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An agent-based model for assessing the financial viability of autonomous mobility on-demand systems used as first and last-mile of public transport trips: A case-study in Rotterdam, the Netherlands

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ABSTRACT

The continuing urbanization and corresponding increase in transport demand are putting pressure on the accessibility, safety, sustainability, livability, and efficiency of urbanized regions. Public transport is regarded as a sustainable mode of transport for these regions and therefore transport policies aim to increase its attractiveness. However, public transport is facing last-mile connectivity problems. The application of Autonomous Mobility on-Demand (AMoD) as a feeder service for public transport hubs can potentially improve the first and last-mile trip leg which increases the attractivity of public transport. However, will such a system be financially viable when applied in an urban area? and what kind of operation will lead to the highest system performance? In this research, this question is addressed by proposing a method that connects macro transport modeling and agent-based modeling (ABM). An existing gravity-based travel demand estimation model built in a macro simulation tool is used to predict passenger demand across all the OD pairs of a city. For those OD pairs that can use the AMoD as first /last mile this is modeled using an agent-based rationale to be able to simulate the behavior of passengers and vehicles within that specific area of the city. The simulation model is applied to the case study area of the south of Rotterdam, in The Netherlands, where metro Station Zuidplein and the rail Station Lombardijen function as two AMoD hubs. Using the case study, the impact of relocation, ridesharing, and charging strategy is assessed in regards to financial viability. Among other insights, results show that the AMoD service leads to a profit on a typical business day for the operating companies despite the high-quality level of the service (very low average waiting time for a vehicle). If this particular system would not consist of automated vehicles and one would have to pay a salary to drivers, it would not be possible to make a profit on a typical business day. Moreover, results show that activating dynamic ridesharing and using wireless fast chargers at the stations results in the most financially viable operation. Activating automatic relocations results in the most costly operation.

1. Introduction

1.1. Problem definition

Urban mobility is under pressure due to the still ongoing urbanization, urban densification, and car-dominated mobility systems, leading to an increase in mobility demand. This endangers accessibility, safety, sustainability, livability, and efficiency in future cities (Ministerie van Infrastructuur en Waterstaat, 2017). Creating more transport capacity, and sacrificing public space, is nowadays no longer the preferred solution as transport policies increasingly focus on stimulating the use of sustainable modes of transport. Public transport (PT) is one of these sustainable modes of transport because of its high capacity and low environmental impacts (Hoogendoorn & van Oort, 2018).

However, the attractiveness of public transport in some urban areas is limited. This is due to the so-called 'last-mile problem', which states that the poor first- and last-mile connectivity is the main cause of PT disutility (Zellner, Massey, Shiftan, Levine, & Arquero, 2016). Therefore, improving the first- and last-mile trip leg can increase the attractiveness of public transport (Scheltes & de Almeida Correia, 2017). This requires a seamless connection of the different public transport modes like bus, tram, metro, and train, resulting in a multimodal transport

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system. A common term for the concept of unifying all PT and emerging transport options in a seamless transport system is Mobility as a Service (MaaS) (Durand, Harms, Hoogendoorn-Lanser, & Zijlstra, 2018).

Recent scientific research is showing that one of the promising options to improve the first- and last-mile trip leg of PT trips is shared and demand-responsive mobility concepts (Alonso-González, van Oort, Cats, & Hoogendoorn, 2017), (Huang, Kockelman, Garikapati, Zhu, & Young, 2021), (Shaheen & Chan, 2016). Nowadays, travelers in some urban areas can already 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). These mobility concepts can provide a flexible option to access and egress trip-legs of public transport trips which can encourage travelers to use PT (Gurumurthy, Kockelman, & Zuniga-Garcia, 2020). However, the existing conventional Mobility-on-Demand (MoD) systems (US Department of Transport, 2020) suffer from multiple operational challenges. The rebalancing problem when vehicles end up clustered at a certain location is one of these challenges (Santos & de Almeida Correia, 2019), (Kek, Cheu, Meng, & Fung, 2009), (Fagnant & Kockelman, 2014), (Lu, Correia, Zhao, Liang, & Lv, 2021), (Jorge, Correia, & Barnhart, 2014). A promising solution to this problem, which is nowadays getting much attention in research, could be the use of automated or autonomous vehicles (AVs) (SAE-level 4 and 5 (SAE International, 2014)). These types of vehicles are expected to be able to relocate themselves autonomously (Scheltes & de Almeida Correia, 2017). Combining autonomous vehicle technology in shared mobility concepts is being designated as Autonomous Mobility on-Demand (AMoD) (Oh et al., 2020), (Basu, Araldo, Akkinepally, et al., 2018).

Scientific literature related to AMoD applications shows that many modeling and simulation studies have been carried out to observe the impact of autonomous vehicle services on current transport systems (Shen, Zhang, & Zhao, 2018), (Marczuk et al., 2015). Many of these studies use agent-based modeling (ABM) to be able to simulate a specific AMoD application to a certain case study location (Fagnant & Kockelman, 2014), (Hyland & Mahmassani, 2018), (Wang, Correia, & Lin, 2019), (Martinez & Viegas, 2017). Agent-based models are microscopic simulation models in which a transport system can be simulated based on the interaction between the agents: passengers and vehicles, on the network. 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 (Dia & Javanshour, 2017). Because studying on-demand transport systems requires a high level of detail on the fleet location and the dynamic requests that pop up along a day, agent-based models are especially appropriate for modeling AMoD systems (Jing, Hu, Zhan, Chen, & Shi, 2020).

However, one aspect of AMoD services that remains underexposed in previous research is their financial viability (Chen & Kockelman, 2016). It is essential to understand if these systems can be financially viable to assess their financial attractiveness which in turn will explain how many companies offering these services we can expect. Having such financial analysis can help policymakers to develop a clear policy framework for autonomous vehicles' usage in urban mobility systems. In a study by Spieser et al. (2014) the authors recognize the importance of financially analysing the implications of automated shared systems, but they focus on analysing the financial impacts on the users and not on the operators (Spieser et al., 2014). A recent paper by Santos and de Correia (2021) dwells specifically on the financial viability of shared automated systems from the operator perspective, but in this case for a regional setting (interurban transport) simplifying the daily operation of these systems and ignoring several aspects of the financial structure of the companies such as management costs.

The financial viability of AMoD systems is strongly dependent on operational characteristics (Spieser et al., 2014). From an operator's perspective, supply-side cost aspects like investment costs, maintenance costs, and fuel costs determine the total costs of AMoD systems. The demand-side of AMoD systems determines the revenues of such systems. From an urban planning perspective, AMoD systems can also generate other types of benefits due to the potential spatial impact like a more efficient use of public space because less parking space is required. However, these benefits are not taken into account in the financial viability from an operator's perspective.

The main objective of this paper is to find if such an AMoD service is financially attractive under a very high level of service offered to the client as the first/last mile of rail trips. AMoD services can be applied under various operational strategies (Chen, Kockelman, & Hanna, 2016). Three main operational strategies were included in this research: (1) relocation strategy, (2) dynamic ridepooling (SAE International, 2021), and (3) charging strategy. Autonomous relocation is regarded as one of the main benefits of AMoD systems compared to manually driven shared vehicle systems. However, relocation trips lead to additional vehicle kilometers. Dynamic ridepooling can lead to more efficient use of vehicles but possibly can also lead to additional vehicle kilometers due to required detours. Fast chargers lead to a shorter vehicle charging time compared to slow chargers but require higher investment costs. A further research question may then be posed: what is the influence of these three operational strategies on the financial viability of the AMoD system when used as the first/last mile? For answering such questions we adopt and implement an ABM specifically built to study the financial performance of the system. We then apply the modeling framework for the case-study of south Rotterdam in the Netherlands.

The remaining part of the paper is structured as follows. The next section describes the methodology adopted to estimate the financial viability of the AMoD system centered on the ABM. The paper continues with the application of the method to the case-study of South Rotterdam. This is followed by the main results and conclusions taken from the research.

2. Methodology

Nowadays, it is not (yet) possible to perform real-life full-scale experiments with demand-responsive, self-driving shared vehicles in dense urban areas. Therefore, to study and evaluate the potential impacts of these systems, a simulation-based methodology is quite suitable. In this section, we start by describing the functionalities of the AMoD system that we want to test and for which we want to estimate the financial viability, including the description of the behavior of travelers and vehicles as the two main entities in such system. Subsequently, a description of the conceptual agent-based model is given including further elaboration on the two main model components: Demand and Supply.

2.1. AMoD system

The AMoD system used as a feeder to PT stations offers two types of services: first-mile and last-mile transport, depending on the origin and destination of the traveler.

- **First-mile transport**: a traveler requests a vehicle that can transport him/her from the origin to the station, where he/she can transfer to a PT mode (blue in Fig. 1).
- **Last-mile transport**: a traveler requests a vehicle that can transport him/her from the station to the destination (green in Fig. 1).

The operational strategies that have been mentioned in the Introduction: (1) relocation strategy, (2) dynamic ridepooling, and (3) charging strategy, have been considered as follows:

1. Relocations in the context of the feeder system imply that vehicles will return to their station after a last-mile operation when no passenger requests are received.
2. Dynamic ridepooling enables the possibility for travelers to share their rides. After the first traveler has been picked up, a second

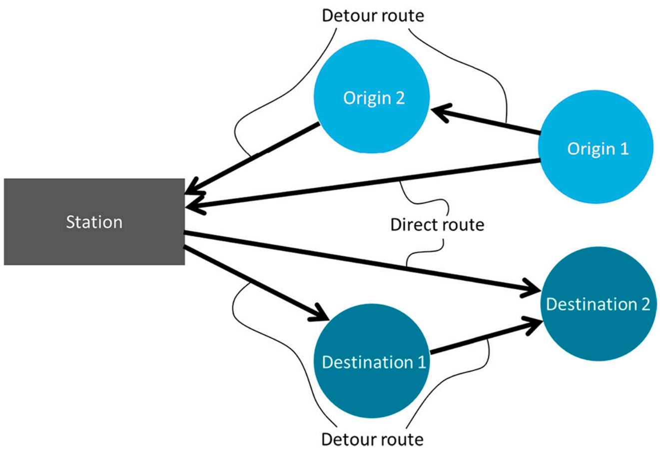

Fig. 1. First-mile transport from Origin to Station and last-mile from Station to Destination.

traveler can be picked up. In the conceptual model, the assumption is made that this is only possible when the required detour to pick up the second passenger is smaller than 25% of the direct travel time of the traveler that has been picked up first. When the destinations of the passengers are not the same the FIFO-principle is applied which means that the first traveler that has entered the vehicle is dropped off first.

3. Two charging strategies are included in this research: slow-charging and fast-charging strategies. The charging facilities are located at the PT station and their location is fixed. However, the number of chargers required is not fixed and depends on the charging demand. The slow chargers lead to lower purchase and installation costs and require less electrical power compared to fast-chargers. However, the charging time of slow-chargers is three times as high compared to fast-chargers (Chen et al., 2016). Therefore the number of chargers required is higher when using slow-chargers compared to using fast-chargers.

Table 1 gives an overview of the pros and cons of the three operational strategies.

Table 1
Overview of the pros and cons of the 3 operational variables included in this research.

	Operational strategy	PROS	CONS
1 	Relocation strategy	The waiting time at the station is minimized	A relocation trip results in additional empty vehicle kilometers
2 	Dynamic Ridepooling	More efficient system due to more transported travelers per vehicle kilometer	Increased passenger travel times due to required detours
3 	Charging Strategy	Fast charging leads to larger system capacity because less operational time is required for charging	Fast charging leads to increase of costs due to higher purchase price and higher peaks in power demand

2.2. Conceptual model

This section describes the main aspects of the simulation model that we used to study the impacts of the operational strategies for AMoD systems on their financial viability. Fig. 2 shows a schematic overview of the model structure which mainly consists of two components: macro-model and micro-model. The macro-model produces the number of trips between origins and destinations made by travelers using AMoD vehicles as the first and last mile in a certain region. The micro-model assigns the passenger trips to the network by simulating the interaction of vehicles and passengers for a typical day. The micro-model eventually produces the key performance indicators which are used to assess the operational strategies. Below, both model components are further explained.

2.3. Macro-model

The travel demand for the AMoD service consists of passenger requests where either the origin or the destination is a train or metro station. This demand is estimated using a gravity-based transport model that can predict the choice behavior of travelers based on the gravity theory. This means that travelers always strive to minimize their travel impedance during a trip such as travel time, travel costs, and the number of transfers.

The macro-model requires network data (supply) and parameters defining the choice behavior of travelers as input (utility functions). An equilibrium is found in the networks of the different modes of transport: car is always present and some models also have a PT mode which may or may not differentiate the several sub-modes such as buses and metro. Such models are supposed to estimate and forecast the relationship between supply and demand in urban transport networks in an aggregated way. However, their usage for demand-responsive systems is questionable given the influence that the operation of the system can have on the supply that can be offered to its clients.

OmniTRANS is a software package that can build and run these types of models and is widely used for transport planning in the Netherlands. The software is developed by the dutch mobility software company DAT Mobility (Dat.mobility webpage, n.d), which is part of Goudappel Groep, and has been used in the case-study.

2.4. Micro-model

The micro-model contains all characteristics of the AMoD system. The modeling technique that is applied to model this system is called Agent-Based Modeling (ABM), which is a microsimulation approach that is suitable to simulate innovative transport systems. ABM offers the possibility to model individual entities that interact with each other in a system, based on pre-specified behavioral rules. Because in the AMoD system travelers and vehicles interact with each other, ABM is ideal for a simulation study like this. The software that is used to develop the micro-model in this paper is Anylogic (Anylogic webpage, n.d), which is based on the Java programming language.

2.5. Connecting the macro- and the micro-model

The demand is defined by aggregated OD matrices in the macro model. Because there are usually OD matrices for three periods of the day: morning-peak, off-peak, and evening-peak, there is the need to use statistical distributions to distribute the demand over a typical day in the micro-model. Next to the travel demand, also the network data from the macro-model is used as input for the micro-model, making a consistent connection between the two model components as far as the network is concerned. Triggered by the demand and using the network, a simulation of the micro-model produces the key performance indicators that are used to evaluate the distinct operational strategies for the system performance of one typical day.

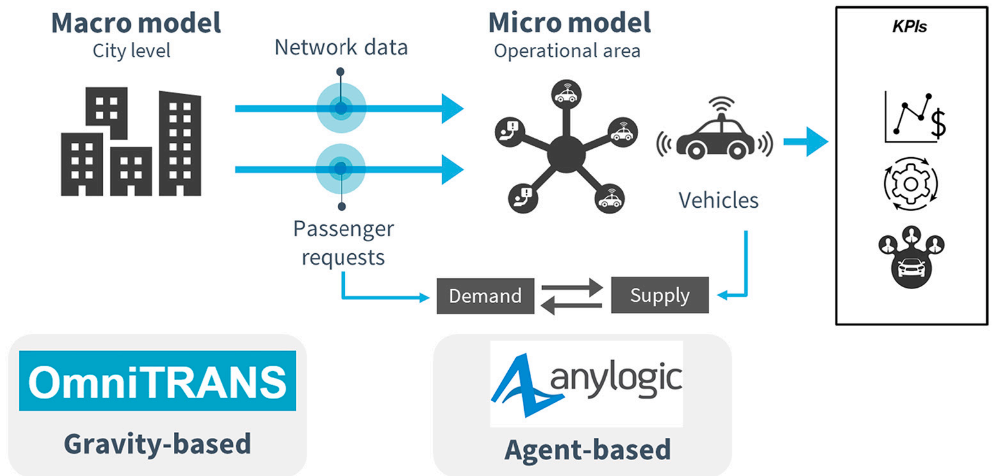

Fig. 2. Schematic overview of the model structure.

2.6. Main methodological limitations

It is important to note that the connection between macro- and micro-model should not be unidirectional since what happens in any area where the AMoD service is operational as a feeder is that the PT supply will naturally be affected which would lead to a different demand in the macro model. In order to have a final solution, there would have to be an iterative process between macro- and micro-model where in the end there would be no such variations in the supply and the demand. The system would be in equilibrium. The problem with such an approach is that macro models cover a whole urban region and tend to have a long computational time. This makes the iterative process quite inefficient if one wants to study several scenarios. Therefore, in this paper, we fix the supply on the micro-model in such a way that a very high quality of service is being provided in the macro model. That is, if one finds the number of vehicles under a certain operational configuration that leads to all demand being satisfied in the micro-model in a very low waiting time, then there is no need to iterate between the two models if such a low waiting time is considered in the macro model. This hinders the possibility of studying varying fleet sizes but it simplifies the computation of the solutions. Still the results are quite relevant because they yield the financial performance of AMoD systems under a very high quality of service provided to the clients, which is usually what is expected from this flexible on-demand transport. All the details of the ABM rationale are explained in the next section where the framework is applied to a case-study. This simplifies the understanding of the whole model logic.

Moreover, the micro-model does not take into account the traffic impacts of AMoD vehicles in congestion. The macro-model is able to assign several demand segments to a network. Based on the amount of traffic and the capacity of the network, the model is able to vary the impedance on links or nodes accordingly, making a specific route less attractive when the amount of traffic is high compared to the capacity. With this, the macro-model does account for congestion effects, which are incorporated in the AMoD demand. However, the demand is aggregated by the macro-model and consequently distributed to a time-based discrete demand pattern for a typical day in the micro-model. Therefore the traffic impacts are not taken into account in the speed of the vehicles and thus the travel time of the travelers. For a reference on how to incorporate such traffic congestion effects in an ABM consult (Wang, Correia, & Hai, 2022).

Finally, the spatial impacts of the AMoD service are not taken into account in this research. It is assumed that the AMoD vehicles can use the existing infrastructure, given by the network of the macro-model. Secondly, it is assumed that these vehicles are able to operate in mixed traffic situations, where they share the infrastructure with other modes of transport. Third, it is assumed that AMoD vehicles are always able to reach the exact origin or destination location and are not required to search for a free parking spot. This requires enough available parking facilities or flexible hop-on/drop-off locations which are known to be scarce and create traffic impedance (Overtoom, Correia, Huang, & Verbraeck, 2020).

3. Application of the ABM to the region of South Rotterdam

To be able to assess the performance of the AMoD system, an application of the conceptual model to a case study location is required. Therefore, the model is applied to a case-study area in the city of Rotterdam, Netherlands. The motivation for choosing Rotterdam can be found in the document called 'OV Visie Rotterdam 2040' in dutch (Gemeente Rotterdam and MRDH, 2018). This document includes the main PT policy measures for the city of Rotterdam during the coming years and presents a tentative prediction of their impacts. The impacts show that despite the proposed improvements of the conventional PT network, the accessibility to jobs using public transport remains poor in the region of South Rotterdam (south of the river Maas) compared to the northern region. The usage of AMoD systems in this area could eventually improve job accessibility using PT. Van der Veen, Annema, Martens, van Arem, and de Correia (2020) also found that the poor accessibility in the areas south of the river Maas hint at the potential for significant improvements.

3.1. Case study simulation model development

Within the study area, two PT stations have been chosen to function as AMoD hubs: Station Zuidplein and Station Rotterdam Lombardijen. Station Zuidplein is a bus and metro station and Station Rotterdam Lombardijen is a bus, tram and train station. These stations are chosen mainly for three reasons: their central location, the expected added value for poorly accessible areas, and the possibility for passengers to transfer to other modes of PT at the stations (bus, metro, train). From the perspective of multimodal accessibility, these transfer possibilities make stations especially suitable to function as AMoD hubs. Moreover, stations allow deploying both first- and last-mile services, whereas local hubs most often allow for only one of the services. In Fig. 3, a PT map of the south area of Rotterdam is given. The stations chosen as AMoD hubs are indicated by the red circles. The vehicle charging facilities are assumed to be located at the stations.

In the macro model, it is assumed that AMoD vehicles can use all of the road network around the stations, bounded by the operational area.

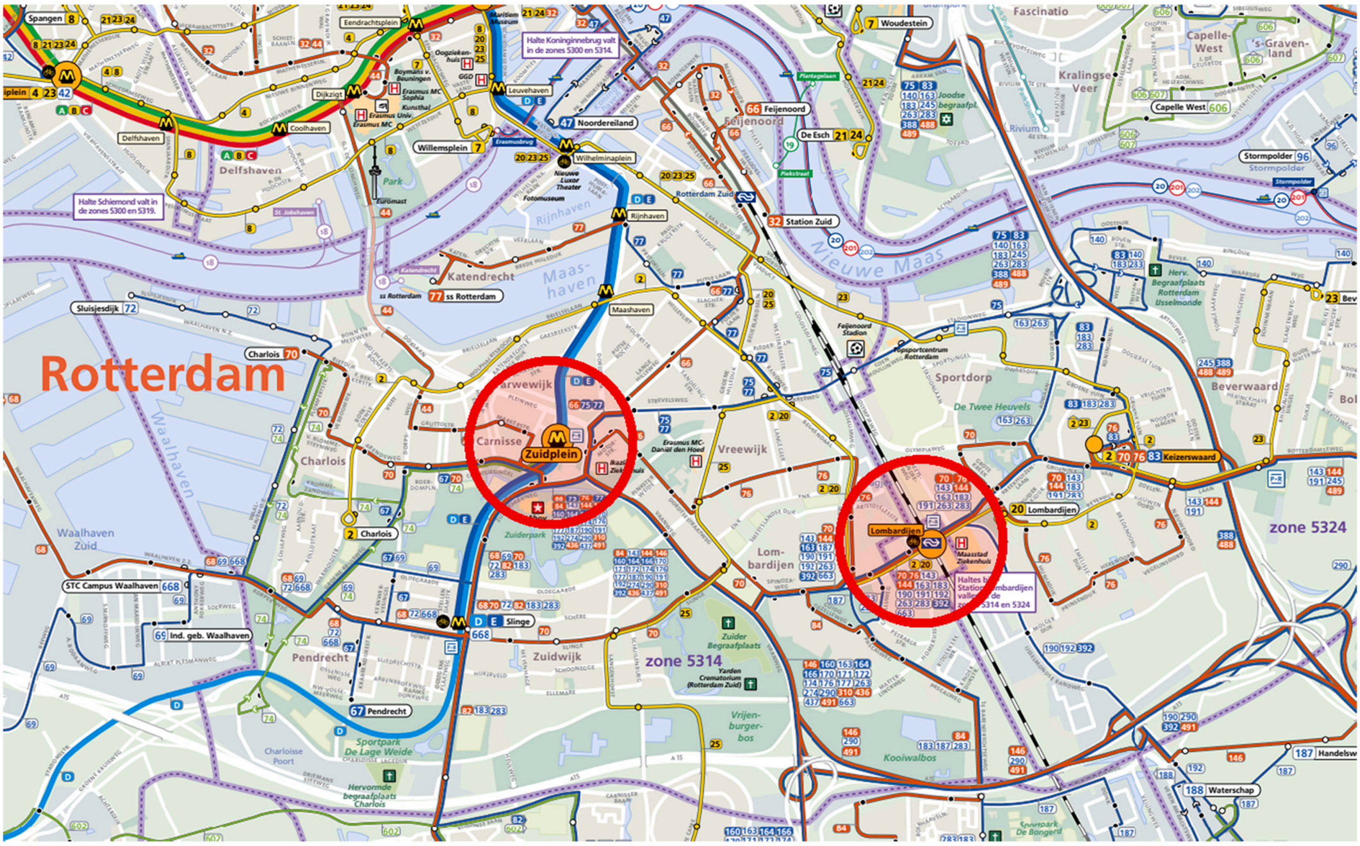

Fig. 3. Public transport map of South Rotterdam (source: MRDH 2019). For this research, the red circles are addes to indicate the AMoD hub locations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

An overview of the network in the macro model is given in Fig. 4. The pink edges indicate the road links that allow AMoD vehicles.

To estimate the travel demand for AMoD services within the case study location, a cut-out of the regional macro model is used, with the permission of MRDH, who is the model owner. This must be done because the model of Rotterdam encompasses a whole region that is not required for this study, namely connections to other municipalities like The Hague. This model has been calibrated on recent traffic counts performed in 2016, which makes it quite accurate. Moreover, the model contains a built-in first- and last-mile transport mode for PT trips that makes it convenient to predict the demand for AMoD services.

At first, the AMoD services are added to the model as such first- and last-mile transport option. Secondly, mode choice behavior parameters on PT AVs are implemented in the model, which are based on existing behavioral research on the topic (Yap, Correia, & Van Arem, 2016). Eventually, the model allows predicting the mode choice of travelers based on the following three attributes: waiting time, transport fare, and travel time.

The macro model produces the mode choice specific travel demand distributed over zones within the study area using the OD-matrices. As it has been referred to before, like many of the macro models used around the world, these matrices are produced for the morning-peak, evening-peak, and the rest of the day. Based on this output, a daily travel demand distribution can be obtained by using the typical distribution which is shown in Fig. 5. In this Figure, a probability density function is plotted which contains a normal distribution around the morning-peak at 08:15 and around the evening-peak at 17:30. In between those peaks, a uniform distribution is assumed because the demand does not show peak behavior during such a period.

The network data and the three mode-specific OD-matrices for morning-peak, evening-peak and rest of the day are fed into the ABM. The OD matrices contain the total number of trips made between the OD-pairs within the study area using the AMoD service. These could be trips from a certain origin within the study area to one of the stations or trips from one of the stations to a certain destination within the study area. In the macro-model as well as in the AMoD ABM, each of the zones in the network is assigned to the nearest station. The AMoD trips can be regarded as trip legs of a larger multimodal trip. The ABM does not account for subsequent or previous trip legs. It is assumed that when a passenger has arrived at the station using the AMoD system, it transfers to a different PT mode to continue his or her journey.

It is also possible that the OD-matrices contain trips that pass through both stations. This happens when a passenger uses the AMoD service to travel to one of the stations, uses a different mode to travel to the other station, and uses the AMoD service to travel to its destination within the study area. However, both stations are located in areas that are mostly residential. Therefore, the number of trips that go through both stations is negligible. Moreover, AMoD trips between both stations are not possible, because the macro-model assumes that the AMoD service is only used as a first- and last-mile mode in a multimodal PT trip.

To be able to simulate these trips for a typical day using an ABM, it is required to determine a certain departure time for each trip. Therefore, the trips in the OD matrices are distributed over the day according to the assumed demand distribution shown in Fig. 6. For all OD pairs, the same distribution is used.

Within the model, the behavior of the agents, Travelers and AVs, is determined according to the defined behavioral rules specified in state charts. The behavioral rules of the agents are mainly based on the concepts found in previous studies on AMoD systems (Shen et al., 2018), (Marczuk et al., 2015) and other autonomous vehicle systems (Scheltes & de Almeida Correia, 2017). The state chart of the AVs is shown in Fig. 6. A state chart defines in which state the agents are and determines

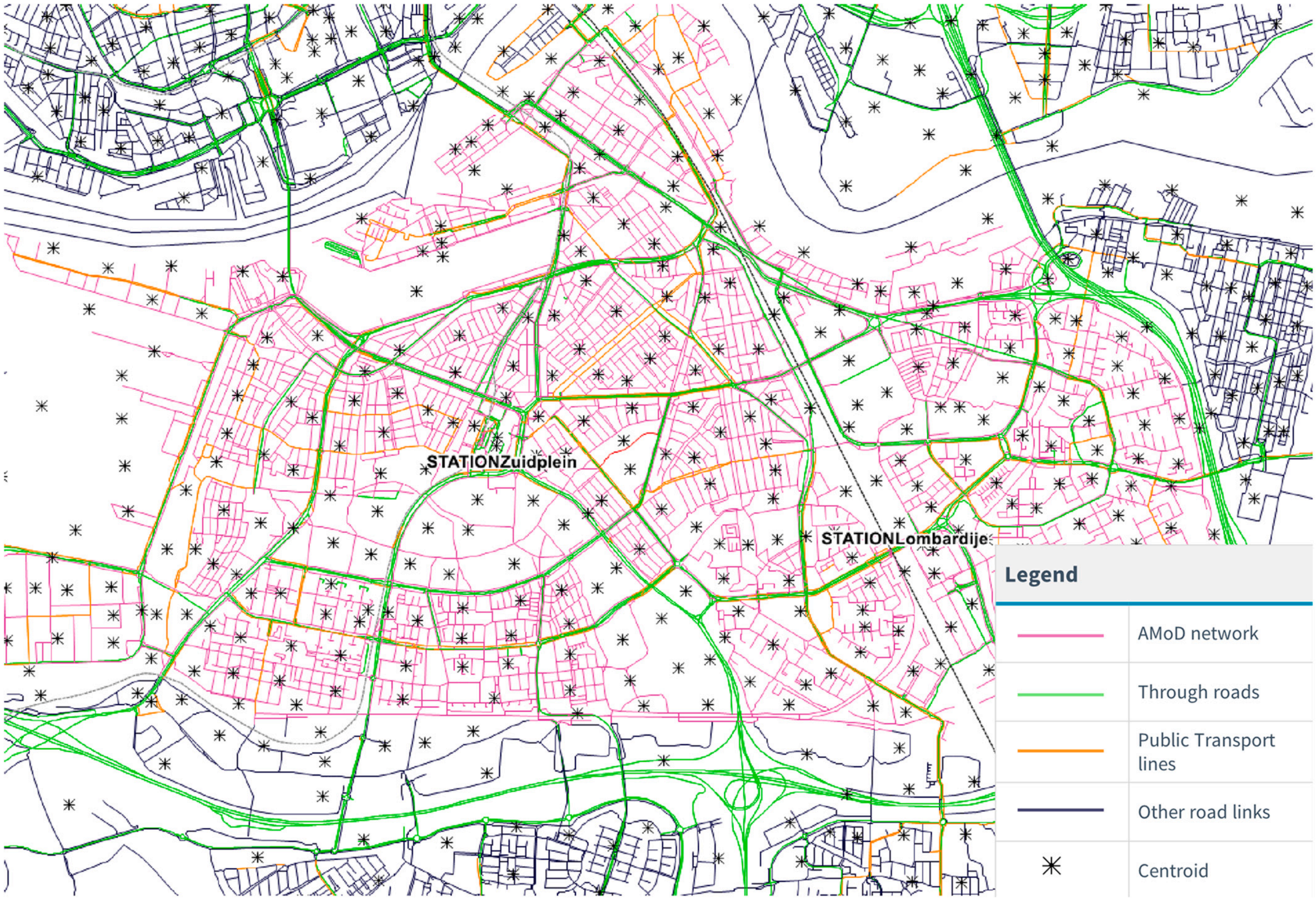

Fig. 4. Overview of the macro-model AMoD network. Source: V-MRDH model in OmniTRANS.

when the agents move to the next state based on predefined conditions. The states are indicated by the yellow rectangles and the state transitions are indicated by the black arrows. On the black arrows, various icons can be observed that indicate the transition's trigger type. The question mark indicates that the arrow imposes the question if the initial defined condition is met. The clock indicates that the transition is time-dependent. The finish flag indicates that the transition is triggered by the arrival of the agent at a certain location.

At the model startup, the AVs enter the state chart and are set to 'Idle'. Triggered by passenger requests, the AVs become operational and start to move to pick-up a passenger for a first-mile trip in 'MovingToTraveler' or to transport a passenger in 'MovingForOperation'. In between those states, the 'Loading_unloading_travelers' state determines the boarding and alighting behavior of the passengers. After a passenger is dropped off, the state chart checks the status of the AV concerning the operational strategy and battery and decides the following action. When the state of charge (SoC) of the AV becomes lower than 25% of the battery capacity, charging is required. In the 'ChargingBattery' state, vehicles will charge their batteries. In Fig. 6 it is visible that the state-chart accounts for both fast-charging and slow-charging. When the vehicle battery is fully charged, the AV again becomes ready for operation in the 'Idle' state. The fleet of AVs is allocated to one of the two stations in the micro-model, distributed proportionally to the AMoD passenger demand to and from each station. Therefore AVs are dedicated to one of the stations and it is not possible to switch between both.

The behavior of passengers in the micro-model is determined by the state chart shown in Fig. 7. At the model startup, the traveler becomes 'Busy'. According to the AMoD demand distribution shown in Fig. 5, the traveler requests a vehicle in the state 'Request_Vehicle'. If a vehicle request is sent, the traveler will wait till a vehicle is available in the state 'WaitingTillAvailable'. If this waiting time exceeds the maximum waiting time of 3 min, the traveler gives up waiting, and it is assumed to continue his/her trip with a different mode of transport and leaves the model. When an available vehicle is found, the vehicle will be assigned to the traveler and he/she will be waiting for the vehicle to arrive in the state of 'Waiting'. When the assigned vehicle location matches the origin of the traveler, the traveler switches to the state of 'Traveling'. When the assigned vehicle location matches the destination of the traveler, the trip is completed.

Running the model in the Anylogic software with activated visualization results in a map on which the vehicles move between the station and the centroids according to realistic travel times from the macro model. Fig. 8 shows a snapshot of the ABM (micro-model) animation during a simulation run. The coloured circles indicate the vehicles. The colour of the circle cores indicates the occupancy of the vehicle and the colour of the outer edge indicates the Battery state of the vehicle. The blue squares indicate the centroids that can function as an Origin or Destination. Moreover, the locations of both stations are indicated. This type of simulation visualization allows verifying the model against its conceptual version.

3.2. Simulation input

To study the impact of the operational strategies, different scenarios were simulated. The input of each scenario consists of a unique set of 3 operational variables. These three variables determine the operational strategy that is simulated. The base scenario uses the most straightforward operational strategy, consisting of a strategy where both relocation

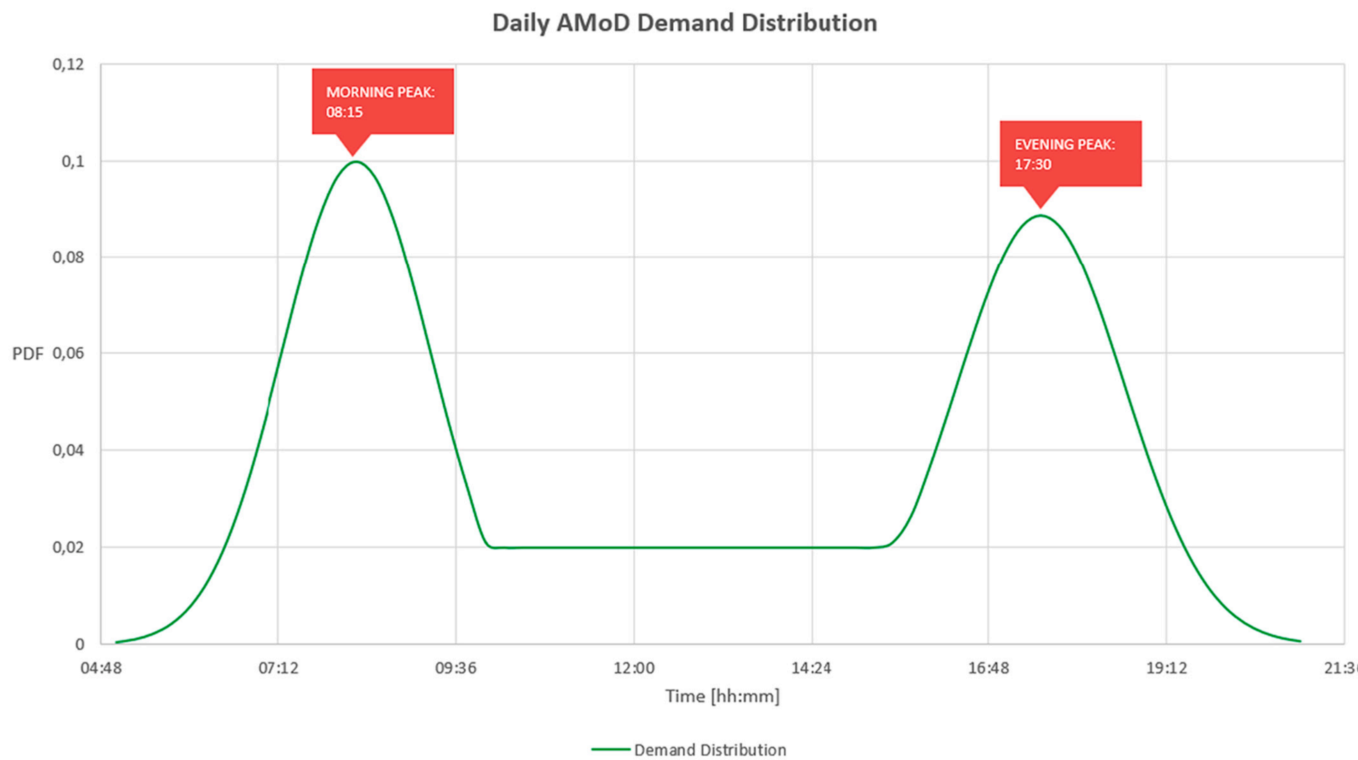

Fig. 5. Assumed distribution of the AMoD demand over a typical day.

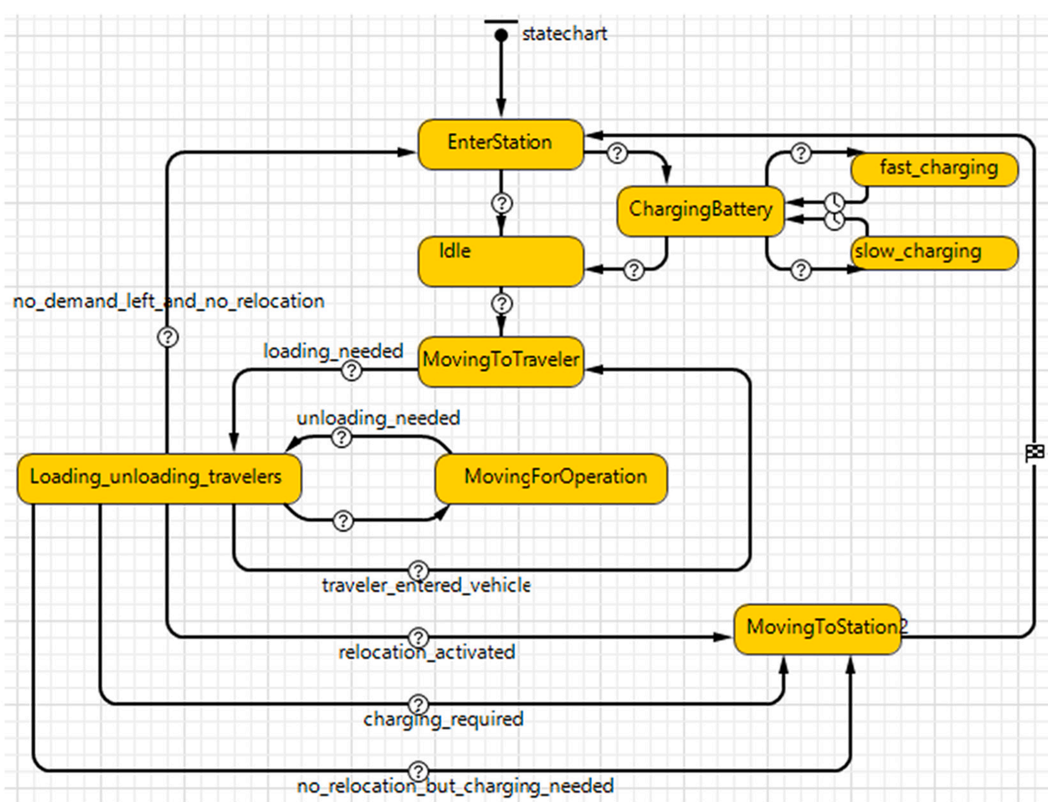

Fig. 6. Statechart determining the behavior of 'AVs' within the micro-model.

and dynamic ridepooling are not activated and slow chargers are used to charge the vehicles. This scenario is used as a reference scenario. The other scenarios that are simulated differ from the base scenario by at least one input variable. An overview of the scenarios that have been simulated can be seen in Table 2.

The type of vehicle that is used in this research is an autonomous

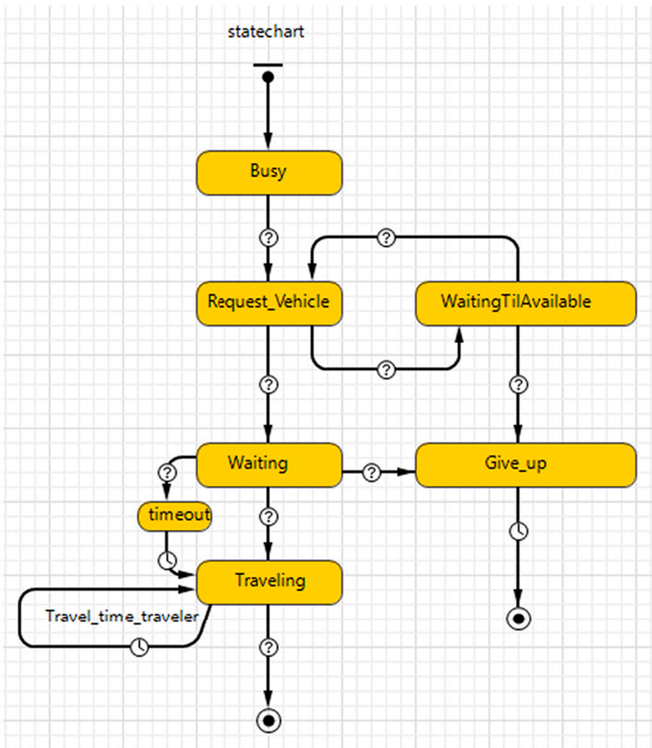

Fig. 7. Statechart determining the behavior of 'Travelers' within the micro-model.

Renault Twizy with a capacity of 2 passengers. The vehicle is small and light, making it easy to manoeuvre in dense urban areas and it is also energy efficient. It is assumed that the vehicles can use the existing car infrastructure within a certain pre-specified operational area. The SAE-level of automation, therefore, is either 4 or 5 (SAE International, 2014). Moreover, the engine of the vehicle is 100% electric.

The energy use of the vehicles is simulated by the differential equation shown in Eq. 1, which describes the kinematic energy that is required to let the vehicle roll at a certain speed. This equation allows taking into account vehicle and network-specific variables and determines the rate at which the battery of the vehicle loses energy. The kinematic energy is equal to the longitudinal force F multiplied by the speed of the vehicle v. The force F is given by the vehicle's longitudinal dynamic equation (Wang, Besselink, & Nijmeijer, 2015), 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 the vehicle inertia. The vehicle speed v is assumed to be constant and equal to 30 km/h. This means that the energy required for 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 weigh 75 kg. The slope of the road is assumed to be equal to zero as no vertical alignment of the road is taken into account in the model. Therefore, the terms F_g and F_i are zero. This leads to a slightly underestimated energy use of the vehicle. However, the slope of the road does not play a prominent role at the case study location due to the absence of hills and mountains. Moreover, the acceleration term is assumed to play a minor role in the total energy use because of the optimized driving style of the AVs.

$$\frac{\Delta(Battery)}{\Delta t} = -Energy_{use}$$

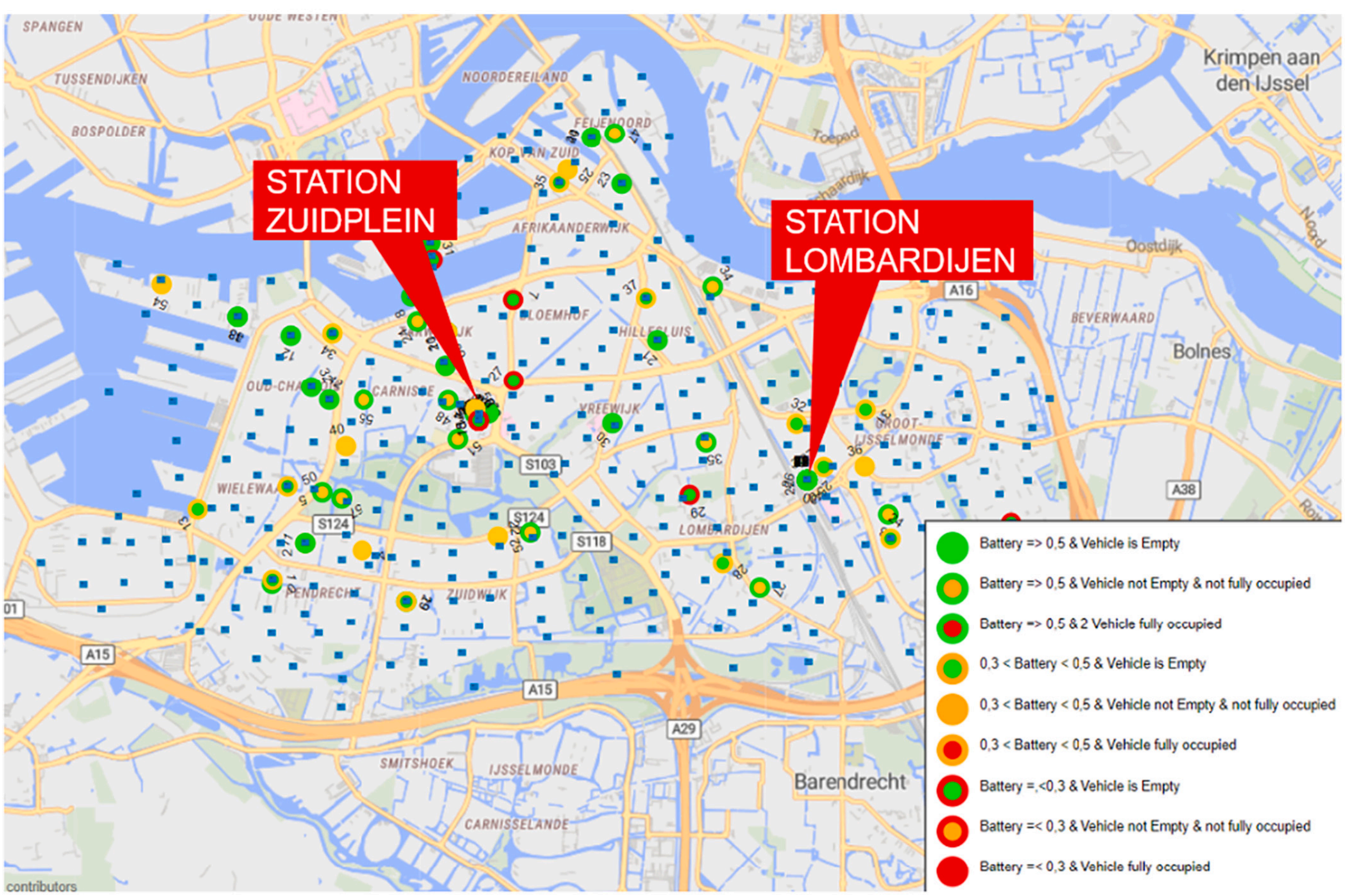

Fig. 8. Snapshot of the micro-model visualization during a simulation run.

Table 2
Overview of the simulated scenarios.

		Relocation	Dynamic ridepooling	Fast-Charging
0	Base Scenario	✗	✗	✗
1	Relocation Scenario	✓	✗	✗
2	Dynamic Ridepooling Scenario	✗	✓	✗
3	Ridepooling and Relocation Scenario	✓	✓	✗
4	Fast-charging Scenario	✗	✗	✓

$$Energy_{use} = F \bullet v$$

$$F = F_r + F_{air} + F_g + F_i = C_{rr}mg + \frac{1}{2}\rho C_d A_v^2 + mgsin(\theta) + ma.$$

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 remaining battery energy divided by the battery capacity gives the State-of-charge (SoC). When the SoC reaches a certain threshold value, the charging of the vehicle agent is required. This threshold value is set to 25% of the total battery capacity. A linear charging curve is considered when charging up to 80% of the total battery capacity. When charging to a SoC that is higher than 80%, there is a chance that the charging curve will become non-linear. To simplify this in the model, the battery is assumed to be fully charged when a SoC of 80% is reached. The simulation model allows using slow chargers (3.3 kW) or fast chargers (7.7 kW). Slow-chargers are less costly compared to fast-chargers but require a higher charging time.

Before the simulation of the several scenarios, and as explained regarding the integration between macro and micro-model, the vehicle fleet size is determined so that all the travel demand from the macro model can be satisfied. This is the case when the number of rejected passengers is equal to zero. This has to be done for every scenario since the operational strategies on each one determine how efficient or not a certain fleet size is in satisfying the trip requests.

Because of the model stochasticity, multiple replications are required to produce stable outputs. The required number of simulation runs has been determined by analysing the output variable 'number of rejected passengers' using the cumulative average. For the base scenario, the cumulative average of this variable becomes stable after 30 simulation runs. Therefore, each scenario was run with 30 replications, each one with a different random seed.

3.3. AMoD financial analysis

To determine the financial viability of AMoD services, the costs and revenues are calculated to show the daily balance of an AMoD operation. In this research, a selection of the most important financial components is comprised of equipment depreciation, energy costs, maintenance costs, management costs (wage expenses) and revenues. According to Spieser et al. (2014), these are the main aspects that determine the costs of a transport service like AMoD. Costs of road-infrastructure adaptation are not taken into account, because this research assumes that the vehicles can use the current infrastructure in mixed traffic situations. Moreover, the costs of a control- and supervisory-center, as well as the required communication infrastructure, are not taken into account.

The daily financial balance is calculated using the following expression:

$$Daily\ balance = R_d - C_{total}$$

$$C_{total} = C_d + C_e + C_m + C_{man}$$

Where:
R_d= Revenues;
C_d= Depreciation costs;
C_e= Energy costs;
C_m= Maintenance costs;
C_{man}= Management costs.

The daily revenues R_d are calculated as transport fare per minute travelled, whose value is based on an existing carsharing system operating in Amsterdam (Bussieck and Vigerske, 2014), multiplied by the total system travel time. The transport fare applied is equal to € 0.31 per minute. However, when dynamic ridepooling is applied, passengers obtain a fixed discount of 50% for sharing their ride. This is done to compensate for their additional trip duration because of detours required to pick up the second passenger.

The daily depreciation costs of the AMoD system are related to the required equipment that consists of vehicles and chargers and are calculated using the following expression:

$$C_{d_{total}} = C_{d_{AV}} + C_{d_{charger}}$$

$$C_{d_{AV}} = fleet_{size} \bullet \frac{C_{AV} - RV_{AV}}{LS_{AV} \bullet 365,25}$$

$$C_{d\_charger} = N^{y}_{chargers} \bullet \frac{C^{y}_{charger} - RV^{y}_{charger}}{LS^{y}_{charger} \bullet 365,25}$$

Where
$C_{d_{total}}$ = Total depreciation costs [€];
$C_{d_{AV}}$ = 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 1 AV [days];
$C_{d_{charger}}$ = Total depreciation costs by chargers [€];
$N^{y}_{chargers}$ = Required number of chargers of type y [chargers];
$C^{y}_{charger}$ = Purchase costs of 1 charger of type y [€];
$RV^{y}_{charger}$ = Residual value of 1 charger of type y [€];
$LS^{y}_{charger}$ = Lifespan of a charger of type y [days];

The depreciation costs, described by Eq. 3, depend on the purchase costs, and the residual value after a certain lifespan. With this equation, we assume a linear depreciation in the value of the required equipment. The energy costs C_e and maintenance costs C_m are directly proportional to the vehicle kilometers driven. The management costs account for the wage expenses of a certain team of people that operates the system and

Table 3
Output values of the key performance indicators for one typical business day.

Indicator	Scenario										
	Base Scenario	Scenario 2 Relocation		Scenario 3 Ridepooling		Scenario 4 R&R		Scenario 5 Fast charging		Preferred Scenario	
	Value	Value	Δ (%)	Value	Δ (%)	Value	Δ (%)	Value	Δ (%)	Value	Δ (%)
Simulation Input:											
Fleet Size	310	290	−6%	310	0%	280	−10%	290	−6%	240	−23%
Ridepooling	No	No	–	Yes	–	Yes	–	No	–	Yes	–
Relocation	No	Yes	–	No	–	Yes	–	No	–	No	–
Fastcharging	No	No	–	No	–	No	–	Yes	–	Yes	–
Slowcharging	Yes	Yes	–	Yes	–	Yes	–	No	–	No	–
System Indicators:											
Transported Passengers	7,010	7,010	0%	7,000	−0.1%	7,010	0%	7,010	0%	6,990	−0.2%
Unsatisfied Passengers	0	0	0%	10	+100%	0	0%	0	0%	20	+100%
Total system distance (km)	24,080	30,870	+28%	23,490	−2%	27,610	+15%	24,180	0%	23,950	−1%
Total system traveltime (min)	23,030	23,040	0%	23,330	+1%	23,650	+3%	23,050	0%	23,360	+1%
Total system waiting time (min)	12,040	10,580	−12%	17,060	+42%	13,120	+9%	12,110	+1%	17,900	+49%
Minimum idle vehicles at Zuidplein	10	0	−79%	40	+213%	10	−61%	20	+35%	20	+43%
Minimum idle vehicles at Lombardijen	40	40	−19%	60	+29%	50	+11%	40	−6%	30	−27%
Passenger Indicators:											
Average waiting time for vehicle arrival (min)	1.8	1.5	−14%	2.5	+42%	1.9	+7%	1.8	0%	2.6	+49%
Maximum waiting time for vehicle arrival (min)	8.6	12.0	+40%	14.6	+70%	12.8	+49%	8.7	+1%	15.0	+75%
Average waiting time for vehicle assignment (min)	0.3	0.3	0%	1.3	+333%	0.1	−66%	0.4	+33%	1.7	+467%
Maximum waiting time for vehicle assignment (min)	0.6	0.4	−23%	2.1	+264%	0,1	−79%	0.6	0%	2.7	+350%
Average travel time (min)	3.3	3.3	0%	3.3	0%	3.4	3%	3.3	0%	3.3	0%
Maximum travel time (min)	8.0	8.0	0%	11.6	+44%	12.1	+51%	8.0	0%	11.2	+39%
Average Trip Distance (km)	1.6	1.6	0%	1.7	+6%	1.7	+6%	1.6	0%	1.7	+6%
Vehicle Indicators:											
Average distance driven (km)	100	128	+28%	118	+19%	128	+29%	111	+11%	135	+36%
Average transported passenger per vehicle	28	27	−5%	32	+14%	30	+6%	31	+8%	38	+33%
% of operational time occupied by pass (%)	16%	20%	+27%	19%	+18%	20%	+27%	17%	+11%	21%	+35%
Average operational time occupied with 0 pass. (min)	77	118	+53%	91	+18%	113	+47%	86	+12%	106	+37%
Average operational time occupied with 1 pass. (min)	74	73	−1%	84	+14%	73	−1%	81	+10%	94	+27%
Average operational time occupied with 2 pass. (min)	0	0	0%	4	+100%	5	+100%	0	0%	4	+100%
Financial Indicators:											
Depreciation costs (€)	€2,500	€2,340	−6%	€2,500	0%	€2,260	−10%	€2,360	−6%	€1,960	−22%
Energy costs (€)	€590	€740	+26%	€570	−4%	€660	+12%	€590	0%	€570	−3%
Maintenance costs (€)	€1,690	€2,160	+28%	€1,640	−2%	€1,930	+15%	€1,690	0%	€1,680	−1%
Management costs (€)	€1,000	€1,000	0%	€1,000	0%	€1,000	0%	€1,000	0%	€1,000	0%
Revenues (€)	€7,140	€7,140	0%	€7,230	+1%	€7,330	+3%	€7,140	0%	€7,240	+1%
Profit (€)	€1,362	€897	−34%	€1,525	+12%	€1,480	+9%	€1,501	+10%	€2,032	+49%
Energy Indicators:											
Total daily energy usage (kWh)	1,480	1,860	+26%	1,420	−4%	1,650	+12%	1,480	0%	1,440	−3%
Maximum energy required at Zuidplein (kW)	240	220	−7%	210	−14%	200	−18%	370	+55%	330	+37%
Maximum energy required at Lombardijen (kW)	80	90	+6%	90	+8%	90	+11%	150	+83%	160	+94%
Number of chargers required	100	90	−3%	90	−8%	90	−10%	70	−30%	60	−35%

provides additional service when required.

4. Results

The results of the simulation experiment consist of several key performance indicators. These indicators are classified using the following categories: System, Energy, Passenger, Vehicle, and Business. Each category belongs to a certain perspective from which the results can be analyzed. The output values of all indicators as a result of the simulation experiment are shown in Table 3.

4.1. System performance indicators

4.1.1. Base Scenario

To serve all demand in the Base Scenario, a fleet of 310 vehicles is needed which is distributed over Station Zuidplein and Station Rotterdam Lombardijen proportionally to the travel demand at each station. The total travel demand on a typical day is equal to 7010 passengers, of which 4115 are related to Station Zuidplein and 2895 to Station Rotterdam Lombardijen. The number of rejected passengers should be equal to zero to be consistent with the demand model. However, due to stochastic effects that occur when generating random seeds, the number of rejected passengers is not exactly 0 but equal to 1 passenger. However, this difference only comes down to 0,01% of the total demand, whose effect can be neglected.

To determine the impact of the operational variables, the output values of the key performance indicators of all scenarios are compared with the reference scenario (base scenario). A description of the most important results per scenario is presented in Table 3 The system performance is described first, and afterwards, the financial viability of each operational strategy of the AMoD service is given.

4.1.2. Relocation scenario

The required vehicle fleet to serve all the demand in the relocation scenario consists of 290 vehicles, which is 20 vehicles fewer than what the base scenario requires. Activating relocation operations leads to an increase in total system driving distance of 3090 km which is 28% higher compared to the base scenario. This increase is mainly the consequence of the additional empty vehicle trips required to relocate the vehicle to the station when a passenger has been delivered and there no further passenger requests are received. As a result of the increase in the total system distance, the operational costs also increased by 28% to € 2160 because energy costs and maintenance costs are directly proportional to the driven distance of the vehicles. However, the level of service increased because the waiting time at the station is minimized leading to an average waiting time of 1.5 min, which is 14% lower compared to the base scenario.

4.1.3. Dynamic ridepooling scenario

To serve all demand in the ridepooling scenario, a fleet size of 310 vehicles is required which is the same as the base scenario. Due to ridepooling, a high waiting time occurs when a detour is needed to pick up a second passenger to share his/her ride with the first entered passenger. As a result, the average waiting time for a vehicle to arrive increased by 42% to 2.5 min. It is assumed in the model that a traveler has a maximum waiting time. When this maximum waiting time is reached, clients leave the system and look for a different mode of transport. Therefore, the number of rejected passengers has increased to 12 passengers. Increasing the fleet size does not lead to a lower number of rejected passengers anymore, because, at this point, the waiting time has become the normative factor for the system capacity. Based on these effects, it can be concluded that applying dynamic ridepooling has a decreasing impact on the system capacity compared to the base scenario. Despite the limited system capacity and 50% fare reduction for passengers that experience a detour, dynamic ridepooling leads to slightly increasing revenues by 1.3%. This is mainly the result of a decrease of vehicle kilometers driven (−2%) per transported passenger.

4.1.4. Ridepooling & relocation scenario

A combined relocation and dynamic ridepooling operational strategy results in zero rejected passengers using a fleet of 280 vehicles. Compared to the base scenario, the ridepooling & relocation scenario can serve the same passenger demand requiring 10% fewer vehicles. Therefore this scenario has a relatively strong positive influence on the system capacity. This can be explained by the positive influence of applying relocation on the passenger waiting time. As a result, the average waiting time decreased from 0.3 min to 0.1 min compared to the base scenario. Due to the smaller required fleet size, the depreciation costs decrease by 10% compared to the base scenario. However, this combination also leads to a 15% increase in the number of total driven kilometers, which leads to an increase of 12% energy costs and 15% maintenance costs in relation to the base scenario.

4.1.5. Fast charging scenario

The use of fast-chargers instead of the regular charging facilities leads to additional investment costs, because the purchase price and installation costs of fast-chargers are assumed to be twice as high compared to the regular slow-chargers. Moreover, the use of fast-chargers leads to higher peaks in the required power to operate the system because these chargers require more power than the regular chargers. However, these additional investment costs lead to a substantial increase in the system capacity. This increase is shown in Fig. 9. This Figure contains 2 charts that result from a simulation of the fast charging scenario and shows the percentage of AVs per state as a function of time.

The left graph of Fig. 9 shows the situation considering the Fast-charging Scenario and the right graph shows the situation considering the Base Scenario where slow-chargers are used. The peak in the percentage of vehicles that are charging at the same moment in time is found after 670 min (17:15), and is equal to 25% using Fast-chargers and 45% using Slow-chargers. This means that due to the use of fast-chargers, 20% additional spare capacity is gained at the evening-peak. Daily, all the demand can be served in the fast charging scenario using a vehicle fleet equal to 290 vehicles, which is 6% less compared to the base scenario. Next to the advantageous impact on the system capacity, using fast-chargers also leads to lower investment costs, because 20% fewer chargers are required.

4.2. Financial results

For each scenario, the daily costs, revenues, and daily balance (profit) are calculated. These are shown in Fig. 10 using a bar chart. This figure shows the finances of a typical daily AMoD operation in each scenario. The purple, blue and green bars indicate consecutively the total costs, total revenues, and daily balance per scenario. As a reference, the purple, blue, and green dashed lines indicate consecutively the total costs, total revenues, and daily balance (profit) of the base scenario. From this graph, one can conclude that all scenarios result in a financially viable operation because there is a profit (positive daily balance) for every scenario. Moreover, it can be concluded that applying Ridepooling and Fast-charging to the AMoD operational strategy leads to an increase in profit. Despite the discount given to the passengers that share their ride in the Ridepooling scenario, an increase in revenue is observed. This is mainly the result of the decreased total vehicle kilometers per passenger.

The revenues per scenario do not show a lot of variation, while the operational costs show larger variations. Fig. 11 shows the costs per scenario divided into different costs aspects. Applying a Relocation strategy leads to higher maintenance and energy costs due to the additional vehicle kilometers required for relocation trips. As a result, the Relocation strategy leads to a decrease in daily profit despite requiring fewer cars. The relocations as defined in this paper are simply not

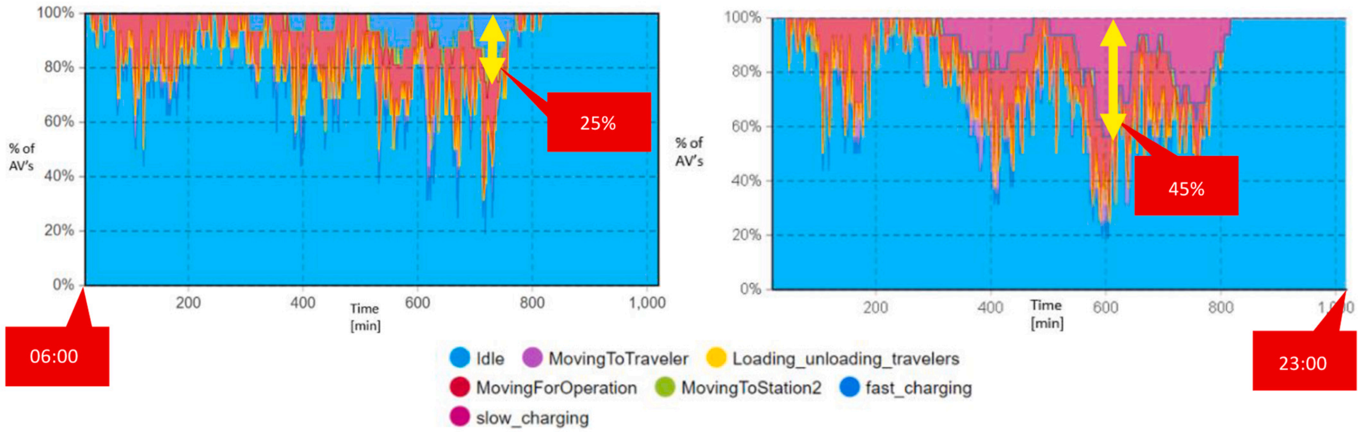

Fig. 9. Stackchart indicating the share of vehicles per state as a function of time for a typical day from 06:00 to 23:00.

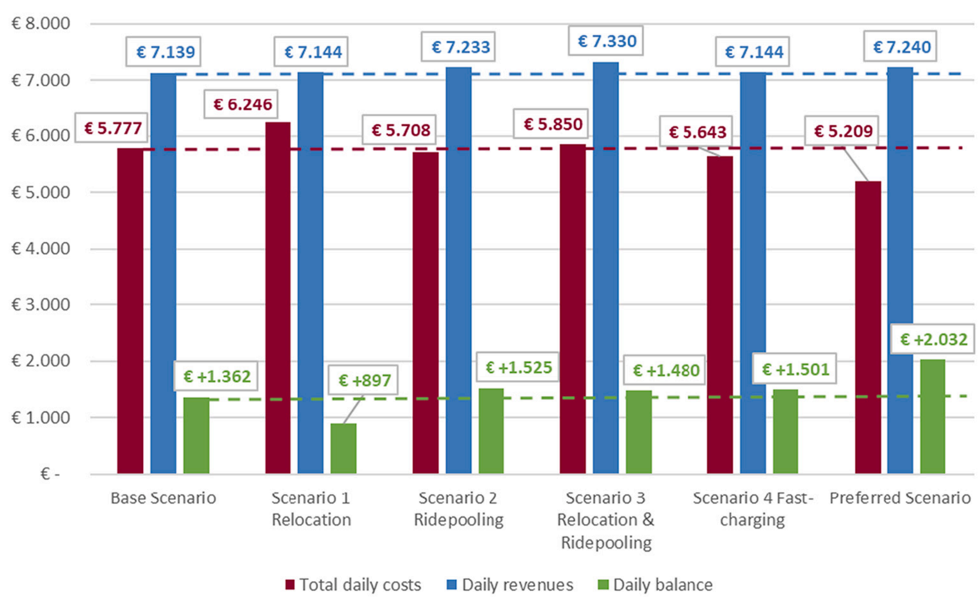

Fig. 10. Overview of the daily costs (purple), revenues (blue) and profit (green) per scenario. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

efficient since the destination of the relocations can only be the station. However, combining Relocation with Ridepooling leads to an increase in daily profit compared to the base scenario.

Taking the financial impacts of the different strategies into account, a 6th scenario has been developed to aim at increasing the profit for the AMoD operation in the south of Rotterdam. This scenario is called the 'Preferred Scenario', of which the revenues and costs are also added to Figs. 10 and 11. In the Preferred Scenario, Ridepooling is combined with the fast-charging strategy. This leads to a substantial decrease in costs because fewer vehicles are required to satisfy all AMoD passenger demand. This is mainly possible because of the positive impact of fast-chargers on the system capacity. Moreover, Ridepooling leads to a more financially beneficial AMoD system because of the increase of passenger kilometers with a decrease in total vehicle kilometers at the same time.

Table 4 gives an overview of the financial statistics of the most profitable scenario. From this table, it can be observed that applying dynamic ridepooling and fast-charging leads to an increase in profit equal to 49,2%. This is mainly the result of the decrease of depreciation costs equal to 21,7%, which is the consequence of the positive impact of the fast-charging strategy.

Based on the results of the financial analysis, it can be concluded that applying an AMoD system can be financially viable under the conditions and assumptions made in the simulation model. All of the simulated scenarios lead to a profit. However, the amount of profit depends on the operational strategy that is applied. This impact on the operational finances is of course one of the main benefits of autonomous vehicles.

In comparison, conventional taxi systems are more costly because of additional salary costs for drivers. Adding a driver to all vehicles in the Base Scenario leads to a conventional taxi system. The additional wage expenses can be calculated using the fleet size, the average operational time per vehicle, and the driver's wages. Assuming that every driver earns a salary equal to the minimum wage in The Netherlands (in 2021), the additional daily costs of conventional taxi systems compared to AMoD systems are 310 (vehicles) x 3.4 (hours) x 9.72 (€) = €10,245. This would lead to significant financial losses using a fare of € 0.31 per minute. To break even, a fare of € 0.70 would have to be applied, which is more than double.

5. Conclusions and recommendations

The main objective of this research was to study the financial

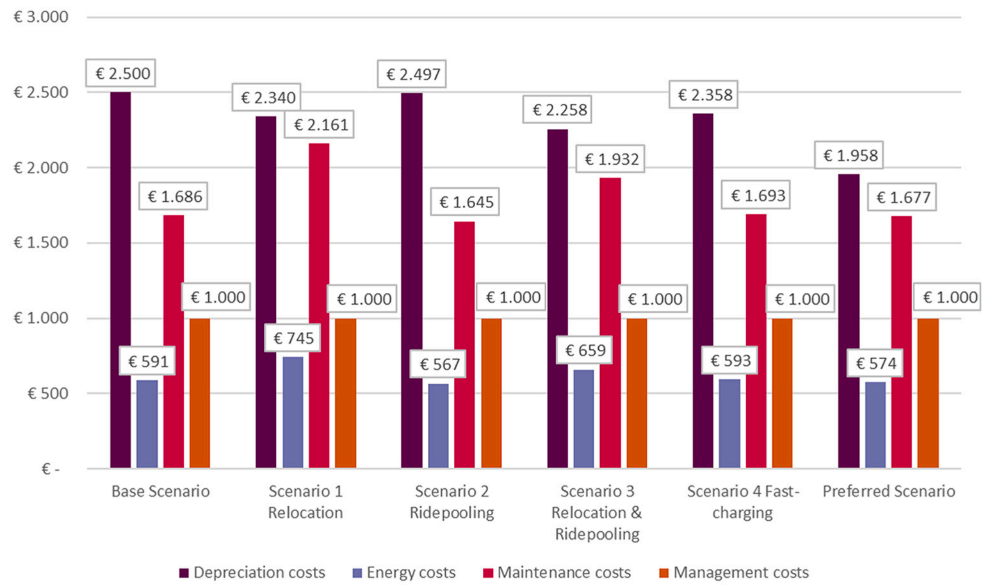

Fig. 11. Bar chart of the daily costs aspects categorized by the costs aspects: Depreciation costs (purple), Energy costs (blue), Maintenance costs (pink), and Management costs (orange). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Daily finances of the most profitable AMoD operation: The Preferred Scenario.

Financial Aspect	Base Scenario	Preferred Scenario	Difference (%)
Depreciation costs	€ 2,500	€ 1,958	−21.7%
Energy costs	€ 591	€ 574	−2.8%
Maintenance costs	€ 1,686	€ 1,677	−0.6%
Management costs	€ 1,000	€ 1,000	0.0%
Daily total costs	€ 5,777	€ 5,209	−9.8%
Daily revenues	€ 7,139	€ 7,240	+1.4%
Daily balance (profit)	€ +1,362	€ +2,032	+49.2%

viability of an AMoD service providing first/last mile transport in addition to public transport. A case study simulation of an AMoD application in the city of Rotterdam was used. Because AMoD services can be applied using various operational strategies, the impact of three operational strategies on the financial viability was analyzed: (1) relocation strategy, (2) dynamic ridepooling, and (3) charging strategy.

The modeling framework that was used consists of two components: a macroscopic and a microscopic model. An existing macro-model was used to estimate the travel demand for AMoD services and a new agent-based simulation (supply) model was developed. These were applied to the case study city of Rotterdam to assess the impact of the operational strategies.

Statically using the framework (no feedback), but with a specific vehicle fleet that results in zero rejected trips to tackle that limitation, it was shown that the AMoD service is financially viable in providing first/last mile transport to two stations. Moreover, it was shown that the operational strategies have an impact on the daily financial balance. Applying the relocation strategy results in the highest total daily costs leading to the lowest daily balance equal to € 897. Activating dynamic ridepooling combined with fast-chargers leads to the most profitable AMoD operation mainly due to the increase of efficiency in the use of vehicle kilometers to transport passengers and the positive impact of fast-chargers on the system capacity. This scenario leads to a daily balance of € 2032 which is 127% higher compared to the daily balance of the relocation scenario and also 49% higher compared to the base scenario.

From an operator's perspective, applying the AMoD system in the south of Rotterdam is shown to be attractive under the modeling assumptions because it is financially viable regardless of the operational strategy. Besides, the AMoD system is desirable from the passengers' perspective because of the low average waiting times compared to existing public transport services in the study area. Transferability of the results to other regions of these results can only be valid for the same land use densities and similar mode choice which determine the amount of demand.

The main issue for future AMoD operators is the high costs of investment, comprising aspects such as the construction of the AMoD hubs, the charging infrastructure and facilities, the fleet of vehicles and the development of operations software. Because AMoD systems are interesting both from a policy perspective and from an operator's perspective, public-private partnerships could play a key role to develop a feasible business model. If these policy challenges can be addressed then the potential benefits of AMoD could be enhanced.

From a methodological perspective, this research showed that it makes sense to use the micro-model as an add-on module to existing traditional gravity-based transport models. The micro-model can be applied to any place in the world to evaluate the AMoD system performance provided that there is a travel demand estimation model available for that specific area. However due to the simplification in the traffic congestion modeling the supply side may not be well characterized in high-density areas where traffic congestion is already a concern, like for example New York City.

This research described a static input-output simulation method. The impact of the demand on the system performance is at the core of this simulation approach. However, in real-life transport systems, also the supply side has an impact on the demand side. Incorporating this impact in a simulation method would lead to a feedback loop simulation approach that converges to equilibrium by multiple iterations. This equilibrium then is the steady state of a transport system. Component-based modeling could be used as a simulation method in order to model this feedback loop approach. However, due to the running time of the macro-model, it was not feasible to search for an equilibrium between supply and demand in the framework used in this research. Therefore, it is important to continue the research with a view to incorporating such feedback.

The demand model used in this research predicts the number of AMoD passengers based on assumptions about the conditional choice behavior of passengers. The conditions under which passengers choose to use the AMoD service play a crucial role in the actual usage of the

AMoD service, and are typically things that depend on the local context. In addition, the actual use also depends on availability, reliability, findability and comfort, which are not explicitly taken into account in this research.

Moreover, this research provides limited insight into the impact of the AMoD system on other transport modes like the car and bus. The micro-model does not account for the traffic impacts of AMoD vehicles. Therefore it is not clear if the urban traffic system as a whole benefits from the AMoD system. Next to traffic impacts, it would be interesting to show what the impact of the implementation of the AMoD system is on the modal share of other competitor modes. The demand model only directly shows the impact on the number of passengers walking and bicycling as first- and last-mile transport. However, public transport modes such 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.

Author statement

This paper has not been published and is not being considered for publication elsewhere.

Data availability

Data will be made available on request.

Acknowledgements

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Appendix A. Overview of simulation results

Indicator	Scenario										
	Base Scenario	Scenario 2 Relocation		Scenario 3 Ridepooling		Scenario 4 R&R		Scenario 5 Fast charging		Preferred Scenario	
	Value	Value	Δ (%)	Value	Δ (%)	Value	Δ (%)	Value	Δ (%)	Value	Δ (%)
Input:											
Fleet Size	310	290	−6%	310	0%	280	−10%	290	−6%	240	−23%
Ridepooling	No	No	–	Yes	–	Yes	–	No	–	Yes	–
Relocation	No	Yes	–	No	–	Yes	–	No	–	No	–
Fastcharging	No	No	–	No	–	No	–	Yes	–	Yes	–
Slowcharging	Yes	Yes	–	Yes	–	Yes	–	No	–	No	–
System:											
Transported Passengers	7010	7010	0%	7000	−0.1%	7010	0%	7010	0%	6990	−0.2%
Unsatisfied Passengers	0	0	0%	10	+100%	0	0%	0	0%	20	+100%
Total system distance (km)	24,080	30,870	+28%	23,490	−2%	27,610	+15%	24,180	0%	23,950	−1%
Total system traveltime (min)	23,030	23,040	0%	23,330	+1%	23,650	+3%	23,050	0%	23,360	+1%
Total system waiting time (min)	12,040	10,580	−12%	17,060	+42%	13,120	+9%	12,110	+1%	17,900	+49%
Minimum idle vehicles at Zuidplein	10	0	−79%	40	+213%	10	−61%	20	+35%	20	+43%
Minimum idle vehicles at Lombardijen	40	40	−19%	60	+29%	50	+11%	40	−6%	30	−27%
Passenger:											
Average waiting time for vehicle arrival (min)	1.8	1.5	−14%	2.5	+42%	1.9	+7%	1.8	0%	2.6	+49%
Maximum waiting time for vehicle arrival (min)	8.6	12.0	+40%	14.6	+70%	12.8	+49%	8.7	+1%	15.0	+75%
Average waiting time for vehicle assignment (min)	0.3	0.3	0%	1.3	+333%	0.1	−66%	0.4	+33%	1.7	+467%
Maximum waiting time for vehicle assignment (min)	0.6	0.4	−23%	2.1	+264%	0,1	−79%	0.6	0%	2.7	+350%
Average travel time (min)	3.3	3.3	0%	3.3	0%	3.4	3%	3.3	0%	3.3	0%
Maximum travel time (min)	8.0	8.0	0%	11.6	+44%	12.1	+51%	8.0	0%	11.2	+39%
Average Trip Distance (km)	1.6	1.6	0%	1.7	+6%	1.7	+6%	1.6	0%	1.7	+6%
Vehicle:											
Average distance driven (km)	100	128	+28%	118	+19%	128	+29%	111	+11%	135	+36%
Average transported passenger per vehicle	28	27	−5%	32	+14%	30	+6%	31	+8%	38	+33%
% of operational time occupied by pass (%)	16%	20%	+27%	19%	+18%	20%	+27%	17%	+11%	21%	+35%
Average operational time occupied with 0 pass. (min)	77	118	+53%	91	+18%	113	+47%	86	+12%	106	+37%
Average operational time occupied with 1 pass. (min)	74	73	−1%	84	+14%	73	−1%	81	+10%	94	+27%
Average operational time occupied with 2 pass. (min)	0	0	0%	4	+100%	5	+100%	0	0%	4	+100%
Financial:											
Depreciation costs (€)	€2500	€2340	−6%	€2500	0%	€2260	−10%	€2360	−6%	€1960	−22%
Energy costs (€)	€590	€740	+26%	€570	−4%	€660	+12%	€590	0%	€570	−3%
Maintenance costs (€)	€1690	€2160	+28%	€1640	−2%	€1930	+15%	€1690	0%	€1680	−1%
Management costs (€)	€1000	€1000	0%	€1000	0%	€1000	0%	€1000	0%	€1000	0%
Revenues (€)	€7140	€7140	0%	€7230	+1%	€7330	+3%	€7140	0%	€7240	+1%
Profit (€)	€1362	€897	−34%	€1525	+12%	€1480	+9%	€1501	+10%	€2032	+49%

(*continued on next page*)

(*continued*)

Indicator	Scenario										
	Base Scenario	Scenario 2 Relocation		Scenario 3 Ridepooling		Scenario 4 R&R		Scenario 5 Fast charging		Preferred Scenario	
	Value	Value	Δ (%)	Value	Δ (%)	Value	Δ (%)	Value	Δ (%)	Value	Δ (%)
Energy:											
Total daily energy usage (kWh)	1480	1860	+26%	1420	−4%	1650	+12%	1480	0%	1440	−3%
Maximum energy required at Zuidplein (kW)	240	220	−7%	210	−14%	200	−18%	370	+55%	330	+37%
Maximum energy required at Lombardijen (kW)	80	90	+6%	90	+8%	90	+11%	150	+83%	160	+94%
Number of chargers required	100	90	−3%	90	−8%	90	−10%	70	−30%	60	−35%

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