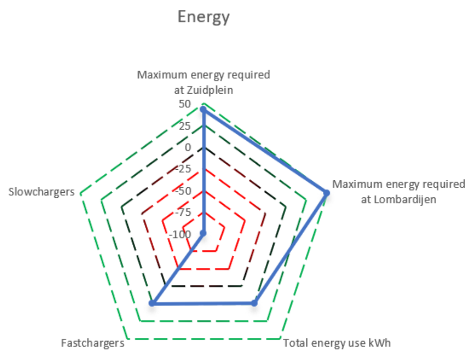

Figure 6.32: Spider plot for Energy related parameters [%]

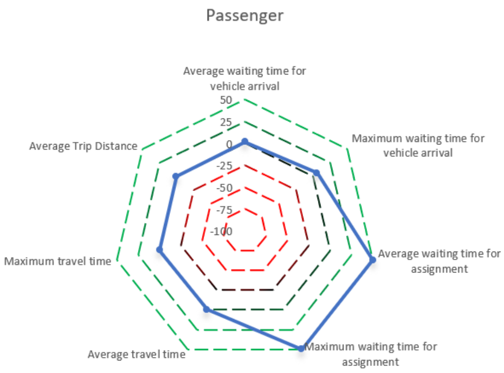

Figure 6.33: Spider plot for Passenger related parameters [%]

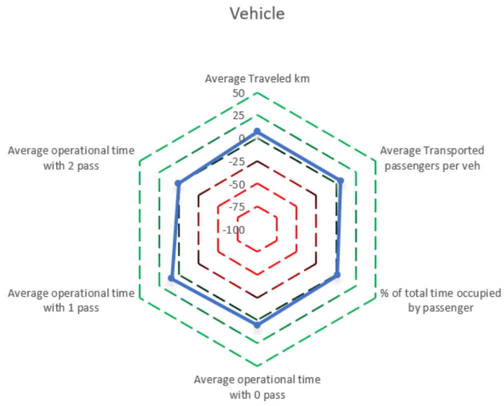

Figure 6.34: Spider plot for Vehicle related parameters [%]

System Perspective

Following from Figure 6.31, from a system perspective, using fast chargers has a positive influence on the system capacity, as the number of rejected passengers has reduced by 8 passengers and the minimum amount of idle vehicles has increased for both stations. For Station Zuidplein this increase is equal to 10 vehicles, which leads to very a very high relative increase which is set to the maximum of 50% for the sake of visualization. For Station Lombardijen this increase is equal to 6 vehicles and accounts for 16,3%.

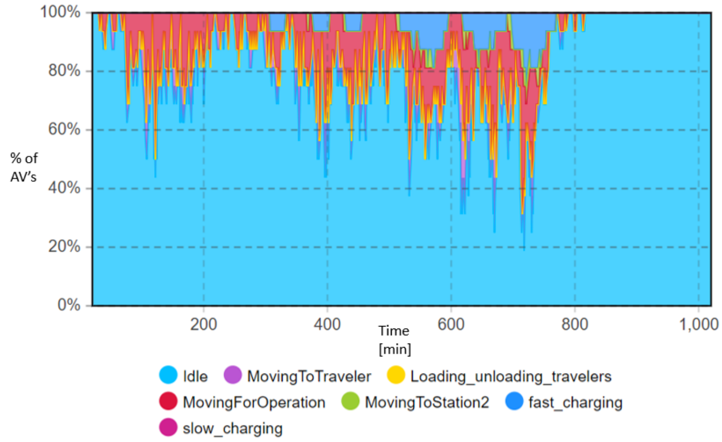

Figure 6.35: Stacked chart showing the share of states of the AV agent as a function of time for the Fast Charging Scenario (Seed 9)

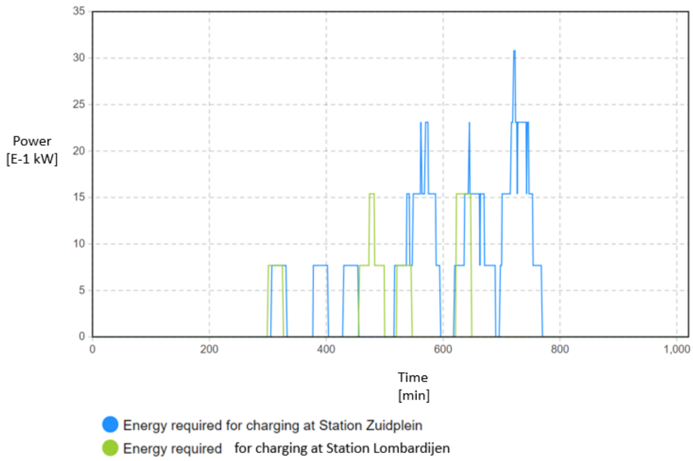

Figure 6.36: Graph indicating the required energy for charging for both stations as a function of time for the Fast Charging Scenario (Seed 9)

Energy Perspective

From an energy perspective, the total energy use is more or less equal to the Base Scenario, but as expected, the peaks in the required energy for charging have increased substantially. At Station Zuidplein, this increase is equal to 42% and for Station Lombardijen 88%. The graph showing the required energy for charging for both stations is given in Figure 6.36. The charging energy demand is more centralized around certain specific moments in time and shows higher steps due to the required power of 7.7 kW. Note that the unit on the y-axis is equal to E^{-1} kW. This gives a maximum required charging power of 343,93 kW at Station Zuidplein and 148,87 kW at Station Lombardijen. The main challenge regarding the operation of this Scenario lies in the dimensioning of the electricity transformer because of the increased peaks in the required power for charging. However, in this research, it is assumed that this problem is the responsibility of the energy provider and the governmental authority.

Passenger perspective

From a passenger perspective, using fast chargers would be advantageous, as the system capacity increases and therefore less waiting time is experienced by the passengers. From the graph in Figure 6.33, one can conclude that the major impact of charging strategy is visible for the waiting time for assignment, which decreases with the maximum percentage of 50%. This the result of the fact that using these fast chargers results in a situation where charging almost does not influence the system capacity anymore. There is a surplus of AVs so waiting time for an assignment should approximately approach 0, which it does because the average waiting time for the Fast Charging Scenario is equal to 0,26 min.

Vehicle Perspective

From a vehicle perspective, the Fast Charging Scenario leads to an increase of average traveled km of 7 % and an increase of operational time, because less time is required for charging. The average number of transported passengers per vehicle therefore also increase. However, this is only equal to 6% as there might also be empty trips involved in the additional vehicle kilometers.

Business perspective

In Table 6.5, the resulting output parameters regarding business perspective are given. The Fast Charging Scenario shows relatively small differences in the total costs compared to the Base Scenario. Resulting from using a more expensive type of chargers, the depreciation costs have increased. However, regarding the relatively small share of depreciation costs that is accounted for by the charging facilities, the increase of depreciation costs is only equal to € 13,-. The maintenance costs show a little decrease in € 13,- because of the small decrease in total system kilometers by 1%. This results in a similar value for total costs. The revenues have increased by € 25,- due to the small increase in total system travel time of 0,35%. Eventually, the effect on the financial viability is relatively small. However, Figure 6.35 shows that there is a large margin regarding the number of vehicles in order to satisfy the demand. This margin is larger than the one found for the Base Scenario shown in Figure 6.1. From a business perspective, using fast chargers is beneficial because the demand can be satisfied with a smaller fleet size than 280 vehicles. This could lead to a relatively large reduction of the depreciation costs as the AV purchase costs play a more dominant role than the charging facilities investment costs.

Table 6.5: Comparison of financial output parameters of the Fast Charging Scenario with respect to Base Scenario

Financial component	Base Scenario	Fast Charging Scenario	Difference
Costs			
Depreciation costs	€ 2.262,-	€ 2.275,-	+ € 13,-
Energy costs	€ 601,-	€ 599,-	- € 2,-
Maintenance costs	€ 1.721,-	€ 1.708,-	- € 13,-
Wage expenses	€ 1.000,-	€ 1.000,-	0
Total costs	**€ 5.584,-**	**€ 5.882,-**	**- € 2,-**
Revenues	**€ 7.147,-**	**€ 7.172,-**	**+ € 25,-**
Daily Balance	**€ 1.564,-**	**€ 1.590,-**	**+ € 27,-**

6.5. Financial Viability overview

To summarize, in this Section an overview is given of the influence of the experimental variables on the financial output parameters. Table 6.6 shows the values of the financial components for all the scenarios and shows the differences with respect to the Base Scenario. From this Table, one can conclude that the Ridesharing Scenario has the most positive impact on the financial viability of the AMoD system with a daily balance equal to a profit of € 1.680,-. This is the result of a combination of an increase in revenues and a decrease in costs. The scenario with the highest total revenue value of € 7.270,- is the Sharing & Relocating Scenario. However, these revenues are produced with additional costs due to an increase of empty trip kilometers required for relocation which results in a total costs value of € 5.863,-. This is not the scenario with the highest costs because the Relocation Scenario accounts for a total costs value of € 6.162,-. The complete overview of the impact of the scenarios on all the output parameters with respect to the Base Scenario is found in Table 6.7 at the end of this Section.

Table 6.6: Overview of the impacts of the Scenarios on the financial components with respect to the Base Scenario

Financial component	**Base Scenario**	**Relocation Scenario**	**Difference**	**Ridesharing Scenario**	**Difference**	**Sharing & Relocating Scenario**	**Difference**	**Fast Charging Scenario**	**Difference**
Costs									
Depreciation costs	€ 2.262,-	€ 2.262,-	0	€ 2.261,-	- € 1,-	€ 2.258,-	- € 4,-	€ 2.275,-	+ € 13,-
Energy costs	€ 601,-	€ 744,-	+ € 143,-	€ 571,-	- € 30,-	€ 663,-	+ € 62,-	€ 599,-	- € 2,-
Maintenance costs	€ 1.721,-	€ 2.157,-	+ € 436,-	€ 1.668,-	- € 53,-	€ 1.941,-	+ € 221,-	€ 1.708,-	- € 13,-
Wage expenses	€ 1.000,-	€ 1.000,-	0	€ 1.000,-	0	€ 1.000,-	0	€ 1.000,-	0
Total costs	**€ 5.584,-**	**€ 6.162,-**	**+ € 578,-**	**€ 5.500,-**	**- € 84,-**	**€ 5.863,-**	**+ € 279,-**	**€ 5.882,-**	**- € 2,-**
Revenues	**€ 7.147,-**	**€ 7.140,-**	**- € 7,-**	**€ 7.180,-**	**+ € 32,-**	**€ 7.270,-**	**+ € 123,-**	**€ 7.172,-**	**+ € 25,-**
Daily Balance	**€ 1.564,-**	**€ 978,-**	**- € 586,-**	**€ 1.680,-**	**+ € 117,-**	**€ 1.408,-**	**- € 156,-**	**€ 1.590,-**	**+ € 27,-**

6.5.1. Costs components

In Figure 6.37, a combined stacked bar chart is shown which indicates the magnitude of the costs components using certain colors. This graph shows that the largest part of the differences in total costs results from the energy costs and maintenance costs. These costs are related to the total system kilometers traveled. So from an operators perspective, in order to minimize the costs, the number of total system kilometers need to be minimized. However, system kilometers are required to transport passengers and to make revenues. The Relocation Scenario, which is characterized by activating relocation, results in the highest costs. This is mainly the result of the additional VKT required for empty relocation trips.

6.5.2. Profit

The Ridesharing Scenario, which is characterized by activating dynamic ridesharing, is the scenario that is most cost-effective and has results in the highest profit equal to 7180 - 5500 = € 1680,- for 1 typical day. However, this scenario shows the most negative impact on the level of service from a passenger perspective. It is therefore uncertain if this alternative is the most financially viable option on the long term as well. Figure 6.38 shows the total revenues and total costs for all scenarios using a bar-chart. The total costs show larger relative differences than the total revenues. This can be explained by the fact that the Anylogic simulation model focuses on the Supply side of the AMoD operation, which is related to the costs of operation. The OmniTRANS demand model has a larger influence on the revenues as this determines the number of passengers using the AMoD system for first- or last-mile transport.

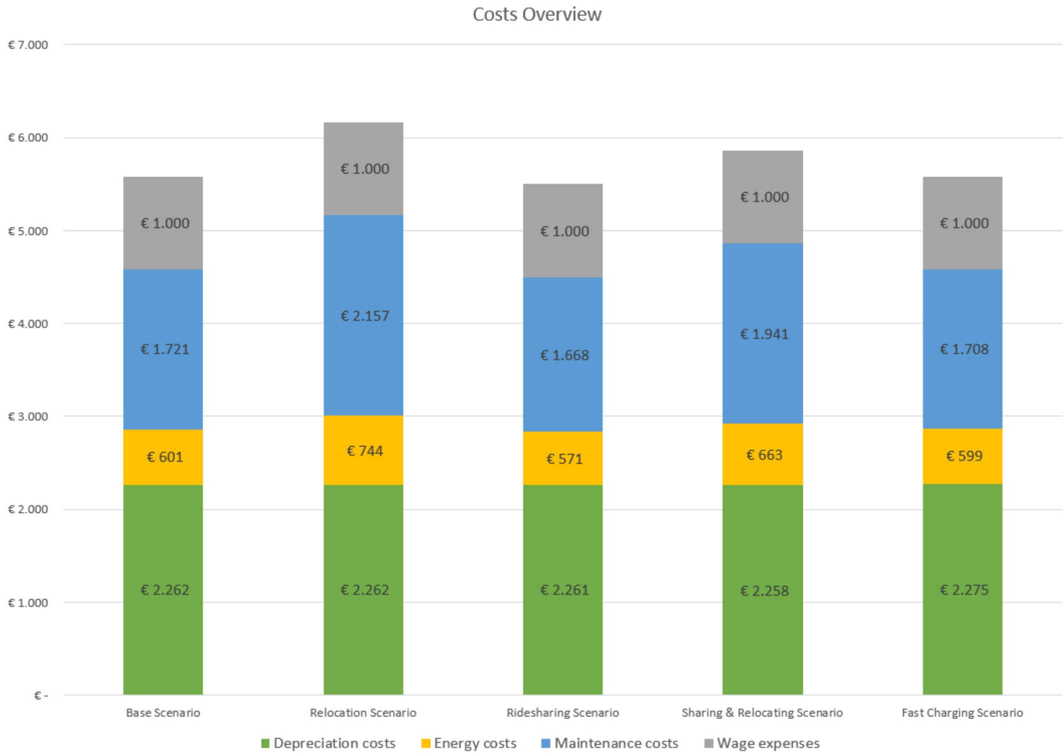

Figure 6.37: Stacked barchart providing an overview of the composition of the costs for all scenarios

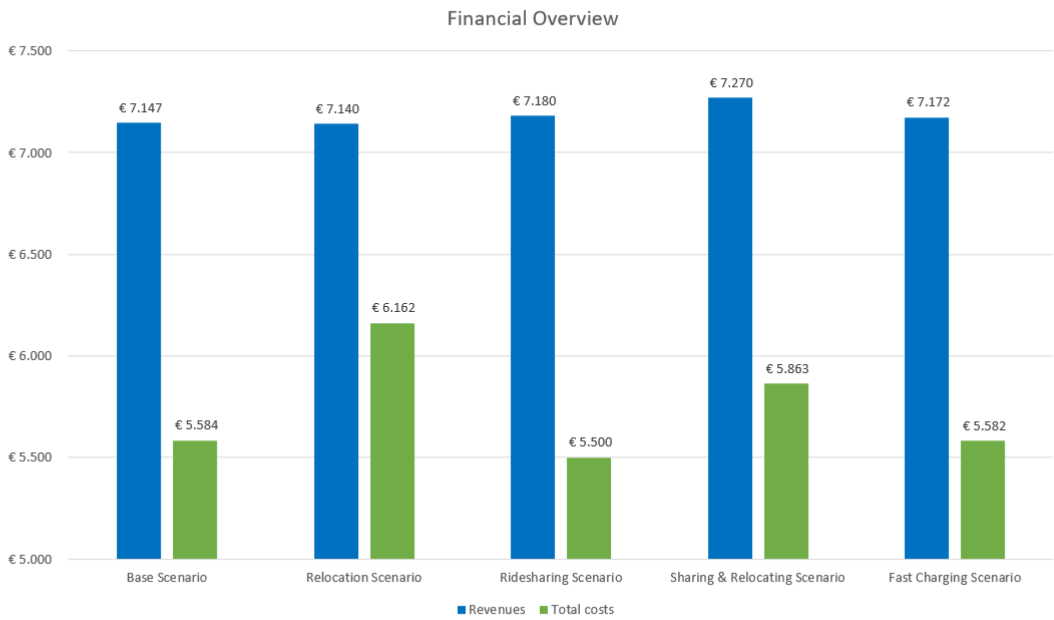

Figure 6.38: Barchart providing an overview of the total costs and revenues for all scenarios

Table 6.7: Overview of the impacts of the Scenarios on the output indicators expressed in % difference with respect to the Base Scenario

Output Indicators	Relative differences with Base Scenario [%]			
	Relocation Scenario	Ridesharing Scenario	Sharing & Relocating Scenario	Fast Charging Scenario
Transported Passengers	0,12	-0,10	0,12	0,15
Rejected Passengers	-63,33	90	-83,33	-83,33
Total system km	25,34	-5	12,82	-0,73
Total system traveltime	-0,1	1,43	3,09	0,35
Total system waiting time	-15,8	38,63	4,22	-1,54
Minimum idle vehicles at Station Zuidplein	-100	725	137,5	387,5
Minimum idle vehicles at Station Lombardijen	16,35	38,46	42,31	16,35
Average waiting time for vehicle arrival	17,08	-39,02	-2,62	-1,46
Maximum waiting time for vehicle arrival	-34,27	-65,88	-43,52	-5,36
Average waiting time for assignment	6,35	-79	77,9	-67,13
Maximum waiting time for assignment	25,83	-60,82	81,71	-64,38
Average travel time	0,22	-1,54	-2,96	0,19
Maximum travel time	0,24	-39,54	-47,54	0,24
Average Trip Distance	-49,67	-1,54	-2,96	0,19
Average Traveled km	26,63	12,81	22,51	6,83
Average Transported pass per veh	-3,33	10,68	1,65	6,15
% of total time occupied by passenger	-19,33	11,00	-12,87	1,48
Average operational time with 0 pass	48,40	9,65	35,10	5,60
Average operational time with 1 pass	1,70	9,66	-1,45	8,64
Average operational time with 2 pass	0,00	100,00	100,00	0,00
Vehicle investment costs	0,00	0,00	0,00	0,00
Charging facilities investment costs	-0,68	-0,68	-9,25	31,51
Depreciation costs	-0,01	-0,04	-0,17	0,58
Energy costs	23,73	-5,06	10,31	-0,39
Maintenance costs	25,34	-3,09	12,82	-0,73
Management costs	0,00	0,00	0,00	0,00
Revenues	-0,10	0,45	1,72	0,35
Maximum charging power required at Zuidplein	-5,91	9,09	9,09	42,12
Maximum charging power required at Lombardijen	15,28	25,00	25,00	87,96
Total system energy use	23,73	-5,06	10,31	-0,39
Number of Fastchargers	0	0	0	100
Number of Slowchargers	-0,68	-2,05	-9,25	-100

6.6. Preferred Scenario

In the previous Sections, the impact of operational variables on the system performances is researched from multiple perspectives. Because this research focuses on the financial viability of AMoD operations, this Section will describe the financial viability analysis of an AMoD operational scenario which is preferred from an operators perspective. Given the knowledge obtained by the prior analysis of the simulation outputs, the aim of the preferred scenario is to obtain a system that is most profitable.

6.6.1. Simulation Settings

In order to obtain a most profitable system, the simulation settings of the operators most preferred alternative include ridesharing, which showed to result in the most improved financial viability with respect to the Base Scenario. Moreover, fast charging seemed to have a minor impact on the costs regarding Section 6.4 but resulted in a larger margin of minimum idle vehicles. Therefore, a fast charging strategy combined with a smaller fleet size is used in this Preferred Scenario. According to model testing, the minimum fleet size, which results in a number of rejected passengers equal to 0, is equal to 24 vehicles when only fast chargers are used. Regarding the sensitivities of the costs and revenues found for the fleet size in the sensitivity analysis in Section 6.1.2, a fleet size of 240 vehicles leads to a larger difference is costs and revenues and therefore the profit is expected to increase as a result of a fleet size reduction from 280 to 240 vehicles. The Preferred Scenario is simulated 30 times for randomly chosen seeds. The averaged output parameters are shown in Table 6.8.

Table 6.8: Comparison of financial output parameters of the Preferred Scenario with respect to Base Scenario

Financial component	Base Scenario	Preferred Scenario	Difference
Costs			
Depreciation costs	€ 2.262,-	€ 1.957,-	- € 305,-
Energy costs	€ 601,-	€ 575,-	- € 26,-
Maintenance costs	€ 1.721,-	€ 1.673,-	- € 48,-
Wage expenses	€ 1.000,-	€ 1.000,-	0
Total costs	**€ 5.584,-**	**€ 5.205,-**	**- € 379,-**
Revenues	**€ 7.147,-**	**€ 7.207,-**	**+ € 60,-**
Daily Balance	**€ 1.564,-**	**€ 2.002,-**	**+ € 438,-**

Table 6.8 shows that compared to the Base Scenario all costs factors have reduced, regardless of the constant wage expenses. The depreciation costs have been reduced substantially by € 305,-. One can conclude that the reduction of depreciation costs resulting from the fleet size reduction outweigh the increase of depreciation costs due to the use of fast chargers. Moreover, the energy costs and maintenance costs have reduced due to a reduced number of total system kilometers which is the result of activating dynamic ridesharing as found in Section 6.3. Eventually, this resulted in a reduction in total costs by € 379,-. An additional effect of activating dynamic ridesharing is the increase of travel time, due to detours required when a ride is shared. This leads to an increase in revenues of € 60,- because the transport fares depend on the total system travel time. Distracting the total costs from the total revenues leads to a profit of € 2.002,- which is higher than the profit for the most financially viable scenario found in Table 6.6 which was equal to € 1680,-. Therefore, it is confirmed that combining the activated dynamic ridesharing strategy and the fast charging strategy using a lower fleet size of 24 vehicles results in the most financially viable AMoD operation, assuming the above costs structure. Moreover, this AMoD operation is able to serve all passenger demand.

6.7. Discussion

This section discusses the results provided in this Chapter from two different perspectives. At first, a comparison with results found in literature is made and secondly, a comparison with operational costs of existing bus lines in the Rotterdam-Zuid area is made. Consecutively, a comparison of the operational costs of the AMoD system with conventional non-automated carsharing and taxi systems is made. Finally, the limitations of both the demand- and supply-model are discussed at the end of this Chapter.

6.7.1. Scientific perspective

The modeling methodology used in this research has to the best of the authors knowledge not been applied for similar case study simulations before. However, some researches show similarities regarding concept and methodology. Therefore, a comparison of the main findings of this research with the related researches is made. All researches simulated a case study where shared autonomous vehicles are implemented in a city using an agent-based model. It is chosen to compare the waiting times of the researches with each other because all researches use this value indicating the level of service of the shared autonomous vehicle operations they modeled. The resulting average waiting times are compared in Table 6.9.

Table 6.9: Comparison of the resulting average waiting time with values found in literature

Research: Case Study	Average waiting time [min]
This research: Rotterdam-Zuid	2,5 - 6,0
Chen et al. 2016: Austin	7,0 - 10,0
Shen et al. 2018: Singapore	6,8
Zhang et al. 2015: Manhattan	2,5 - 5
Marczuk et al. 2015: Singapore	1,8 - 6,1
Bischoff et al. 2016: Berlin	2,5 - 8,5

From Table 6.9, one can conclude that the average waiting time found in this research, which is defined as the sum of the waiting time for assignment and the waiting time for vehicle arrival, is similar with the values found in previous research. However, the waiting times largely depend on the assumptions made regarding the fleet size and hub locations, as these profoundly influence the waiting times of passengers. Moreover, the scale of the AV operations plays a role, because in [49] and [41] the AVs are deployed as being taxi's and substituting conventional taxi systems, while in [36] and [30] the AVs are deployed as a first- and last-mile solution for public transport.

6.7.2. Existing bus services

In order to put the results into perspective, the operational costs of AMoD systems are compared with the operational costs of bus services that operate within the study area because AMoD- and bus-services are potential future competitors for first- and last-mile transport. The bus lines taken into account are only operational within the study area. The number of bus-trips per day of these lines is obtained from the website of OpenOV [73], where this data is publicly available. Note that this is the number of trips made by the bus-lines, regardless of the demand. The duration of the rides is obtained by using the timetable of the bus-lines [4]. A multiplication of the number of bus-trips with the duration of the trips results in the operational time per bus line. The costs per operational hour of bus lines in The Netherlands can be calculated by multiplying the operation time with the indicator estimated by the Dutch knowledge institute CROW [74], which holds a value of € 108,- per operational hour. This number accounts for personnel costs, material costs, maintenance costs, fuel costs and overhead costs. Summing up the operational costs of the bus lines accounted for, results in the total operational costs of bus services in the study area for 1 typical working day. The results are given in Table 6.10.

Table 6.10: Comparison of the total daily costs with existing bus lines in the study area

Bus line	Bus-trips per working day [-]	Bus-trip duration [min]	Operation time [h]	Operational costs per day [€]
66	104	39	67,6	€ 7.301,-
67	46	14	10,7	€ 1.159,-
70	111	40	74	€ 7.992,-
72	14	19	4,4	€ 479,-
74	6,5	28	3	€ 328,-
76	91	36	54,6	€ 5.897,-
77	54	30	27	€ 2.916,-
Total	**426,5**		**241,4**	**€ 26.071,-**
Base Scenario AMoD			**819,4**	**€ 5.584,-**

In Table 6.10, the total daily operational costs of the existing bus lines in the study area and the Base Scenario of the AMoD system are given. The operation time of the Base Scenario AMoD system is calculated by dividing the number of total system kilometers by the speed, which results in $\frac{24582,41}{30}$ = 819,4 h. Comparing the bus system with the AMoD system shows that the total operational costs of bus systems are higher while this operation comprises a lower operation time. This is the result of the high operational costs per operational hour. Calculating the costs per operation hour of the AMoD system gives $\frac{5.584}{819,4}$ = € 6,81, which is substantially lower than the cost per operation hour of bus lines, which is equal to € 108,-.

Assuming a scenario where the existing bus lines transport an equal amount of passenger as the AMoD system, the operational costs of bus-lines would be 26071 - 5584 = € 20.487,- more expensive than the AMoD system. The required ridership of the bus-lines for this demand can be calculated using the capacity per bus. The bus type used for the bus-lines taken into account is the Mercedes-Benz Citaro 0530 [4], which has a crush capacity of 98 passengers. This capacity comprises the seating and standing capacity. In order to determine the total capacity of the bus-lines, the number of bus-trips is multiplied by the capacity per bus. This results in a total capacity of the bus system in the study area equal to 426,5 x 98 = 41797 passengers. Consequently, the average ridership of the bus-lines has to be equal to $\frac{7009}{41797} \cdot 100 = 16,8\%$ in order to transport an equal amount of passengers.

6.7.3. Non-automated mobility services

In order to show the cost impact of the automation, the costs of the AMoD system are compared to the costs of existing non-automated mobility services. The costs of non-automated mobility services are calculated by adding the wage expenses required for additional personnel. Three non-automated mobility services are taken into account:

1. Adding relocation personnel to the AMoD Base Scenario results in a conventional carsharing system,
2. Adding drivers to the AMoD Relocation Scenario results in a conventional taxi system with a vehicle capacity equal to 1 passenger,
3. Adding drivers to the AMoD Sharing & Relocating Scenario results in a conventional taxi system with ridesharing.

Adding a driver to the Ridesharing Scenario is not taken into account because it is not able to relate this concept to an existing mobility concept. A passenger using a shared vehicle would not have an incentive to make a detour to pick up a second passenger. It is important to take into account that this comparison uses a simplification of the additional costs and uses equal assumptions as are used for the AMoD system. The resulting costs are summarized in Figure 6.39

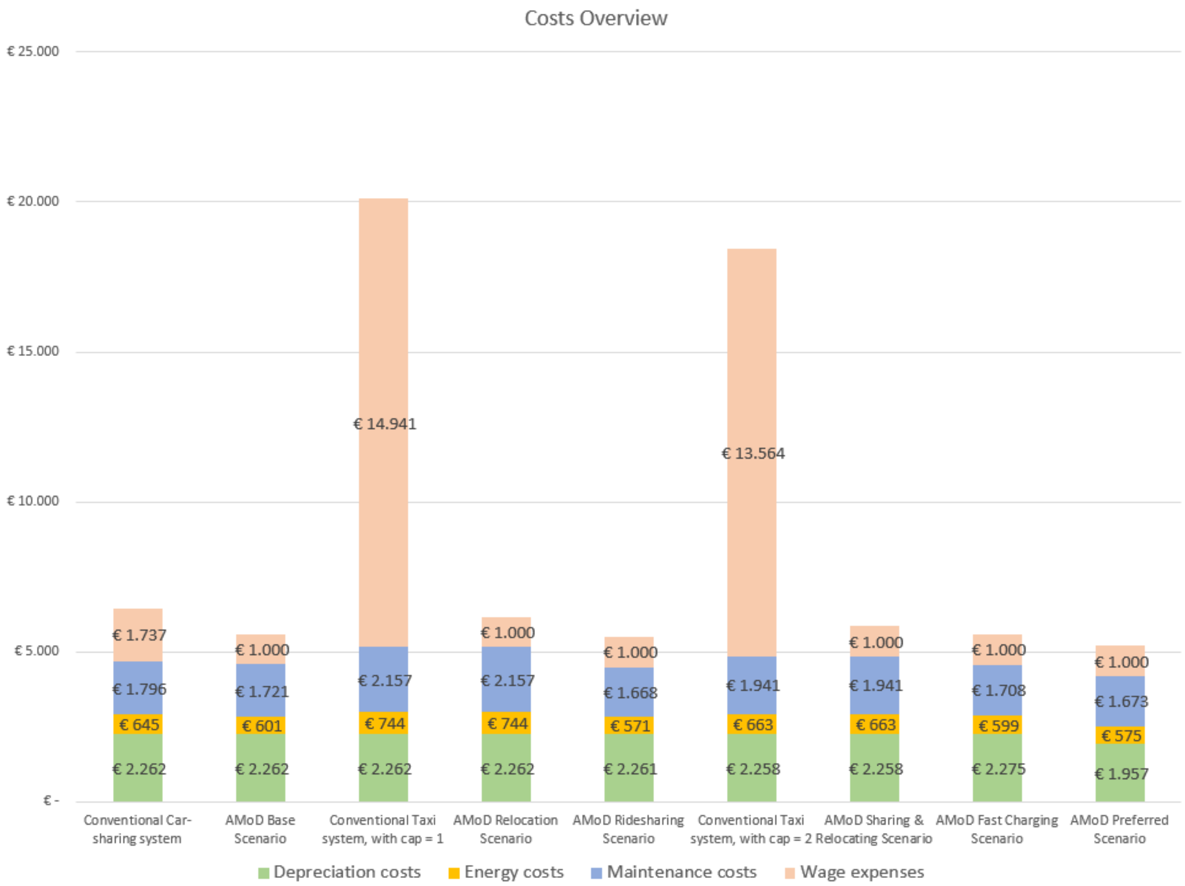

Figure 6.39: Stacked barchart providing an overview of the composition of the costs for all AMoD operations including the non-automated operations

Conventional carsharing

Conventional carsharing systems initially do not require a driver, because passengers can drive a shared vehicle themselves. However, as the vehicles tend to end up at undesired locations causing vehicle imbalance, drivers are required to relocate the vehicles back to the station. Moreover, when vehicles need to charge, a relocation trip is required back to the station where the charging facilities are located. A simulation of the Base Scenario shows that the number of vehicles that end up throughout the study area is equal to 170. On top of that, determined from the graph in Figure 6.4 that shows the required power for charging, 290 vehicles required charging during the day. Only last-mile operational vehicles need a relocation trip since first-mile operational vehicles end up at the charging facility location already.

Because 54 % of the trips are last-mile operations, 0,54 x 290 = 157 vehicles need an relocation trip in order to charge. A summation gives the number of relocation trips required which is equal to, 170 + 157 = 327. Using an average trip distance of 1,64 km and assuming each relocation trip requires a back and forth trip, the total driving time required for relocation is equal to $\frac{327 \cdot 2 \cdot 1,64}{30} = 36$ h. Assuming an hourly driver salary of 17,3 per hour, based on a monthly salary of € 3000,-, the additional wage expenses due to vehicle relocation is equal to 36 x 17,3 = € 618,-. The additional energy costs for 327 trips with an average distance of 1,64 km and an energy price of € 0,04 per km are equal to 327 x 2 x 1,64 x 0,04 = € 44,-. Moreover, the additional maintenance costs for a maintenance price of € 0,07 per km is equal to 327 x 2 x 1,64 x 0,07 = € 75,-. The total additional costs are therefore equal to 618 + 44 + 75 = € 737,-. With a total revenues value equal to € 7.147,49 and the initial total costs value equal to 5583,93, the profit of this carsharing system is equal to 7147,49 - (737 + 5583,93) = € 707,99. However, these costs do not account for personnel scheduling and the effort required to transport the relocation driver to the vehicle. Moreover, the duration of the driver trip from its origin to the vehicle that has to be relocated is assumed to be equal to the duration of the relocation trip.

Conventional Taxi
Adding a driver to the Relocation Scenario of the AMoD system would lead to a conventional taxi system that is station-based, which means that if no passenger requests are received, the taxi's will drive back to the station where they will wait for new passenger requests. The additional costs of adding drivers to the AMoD Relocation Scenario would only comprise additional wage expenses due to driver salaries. Because no additional kilometers are required, equal energy costs and maintenance costs are used. The additional wage expenses can be calculated using the number of operational vehicles which is equal to the fleet size minus the minimum number of idle vehicles. For the Relocation Scenario, this leads to 280 - 40 = 240 vehicles. Multiplying this number with an average operational time per vehicle equal to 3,4 h, results in a total operational time of 240 x 3,4 = 806 h. Using an hourly salary of € 17,3, the total additional wage expenses are equal to 806 x 17,3 = € 13.940,- which is a substantial amount of money. This shows that a conventional taxi system using fares of 0,31 per minute leads to significant financial losses. In Figure 6.39, it is shown that the total operational costs of this taxi system are slightly higher than € 20.000,-. To break even, with a total system travel time equal to 23033 min, a fare equal to $\frac{20000}{23033}$ = € 0,87 per traveled minute must be maintained, which is almost 3 times as expensive as the fare of AMoD services.

Conventional Taxi with ridesharing
When a driver is applied to the Sharing & Relocating Scenario of the AMoD system, it would lead to additional wage expenses as is described above for the Relocation Scenario with a driver. However, as a result of ridesharing, less operational vehicles are required to transport an equal amount of passengers. For the Sharing & Relocation Scenario, the number of operational vehicles is equal to 280 - 65 = 225. The average operational time of this scenario is equal to 3,22 h. This leads to a total operational time of 225 x 3,22 = 726 h, which result in additional wage expenses equal to 726 x 17,3 = € 12.560,-. Similarly to the conventional taxi system, this substantial amount of additional costs leads to financial losses. In order to make this taxi with ridesharing system profitable, a higher transport fare must be maintained. Regarding the total costs equal to € 18.500,-, in order to break even with a total system travel time equal to 23769 min, a fare of $\frac{18500}{23769}$ = € 0,78 per traveled minute must be maintained. This is 2,5 times as high as the fare of AMoD services.

Concluding from the comparison of the AMoD scenarios with conventional non-automated mobility services, using non-automated taxi systems with equal operational characteristics and conditions as AMoD services will lead to financially unfeasible systems. However, conventional car-sharing systems result in limited additional wage expenses and is still financially viable based on this financial analysis. However, the main challenge for this system is to optimize the schedule of the relocation drivers, minimizing the salary costs.

6.7.4. Model limitations
In the following subsections, the limitations of the demand- and the supply-model are described. It is important to take these limitations into account in the final conclusion, as it might influence the interpretation of the results.

OmniTRANS demand model
The demand model used, contains limited possibilities for including parameters on choice preferences regarding the AV as a first- and last-mile mode. In this model, the passenger choice behavior is based on the AV speed, waiting time and fare. However, other choice preference factors might play a role in the eventual passenger choice behavior. Moreover, the choice parameters used were obtained from stated preference surveys carried out in Austin [19] and an online panel in The Netherlands [20]. Therefore, the model is not optimally calibrated for the exact case study location.

One of the choice preference factors that is not taken into account in the demand model is the willingness of passengers to share a ride, while dynamic ridesharing is taken into account in the supply model, assuming that every passenger would accept a detour that at maximum results in 25 % additional travel time. This leads to two limitations. The first limitation is about the fact that in reality, not every person would accept 25% additional travel time to let someone else share their ride. The second limitation is that the demand model does not account for offering discounts to passengers that share their ride, which might affect their choice behavior. Providing passengers with such incentives could increase the willingness to share a ride. In order to gather knowledge on the case study location specific passenger choice behavior, a stated preference survey must be carried out that accounts for the choice preference factors which are not taken into account in this research.

Because of the size of the model and its relatively high requirement of computational resources, it was not feasible to check the sensitivity of the model assumptions, which are therefore unclear. However, the output of the model strongly depends on the model assumptions. A lack of insight in the sensitivity of the input assumptions could lead to an overestimation of the demand [75]. This is especially essential for this research because the demand model produces its outputs in an early stage of the research, and the consequential supply model performance depends on this output. A quick-scan model version of the large model would be helpful to gain insight into the sensitivity of the model to the input parameters.

The essential input parameter of the demand model is the fare since the fare has both an influence on the passenger demand and as well on the eventual revenues in the supply-model. In this research, limited insight is given in the sensitivity of the passenger demand resulting from changes in the fare. If the sensitivity would be known, the fare could be optimized from an operators perspective to maximize the profit accordingly.

Anylogic supply model

Below, a description of the limitations of the Anylogic supply model is given. They are categorized by General, Passenger Behavior, Spatial Impacts and Charging Strategies.

General

The Anylogic model takes a limited amount of costs aspects into account. In reality, additional costs factors not taken into account might influence the financial viability which would result to an overestimation of the financial viability in the Anylogic supply-model. Costs aspects as insurance, registration and taxes are not taken into account. Moreover, a static demand is used, that is assumed to be the demand for a typical day. However, the demand differs per day. During weekends, fewer trips will be observed in the morning- and evening-peaks than at working days. Consequently, the financial viability of AMoD operations will vary per day. It is recommended for future research to use multiple demand scenarios to account for uncertainties in demand variations. Moreover, the costs of charging facilities are low compared with assumptions made in similar researches [51]. The financial impact of using fast chargers instead of slow chargers is therefore relatively low.

The number of vehicles assigned to Station Lombardijen seems overestimated. In the supply model, the distribution of vehicles is based on the number of centroids having Station Lombardijen as the nearest station. However, the demand generated in these centroids shows substantially lower numbers then the centroids assigned to Station Zuidplein. Therefore, using Station Zuidplein as normative in the determination of the fleet size resulted in a slight overestimation of the number of minimum idle vehicles at Station Lombardijen. This could be avoided by determining the fleet size based on the demand instead of based on the network.

Moreover, regarding the network, all of the centroids are connected to their nearest station. The connections between centroids and stations are therefore fixed. However, in an optimized system, these connections should not be fixed. When there is a surplus of vehicles at Station Lombardijen and a shortage of vehicles at Station Zuidplein, vehicles waiting in an idle state at Station Lombardijen should be able to serve the requests from centroids that are assigned to Station Zuidplein.

As a result of the model abstraction, certain zones eventually generate a demand equal to 0 while the demand was not yet 0 resulting from the demand model. Before the abstraction, a total demand number of 7009 passengers was distributed over the day. Assuming that a certain centroid generates a demand equal to 0,05 % of the total number of trips. This would result in 0,05 / 100 * 7009 = 3,5 passengers. However, after the abstraction, as 1 agent represents 10 passengers, this results in 0,05 / 100 * 700,9 = 0,35 passengers which is 0 after rounding.

Passenger behavior

The Traveler agents in the Anylogic model are assumed to be homogeneous. In reality, passengers do not always show equal behavior. This is the result of variability in their socio-demographic characteristics like, e.g. age, gender and income. Moreover, passengers might have different travel purposes that influence their travel behavior. Including this variability might have an impact on the price sensitivities.

The model only provides the opportunity to let passengers share their ride with 1 passenger at maximum. However, applying dynamic ridesharing on higher capacity vehicles like taxi's could lead to more substantial detours which lead to longer travel times. Moreover, the vehicle characteristics are playing an essential role in passenger behavior regarding ridesharing. Sharing a ride with a Renault Twizy would possibly lead to problems as the comfort for the passenger sitting on the backseat is limited and the passengers do not have their own private space. Choosing a different vehicle type which accounts for a larger and more comfortable private in-vehicle space could improve the comfort and passenger experience but might be less suitable for usage in dense urban areas and mixed traffic situations.

Spatial impacts

The impact of the AMoD system on the Land Use is not incorporated in the supply model. As it is expected that the job accessibility of the Rotterdam-Zuid area will improve as a result of the AMoD system, people could be increasingly attracted to settle in this area which might even lead to an increase in population living in this area. This only reinforces the urbanization and therefore the AMoD system might have a negative impact on the urban mobility system on the long term [75]. Moreover, the impact of the number of vehicles on the depot size required at the stations is a spatial impact that has not been taken into account. With a fleet size of 280 vehicles, of which 164 vehicles are assigned to Station Zuidplein, there is a substantial amount of space required to park the vehicles. Moreover, charging facilities need to be installed at these stations. In reality, it might be challenging to build such depots because of the urban density in the case study area.

The impact of AMoD on congestion in urban areas is not being taken into account in the supply model. In reality, congestion influences the performance indicators because more extended travel and waiting times are experienced. This might negatively influence the performance indicators from a passengers perspective. From an operators perspective, congestion leads to a reduced number of passengers that can be transported. However, as the revenues depend on the travel time, longer travel times have a positive influence on the revenues.

Charging Strategies

The model has provided limited insight into the impact of charging strategies as only two types of chargers are taken into account in two scenarios. However, combining the types of chargers in 1 scenario could result in a better spread of charging power demand over time and less impact on the system capacity when fast charging is applied just before or just after the peaks in the daily AV demand pattern.

Moreover, the AVs are assigned to the station which is equal to their initial location. When the AVs have to charge, they will always move back to this station, since this is the nearest station. However, the amount of charging vehicles could be distributed more evenly over the stations in order to lower the peaks in demand for energy required for charging. In this situation, the vehicle will choose its charging location based on the number of vehicles that are charging at the stations instead of its distance to the stations.

7

Conclusions & Recommendations

This research focuses on the financial viability assessment of AMoD operations varying in relocation strategy, ridesharing strategy and charging strategy. In this research, an existing traditional gravity-based travel demand estimation model is used to generate demand data. This data is used as an input for a newly developed add-on agent-based supply module of the AMoD-system which is applied to the Rotterdam-Zuid case study area. Chapter 7 describes the conclusion in Section 7.1 by answering the sub research questions and the main research question. Section 7.2 describes recommendations for future work related to this research categorized by Science, Policy and Consultancy.

7.1. Conclusions

The objective of this research is to assess the financial viability of AMoD systems implemented at specific locations in urban areas, varying the operational characteristics in order to investigate which operation is the most financially viable for those locations. By connecting a traditional gravity-based demand estimation model with a newly developed agent-based supply model, a model is developed. Simulation of this model results in key performance indicators. By analyzing these indicators, the impact of the operational variables on the AMoD system performance is determined. The obtained knowledge on these impacts is applied in the Preferred Scenario, which consists of a set of simulation settings resulting in the most financially viable AMoD operation. In this Section, the answers to the sub- and main research questions of this research are provided.

7.1.1. Sub research questions

The answers to the sub research questions are given by number below.

1. ***What are the characteristics and model requirements of Autonomous Mobility on-Demand services applied as first- and last-mile transport in urban areas?***

From literature, the AMoD system characteristics are obtained. Using this knowledge, in Chapter 3, a conceptual description of the AMoD system is provided including a description of the main behavioral aspects of the agents traveler and passenger. Passengers can request a vehicle for two types of operations: first-mile and last-mile operation. The first-mile operation transports a passenger from their Origin to the station to transfer to a different mode of public transport, and the last-mile operation transports a passenger from the station to its final Destination. The departure times of the passengers are defined by demand data and the locations of the Origins and Destinations are defined by network data. Using a Control Interface, the passenger requests can be connected and assigned to vehicles. The vehicle becomes active when a passenger request is received and starts checking for passengers to join, checks if there is a detour required and checks if the vehicle is fully occupied. Inside the model, the performance of the AMoD system, which is defined by indicators, depends on the behavior of the travelers and the passengers. Using these required indicators, the eventual assessment of the operational scenarios varying relocation strategy, ridesharing strategy and charging strategy can be carried out. Therefore, the main model requirements are the vehicle and passenger behavior as described, combined with the possibility to include variable relocation strategies, ridesharing strategies and charging strategies.

2. ***Which public transport stations in Rotterdam-Zuid are preferred to function as a hub for Autonomous Mobility on-Demand services?***

Because the OV Visie 2040 [3] document, which is written by the municipality of Rotterdam and the MRDH in cooperation with Goudappel Coffeng B.V., is used as a motivation for this research, the Rotterdam-Zuid area was chosen as the case study area. However, within this area, certain hub locations had to be chosen that could function as a station for the AMoD-system. This is done by evaluating the existing stations within the case study area, based on the minimization of travel times, maximization of spatial coverage, maximization of expected benefit for low accessible areas and maximization of public transport connectivity. The stations that scored best for these criteria were Zuidplein and Lombardijen. According to this evaluation, it is concluded that these two stations are preferred to function as a hub for Autonomous Mobility on-Demand services.

3. ***What assumptions on the passenger choice behavior regarding automated vehicles are required in order to add the AV as a mode for first- and last-mile transport in the existing gravity-based travel demand estimation model in OmniTRANS?***

From literature [20], [19], [22], [21], it is concluded that there is a large number of factors that could influence the mode choice of passengers including AV as an alternative. However, studies show different applications of AVs. The demand model which is used is a traditional gravity-based travel demand estimation model build in the software called OmniTRANS. Within this model, the first- and last-mile transport is part of a public transport trip which is being generated by the OtTransit class. Applying the AV to this class resulted in a situation where the AV competes with the modes walking and bicycling, which were the only two options for first- and last-mile transport before the AV was added.

In the OmniTRANS model, passengers make their mode choice for first- and last-mile transport according to minimizing their travel resistance, which is defined by mode specific skim-matrices. The skim-matrices contain the travel times for all O/D-pairs possible, which are based on the mode specific network speeds. Therefore, the AV speed is a factor influencing the passenger mode choice. Based on literature [19], a speed of 30 km/h is assumed. However, also the fares and waiting times are choice factors that are taken into account. This is done by using matrix modification factors. The fare of € 0,31 per min [71] and a VoT equal to € 12,30 [20] result in a multiplication factor of 1,51 which reduces the effective speed of the AV to a value of 19,9 km/h. The waiting times are assumed to be 3 min [58], which lead to a summation of the travel times of all O/D-pairs by 3 min. Because of OmniTRANS model limitations, it is assumed that only these 3 choice parameters are required to add the AV as a mode for first- and last-mile transport in the existing gravity-based travel demand estimation model in OmniTRANS.

4. ***What is the demand for Autonomous Mobility on-Demand services on the specific case study locations?***

The demand for AMoD systems is obtained by running the demand model. This model generates and distributes the demand over the centroids. Eventually, the demand model produces 6 relevant O/D-matrices with a size of 8000 X 8000 centroids that consist of first- and last-mile matrices for 3 periods of the day: morning-peak, off-peak and evening-peak. At first, a sample of the total matrices has been extracted by only taking into account the Origins within the study area for first-mile matrices and only the Destinations in the study area for last-mile matrices. The obtained matrices are the case study sample matrices, which have a size of 332 X 8000 for first-mile operations and 8000 X 332 for last-mile operations. Afterwards, the totals of the relevant centroids have been calculated. For each of the centroids, this total number of trips is expressed as a percentage of the total demand for that matrix. These percentages determine the distribution of total trips over the centroids. Moreover, the total number of AV trips is calculated for 1 day and resulted in 7009 trips. Both the distribution over centroids and the total number of AV trips are used as input for the supply model and represents the demand for AMoD services. In the Anylogic supply model, the total number of AV trips is distributed over time according to an assumed daily demand distribution, which is normally distributed in the morning- and evening-peak and uniformly distributed in the off-peak time of day. The centroids are connected with the station based on the minimization of the distance to the station.

5. ***How can one ensure a consistent connection between an agent-based micro-simulation model and an existing gravity travel demand estimation model?***

Connecting the Anylogic model to the OmniTRANS model required consistencies in the assumptions made for both models. The characteristics of the AV alternative as used in the demand model should be consistent with the characteristics of the vehicle in the Anylogic model. In both models, equal speeds and fares are used. Besides, the average waiting time resulting from the Anylogic simulation showed similarities with the OmniTRANS input value for the average waiting time. The fleet size used in Anylogic is chosen large enough to satisfy all demand in order to avoid the fleet size to limit the system capacity. This ensures consistency, because the fleet size is infinite in the demand model.

6. ***What is the influence of the operational variables: relocation strategy, dynamic ridesharing and charging strategy on the performance of Autonomous Mobility on-Demand systems?***

To evaluate the performance of AMoD systems for varying operational variables, the Anylogic agent-based simulation model was developed providing the opportunity to run distinct operational scenarios. To study what the direct impact is of the relocation strategy, dynamic ridesharing and charging strategy, at first the Base Scenario is simulated. Afterwards, the impact of the operational variables is studied by every time change 1 operational variable with respect to the base scenario, and simulate that scenario. The results of these simulations show the direct impact of a change in strategy. From the results analysis in Chapter 6, one can conclude that activating automatic relocation, does increase the level of service from a passenger perspective but implies more total system kilometers due to empty vehicle trips. Regarding dynamic ridesharing, the observed impact was a lower number of total system kilometers, due to trips where passengers share their ride. Moreover, an increase of travel time is observed, due to detours required to pick up the second passenger. As for the type of charger used, the results show that using fast chargers instead of slow chargers results in an increase in the level of service from a passenger perspective. The average waiting time is decreased because the charging of the vehicles takes shorter and therefore more vehicles are available to satisfy the demand.

7.1.2. Main research question

The main research question, as presented in Chapter 1, is formulated as follows:

- ***What is the financial viability of Autonomous Mobility on-Demand operations in urban areas?***

The main research question can be answered using the output indicators of the simulated scenarios from a business perspective, that shows the costs and the revenues of a certain operation for 1 typical day. One can conclude that the total costs show a high sensitivity to the total system kilometers, as both the energy- and maintenance costs are directly proportional to the total system kilometers. Therefore, from an operators perspective, it is most profitable to reduce the number of kilometers per transported passenger. Accordingly, activating dynamic ridesharing results in the lowest costs scenario because the number of passengers transported per vehicle kilometer is higher than without dynamic ridesharing. Moreover, resulting from the sensitivity analysis, it is known that the total costs are relatively sensitive to the vehicle purchase price and fleet size variations.

Activating automatic relocation results in the most costly operation, because of the empty vehicle kilometers required to relocate the vehicle after an operation. Regarding the revenues, the operation that is preferable from an operators perspective is a combined operation where passengers can share their rides, and the AVs relocate themselves automatically back to the station when there is no demand left to serve. However, the costs for this operation are not most preferable from an operators perspective as the empty vehicle kilometers of relocation trips lead to additional costs, compared to the operation without relocation.

Taking the individual impacts of the operational variables into account, a simulation has been done of the preferred operational scenario, using a set of simulation settings that shows the most positive effect on the financial viability. In this operational scenario, the battery charging time is reduced as a result of the usage of fast chargers. Moreover, passengers are able to share their ride. Finally, the increased efficiency of the vehicle used due to ridesharing enabled the opportunity to use a lower fleet size, which is still able to satisfy all demand. Therefore, also a lower fleet size was used. As the depreciation costs showed to be substantially sensitive to fleet size variations, this fleet size reduction resulted in a substantial reduction of the total costs. Due to activated ridesharing, a higher number of passengers is transported with a lower number of kilometers. This resulted in higher revenues and lower energy and maintenance costs, resulting in an increased profit compared to all the other scenarios simulated. So in the end, the financial viability of the AMoD system applied to Station Zuidplein and Station Lombardijen to function as a first- and last-mile feeder service for public transport is most financially viable when operated using dynamic ridesharing and a fast charging strategy.

From an operators perspective, the AMoD system shows promising results, compared to existing public transport services. A substitution of the existing bus-lines in Rotterdam-Zuid with the AMoD system results in a substantial reduction of the total operational costs. Moreover, compared to conventional taxi systems, the AMoD system saves a large amount of expenses due to the absence of driver salaries in the calculation of the total operational costs. The low average waiting times found for the AMoD service are beneficial for the public transport accessibility of Rotterdam-Zuid. Moreover, because the Renault Twizy is fully electrical, the pollution is reduced, which is beneficial for the livability of the Rotterdam-Zuid area.

7.2. Recommendations

This Section provides recommendations for the categories: Science, Policy and Consultancy. The category Science contains recommendations for further research based on the findings in this research. The category Policy contains recommendations for policymakers that focus on policies around the implementation of AMoD systems. The category Consultancy comprises possible applications of the AMoD model for consultancy practices.

7.2.1. Research

As the demand and supply have a mutual relationship, it would be interesting to see what the impact of the key performance indicators would be when this is fed back into the demand model. From a methodological perspective, this would lead to a component-based simulation structure which functions as a feedback loop. Using this loop, operational variables could be optimized. However, this would require the demand model to provide the opportunity to use the output of the supply model as the input of the demand model. The main challenge to make this a feasible simulation study is the computational resources available since the demand model currently is relatively demanding regarding computational power and time. However, another option might be to use a different demand model that is able to make a cutout of the original model and only simulates the trip generation and distribution and assignment for the specific area where the AMoD systems are applied. This would speed up the simulation and improve the feasibility of carrying out multiple iterations in order to reach a stable optimum.

When the simulation time of the demand-model would be reduced substantially, it would also become increasingly feasible to analyze the sensitivity of the demand model for the skim modification factors: vehicle speed, waiting time and fare. An increase of the vehicle speed would lead to lower impedance values is the skim matrices, resulting in a higher number of trips. However, an increase of the waiting time and the fare would lead to higher impedance values in the skim matrices, resulting in a reduction of the number of trips. When the sensitivity of these factors is known, appropriate advice could be given to AMoD operators in order to steer the values of the input parameters to increase the profit.

AMoD implications

To take into account the spatial implications of AMoD systems in research, a more detailed discretization is required. Because zones are used in the OmniTRANS demand model, a certain spatial discretization is applied that simplifies the origin and destination locations of events. However, in reality, a vehicle must be requested at any location within the study area. This requires a more detailed spatial resolution of the demand model, which in the end will result in more detailed analysis to be able to evaluate where flex-parking spots are required to facilitate loading/unloading. Moreover, the traffic impact of AMoD systems could be analyzed using such a model.

This research provides limited insight into the impact of the implementation of the AMoD system on the modal share of other competitor modes. The demand model used in this research only directly shows the impact on the number of passengers walking and bicycling as first- and last-mile transport. However, public transport modes as buses and trams are also used as first- and last-mile transport in the Rotterdam-Zuid area to get to the central station. Therefore, to assess the competitive position of AMoD systems in this specific area, one has to evaluate the impact on the share of buses and trams as well. Moreover, the impact on car usage could show if the AMoD system eventually succeeded in making public transport more attractive.

Disregarded Strategies
The model has the opportunity to evaluate many more strategies regarding relocation, ridesharing and charging. The simulation experiment only took into account a relocation strategy that was inactivated or activated, which are static strategies. However, also dynamic strategies could be simulated, that incorporates a changing strategy over time. Moreover, regarding relocation, the vehicles could be forced to relocate automatically to strategically advantageous points that account for a high share of the total AV demand. This will lead to lower waiting times and less empty vehicle trips and therefore might be more financially beneficial for an operator. Regarding dynamic ridesharing strategies, the vehicle capacity could be optimized using the model. Using a higher vehicle capacity than 2 and letting various passengers share their ride, would result in different assumptions on maximum detour constraints, as more passengers with different Origins could lead to more detour kilometers required.

As for charging strategies, in this research, only a static distinction is made between slow chargers and fast chargers in the evaluated scenarios. However, more dynamic alternatives could lead to optimized distribution of the required power for charging. When regarding the vehicle charging as part of an energy grid, strategies as Smart Charging [76] could lead to an optimized integration of electric vehicles within the existing energy distribution system infrastructure. Charging overnight, would from an energy supplier's perspective lead to lower peaks in the energy demand. However, this requires the vehicles to have a more extended range, because their battery and resulting range has to be sufficient for the average number of total traveled kilometers per day. So the model could also be used to optimize the vehicle type or vehicle characteristics.

Next to the variation in charging speeds over time, variations in the spatial distribution of charging facilities could improve the system performance. Applying more charging points throughout the city at strategically beneficial locations could reduce the empty vehicle kilometers required for vehicles when they have to charge. The location of the charging points could be formulated mathematically as a hub location problem and eventually be optimized.

In this research, limited variability is taken into account regarding the assumptions on financial related input parameters. These parameters are not as stable in reality as is assumed in this research. Energy prices vary over time due to variations in economic situations. Moreover, economic situations might influence vehicle purchase prices. Since these financial input parameters are essential for the financial viability analysis, it might be valuable to assume certain scenarios that account for variability in the value of these parameters in further research. It is recommended for further research to use a low-cost, mid-cost and high-cost scenario that could give insight into the impact of the input variations.

7.2.2. Policy
In order to implement the AMoD systems in urban areas, policies on integrating autonomous vehicle systems with existing public transport systems are required. The results of this research can bring the role and impacts of AMoD systems on the current urban mobility system to the understanding of transport authorities. In The Netherlands, regional transport authorities, which consist of representatives of the municipalities of that region, are responsible for the tendering and granting of public transport concessions. Consequently, the operator that is chosen based on the best bid is allowed to provide the AMoD service for a certain period of years. When the concession ends, the tendering process starts again, facilitating competition between operators. Regarding the case study of this research, the transport authority is the MRDH and the municipality is of the city of Rotterdam.

Because the charging infrastructure required is the responsibility of the operator, it has to invest a substantial amount of money to be able to start the service. This amount mainly comprises the vehicle purchase costs and the charging infrastructure purchase costs. When a public transport concession is terminated, this could lead to problems because the existing charging infrastructure is owned by the old operator. To avoid this problem, the MRDH or the municipality of Rotterdam could subsidize the charging infrastructure. The financial analysis showed that the charging infrastructure played a minor role in the total investment costs, which makes the investment feasible. Moreover, the benefits resulting from the AMoD operations could lead to significant benefits for the city of Rotterdam, regarding improved urban mobility and reduced emissions. This could be a reason for the municipality of Rotterdam to play a stimulating role by giving an incentive to AMoD operators.

7.2.3. Consultancy

The newly developed Anylogic model has a broad range of applications because of its modularity. The model can be used as an add-on component applied to various types of existing models. Moreover, it can be applied to all areas constrained by data availability. Goudappel Coffeng B.V. has extensive resources of transport models that are built using the software OmniTRANS. However, these transport models are aggregated models based on gravity theory, which limits the applicability of the model to predict the impact of specific policy measures on specific population groups, which have distinct behavioral characteristics. The new version of OmniTRANS, OmniTRANS Next, is already able to account for dynamic traffic assignments, but is still gravity-based which limits their applicability when applying these models to predict the impact of innovative mobility concepts that require a more fine-grained scale like, e.g. shared-mobility, Mobility-as-a-Service and AVs.

As the AV market is expected to grow in the nearby future and computers are able to handle an increasing amount of data, it is recommended to increasingly use agent-based models for consultancy practices and put effort into combining the existing transport models with agent-based add-on models. Many different software packages that facilitate for agent-based modeling are available. Regarding this research, it is recommended to use Anylogic, because of its ability to connect to databases and other software packages like GIS and transport demand estimation models. Moreover, the interface of Anylogic is highly accessible and limited programming experience is required to build a model, regardless of the extensive range of possible applications of Anylogic.

Putting modeling into practice, Goudappel Coffeng B.V. offers advice to clients who are often based on model outputs. AMoD operators could function as a client in consultancy practices. In this case, the client would primarily focus on the output indicators from a business perspective. The final advice would be to implement the operation that leads to a maximized profit. Next to transport operators, governmental authorities could function as a client. When a governmental authority, has a desire to add AMoD systems to their mobility system, the model could predict the impact on the city's mobility system. The client has to provide data on the network and the exact location they want to deploy the AMoD system at and demand data if readily available. One of the main advantages of the Anylogic model is that it is relatively easy to connect with databases that contain network data and demand data. Running the model would result in statistics indicating the impact of the AMoD system on the desired location. In this case, the client would focus on the indicators determining the level of service provided. The final advice would be to implement the operation that leads to a maximized level of service, increasing the quality of the urban mobility system.

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