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From Traditional to Automated Mobility on Demand: A Comprehensive Framework for Modeling On-Demand Services in SimMobility

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Abstract

Mobility on demand (MoD) systems have recently emerged as a promising paradigm for sustainable personal urban mobility in cities. In the context of multi-agent simulation technology, the state-of-the-art lacks a platform that captures the dynamics between decentralized driver decision-making and the centralized coordinated decision-making. This work aims to fill this gap by introducing a comprehensive framework that models various facets of MoD, namely heterogeneous MoD driver decision-making and coordinated fleet management within SimMobility, an agent- and activity-based demand model integrated with a dynamic multi-modal network assignment model. To facilitate such a study, we propose an event-based modeling framework. Behavioral models were estimated to characterize the decision-making of drivers using a GPS dataset from a major MoD fleet operator in Singapore. The proposed framework was designed to accommodate behaviors of multiple on-demand services such as traditional MoD, Lyft-like services, and automated MoD (AMoD) services which interact with traffic simulators and a multi-modal transportation network. We demonstrate the benefits of the proposed framework through a large-scale case study in Singapore comparing the fully decentralized traditional MoD with the future AMoD services in a realistic simulation setting. We found that AMoD results in a more efficient service even with increased demand. Parking strategies and fleet sizes will also have an effect on user satisfaction and network performance.

A majority of past research efforts have been devoted to modeling and optimizing mobility on demand (MoD) fleet operations (*1*). Much less attention has been paid to the decentralized nature of the MoD decision-making process (*2*), which arises from the dependency of current MoD systems on drivers and their decision power. In the context of multi-agent simulation technology, although some facets of centralized MoD operations—such as street pickups, queueing, routing, and fleet dispatch—have been modeled, there is no platform that captures the dynamics between decentralized driver decision-making and centralized decision-making. Such a decentralized perspective is critical in modeling MoD systems and the potential impacts of automation, as drivers can only be informed, incentivized, or coordinated but not centrally controlled (*3*).

This work aims to fill this gap by introducing a comprehensive framework that models various facets of MoD driver behavior along with a decentralized fleet management system within an agent-based demand-supply simulator, SimMobility Mid-Term. The SimMobility Mid-Term (MT) simulator is an agent- and activity-based demand model integrated with a dynamic multi-modal network assignment model (*4*). The traffic dynamics are simulated using a multi-modal mesoscopic

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simulator (supply simulator). MT is part of a much larger simulation platform that also contains long-term and short-term models. Simulating MoD services is extremely challenging because of complex interactions between independent drivers, the central controller, and travelers' decision processes. To facilitate the study of such a complex and partially decentralized system, we propose an event-based modeling framework. In this framework, the drivers, the controllers, and the travelers are represented as separate decision agents making plans and event-triggered actions. Behavioral models were estimated to characterize the decision-making of drivers using a GPS dataset from a major MoD fleet operator in Singapore in 2013, containing position and service status data over 30 days. A unified framework was developed to model the operation of both traditional MoD fleets and emerging ride-hailing services such as Uber and Lyft-like services. The specific behaviors of MoD service drivers are modeled within a discrete-choice framework. Specifically, the following models are proposed: i) Break; ii) Cruise/Not to Cruise; iii) Stand Choice (choice among the available MoD stands); iv) Zone Choice during cruising Model; and v) Route Choice. The suggested models can reflect strategic decisions made by the driver.

While traditional MoD actions are made by the driver, some MoD services can coordinate some of the processes above. Ultimately, automated MoD (AMoD) services could fully control and optimize all decision-making processes. The AMoD controller would for example process travelers' service requests and assign them to a given vehicle after considering its current occupancy (and potential route), whether the passenger is willing to share the ride or not, time to reach the pickup location, and the travel time to final destination. Thus, an MoD controller agent in simulation should capture MoD service status, updated vehicle locations, and then monitor vehicle movements through the network, reacting to incoming requests and changes on the network and in fleet performance accordingly. A framework to handle MoD controllers in SimMobility was presented in (*4*) and integrated within the calibrated SimMobility model of Singapore (for details on the estimation, implementation and validation of the Singapore model, the reader is referred to (*4*)). In this paper, we have extended the MoD controller framework with several features for service driver behavior modeling and simulation, and demonstrate it through a case study in Singapore, where different MoD services are been modeled. Specifically, traditional MoD is simulated and compared with AMoD. The current work has five major contributions: 1) development of a comprehensive event-based framework that addresses complex behaviors and interactions of service drivers, MoD centralized operation, and travelers; 2) incorporation of the proposed framework within a highly realistic agent-based simulation platform, SimMobility; 3) evaluation of the suggested framework against real-world data; 4) demonstration of the proposed framework through a case study of Singapore; and 5) showcasing of the use of the proposed framework in the evaluation of potential mechanisms and policies when deploying MoD services.

The rest of the paper is structured as follows. The next section provides a literature review on recent MoD and MoD services modeling and simulation. We then introduce the MoD framework, including the behavioral models and the MoD controller. This is followed by a case study demonstrating the use of the MoD framework for modeling traditional MoD vs AMoD services in Singapore. Finally, we present the main conclusions and findings of this work.

Literature Review

Many past research efforts have been devoted to the modeling of MoD fleet operations. Using the current extensive review of MoD service modeling and simulation literature (*1*), we discuss the latest studies, focusing on three streams: 1) large-scale simulations of MoD services; 2) theoretical and mathematical models to describe different MoD services aspects; and 3) data driven studies of MoD behavior.

Within the context of the large-scale simulation of MoD services, a majority of past research has used microscopic simulation. (*5*) used MATSim for the modeling of MoD services in Barcelona and Berlin and focused on assessing the performance of two MoD dispatching strategies in balancing supply and demand. The first strategy always serves waiting requests by dispatching the nearest idle MoD, but this method has poor performance under high demand. The second strategy is a balancing strategy that minimizes pickup trip times instead of serving requests in the first in first out (FIFO) order. However, neither strategy simulated real MoD behavior. (*6*) also used MATSim to simulate the interaction between newly introduced autonomous vehicle MoD services with the existing means of transport. They used a simplified version of a greedy controller in a MATSim scenario of the city of Sioux Falls, South Dakota, U.S.A. Neither effort using MATSim modeled the behavior of the MoD driver but used random choices. (*7*) studied booking strategies for an MoD dispatching system. The study identifies two types of booking: Current Booking (CBK), where the customers make a booking call for an MoD to arrive as soon as possible; and Advance Booking (ABK), where customers indicate a pickup time which is at least in half an hour later. In the simulation model, the central region of Singapore was chosen as the study area. The results of the study show that advanced booking benefits small MoD operators with comparatively low booking demand but is ineffective for larger MoD operators with high booking demands. (*2*) used MoDSim to model MoD behavior at the macro-level. MoDSim is designed to be a decentralized discrete event simulation; it models MoD drivers' cruising/roaming behavior while treating the traffic condition in the network as exogenous. Singapore was used as the study area. (*8*) developed a mathematical model for real-time high-capacity ride-sharing. The model was experimentally validated with New York City MoD data, and results showed that 98% of MoD rides currently served by over 13,000 MoD drivers could be served with just 3,000 MoD vehicles via automation and sharing.

The second stream of research focuses on small scale optimization problems and empirical models used to describe the different aspects of MoD services. (*9*) studied the MoD dispatching system in Singapore and proposed a method where the MoD assigned a booking job to the one with the shortest time path, reaching the customer in the shortest time determined by real-time traffic conditions. The microscopic simulation was performed in a small toy network. (*1*) proposed and tested an agent-based simulation model focused on a shared MoD service. The proposed system optimizes fares and travel time savings for passengers. The simulation did not include a dynamic traffic model or a dynamic demand model. (*10*) focused on e-hailing, proposing a spatial equilibrium model to balance supply and demand of MoD services.

(*11*) explored the market demand potential of a shared-ride MoD. They presented an integrated choice and latent variable modeling framework for modeling the number of times per week a shared-ride MoD would be used if it were implemented at the American University of Beirut campus. A series of studies by Wong et al. (see, for example, (*12*)) extensively details the customer-searching behavior of MoD drivers over different periods of time. (*13*) explored methods of optimizing MoD personalized services. However, this simulation ignores actual traffic conditions on the network.

The third stream of research consists of data driven studies that were used to draw insight into the behavior of MoD drivers. (*14*) used a stated preference survey of 400 MoD drivers conducted in 2000 in Hong Kong to estimate a multinomial logit choice model for MoD customer-searching behavior and discovered that the journey time, toll, and waiting time were found to be significant factors in the choices drivers made at the 1% level. (*15*) used the complete trace information from 3,590 MoD drivers in Beijing to understand passenger denial behavior of MoD drivers. (*16*) focused on the willingness of MoD drivers to drive to the airport empty and used AVL data from 8,954 MoD drivers during a period of five weekdays in Shanghai. Their analysis revealed that airport-serving MoD drivers earn significantly less in most time periods during the day, but vacant MoD drivers are still more likely to serve the airport if they have relatively higher profits in airport-originated trips. (*17*) investigated the factors contributing to single-trip MoD efficiency. By evaluating MoD performance using GPS data from 2,000 MoD drivers in Wuhan in 2013, they found that high-performing, efficient drivers operate further away from downtown areas and navigate through the whole city, changing locations consistently to obtain the best traffic conditions.

Methodologies used so far in the literature focused mainly on MoD dispatching algorithms with very limited large-scale applications. Others used a real-world data to understand a specific MoD driver behavior, but none of them tried to capture the full set of behavior of the MoD driver, or combine all the pieces into one comprehensive framework that could address the complex behaviors and interactions of MoD drivers, fleet controllers, travelers, congestion, and other modes. In this study we intend to fill this gap by developing a comprehensive tool to predict and evaluate the impact of the transformation of on-demand services using SimMobility simulator.

Methodology and Framework

Overview of SimMobility Mid-Term Simulator

SimMobility (MT) simulator is an agent-based, fully econometric, and activity-based demand model integrated with a dynamic traffic assignment model (*3, 4*). It is capable of simulating daily travel at the individual level. The traffic dynamics are simulated using a mesoscopic simulator. Figure 1 presents the modeling framework structure of the MT simulator in SimMobility. In this specific study, at the pre-day level (agent planning stage), different MoD services are introduced, such as traditional MoD, Uber, and Lyft-like services and, possibly, AMoD services alongside with traditional modes (car, etc.) to allow the synthetic population of agents to choose from all modes of interest for the trips associated with all planned activities. These modes are included in the combined mode-destination choice models as part of an agent's choice set. The outcome of pre-day models is the daily activity schedule (DAS) which is an input to the within-day and supply simulators. At the within-day and supply level, the DASs of all individuals are simulated, that is, agents' plans become actions, and it is where the MoD driver behavior framework was implemented. The MoD driver behavior framework is the key innovation of this work and will be discussed in detail in the next section. Uber and Lyft-like services, and AMoD services are handled by the MoD controller, which is an external entity to SimMobility (presented in detail below).

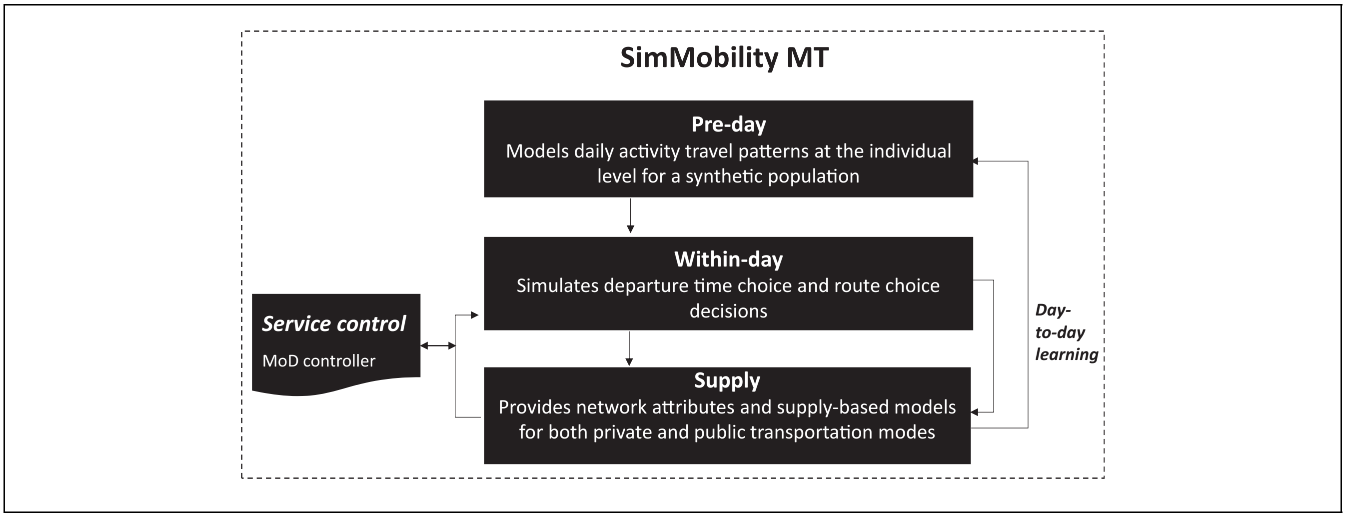

Figure 1. SimMobility MidTerm (MT) structure.

Flexible Mobility On-Demand Framework

To facilitate the study of complex interactions between independent drivers, the central controller, and travelers' decisions, we propose an event-based modeling framework. Here, drivers, controllers, and travelers are represented as separate decision agents with decision-making triggered by specific events. In the next sections we will describe each of these three agents in our proposed framework, their decision-making dimensions and their trigger events. It is worth noting that for the service drivers, the richest set of decision dimensions is that of the traditional MoD driver, that is, the (almost independent) taxi driver. Therefore, we will first describe this set of decisions which will later be modified and extended to accommodate other MoD driver behavior, such as ride-hailing and shared services.

Traveler Agent

As part of the DAS generated by pre-day, an agent has an MoD mode assigned, as well as start and end times of activity and exact location. When the time of simulation reached its MoD journey starting time, the agent will either: 1) start searching for an MoD driver on the street, either by hailing or by walking to the closest MoD stand; or 2) request an MoD and wait for pickup. Her request is added to a FIFO array of potential clients for an MoD at that link and waits for the MoD acceptance. As for the Uber, and Lyft-like traveler, its meeting point with the driver will be at her home or activity location. The Uber, and Lyft-like traveler cannot be picked up at the MoD stand.

Mobility On-Demand Driver Agent

The traditional MoD drivers are modeled as agents with their own preferences. They can choose their next move and their next client. Their interactions with the travelers are a result of driver choice. For the traditional MoD driver, we embed in the drivers the knowledge of the historical space and time distribution of the clients, based on historical demand data. The information is then used by MoD drivers to choose the most adequate MoD stands at which to stop at different hours of the day and to choose the most attractive routes for finding clients in the street.

State Vector of the MoD Driver. An MoD driver is at any moment in one state of the state vector. To allow for different MoD services, the proposed state vector is composed of the following Boolean variables:

Booked (B)	An MoD driver is on its way to pick up a customer. The MoD vehicle is booked after it interacts with the controller.
Occupied (O)	A client is in the MoD vehicle, and the MoD driver is heading toward the client's destination.
Queueing (Q)	The MoD driver is in a queue at an MoD stand to pick up a client.
Cruising (C)	An MoD driver is searching the streets to find the next client. More generally, it represents a vehicle ready to take a passenger.
Direct-to-destination (D)	The variable describes a state in which the MoD driver goes directly to a specific destination. She will not make intermediate stops or pickups until she reaches the destination.
Break (K)	The MoD driver is on a break; the driver will be temporarily unavailable to accept any kind of request.

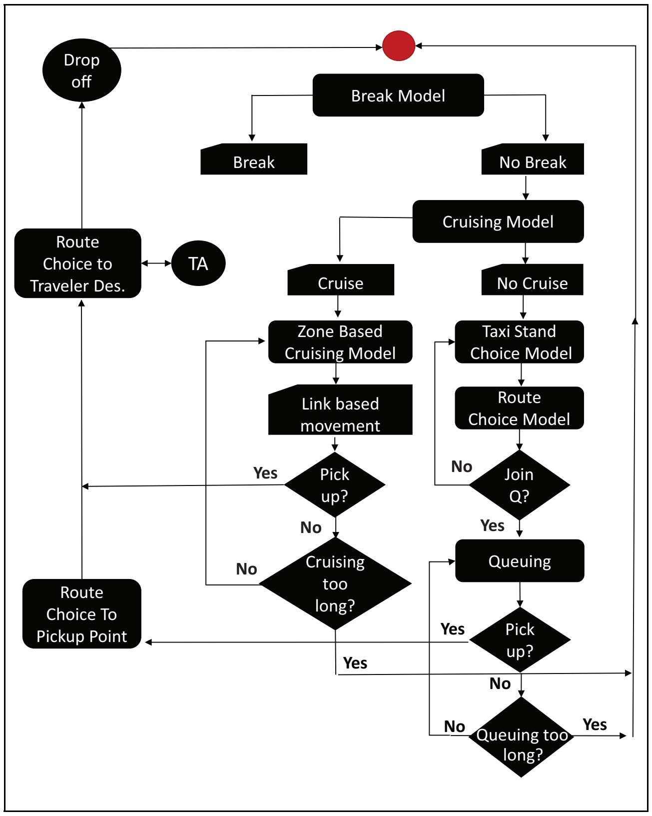

Figure 2. Traditional MoD driver behavior framework.

Events Influencing the MoD Driver Agent. The designed framework is event driven and there are seven major event types that influence the MoD driver agent as follows:

Pickup event: This event occurs when the MoD driver picks up a traveler. The pickup can happen on-road or at any stopping bay; we treat different bays as an MoD stand.

Drop-off event: This event occurs when the MoD reaches the destination of the traveler. After this event, the MoD driver re-evaluates her strategy.

Join queue event: This event occurs when the MoD driver reaches the MoD stand. The MoD driver can join the queue at the stand only if the number of drivers already queueing at the stand is below capacity.

Controller request event: This event describes the messages the controller sends to the MoD driver regarding the pickup request. This event can occur at any time.

Cruising for too long event: This event is triggered when the MoD driver has been cruising unsuccessfully for too long. Afterward, the MoD driver will choose "do not cruise."

Queueing for too long event: This event is triggered when the MoD driver has been queueing unsuccessfully for too long at an MoD stand. After this event, the MoD driver re-evaluates her strategy.

Figure 2 describes the traditional MoD driver behavior framework, showing the decision models and choices. The simulation starts by loading the agents at their home location as defined in the synthetic population. The MoD driver's initial decision will be to work or to take a break; if the driver decides to take a break, her state will change to break activity whose duration is predetermined. Location and time information will be kept in the simulation.

If the MoD driver chooses to cruise, she will search the streets to find a client. She can do so by moving toward a predetermined zone, then the zone-based cruising model will be activated first and the route choice model will be activated second. After reaching the desired zone, the MoD driver will cruise randomly from link to link with no specific target. The MoD will choose the desirable zone according to the historical demand. If a client is found, the MoD driver will pick her up; the route choice model will be activated, and the MoD will move toward the client destination. If the MoD driver is cruising for too long, she will change her state to "do not cruise," else, she will go to her initial decision of whether to take a break.

In the case of a coordinated ride-hailing driver behavior framework, a majority of the decisions are taken out so that the driver cannot: 1) choose whether to cruise or not to cruise; 2) choose to go to an MoD stand, queue, and pick up a passenger there; 3) choose to pick up passengers on the street; or 4) choose her next zone to in which to cruise. On the interaction between the driver and the MoD controller see Section 3.5. Note that travelers' choices are not modeled in detail and will be incorporated in future research.

MoD Controller: The Case of Automated MoD

The model of automated MoD (AMoD) builds upon our previous work (*18*), extended to handle new capabilities, for instance, parking, handling single or shareable ride requests, and so forth. An AMoD service consists of a fleet of *vehicles* and a *controller*. The interactions between the user, the controller and the vehicles are depicted in Figure 3. Users send *trip requests* to the controller, which assigns them to vehicles in the form of *schedules*. The controller computes and continuously updates a schedule for each vehicle, which dictates the sequence of operations, that is, pickup, drop-off, and so forth, that the vehicle will perform. It is worth emphasizing the main difference between MoD and AMoD services: the former

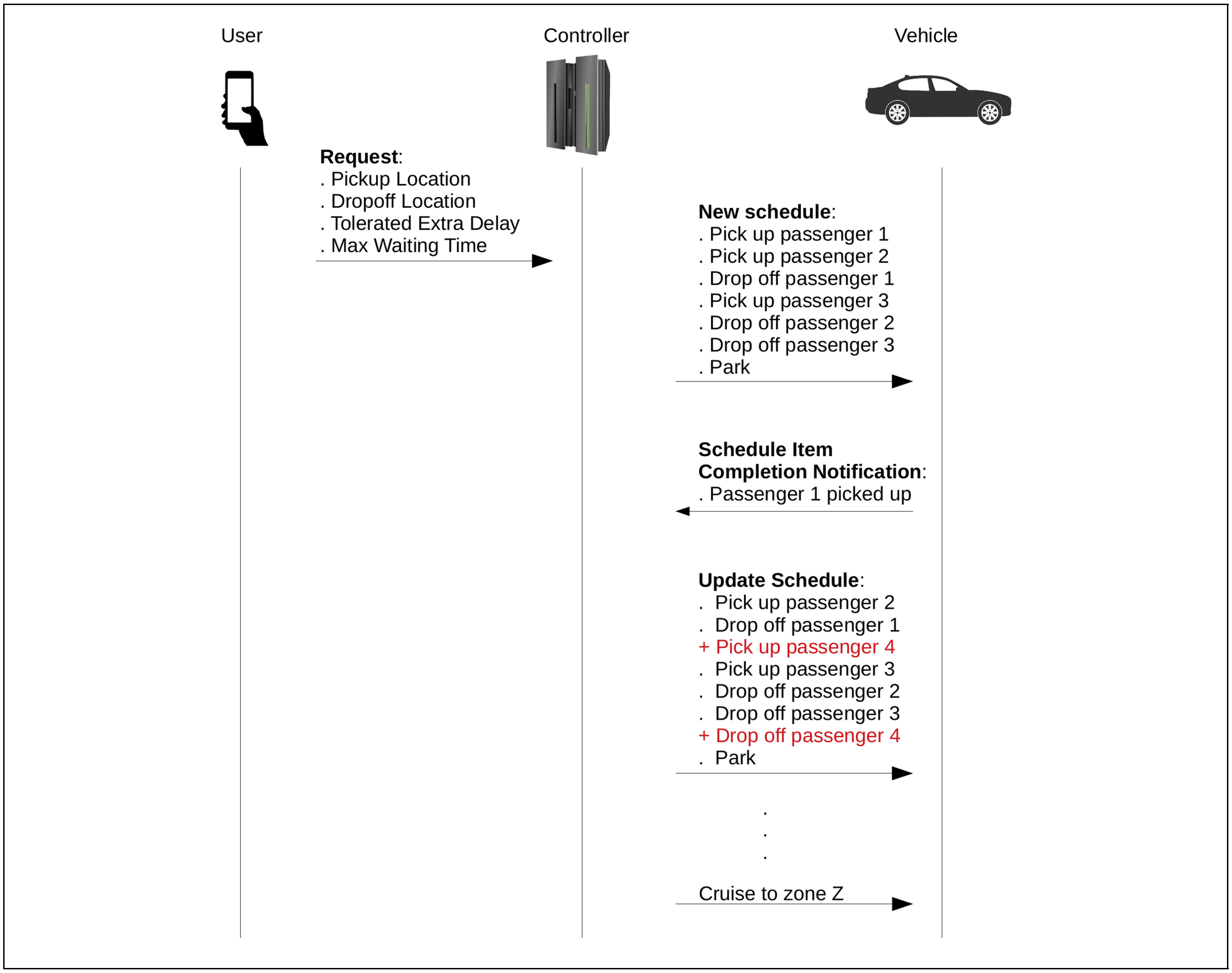

Figure 3. Interactions between agents in the model of AMoD service.

are driven by the choices and the experience of the drivers, while the latter are fully determined by a centralized controller and vehicles follow the instructions given in the schedule.

User Requirements. In the trip request, the user specifies: *pickup* and *drop-off* locations; *shareability*, indicating whether the user is willing to share her ride with other users or not; the *maximum waiting time* she is willing to accept; and the tolerated *delay* at arrival, that is, the amount of additional delay she can accept with respect to the minimum travel time possible. With the *tolerated delay*, the user declares an upper bound of the delay she is willing to accept. In brief, we call the *time constraints* of a trip request its maximum waiting time and tolerated extra delay.

Controller-Vehicle Interaction. As explained before, the activities of the vehicles are completely determined by the centralized controller, by means of schedules computed by the controller and sent to vehicles. At any time, each vehicle has a *schedule*, which is a sequence of *commands* that can be of the following types:

- *Pickup* a user; this includes the user-ID and the related trip request containing all the user requirements.
- *Drop-off* a user: similar to the pickup command.
- *Cruise* to a certain zone.
- *Go to park* at a certain node.

The commands in a schedule can be arranged in any plausible order ensuring, for example, that a drop-off for any user comes after the respective pickup and that the number of passengers never exceeds the number of seats available in the vehicle.

Schedule Computation. The controller continuously collects request from users and periodically, that is, every 10 s, computes or updates vehicle schedules to match them. The controller computes feasible schedules. A schedule is *feasible* if: i) all its pickups can be performed respecting the maximum waiting time specified in the respective trip request; and ii) all its drop-offs can be performed respecting the tolerated extra-time specified in the respective trip request. Note that if a feasible schedule is updated inserting the pickup and the drop-off of a new user, to ensure that the new schedule is still feasible, not only must we check that the time constraints of the new user are met, but we have also to consider that the insertion of the new pickups and drop-offs may imply a detour for the vehicle that could delay the pickup of the drop-offs of the passengers previously inserted in the schedule, possibly violating their time constraints. If a modified schedule is unfeasible, the modification is not accepted, that is, the new passenger cannot be served by that vehicle and the controller will attempt to match her to another vehicle. The controller is able to handle both shareable and non-shareable requests. To do so, first the shareable requests are matched to the available vehicles with some available seats, using the insertion heuristic detailed in (*18*). Then, the controller matches the non-shareable requests with the closest empty vehicles. Finally, updated schedules are sent to the vehicles.

Case Study: From Traditional to Automated Mobility on Demand in Singapore

Researchers who have focused on the algorithms to optimize fleet operations, have claimed the superiority of AMoD over MoD and supported the assumption that AMoD will improve urban mobility. While research has produced its claims overlooking the effect of congestion and an accurate model of drivers, the second side has been represented, with few exceptions, by conceptual or economic reasoning, with lack of quantifiable results. To fully understand the impact of shifting from current human-driven MoD to future AMoD, we claim it is necessary to accurately model driver behavior, which has been overlooked in current studies on AMoD. We demonstrate the validity of this claim by comparing accurately modeled traditional MoD services and future AMoD in Singapore.

Model Estimation

For the estimation of each of the driver decision dimensions, a GPS dataset collected from a major MoD fleet operator in Singapore in 2013 was used. This dataset contains more 25 million records each day for a period of 30 days, and containing vehicle number, time, position, and service status data. The MoD fleet size was fixed according to the information provided by the Land Transport Authority in Singapore (*19*). The simulation is focused on reproducing MoD driver behaviors in a typical working day in a city. MoD driver agents are identified by a synthetic population generated for Singapore for 2012. Their start time of work and shift duration were modeled by fitting a distribution based on MoD GPS data, which was then used to determine each driver's starting time and shift duration. In Figure 4*a* and *b* the distribution of shift duration and shift starting time, as obtained using the GPS traces, is presented (in blue).

The specific behaviors of the traditional MoD drivers are modeled using a discrete-choice framework. Five are estimated, namely: i) *Break Model*; ii) *Cruising Model*; iii) *Stand Choice Model*; iv) *Zone-Based Cruising Model*; and v) *Route Choice Model*.

Break Model. The break model was estimated as a binary logit model estimating the probability of an MoD driver taking a break. A subsample of 39,831 observations taken from the GPS dataset was used for the model estimation. Table 1 shows the estimation results of the break model. The directions of the effects of all variables are theoretically consistent. 86% of breaks take place outside the central business district (CBD) and 50% of the drivers take a break within 5 h of their previous one.

Spatial Choice Model: Stand Choice. The second model is for simulating the choice of a stand. It is estimated as a location choice model using the multinomial logit formulation for the probability of an MoD driver choosing a specific stand from 214 alternative stations scattered around in the network. We used a subsample of 2,324 observations taken from the GPS dataset. Table 1 presents the parameter estimates for the stand choice model. The directions of the effects of all variables are theoretically reasonable, with an estimated marginal effect of travel cost per kilometer of 0.24.

Integrated Spatial Choice: Zone-Based Cruising and Route Choice Model. We estimated a multi-level decision model for the cruising zone selection and the route selection to reach the zone, using the nested logit formulation. The model

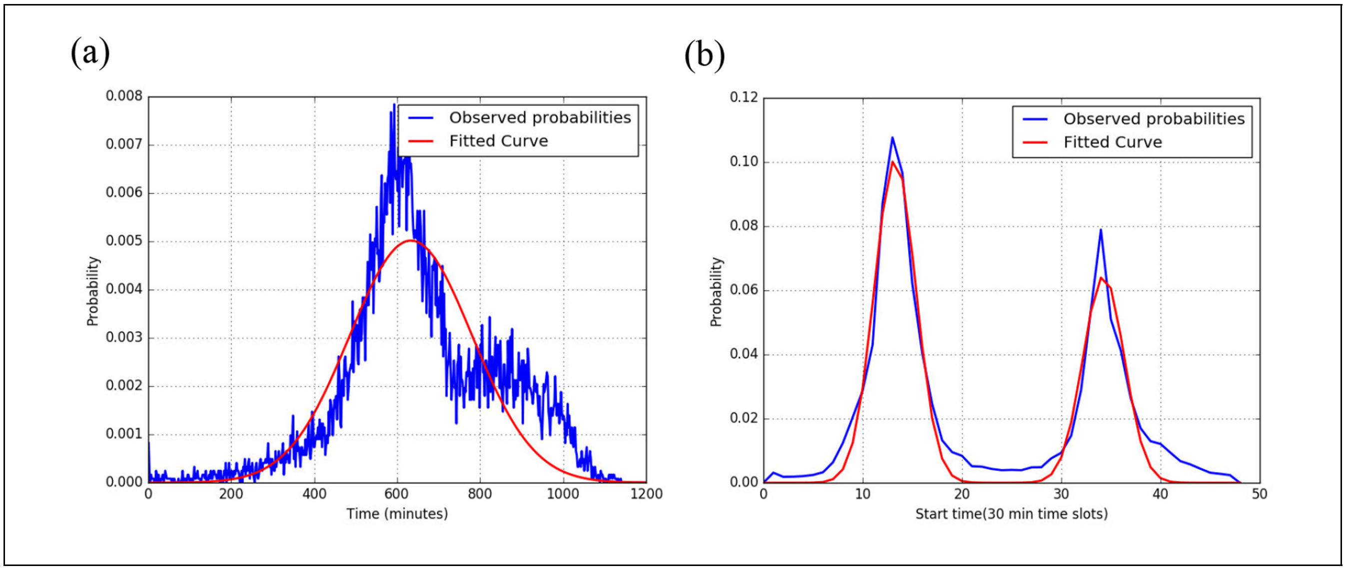

Figure 4. The distribution of: (*a*) shift duration; and (*b*) shift starting time.

Table 1. The MoD Driver Behavior Model Estimates

Variable	Coefficient	Asymptotic standard error	*t* statistic	Summary statistics
		Break model		
Break constant	–3.03	0.0457	–66.28	Number of
In CBD dummy	–0.47	0.0451	10.43	observations = 39,831
Log employment	0.19	0.0165	11.5	$\mathscr{L}(0) = -27{,}608.74$
Travel cost to the nearest stand (SGD)	–0.473	0.0744	–6.36	$\mathscr{L}(\beta) = -14{,}377.43$
Time passed from the last break (h)	0.0633	0.00343	18.44	$\rho^2 = 0.479$
Time left to the end of the shift (h)	0.0557	0.00402	13.84	
Number of previous breaks	–0.365	0.00787	46.32	
		Stand choice model		
Break constant	2	0.0896	22.37	Num. observations = 2324
In CBD dummy	–1.24	0.0944	–13.19	
Log employment	–0.299	0.0212	–1.41	$\mathscr{L}(0) = -12{,}254.165$
Travel cost to the nearest stand (SGD)	–5.02	0.432	–11.88	$\mathscr{L}(\beta) = -5{,}720.485$
Time passed from the last break (h)	1.08	0.188	–5.72	$\rho^2 = 0.533$
Time left to the end of the shift (h)	1.75	0.0674	25.94	
Number of previous breaks	2.31	0.0792	29.16	
		Integrated spatial choice and route choice model		
In CBD dummy	1.38	0.0748	18.41	Number of
Stand dummy	0.633	0.0427	14.81	observations = 4999
Route choice logsum	0.00313	0.000452	6.93	$\mathscr{L}(0) = -34{,}924.773$
Log scale parameter	0.799	0.0102	78.6	$\mathscr{L}(\beta) = -31{,}192.34$
Zone's area (km^2)	2.38	0.175	13.59	$\rho^2 = 0.107$
		Cruise choice model		
Cruise constant	0.639	0.0468	13.65	Number of
Time left to the end of the shift (h)	0.0144	0.00436	3.31	observations = 13742
In CBD dummy	–0.354	0.0541	–6.53	$\mathscr{L}(0) = -9{,}525.229$
Total pickup at the stand	–0.147	0.0403	–3.64	$\mathscr{L}(\beta) = -7{,}624.537$
Employment density (1/km^2)	–0.0314	0.00329	–9.52	$\rho^2 = 0.200$
Travel distance to stand (km)	0.595	0.0373	15.95	

Note: Coefficient estimates and "t-statistics" for the variables or constants of each of the models are given in Table 1. Table 1 also gives the log likelihood function if all values were 0, $\mathscr{L}$(O), the log likelihood function for the actual estimates, $\mathscr{L}(\beta)$, the number of observations , and ρ^2 is the Roh-square for the initial model.

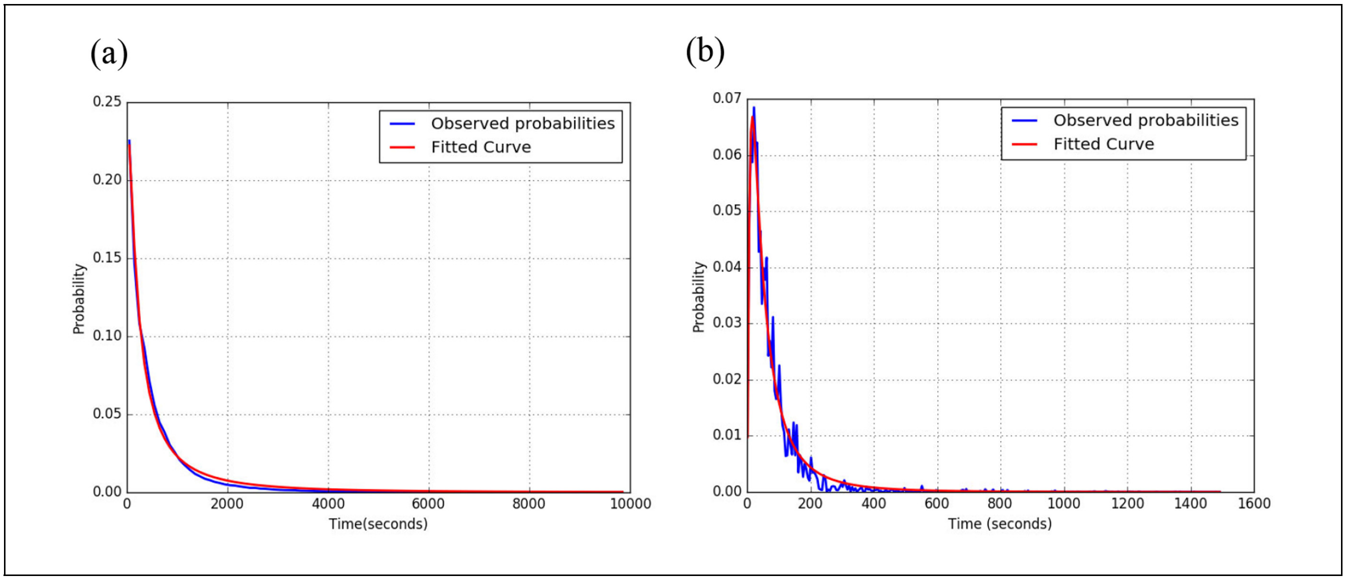

Figure 5. The distribution of: (*a*) cruising duration; and (*b*) queueing duration.

was estimated by the sequential estimation procedure. At the upper level of this model, the probability of choosing a specific zone to cruise in among all 1,169 traffic zones, is estimated while at the lower level, a specific route to reach this zone is chosen. The data used were a subsample of 4,000 observations taken from the GPS dataset. As the number of alternatives is very large, the ρ^2 is small, as expected. Surprisingly, many highly visited cruise zones are not in the CBD. In fact, the most visited zone is outside the CBD with more than 1,580 pickups.

Cruise Choice Model. The cruise/no cruise choice model was estimated as a binary logit model, which estimates the probability of an MoD driver cruising. The data used were a subsample of 13,742 observations taken from the GPS dataset. Table 1 presents the parameter estimates for this model. The directions of the effects of all variables are theoretically reasonable. Interestingly, it was found that as the employment density increases, the driver is less likely to cruise. In Singapore, the high employment areas are also characterized by many stands which makes the search for customers easy. Overall 30% of the drivers choose to go to a stand while the rest choose to cruise.

Cruising for too long, and queueing for too long are handled by drawing a unique value for each driver from the distribution obtained using the GPS data. In Figure 5, the distribution of cruising and queueing durations, as obtained using the GPS traces, is presented (in blue) as well as a log-normal curve that was fitted (in red).

Study Area

Our study was conducted using a representative synthetic population and network of Singapore. The total area of Singapore is 721.5 km^2 with a population of 5.3 million in 2012 (*20*). In Singapore, passengers make over 8 million trips on a daily basis with an average stop rate of 1.5 per individual. Singapore has a developed transportation system with 3,356 km of roads which includes 10 expressways. The public transportation system consists of 15 Mass Rapid Transit (MRT) and Light Rail Transit (LRT) lines with a total of 124 subway stations (92 MRT stops and 32 LRT stops) and 728 bus lines spanning the island with a total of 4,607 bus stops. The road network consists of 6,220 nodes (intersections), 30,585 segments (road sections with homogeneous geometry) and 14,799 links (groups of one or more segments with similar properties). Singapore Island is divided into 1,169 Traffic Analysis Zones (TAZs).

Experimental Design

Two different scenarios are designed and simulated. We consider a "traditional MoD only" scenario where traditional MoD is operated for on-demand service delivery. The available modes are: single occupancy car (Car); sharing with one passenger (Car Sharing 2); sharing with two passengers (Car Sharing 3); Private Bus; public bus; MRT; Motorcycle; Walk; and traditional MoD. The modal availabilities are in accordance with our study area, which we describe in the following section. In the second scenario we introduce automated MoD, replacing

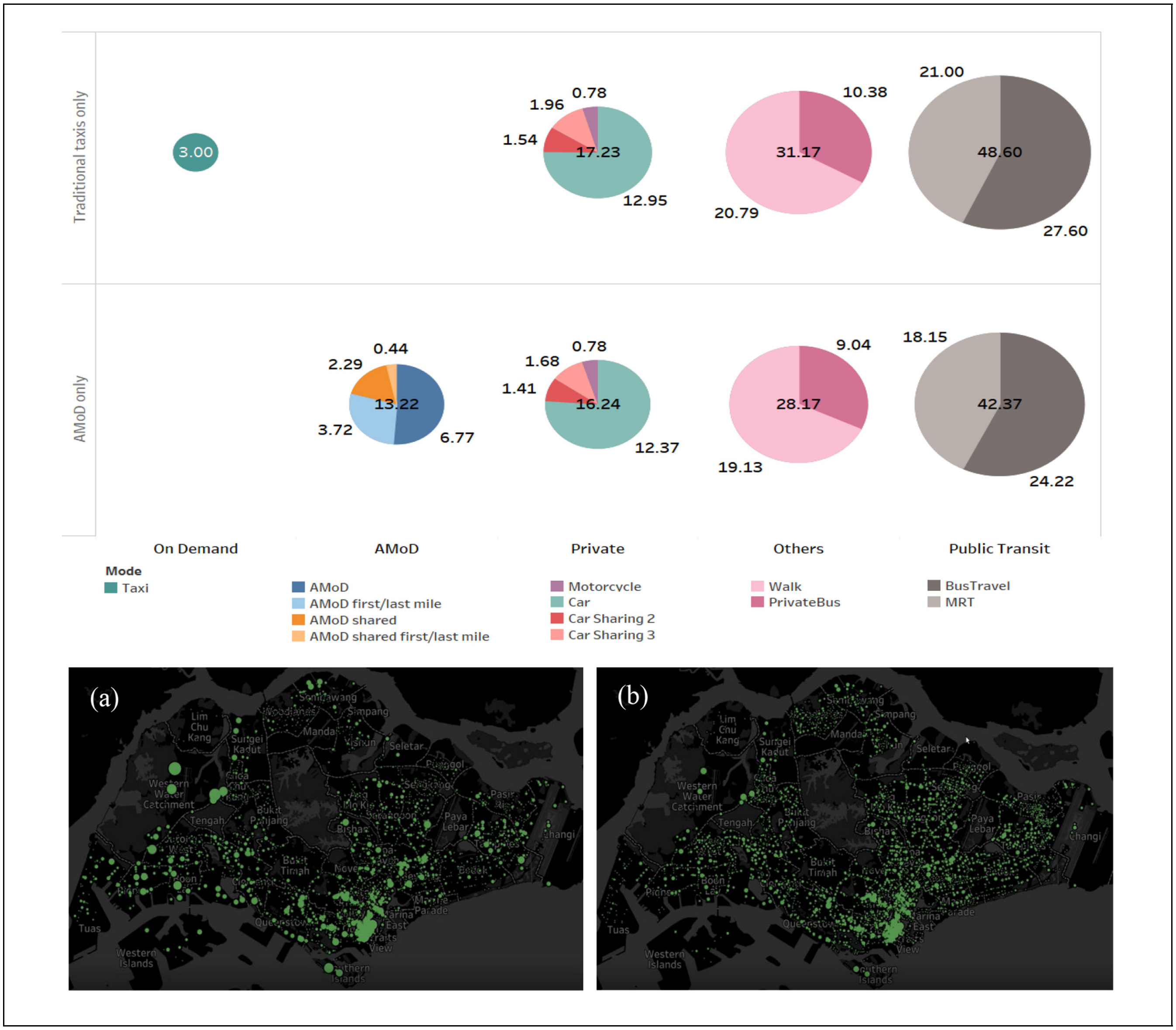

Figure 6. Mode share and demand profile during morning peak for: (*a*) traditional MoD; and (*b*) automated mobility on demand services.

a traditional MoD service with two new modes: AMoD as a non-shared, driverless ride (AMoD) and AMoD as a shared ride (AMoD Pool), while the availability of all other modes from the base case scenario stays the same. We refer to this scenario as "AMoD only" scenario. To generate the demand for AMoD modes, given the absence of appropriate data, we assumed that individual preference toward AMoD is similar to that of MoD with some modifications. The first set of assumptions is that a single AMoD ride will be 50% cheaper compared with MoD, and that a shared ride will be 30% cheaper than a single ride (*21*). We also implemented a distance-based additional in-vehicle travel time for the passengers who share the vehicle with other passengers (based on current Uber data). Furthermore, we have added the expected additional waiting time for the AMoD Pool rider. We conduct morning peak (06:00–10:00 a.m.) simulations for each scenario in SimMobility using the Singapore network. The results are summarized in the following section. We also compare the impacts of fleet size and parking strategies for AMoD on network performance.

Results and Discussion

The mode share distribution for each scenario, and the demand locations for MoD and AMoD are shown in Figure 6. In the "traditional MoD only" case, MRT and Public bus (PT) account for 48.6% of the share, while

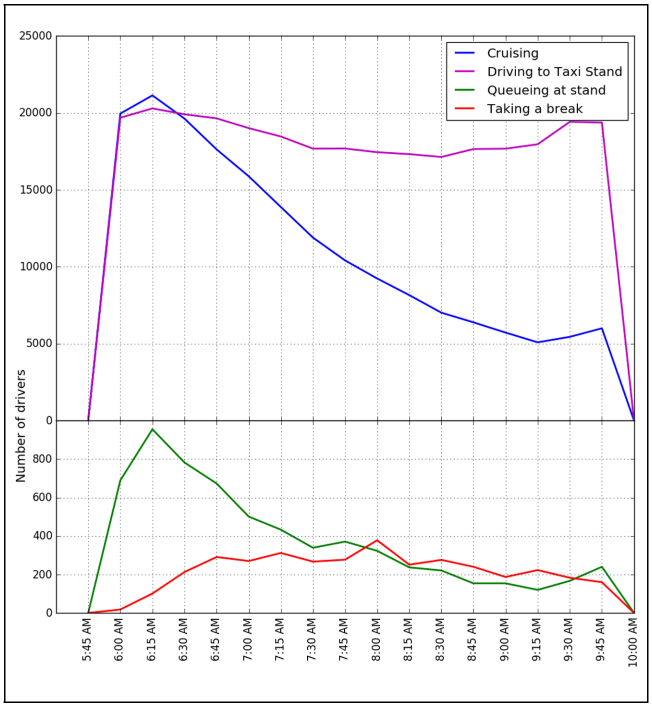

Figure 7. MoD driver behavior during simulation.

Walk is about 20% of the share, and Private Bus 10%. Private car accounts for 12% of the share, and an additional 4.3% will share the Car with passengers. The traditional MoD service consists of 3% of the share. In the "AMoD only" scenario, where AMoD services are offered as a substitute for traditional MoD services, we see a significant reduction in PT mode share of more than 6%, with a shift toward AMoD, which consists of 13.2%. We also observe a small reduction in Walk and Private Bus, as well as in Car Sharing modes, while there is no change in the Car mode share.

Figure 7 shows the activity of the traditional MoD drivers under the models specified in section 4. As expected, the number of drivers queueing at the MoD stands and cruising reduces during peak hours. On average, drivers spend 8 min cruising and 2 min queueing during the morning peak.

In Figure 8, we observe the performance of the controller with regard to trip request satisfaction under various fleet loadings. Based on these results and on those in Figure 9, the 45,000-fleet case appears as the user-optimal case. To compare this with the alternate strategy where vehicles are cruising, instead of parked, we compare the 36,000-fleet case under both conditions. Comparing Figure 8*c* and *d*, we see that waiting time is slightly lower under the parking strategy (as indicated by the area between the blue and orange curves). Overall, parking ensures that demand is ultimately met, as can be seen toward the end of the curves in both Figure 8*c* and *d*. Note that Figure 8 counts the requests, pickups, and drop-offs observed in each 5-min interval. Obviously, not all the requests sent in a certain 5-min interval are picked up and dropped off in the same interval, as they will be served later. The request-to-drop-off ratio is highest at about 8:00 a.m. and narrows down toward the end of the observed scenario. When the service is not well configured, for example, with 36,000 vehicles and no parking, the number of requests served does not recover the number of requests sent, while using parking solves this problem.

In Figure 10 we compare driver behavior and fleet management between the "traditional MoD only" and the "AMoD only" scenarios. Note that MoD vehicles are not parked or driven to a pre-specified location to pick up. Instead, passengers are picked up while hailing or waiting at the taxi stand. In the AMoD case, the fleet is more efficiently managed, as they are introduced incrementally, while MoD drivers are introduced according to their shift starting time. As the MoD shifts are set inefficiently, they spend a lot of time cruising. However, this inefficiency is greatly reduced toward the end of peak period.

In Figure 9 we report the impact on user-metrics of the different services, under different settings. Journey times (JT) do not include waiting times (W), which are represented separately. As expected, the shared requests experience higher waiting times. The increase in fleet size is clearly beneficial for non-shared requests, while its impact is less pronounced for the shared. This can be explained by the interest of the operator in decreasing the miles traveled: even if a large fleet is available, it will try to serve the shared requests with as few active vehicles as possible, as long as the user requirements are satisfied. This is reflected in the matching algorithm we have used (*18*). It is clear from Figure 9 that the 45,000 AMoD fleet case is user-optimal. A limitation of the simulation framework at the time this experiment was carried out is that taxi waiting times are not given explicitly. However, as can be seen from the average JT, similar levels of service are provided by both the AMoD and the traditional MoD cases. In Table 2, we compare average travel times and distances for passenger-vehicle trips for the two scenarios. These indicate that the overall patterns for single-passenger trips are largely unchanged. As expected, travel times for AMoD Pool are about 50% greater on average.

Conclusion

We have demonstrated an agent-based simulation of daily activity patterns and movements in a dense urban network, using Singapore as a case study. Importantly, we have modeled in adequate fashion the behavior and

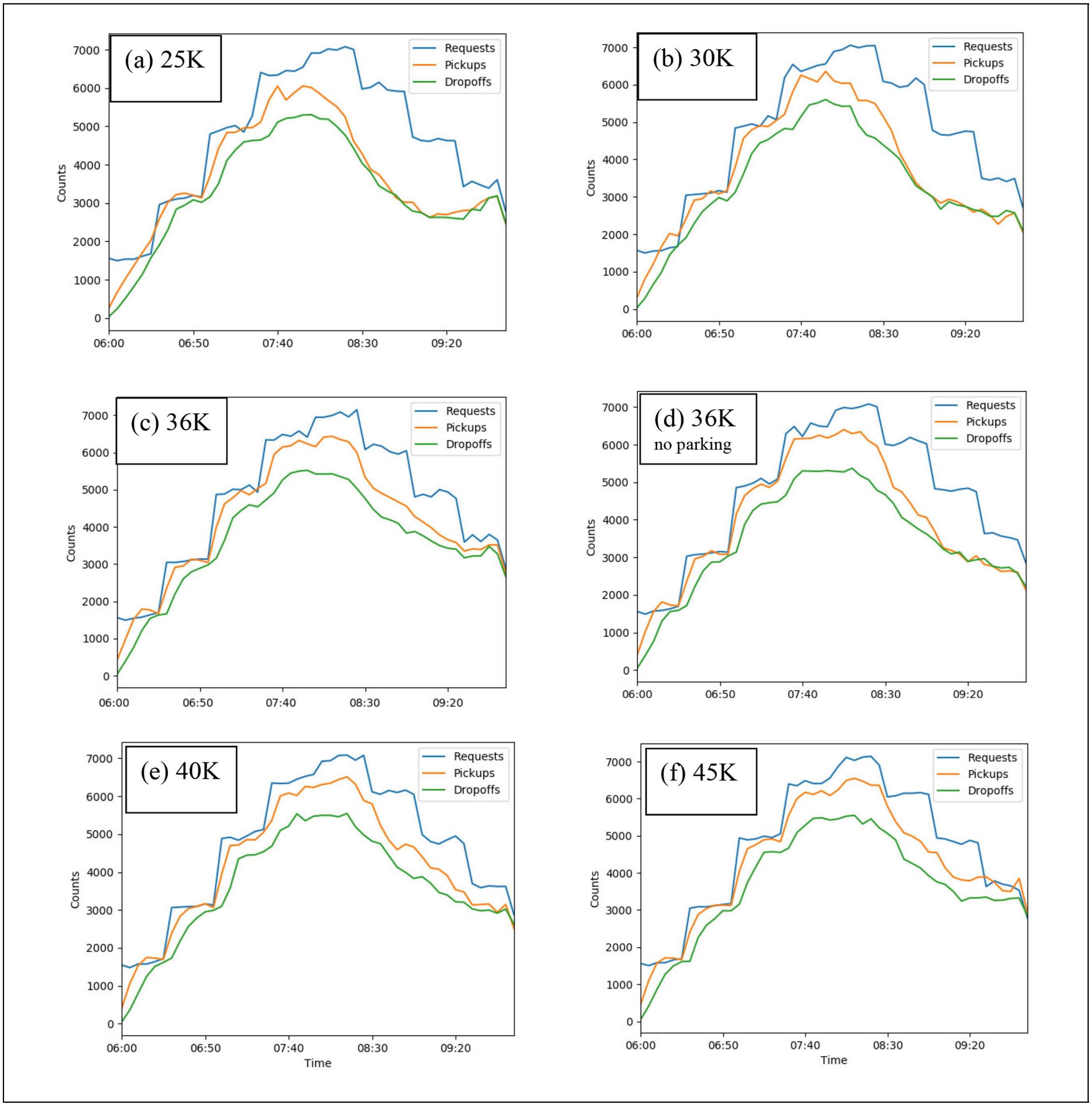

Figure 8. Controller performance for AMoD service under various fleet size scenarios, all implemented with parking except (*d*).

movement of traditional MoD services and compared comprehensively how this performs relative to the near-futuristic automated MoD service. Our simulator—SimMobility—has enabled us to test the impacts on network performance of the user-optimal automated case to the traditional case.

A key finding of this research is that a significant reduction in PT modes (12%) and a dramatic increase in mobility on-demand share (four times greater) are observed when AMoD services are offered as a substitute for traditional MoD services. Additionally, while demand for AMoD is over four times greater than that of traditional MoD, only about twice as many fleets are required to satisfy the increased demand levels. In the "traditional MoD only" case, there are 20,000 taxis available during the morning peak. For the "AMoD

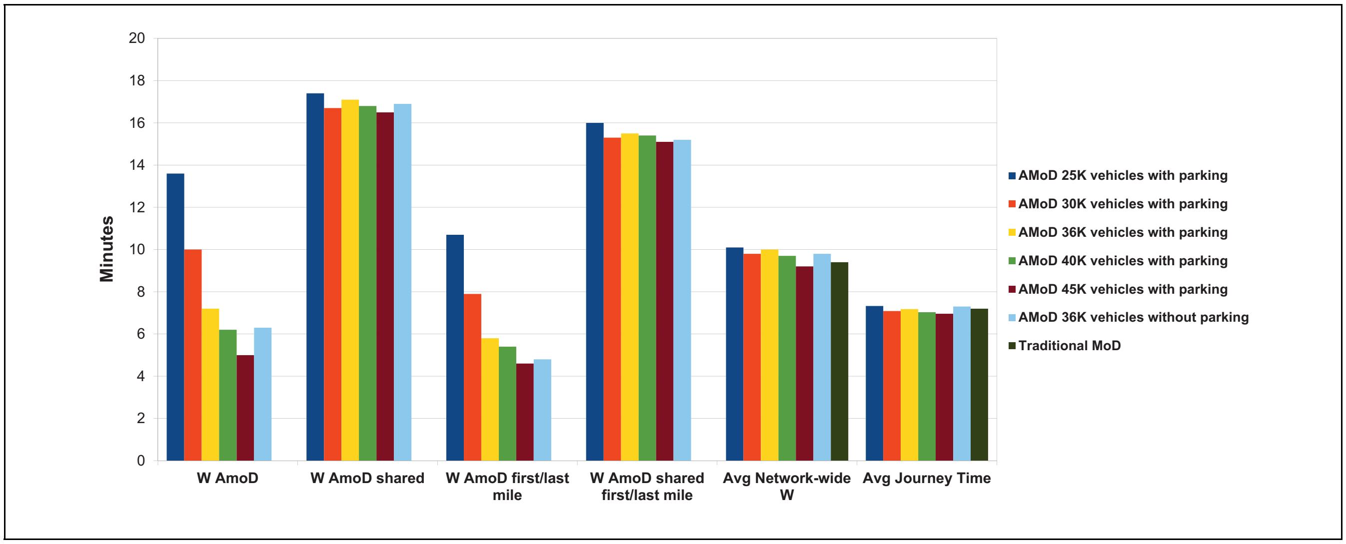

Figure 9. Waiting time (W) across automated on-demand modes for the different scenarios (in minutes). Average network-wide W is the average W over buses, trains, and MoD. Journey time captures average travel time across all modes.

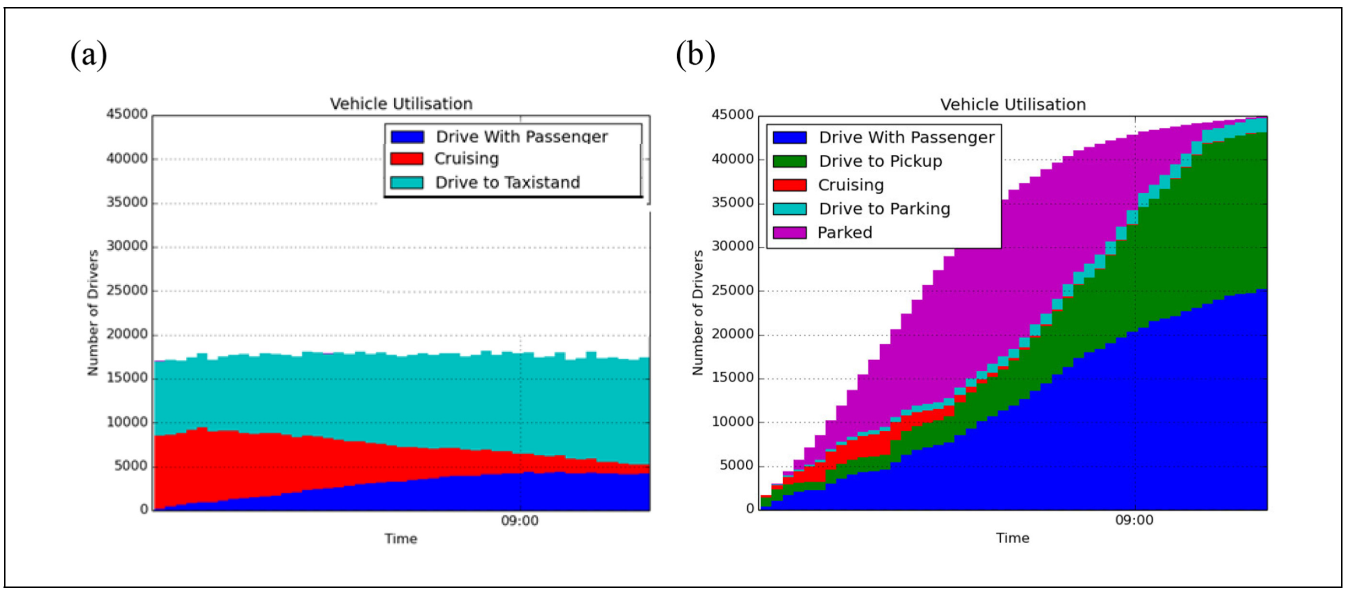

Figure 10. Vehicle utilization profiles for: (*a*) "Traditional MoD only" (20,000 vehicles); and (*b*) "AMoD only" (45,000 vehicles) scenarios.

Table 2. Average Travel Times and Distances for Passenger-Vehicle Trips in Both Scenarios

Scenario	MoD avg. travel time (min)	MoD avg. trip distance (km)	AMoD avg. travel time (min)	AMoD avg. trip distance (km)	AMoD pool avg. travel time (min)	AMoD pool avg. trip distance (km)	Car avg. travel time (min)	Car avg. travel distance (km)
Traditional MoD	14.5	10.1	na	na	na	na	14.6	9.4
AMoD	na	na	13.2	8.0	20.3	13.7	15.6	10.0

only" case, we employed simulation tests to obtain the user-optimal fleet size of 45,000 for the same period, servicing 0.2 million trips (over 5 times those of traditional MoD). This demonstrates that AMoD fleets are more efficiently managed compared with MoD fleets, and have the potential to improve urban mobility outcomes with the same level of service, at likely lower costs. We also show that when ride-sharing is predominant, then fewer fleets can serve the demand just as efficiently.

Our further avenues of research include quantifying the cost implications of AMoD implementation strategies and comparing their respective benefits. Given our capabilities to sufficiently model current Uber-like mobility on demand systems, we would like to further investigate driver behavior under today's MoD frameworks.

The differences in urban form and rates of technological and infrastructural development indicate that the introduction of AMoD services will have widely varying impacts. There are critical questions to be answered regarding its effects on congestion, parking and public transportation ridership. To better understand these future patterns, we are currently developing prototype cities representing distinct urban typologies. By simulating relevant scenarios in these prototype cities, we can further obtain insights into policy intersections for the best outcomes for AMoD service implementation.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: B. Nahmias-Biran, J. B. Oke, A. Araldo, K. Basak, R. Seshadri, A. Akkinepally, C. L. Azevedo, M. Ben-Akiva; analysis and interpretation of results: B. Nahmias-Biran, J. B. Oke, N. Kumar, A. Araldo, K. Basak, C. L. Azevedo; draft manuscript preparation: B. Nahmias-Biran, J. B. Oke, K. Basak, C. L. Azevedo. All authors reviewed the results and approved the final version of the manuscript.

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