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Modeling the competition between multiple Automated Mobility on-Demand operators: An agent-based approach

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ABSTRACT

Automated Mobility-on-Demand (AMoD) systems, in which fleets of automated vehicles provide on-demand services, are expected to transform urban mobility systems. Motivated by the rapid development of AMoD services delivered by self-driving car companies, an agent-based model (ABM) has been developed to study the coexistence phenomena of multiple AMoD operators competing for customers. The ABM is used to investigate how changes in pricing strategies, assignment methods, and fleet sizes affect travelers' choice of different AMoD services and the operating performance of competing operators in the case-study city of The Hague, in the Netherlands. Findings suggest that an optimal assignment algorithm can reduce the average waiting time by up to 24% compared to a simple heuristic algorithm. We also find that a larger fleet could increase demand but lead to higher waiting times for its users and higher travel times for competing operators' users due to the added congestion. Notably, pricing strategies can significantly affect travelers' choice of AMoD services, but the effect depends strongly on the time of the day. Low-priced AMoD services can provide high service levels and effectively attract more demand, with up to 64.7% of customers choosing the very early morning service [5:30 AM,7:20 AM]. In the subsequent morning hours, high-priced AMoD services are more competitive in attracting customers as more idle vehicles are available. Based on the quantitative analysis, policies are recommended for the government and service operators.

1. Introduction

Automated Vehicles (AVs) offer a unique opportunity for changing urban mobility in the future. Combining AVs with ride-hailing technology creates the chance for a paradigm shift in urban mobility systems. A transition to Automated Mobility-on-Demand (AMoD) systems for both people and goods is actually already underway. Given the strong possibility that there will be widely available AMoD services in the future, various studies have investigated the impacts of introducing AMoD systems into cities [1,2].

The emerging AV industry can be described as a marketplace where no single organization has enough influence and resources to dominate the entire market. In a future urban mobility system, it will be natural that fleets of SAVs will be operated by different AMoD companies to meet mobility needs in urban areas. Current research focuses on exploring the

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impact of AMoD services performed by a single operator and ignores the study of AMoD systems with multiple operators competing for customers in urban areas. This paper aims to develop a new agent-based model (ABM) for future AMoD systems that are characterized by multiple competing operators in the same urban area. Notably, we explore the potential of operating strategies (e.g., fleet sizes, assignment strategies, pricing strategies) on travelers' choices through scenarios and a case study.

The remainder of the paper is structured as follows. Section 2 provides the current state of research on modeling urban AMoD systems, emphasizing supply and demand interactions. Section 3 describes the modeling rationale. A detailed description of the model implementation and its application is presented in Section 4. Section 5 provides an analysis of the results of applying the model to the case study city of The Hague in The Netherlands. In Section 6, we discuss the main findings and provide recommendations for different stakeholders. The main conclusions are drawn in the final section, and future research directions are discussed.

2. Background

2.1. Modeling single-operator AMoD systems

Burns et al. [3] examined the cost and operating performance of AMoD systems to serve the existing travel demand satisfied by private vehicles. They found that AMoD systems are compelling because they could provide mobility services with shorter waiting times and low operating costs. Fagnant and Kockelman [4] investigated the travel and environmental implications of AMoD systems using exogenous demand. Their findings indicated that Shared Automated Vehicles (SAV) could improve vehicle utilization and reduce negative environmental impacts. Several works focused on the operational efficiency of AMoD systems and gave insights into the operational aspects of parking, relocation, charging, dispatching, and routing [5–9]. Wang et al. [10] investigated the travel and energy impacts of forming platoons in an urban AMoD system. Some studies have provided an assessment of operating AMoD systems when combining public transportation options [11,12]. Modeling frameworks in the above studies use either static demand imposed for AMoD systems or exogenously determined modal share for the AMoD service and public transportation options. Therefore, the behavioral response to the level of AMoD services is usually not captured.

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

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

Chen and Kockelman [13] have incorporated different fare schemes in the mode choice model to examine the impact of electric AMoD service pricing strategies on mode share and fleet performance. Bösch et al. [14] provided a cost-based analysis of AMoD services. The study by Bösch et al. [14] considered user-case-specific preference for modes of transportation. The mode choice was determined according to the operating cost of the AMoD service. Pinto et al. [15] formulated a modeling framework to solve the problem of redesigning a bus network while introducing an AMoD service. The modal share for the AMoD service and the bus service was determined endogenously, based on the bus service's frequency and the AMoD fleet's performance. Wen et al. [16] formulated a modeling framework to evaluate an integrated AMoD and public transportation system in which shared-use AVs provide a connection service to rail stations in low-density areas. The modeling framework captured the changes in travelers' behavior in response to the operating policies. Dandl et al. [17] proposed a new simulation framework for AMoD systems that focuses on asynchronous approaches to computing decisions for a fleet operator in serving demand. The asynchronous framework is used to address the trade-off between computational complexity and policy optimality of operators. Narayan et al. [18] studied the problem of combining scheduled and fixed-route transit systems with AV fleets, where AVs provide either connection service to transit services or direct door-to-door services in a demand-responsive fashion. Using the MATSim framework, the demand for transit services, exclusive AV services, and integrated AV-transit systems was endogenously determined. Oh et al. [19] examined the impact of introducing AMoD systems into the existing transportation system in Singapore through SimMobility, which was an integrated agent-based and activity-based simulation framework. The responsiveness of demand to the change in the fleet supply and operations was explicitly modeled. Hörl et al. [20] simulated AMoD systems in a multimodal transportation system in Zurich using MATSim. The proposed modeling framework can model the customers' response to the level of service attributes (waiting time and price). In particular, their study proposed a cost-covering pricing scheme for the AMoD fleet. The relationship between AMoD demand (served requests) and fleet size was established under the constraint of providing a cost-covering AMoD service.

2.3. Modeling single-operator MoD or carsharing systems considering the supply–demand interaction

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

Vasconcelos et al. [21] presented a cost–benefit analysis method to analyze and compare the performance of one-way carsharing systems with and without vehicle relocation in the presence of private transport (private cars and motorcycles) and public transport. To simulate the behavioral response to the different transport modes, a discrete choice model was incorporated to allocate travelers to the transport modes in the city of Lisbon. One of the findings suggested that the use of electric vehicles in one-way carsharing systems can achieve environmental benefits, while vehicle relocations can counteract the environmental benefits due to the additional relocation kilometers. Lu et al. [22] proposed an optimization model to examine the effect of pricing and vehicle relocation strategies on the performance of one-way carsharing systems, taking into account the competition with private cars. A logit model was incorporated into the optimization method to calculate the probability of the alternative choices. Findings suggested that combining a vehicle relocation strategy with a strategy of varying prices depending on vehicle stock can effectively balance the trade-off between the operator's profit and travelers' cost. Djavadian and Chow [23] developed a modeling framework to incorporate an agent-based day-to-day adjustment process for both an MoD operator and travelers. In the modeled two-sided transportation market, travelers can adjust their behaviors to choose a transport service, while the MoD operator can adjust the service offered using within-day operating policies and day-to-day fleet size policy. The modeling framework was applied to a first/last mile problem with an emphasis on testing the sensitivity of within-day operating policies and fare price. Liu et al. [24] developed a framework to model the customers' choice for MoD systems in the multimodal transportation system aiming to optimize MoD fleet size and fare.

2.4. Modeling multiple-operator MoD systems with exogenous demand

In all the above studies on AMoD, MoD, and carsharing systems, the services are assumed to be managed by a single operator. The phenomena associated with the coexistence of multiple AMoD operators are overlooked.

With the rapid growth of the ride-hailing market, multiple commercial MoD companies (e.g., Uber, Lyft, and Didi Chuxing) are operating their services simultaneously with other companies. Séjourné et al. [25] studied the overall system's efficiency in a situation where multiple MoD platforms coexist and independently manage vehicles to meet a fixed demand. Pandey et al. [26] presented an optimization-based approach to study cooperative and competitive assignments between multiple ridesharing operators. The proposed assignment method solved the coordinated assignment problems in multiple-operator situations without lowering the level of service compared to a fully centralized assignment. The modeling framework quantified the impact of customer preference on assignment results with varying percentages. Kondor et al. [27] quantified the cost of adding more vehicles to serve demand when the market is segmented in the urban mobility system. They compared the cost of non-coordinated urban MoD systems with multiple operators to the cost of operating the vehicle fleet by a single operator for different cities. Their findings suggest that the total fleet needs to be increased by up to 67% to serve the given demand in non-coordinated urban MoD systems.

Despite the fact that AMoD systems are analogous to MoD systems, both of which rely on ride-hailing technology, underneath, the two systems differ because of the adoption of AV technology in AMoD systems. First, automation is expected to lengthen vehicle lifespan and lower maintenance requirements, leading to a reduction in operating costs [28]. The elimination of drivers can further reduce the operating cost in AMoD systems [14]. Second, vehicles in AMoD systems can be fully controlled by the fleet management center and made to comply with the management's decisions. Therefore, efficient operations related to vehicle dispatching and routing can be performed without drivers interfering [29,30].

2.5. Research limitations in the literature

To our best knowledge, the phenomena associated with the coexistence of multiple AMoD operators competing for customers are overlooked. There is no modeling framework to study this phenomenon in the current literature, and insights into how to develop effective operating strategies by AMoD operators competing for customers are lacking.

We are aware of studies that model MoD systems with multiple operators (analogous to AMoD systems) using analytical methods (as referred to above). However, the development of analytical methods in existing studies has limitations. Analytical methods do not capture the network congestion effect while multiple MoD operators provide demand-responsive services in a shared road network. Moreover, the mode choice behavior of the travelers is not considered. Therefore, the competition between MoD operators for customers is not modeled realistically. Furthermore, the impact of operating policies (fleet size, fare price, and vehicle-to-passenger assignment) on the level of service as well as demand (travelers' choice decision) in multiple-operator systems is not examined.

Agent-based modeling can overcome the shortcomings of analytical methods identified in the existing literature [31–33]. Agent-based techniques can model a system with a high level of detail (e.g., travelers' behavior), leading to a high model resolution. Moreover, agent-based modeling can realistically represent multiple interactions between multiple entities (e.g., vehicle-to-vehicle and vehicle-to-traveler interactions or the effect of operating strategies of an operator on the system performance of competing operators) with a modular design. Furthermore, it is easy to make changes to the model assumptions and specifications (e.g., operating strategies) given the flexibility of this modeling approach. Therefore agent-based modeling is well suited to our study on modeling urban AMoD systems characterized by multiple entities and multiple facets of interactions between entities.

2.6. Research contributions

Inspired by multiple MOD operators and motivated by the rapid development of AMoD solutions by self-driving car companies (e.g., Waymo, Baidu, Mercedes-Benz), an Agent-Based Model (ABM) has been developed for modeling a new multiple-operator AMoD system in which operators competes for customers. Notably, we take advantage of agent-based modeling to address the identified limitations of analytical methods. To achieve this, the developed ABM with a modular architecture consists of a demand component, a fleet service management component, and a traffic management component.

The main contributions of this paper are summarized into four main points:

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

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

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

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

3. Model rationale

The following are the main ABM assumptions:

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

3.1. Model overview

The modeling framework with three main components is presented in Fig. 1. The demand component includes a demand generator and a mode choice component. The demand generator is used to generate individual travelers with spatial and temporal attributes. The decision-making mechanism for travelers is considered by incorporating the mode choice component into the agent-based framework; the mode choice component allocates the time-dependent requests from the travelers to the different AMoD services according to the level of service attributes. Therefore, in reality, it is a service choice module since the mode is the same. Price with other choice attributes (i.e., out-of-vehicle waiting time and in-vehicle travel time) that can be measured in the simulation is incorporated into the discrete choice model in which travelers' preferences toward AMoD services are decided.

A centralized traffic management center that consists of a traffic simulation component and routing component is designed. It can determine the current state of network conditions and inform the different SAVs which route to take. These routes are computed at two moments: toward picking up a client and traveling with a client to his/her destination. The traffic management center has full knowledge of the network and traffic conditions. Therefore, we envision a system whereby the traffic operator will provide the routing information to AVs in a centralized manner independently of how many companies are providing AMoD services.

In the fleet management center, the vehicle-to-passenger assignment component is responsible for matching incoming requests of travelers with the available vehicles of an operator. The interaction between individual vehicles and individual

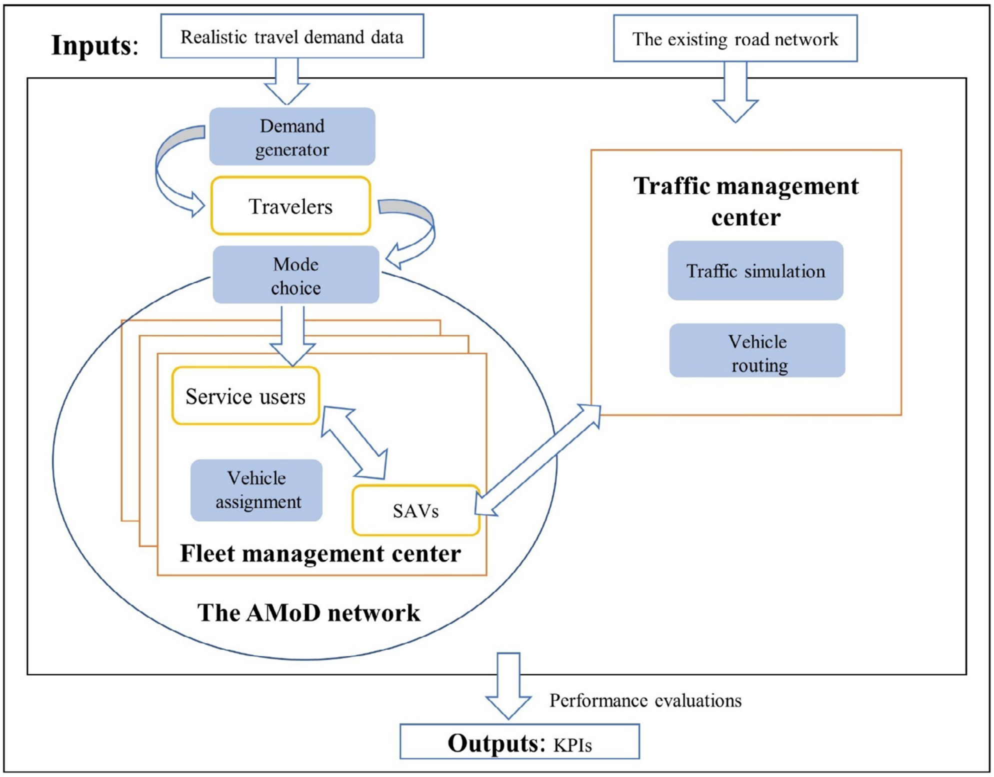


Fig. 1. The conceptual simulation framework for multiple operators.

travel requests for each operator is explicitly captured in the vehicle-to-request assignment process; thus, the model framework has the capability of evaluating the impact of SAVs which can be measured with different key performance indicators such as the empty movements to pickups clients. In the following sections, detailed descriptions of the functions of each component are given.

3.2. Mode choice component

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

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

$$V_i = V\left(w_i\right) + V\left(t_i\right) + V\left(f_i\right) \tag{1}$$

The alternative i with the highest utility will have the highest probability of being chosen by customer k relative to other travel options (the other two AMoD services in this case).

The probability of choosing alternative i for an MNL is described by the logit expression:

$$\Pr\left(i\right) = \frac{\exp\left(V_i\right)}{\sum_{i=1}^{3}(exp(V_i))} \tag{2}$$

3.2.1. Discomfort of the out-of-vehicle waiting time for a vehicle $V(w_i)$

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

$$w_a = \boldsymbol{\varphi} * \boldsymbol{m} \tag{3}$$

$$w_p = t_{max}\left(\frac{N_i - n_i}{N_i}\right) \tag{4}$$

$$\begin{aligned} V(w_i) &= -(\boldsymbol{\alpha} * VOTT_{AMoD}) * w_a - (\boldsymbol{\alpha} * VOTT_{AMoD}) * w_p \\ &= -(\boldsymbol{\alpha} * VOTT_{AMoD}) * (\boldsymbol{\varphi} * \boldsymbol{m}) - (\boldsymbol{\alpha} * VOTT_{AMoD}) * \left(\frac{N_i - n_i}{N_i}\right) * t_{max} \end{aligned} \tag{5}$$

Where,

w_a is the expected assignment time.

w_p is the expected pickup time.

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

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

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

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

N_i is the total number of vehicles of operator *i*.

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

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

3.2.2. Disutility of in-vehicle travel time $V(t_i)$

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

$$V(t_i) = -s_i * VOTT_{AMoD} \tag{6}$$

Where,

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

3.2.3. Disutility of fare $V(f_i)$

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

$$V(f_i) = -\varepsilon * \eta * (c + m * d_{ik} + n * s_{ik}) \tag{7}$$

where,

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

c is the base fare for MoD services.

m is the distance-based fare for MoD services.

n is the time-based fare for MoD services.

ε is the controlling factor of a pricing strategy.

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

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

In the second pricing strategy, the fare of a specific operator is estimated according to the vehicle availability and future demand in an area (TAZ: Traffic Analysis Zone) where travelers request AMoD services. A rule-based supply–demand balancing pricing strategy aims to encourage travelers to use AMoD services when the vehicle supply is high and discourage travelers from using AMoD services when there is a vehicle shortage. The parameter ε follows the work suggested by Chen and Kockelman [13].

$$\varepsilon = \begin{cases} 0.5, & p_{av} * p_{ad} < 0.1 \\ 1, & 0.1 < p_{av} * p_{ad} < 10 \\ 2, & 10 < p_{av} * p_{ad} \end{cases} \tag{8}$$

Where

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

p_{ad} is the proportion of the anticipated demand that will be generated in a TAZ (origin) to the anticipated demand in the entire study area. A larger p_{ad} means a high volume of requests in a TAZ, while a smaller value indicates fewer requests are made in a TAZ compared to the other TAZs. It is noted that the anticipated demand is the number of travel requests in the subsequent time interval. Individual travel requests in the subsequent time interval are not generated, but the anticipated number of travel requests is calculated.

3.3. The interaction between vehicles and travelers for each AMoD company

In AMoD systems, decisions on assigning vehicles to serve travel requests are made immediately. The behavior of travelers and vehicles is further depicted in Fig. 2. The assignment component knows the current vehicle locations and ascertains the states of all of them: upon receiving a trip request, it determines which vehicles in the fleet are able to reach the customer. Once the assignment has been done, the information on travelers' locations is sent to the assigned vehicles and the traveler is notified about the vehicle details. The assigned vehicle will transition from the idle to the in-service state when arriving at the traveler's origin location, while the state of a traveler will transition from "waiting for the vehicle arrival" to "traveling in the assigned vehicle". Once a traveler is assigned a vehicle, the AMoD service cannot be canceled. After reaching the destination location, the traveler switches to a served state. To avoid unrealistically long assignment times, travelers can remain unserved when there are no available vehicles and use a private car as referred to in model assumptions.

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

The optimal assignment algorithm is implemented to assign available vehicles to incoming travel requests. The method can assign a group of available vehicles $V = \{v_0, v_1, \ldots, v_n\}$ to bundled travel requests $R = \{r_0, r_1, \ldots, r_n\}$ to minimize the total pickup travel distance of the bundled travel requests.

For every travel request in the set R, the group of vehicles V is found by searching for the closest idle vehicles of each travel request in the set R. We construct the $n \times n$ cost matrix C where the element in the ith row and jth column represent the cost of assigning jth vehicle to the ith request. The cost c_{ij} is weighted by the Euclidean distance between the location of each vehicle j and the origin of each traveler i. The closest idle vehicles can be assigned to serve the time-dependent requests. However, cost varies depending on the vehicle-to-request assignment. The Hungarian assignment is used to assign one vehicle in V to serve a travel request in R with the objective of minimizing the total cost (total distance between vehicles and requests) [34]. It is noted that the size of bundled travel requests in R varies over time according to the demand that coincides in the same time interval Δt. The Hungarian algorithm described in Algorithm 1 is used to deal with the minimum cost assignment problem.

In addition, a simple heuristic algorithm for the request-to-vehicle assignment is also implemented in the modeling framework. In the simple heuristic algorithm, each fleet operator assigns the closest available vehicles within a search distance to serve travel requests. The real-time SAV assignment decision of fleet operators is based on the Euclidean distance. Priority is given to trips that request the service earlier.

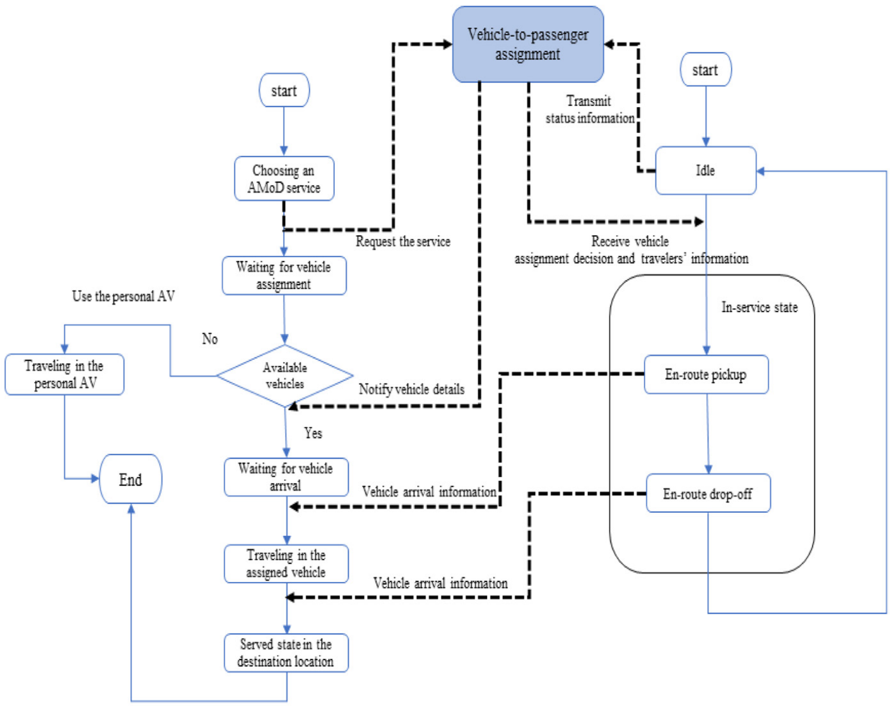


Fig. 2. The interaction between individual vehicles and individual travelers.

Algorithm 1. Pseudocode for the Hungarian vehicle-to-passenger assignment method

INPUT: travel requests of an AMoD service $R = \{r_0, r_1, \ldots, r_m\}$ at a time interval Δt

FOR each request r_i in the set R
    Search a closet idle vehicle according to the Euclidean distance within the radius;
    IF there is an idle vehicle
        add the found vehicles v_i into the available vehicle set V;
    ELSE
        remove r_i from the set R;//The request cannot be served by AMoD services;
    ENDIF
ENDFOR
IF the set V of available vehicles for the set R of travel requests is not empty
    Construct the $n \times n$ matrix of assignment cost representing assigning each vehicle in the set $V = \{v_0, v_1, \ldots, v_n\}$ to a request in the set $R = \{r_0, r_1, \ldots, r_n\}$;
    Apply the Hungarian method to the assignment cost matrix;
    Find optimal request-vehicle assignment from the resulting cost matrix;
ENDIF

OUTPUT: Request-vehicle pairs

3.4. A mesoscopic traffic simulation and route calculation

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

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

The mesoscopic traffic simulation model combines a microscopic level representation of individual vehicles (which is already present for the shared vehicles) with a macroscopic description of traffic patterns [35,36].The traffic simulation

(a) The road network of the Zuidvleugel region (b) The selected road network for the case study

Fig. 3. Road network.

model includes both a link movement and node transfer step. The rules of link movement and node transfer will govern the movement of individual vehicles operated by the different AMoD operators. Notably, individual vehicular movements experience a speed calculated by a macroscopic speed-density relationship. The speeds of the vehicles are updated based on the changed vehicle density on the road segments [10]. When the density d is less than the critical density d_c, the speed V can be calculated: $V = v_0\left(1 - \frac{d}{d_j}\right)$. v_0 is the maximum speed while respecting the urban speed limit, and d_j is the jam density. When the density d exceeds the critical density d_c, the speed is calculated: $V = \gamma\left(\frac{1}{d} - \frac{1}{d_j}\right)$. γ is a parameter that can be estimated as $\gamma = v_0 d_c$ from the requirement that $v(d)$ should be continuous at the point $d = d_c$.

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

4.1. Urban road network

The simulation model is developed in Anylogic proprietary modeling platform coded with Java programming language. Fig. 3(a) displays the road network of the Zuidvleugel region. The tailored road network and the locations of centroids of the TAZs used for the study are shown in Fig. 3(b).

Regarding the road attributes (free-flow speed, speed at capacity, and traffic capacity), the deployment of AVs has not yet occurred in a city; therefore, there is no empirical data to calibrate the traffic-related parameters for automated driving. We keep the attributes of different road types, such as urban roads, rural roads, and local roads, that come from the original transport model, naturally based on existing human-driven vehicles [10].

The TAZs are not displayed in the model environment, but their centroids are used as the points for injecting requests into the network. As depicted in Fig. 3(b), 49 nodes specified in yellow color are designed as the origins and destinations of all the travel requests. All travelers are thus picked up from those service points and dropped off at the same service point. These are also the locations where the vehicles stay idle, waiting for requests.

4.2. Demand data and fleet deployment

The total private transport demand in the region of Zuidvleugel (285 TAZs) is 270,050 trips by car in the morning peak hours (5:30 AM to 10:00 AM). 27,452 trips happen within the boundaries of the selected study area of The Hague. However, intrazonal trips are not modeled. Therefore, the generated effective requests amount to approximately 25,800.

The demand is distributed over 18 time intervals in the morning peak period, each of which has a temporal step length of 15 min, starting from 5:30 AM to 10:00 AM. The OD matrix contains 2401 non-zero pairs between 49 TAZs. Fig. 4 shows the departure time distribution. A demand generator generates individual travel requests based on aggregate travel data (available in the form of an OD Matrix) and departure time. Individual requests are characterized by origin, destination, and request time. Requests for each OD pair can be allocated among operators using a mode choice component.

Regarding fleet deployment, we denote the average number of vehicles of each operator $i \in I = \{1, 2, 3\}$ at each centroid (service point) as n_{o_i}. The average is used because the fleet is proportionally distributed as a function of the total demand of each centroid in the simulation period. We define N as the average number of vehicles deployed by all operators in each centroid (service point) of the model. Then, we have the average total number of vehicles at a service point given as $N = n_{o_1} + n_{o_2} + n_{o_3}$.

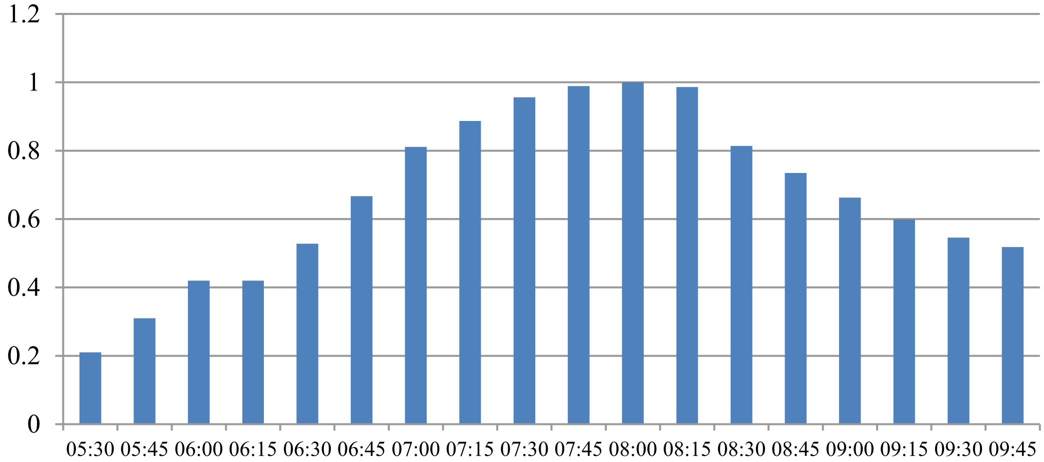


Fig. 4. The departure time distribution per 15 min of OD matrix.

4.3. Simulation parameters

Table 1 gives a summary of model parameters and case study characteristics for the base scenario. Regarding the values of parameters in the MNL, the monetary value of out-of-vehicle waiting time is larger than the monetary value of in-vehicle travel time. There is evidence that the out-of-vehicle waiting time multiplier is between 1.6 to 2.2 times the in-vehicle travel time in the Dutch context [37,38]. In this study, the multiplier $\boldsymbol{\alpha}$ is set to 2. That means the out-of-vehicle waiting time is valued twice as much as the VOTT of the AMoD mode.

The VOTT inside AMoD is still uncertain, given the lack of experience with these vehicles. The VOTT in AMoD vehicles is estimated based on VOTT in private cars and on the transit mode (bus, tram, and metro). In the Netherlands, the VOTT on private cars mode and transit mode is valued at about 9.25 euros per hour and 7.75 euros per hour, respectively, for commuting purposes [39]. Travelers in AVs can perform productive and leisure activities without having to drive in private cars or having to stand in transit mode. VOTT in AMoD vehicles is supposed to be lower than in a private car mode and transit mode for that fact. The value of IVTT in AMoD vehicles is valued at about a 35% reduction of the VOTT in private cars [40,41]. In this study, VOTT in AMoD vehicles is valued at 6.01 euros per hour.

We are using the UberX fare structure that is active in the Netherlands. We consider a baseline pricing scenario, 60% of the existing MoD. Then, we have $\eta = 0.6$ $c = 1.4$ euros, $m = 1.2$ euros per km, $n = 0.26$ euros per min in Eq. (7).

Regarding the valuation of the controlling factor ε that is used in pricing strategies, we have $\varepsilon = 1.0$ in the baseline scenarios and $\varepsilon = 0.8$ when a 20% discount is tested. In the scenario where the supply–demand balancing pricing strategy is applied, the value of ε is given through a step function in Eq. (8).

In relation to the vehicle type used in this study, carmakers (Renault UK, Toyota) are producing and marketing small driving pods. The small vehicles can take up less road and parking space. Moreover, small-sized vehicles can save more energy with reduced weight [10]. Hence, we assume that purposely designed small SAVs are suitable for urban mobility applications, and could be available and affordable for future large-scale deployment.

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

5. Results and discussion

We aim at generating insights into the competition between AMoD operators. The fleet sizes, pricing strategies, and assignment strategies are factors that influence the level of service offered by competing AMoD operators. The mode chosen by travelers is determined based on the levels of service which in turn affects the levels of service through the usage of the system. Therefore, we examine how operating strategies affect the demand as well as the operating performance.

Table 1
A Summary of the model parameters for the base scenario.

Parameter/characteristics	Value
Road segments	836
Road nodes	510
Total travel requests (Z)	25,800 trips
Service points (centroids)(denoted by s)	49
Fleet operators I	{operator 1, operator 2, operator 3}
Vehicle assignment Time interval Δt	20 s
The search distance for vehicle assignment	6000 m
The VOTT inside AMoD vehicles	6.01 euros per hour
The multiplier $\boldsymbol{\alpha}$	2
The controlling factor ε used in pricing strategies in the baseline scenario	1
The controlling factor ε used in pricing strategies in the discount pricing scenario	0.8
η is the saving factor for AMoD services	0.6
c is the base fare for MoD services.	1.4 euros
m is the distance-based fare for MoD services.	1.2 euros per km
n is the time-based fare for MoD services.	0.26 euros per min
Vehicle seat capacity	1 person (no pooling)
The number of vehicles per centroid at the beginning of the simulation (N)	60 vehicles (20 vehicles for each operator)
VOTT in AMoD vehicles	6.01 euros per hour
Vehicles increment of operator 1 per service point Δg for sensitivity analysis	10 vehicles (e.g., $2 * \Delta g = 20$ vehicles)

Table 2
Operating performance for different assignment strategies.

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

5.1. Analysis of the competition scenarios: effect of assignment strategies on operating performance

Two different methods of assigning vehicles to passengers (a simple heuristic algorithm and an optimal assignment algorithm, as described in Section 3.4) are implemented and compared for the base scenario. As shown in Table 2, compared to the simple heuristic algorithm, the optimal assignment algorithm can reduce the average waiting time by up to 2 min, which is a 24% reduction in the average waiting time of the overall AMoD system. The main reason is that the optimal assignment method can optimally match bundled requests with available vehicles to minimize the total pickup distance for bundled requests. Simulation results show that the optimal assignment algorithm generates fewer empty vehicle kilometers traveled (VKT), resulting in a significant reduction of 5511 km for the morning hours than the scenarios using the simple heuristic algorithm.

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

5.2. Analysis of the competition scenarios: effect of fleet size

The simulation results in Table 3 show that travel requests shift drastically from operators o_2 and o_3 to operator o_1 when the number of vehicles of operator o_1 increases compared to the base scenario of equal fleet size among operators.

Table 3
Demand for different vehicle increments.

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

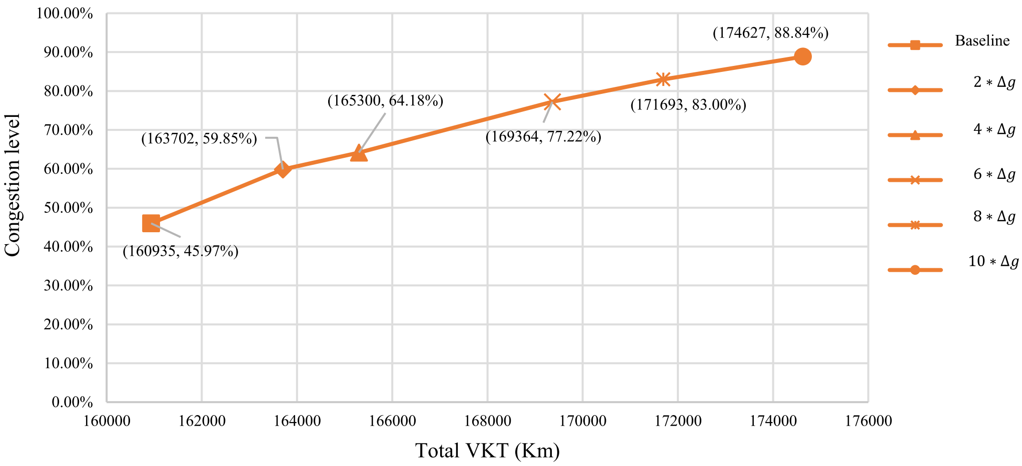


Fig. 5. The relationship between total VKT and congestion levels.

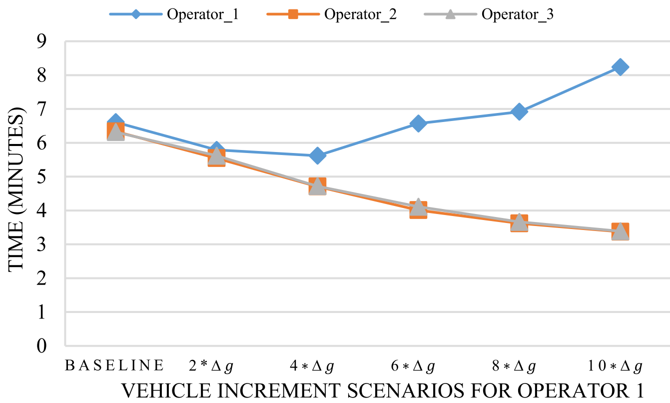
The increases are done as referred in Table 1 with a value of Δg of 10 vehicles. More demand chooses the operator o_1 in response to the added vehicle availability. It is suggested that demand for an operator can be significantly affected by the fleet size of competing operators. This is because a large fleet size increases the number of potentially available vehicles, which is a competitive factor in evaluating service levels and assigning vehicles to incoming travel requests.

Moreover, simulation results in Table 3 show that the total demand served by the urban multiple-operator systems rises as the fleet size of operator o_1 increases. This is due to the assumption that the urban private car demand is very high, and travelers can remain unserved when there are no available vehicles. A large fleet of operator 1 can increase the overall number of available vehicles; thus, more demand (attracted from competitors and not served without available vehicles) is served.

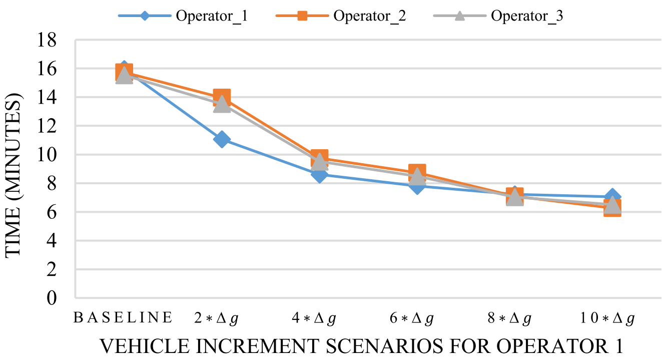
When the total demand increases, more VKT will be needed to serve increased demand, resulting in a more congested road network. We introduce the indicator of congestion level to evaluate the road traffic conditions. In the baseline scenario, a 45.97% congestion level represents the additional 45.97% time required on average to travel from origin to destination compared to the uncongested travel time. Fig. 5 illustrates the established relationship between the total VKT and congestion levels. We find that the total VKT in AMoD with multiple operators is growing as the fleet of operator o_1 increases. Meanwhile, the congestion level is increasing with the rise in the total VKT. Compared to the baseline scenario, 17% more served demand (see Table 3) for the entire multiple-operator AMoD system leads to an 8.51% VKT increase, reaching 174 626 km in the $10 * \Delta g$ scenario, and the congestion level soars from 45.97% to 88.84% (Fig. 5).

The analysis of the waiting times is performed; we use the average waiting times, the 90% quantile of the distribution of the waiting times and the 96% quantile of the distribution of the waiting times (Fig. 6). Take the 90% quantile of the waiting times as an example: we are finding a waiting time where 90% of the trips are lower than that.

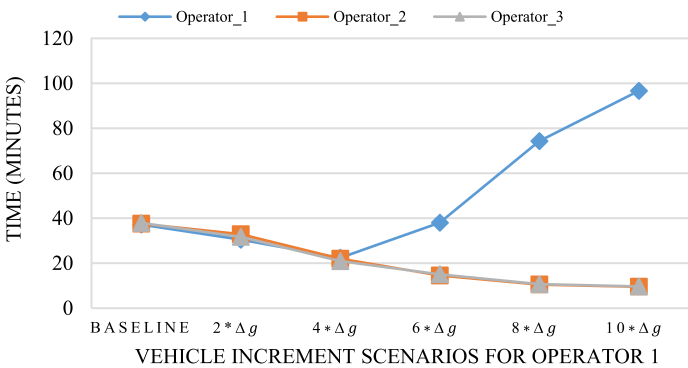
Given the demand results (requests for the service of an operator) (in Table 3), more demand shifts to the operator o_1 when its number of vehicles increases, while the demand for the service of the other operators (operator o_2 and operator



(a) Average waiting times for different scenarios



(b) 90 % quantile waiting times for different scenarios



(c) 96 % quantile waiting times for different scenarios

Fig. 6. Waiting time analysis.

o_3) is reduced. Therefore, from the simulation results in Fig. 6(a), we can see that the average waiting times for travelers choosing the service offered by operator o_2 and operator o_3 fall as the demand shifts to operator o_1.

A large fleet size leads to low waiting times. The average waiting times of operator o_1 decline with the increase in its number of vehicles; however, there is an increasing trend in average waiting times of all served requests when the vehicle increment is higher than $6 * \Delta g$ (60 vehicles per pickup point). Generally speaking, a larger fleet size could reduce the average waiting times in scenarios where AMoD systems replace conventional bus services in a regional area or provide feeder (first-mile or last-mile) services to complement public transit services. However, in a high-demand urban area, a large fleet size may increase the average waiting time, according to our results. This is because the added demand of

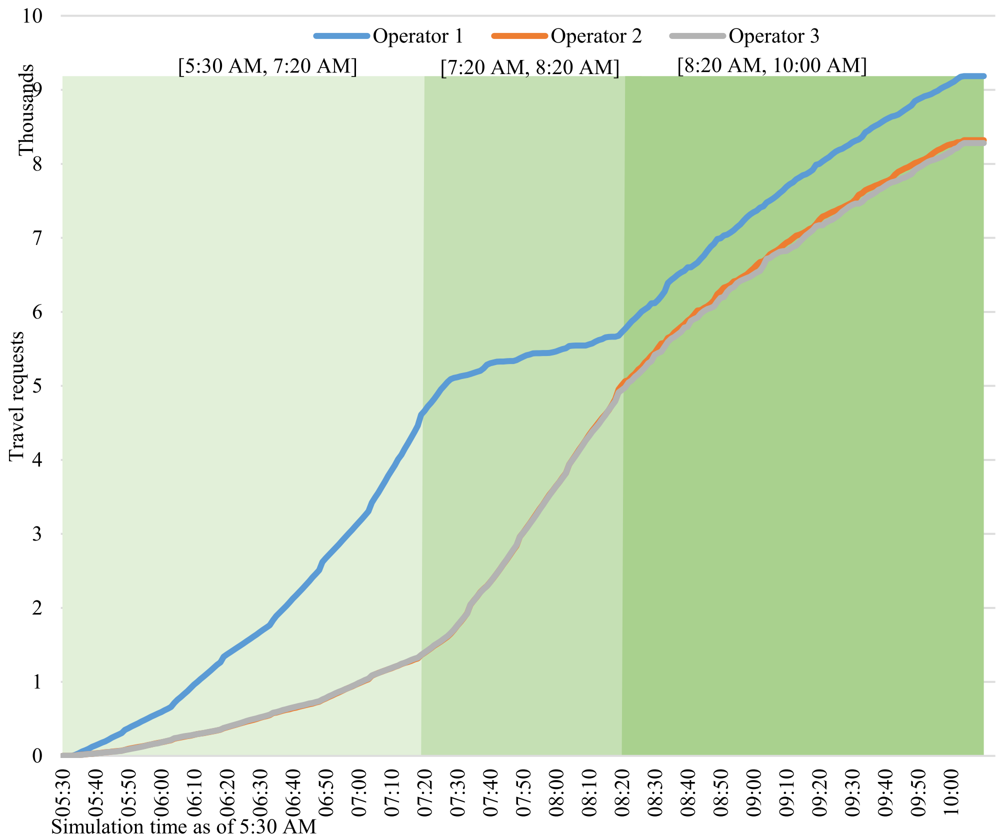


Fig. 7. Demand share for different AMoD operators for discount pricing.

operator 1 is not just brought from the other operators but also from the demand that was not being served before. We found that more VKT are needed to serve the increased demand, resulting in a more congested road network. When traffic moves at lower speeds on a congested urban road network, travel and waiting times of served travelers increase. We found that some served requests experienced long waiting times as measured by an extreme value of 96% quantile waiting time in the waiting time distribution. Simulation results in Fig. 7(b) show that the 90% quantile of the waiting times of operator o_1 decline and then level off as the vehicle fleet increases, while the 90% quantile of the waiting times of operators o_2 and o_3 have a declining trend. Simulation results suggest that a few served travelers have long waiting times with a larger fleet size (i.e., in the vehicle increment scenarios of $10 * \Delta g$) compared to operator 2 and operator 3. Simulation results in Fig. 6(c) show that the 96% quantile of the waiting times of operator o_1 declines and then rises significantly in the scenarios with vehicle increments on the fleet. Surprisingly, the 96% quantile of the waiting times are found from simulation results at the level of 38.01 min, 74.30 min, and 96.65 min for the vehicle increment scenarios of $6 * \Delta g$, $8 * \Delta g$, and $10 * \Delta g$. Therefore, the larger fleet can serve more travel requests, but this leads to extremely long waiting times for just a few travelers.

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

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

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

Table 4
Operating performance for the discount pricing strategy.

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

5.3. Effect of pricing strategies on service uptake and operating performance

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

5.3.1. Discount pricing strategy

We study the effect of the discount pricing strategy on attracting customers in the morning hours. A closer look at the chart in Fig. 8 shows that the volume of requests for the different AMoD operators changes at different rates over time.

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

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

In the mid-morning period [8:20 AM, 10:00 AM], the same increasing rate of users is observed for all three operators, two of which are offering a regular-price service. Simulation results in Fig. 7 indicate that the number of users increases similarly for all operators, by about 3300. This suggests that the discount pricing strategy has no advantage in attracting more demand at this time of day, ceteris paribus. For the same time, simulation results in Fig. 8 indicate that the total number of vehicles driving on the network is at the highest level, which could lead to bad traffic conditions.

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

Regarding the service levels in terms of waiting time and travel times, the operator that offers the discount can provide a service with shorter waiting and travel times than the regular-price services of the other operators. The simulation results in Table 4 show that the average waiting and travel times of operator o_2 and operator o_3 are more than double those of operator o_1. The 96% quantile waiting time of operator o_1 is located around 7.06 min, while operator o_2 and operator o_3 have a larger 96% quantile waiting time of about 11 min. The 96% quantile travel times of operator o_2 and operator o_3 are significantly larger than that of operator o_1. The reason for this is that up to 64.7% of the travel requests served by operator o_1 are in the very early morning [5:30 AM,7:20 AM] when fewer vehicles are driving on the network, as shown in Fig. 8. We also see that the number of in-service vehicles from operator o_2 and operator o_3 is much higher than that of operator o_1 in the early morning [7:20 AM, 8:20 AM] and mid-morning hours [8:20 AM, 10:00 AM]. This indicates that the users of the services of operators o_2 and o_3 are transported at a time when the number of vehicles on the road is the highest. This leads to increased waiting and travel times of operator o_2 and operator o_3.

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

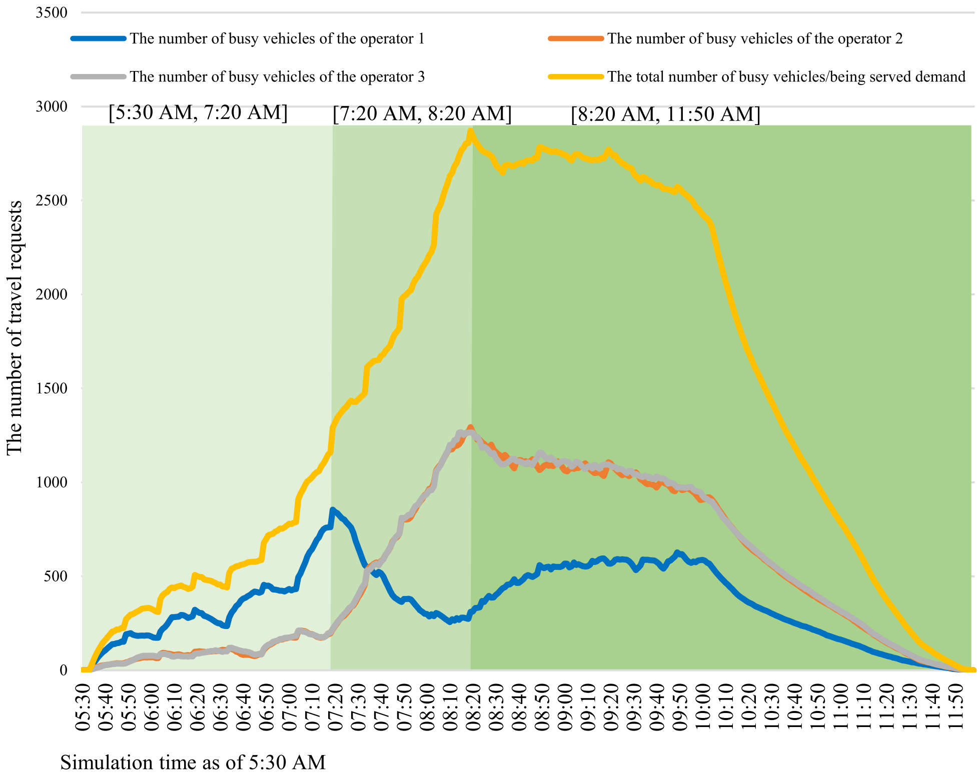


Fig. 8. The number of busy vehicles circulating across the road network for discount pricing.

Therefore, careful consideration is required when planning to apply flexible discount pricing strategies under certain demand scenarios.

5.3.2. Supply–demand balancing pricing strategy

Regarding the simulation scenario related to the supply–demand balancing pricing strategy, the simulation results in Fig. 9 suggest different demand shares in AMoD services offered by the different operators, where one of them (operator o_1) applies the supply–demand balancing pricing strategy. Results show that the number of requests for the service provided by operator o_1 levels off in two periods, namely, [7:00 AM, 7:20 AM] and [7:35 AM, 7:50 AM]. The supply–demand balancing pricing strategy can raise the price according to the relationship established between anticipated demand and available vehicles. In this situation, competing AMoD services become viable travel options. Instead of choosing the high-priced service, customers use the regular-priced service. Simulation results indicate that the number of travelers who use the services of another operator (o_2, o_3), instead of the service provided by operator o_1, increases rapidly. As shown in Fig. 10, the number of in-service vehicles of operator o_1 falls rapidly, while the number of the other operators' vehicles engaged in transporting customers increases.

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

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

We can also analyze the waiting times, the travel times, and the empty pickup VKT (in Table 5) to evaluate the impact of the supply–demand balancing strategy on service quality.

The simulation results in Table 5 show that the supply–demand balancing pricing strategy leads to a reduction in the total number of served requests for the service provided by operator o_1. This is plausible because travelers opt for

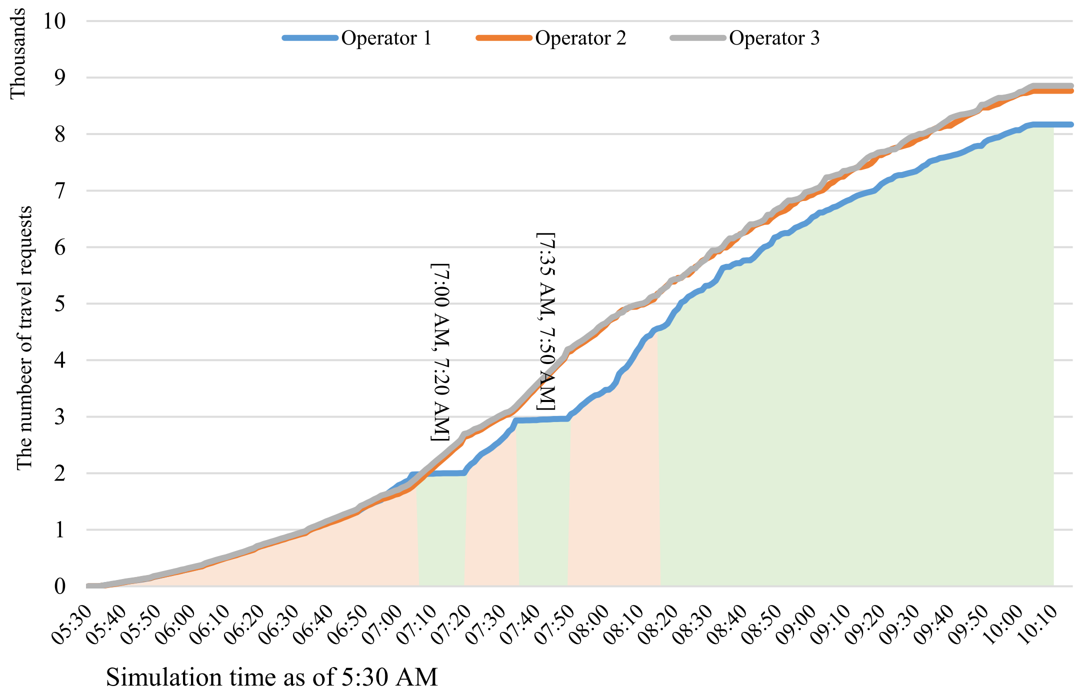


Fig. 9. The number of travel requests for different AMoD operators for supply–demand balancing pricing.

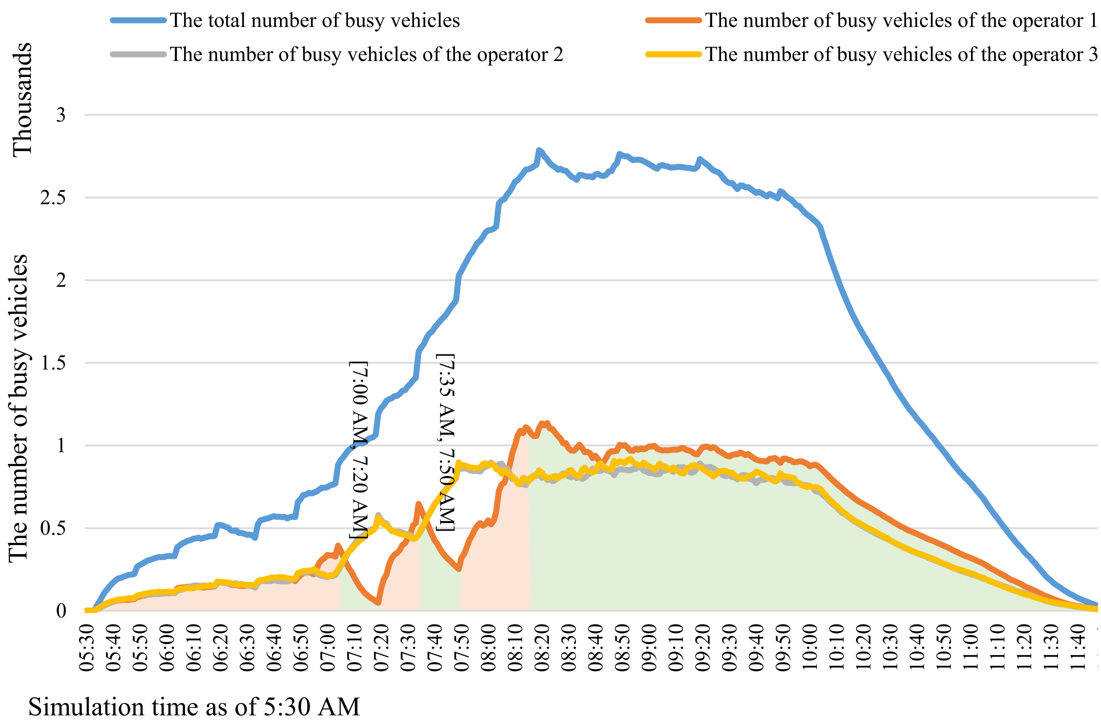


Fig. 10. The number of busy vehicles across the road network for supply–demand balancing pricing.

the alternative service with the regular price in the morning [7:00 AM, 7:50 AM] (as shown in Fig. 9) rather than the high-priced service prompted by the supply–demand balancing strategy.

Table 5
Operating performance for the supply–demand balancing pricing strategy.

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

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

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

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

6. General discussion and recommendations

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

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

Regarding fleet size, interesting findings are that a larger fleet size can attract more demand to choose an operator's service in the scenario of multiple AMoD operators competing for customers; however, an operator's fleet size growth leads to more congestion over the road network. As a result, the service levels are degraded in terms of waiting and travel times. It means that in the multiple-operator system, the travelers faced long waiting and travel times. Because of the convenience and low price of the AMoD services, travelers (commuters) are most likely to choose the AMoD service provided by different operators. Similar to the evidence that the entrance of multiple transportation network companies into the existing urban mobility system can increase congestion [42], our results suggest that the entry of multiple AMoD operators without regulating fleet sizes can cause worse travel conditions. In this regard, future cities may experience severe congestion externalities (e.g., emissions and traffic accidents). The city authorities need, therefore, to develop regulations to avoid the negative impact of an unregulated market.

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

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

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

7. Conclusions and future directions

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

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

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

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

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

CRediT authorship contribution statement

Senlei Wang: Conceptualization, Methodology, Software, Validation, Data curation, Formal analysis, Writing – original draft, Visualization, Investigation, Project administration. **Gonçalo Homem de Almeida Correia:** Supervision, Writing – review & editing. **Hai Xiang Lin:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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