FROM TRADITIONAL TO AUTOMATED MOBILITY ON DEMAND: A COMPREHENSIVE FRAMEWORK FOR MODELLING 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's 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 heterogenous MoD driver's 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 modelling framework. Behavioral models were estimated to characterize decision making of drivers using a GPS dataset from a major MoD fleet operator in Singapore was used. 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 simulator 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 more efficient service even with increased demand. Parking strategies and fleet size will also have an effect on user satisfaction and network performance.

1 INTRODUCTION

A majority of past research efforts have been devoted to modelling and optimizing Mobility on Demand (MoD) fleet operations *(1)*. Much less attention has been made to the decentralized nature of MoD decision making process *(2)*. Such nature 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 pick-ups, queueing, routing, and fleet dispatch—have been modelled, there is no platform that captures the dynamics between decentralized driver's decision-making and the centralized decision making. Such 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's behavior along with a decentralized fleet management system within an agent-based demand-supply simulator, SimMobility Mid-Term. SimMobility Mid-Term (MT) simulator is an agent- and activity-based demand model integrated with a dynamic multimodal network assignment model (4). The traffic dynamics are simulated using a multi-modal mesoscopic 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 modelling 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 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 modelled 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 stand), (iv) Zone Choice during cruising Model and (v) Route Choice. The suggested models can reflect strategic decisions made by the driver.

While traditional MoDs 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 decisions making processes. The AMoD controller would for example process traveler's 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 to the pick-up location and the travel time to final destination. Thus, an MoD controller agent in simulation should capture MoD service status, updated vehicle locations and monitor vehicle movement through the network, reacting to incoming requests and changes on network and fleet perofrmance accordingly. A framework to handle MoD controllers in SimMobility was presented in *(5)* 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 modelling and simulation, and demonstrate it through a case study of Singapore, where different MoD services are been modeled. Specifically, traditional MoDs are been simulated and compared to 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) showcase 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. Section 2 provides a literature review on recent MoD and MoD services modeling and simulation. Section 3 introduces the MoD framework, including the behavioral models and the MoD controller. Section 4 includes a case study demonstrating the use of the MoD framework for modeling traditional MoDs vs AMoD services in Singapore. Finally, Section 5 presents the main conclusions and findings of this work.

2 LITERATURE REVIEW

Many past research efforts have been devoted to the modeling of the MoD fleet operations. Leveraging on *(1)* extensive review of MoD services modeling and simulation literature, we review the latest studies and focus 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.

With the context of large scale simulation of MoD services, majority of past research 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 awaiting 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 FIFO order. However, neither strategy simulated real MoD behavior. *(7)* also used MATSim to simulate the interaction between newly introduced autonomous vehicle MoD services with the existing means of transport. They used simplified version of greedy controller in a MATSim scenario of the city of Sioux Falls, South Dakota, USA. Both pieces of literature that used MATSim didn’t model the behavior of the MoD driver but used random choices. *(8)* studied booking strategies for a MoD dispatching system. The study identifies two types of booking: Current Booking (CBK), where the customers makes a booking call for a 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 demands 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 focuses on modeling MoD drivers’ cruising/roaming behavior while it treat the traffic condition in the network as exogenous. Singapore was used as the study area. *(10)* 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 MoDs could be served with just 3,000 MoDs of capacity four.

The second stream of research focus on small scale optimization problems and empirical models used to describe the different aspects of MoD services, most of them focused on the MoD-dispatching system. *(11)* studied the MoD dispatching system in Singapore and proposed a system where the MoD assigned a booking job is the one with the shortest time path, reaching the customer in the shortest time determined by real-time traffic conditions. The microscopic simulation was used in a small toy. *(12)*used MITSIMLab to study multi-agent MoD-dispatch with the purpose of investigating ways to improve its general performance. MoD operations were simulated in a small toy network; they found that dispatching MoDs by using the shortest-time paths computed using real-time traffic information is more efficient than the current dispatch methods, which were based on shortest straight-line distance. *(13)*proposed a MoD control strategy in which both the MoD and the customer are equipped with mobile devices that can communicate with each other within limited searching ranges. *(1)*proposed and tested an agent-based simulation model focused on a shared-MoD service. The system proposed optimizes fare and travel time savings to passengers. The simulation did not include a dynamic traffic model or a dynamic demand model. *(14)*focused on e-hailing, proposing a spatial equilibrium model to balance supply and demand of MoD services.

*(15)*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. *(16)*- *(18)* extensively details the customer-searching behavior of MoD drivers over different periods of time. *(19), (20)*also studied MoD customer search behavior. They developed models for analyzing combinations of supply and demand while maximizing the revenue of each MoD driver at an individual level. *(21)*explored methods of optimizing mobility on demand personalized services. However, this simulation ignores actual traffic conditions on the network.

The third stream of research focused on data driven studies that were used to draw insight into the behavior of MoD drivers. *(22)* 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. *(23)*- *(24)* used the complete trace information from 3590 MoDs in Beijing to understand passenger denial behavior of MoD drivers. *(25)*focused on the willingness of MoD-drivers to drive to the airport empty and used AVL data from 8,954 MoDs during a period of five weekdays in Shanghai. Their analysis revealed that airport serving MoDs 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. *(26)*investigated the factors contributing to single rip MoD efficiency. By evaluating MoD performance using GPS data from 2000 MoDs in Wuhan in 2013, they found that top, efficient drivers operate far away from downtown areas and navigate through the whole city, changing locations consistently to regains with good 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 can 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.

3 METHODOLOGY AND FRAMEWORK

3.1 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 levels. 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 MoDs, 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 DAS of all individuals are simulated, i.e. agent's 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 been handled by the MoD controller, which is an external entity to SimMobility (presented in detail in section 3.3).

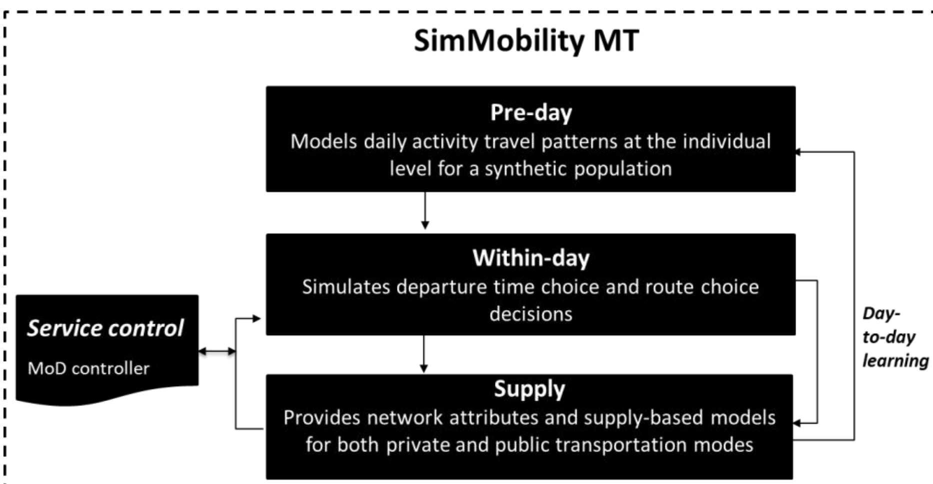

Figure 1: SimMobility MidTerm (MT) structure

3.2 Flexible Mobility On-Demand Framework

In order to facilitate the study of complex interactions between independent drivers, the central controller and travelers' decisions, we propose an event-based modelling framework. Here, the drivers, the controllers, and the 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, i.e. 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.

3.3 Traveler Agent

As part of the Day Activity Schedule (DAS) generated by pre-day, an agent has an MoD mode assigned to her, as well as start and end time of activity and exact location.When the time of simulation reached its MoD journey starting time, she will either 1) start searching for a MoD driver on the street either by hailing or by walking to the closest MoD stand nearby or 2) request for an MoD for pick up and wait for available MoD. Her request is added to a first in, first out array of potential clients for a 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 his home or activity location. The Uber, and Lyft-like traveler cannot be picked up at the MoD stand or at the road network.

3.4 Mobility On-Demand Driver Agent

The traditional MoD-drivers are modelled as agents with their own preferences. They can choose their next move and their next client. Their interactions with the travelers is a result of driver's choice. For the traditional MoD driver, we embed in the drivers the knowledge about 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 to stop at different hours of the day and choose the most attractive routes for finding clients in the street.

3.4.1 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)	A 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 towards the client's destination.
Queueing (Q)	The MoD driver is in a queue at a MoD stand to pick up a client.
Cruising (C)	A MoD driver is searching the streets to find the next client. More generally, it represents that the vehicle is ready to take a passenger.
Direct-to-destination (D)	The variable describes a state where the MoD driver is direct 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 temporarily will not be available to accept any kind of requests.

3.4.2 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:

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

Drop-off event: This event occurs when the MoD reaches the destination of the traveler. After this event, the MoD-driver reevaluates his strategy.
Join queue event: This event occurs when the MoD reaches the MoD-stand. The MoD can join the queue at the stand only if the number of MoDes already queueing at the stand is no more than MoD stand capacity.
Controller request event: This event describes the messages the controller sends to the MoD driver regarding the pick-up 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".
Queuing for too long event: This event is triggered when the MoD-driver has been queuing unsuccessfully for too long at a MoD-stand. After this event, the MoD-driver reevaluates his strategy.

Figure 2 describes the traditional MoD driver behavior framework while the squares represent decision model and the others represent a choice. 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 pre-determined. Location and time information will be kept in the simulation.

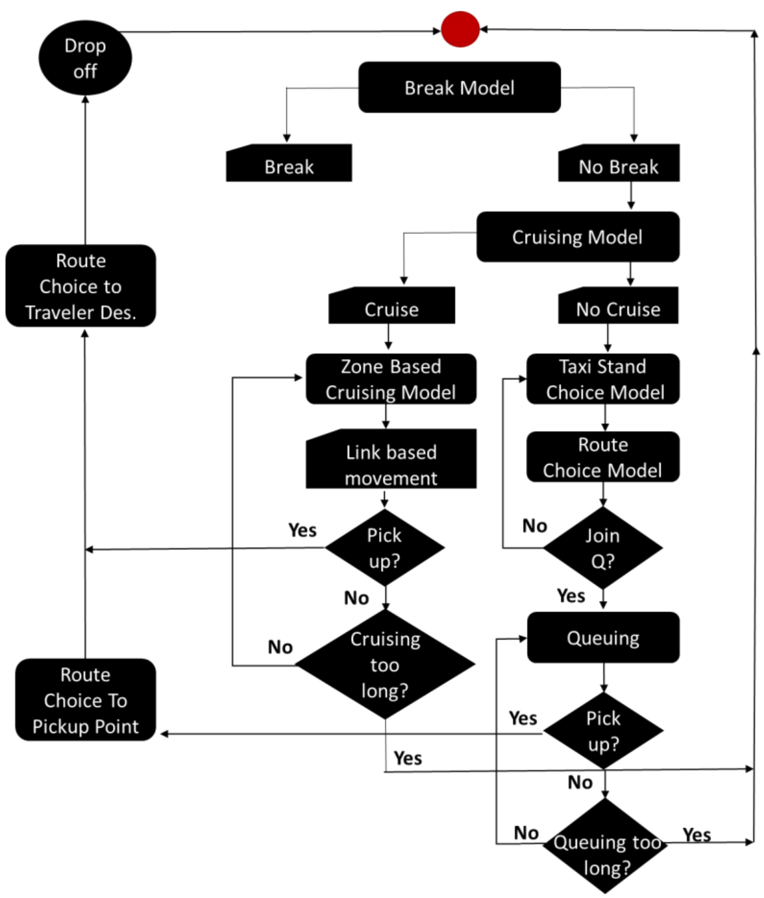

Figure 2: Traditional MoD driver behavior framework

If the MoD driver chooses to cruise, she will search the streets to find a client. She can do so by moving towards 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 link by link, i.e., she will start to cruise randomly, 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 towards 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, whether to take a break or not.

In case of a coordinated ride-hailing driver behavior framework, majority of the decisions were taking out so that the driver cannot: (1) chose whether to cruise or not to cruise (2) chose to go to a MoD stand, queue, and pick up a passenger there (3) chose to pick up passengers on the street (4) chose her next zone to cruise in. On the interaction between the driver and the MoD controller see section 3.5. Note that traveler’s choices are not modeled in detail and will be incorporated in future research.

3.5 MoD Controller: the case of Automated MoD

The model of Automated Mobility on Demand (AMoD) builds upon our previous work *(5)*, extended to handle new capabilities, for instance parking, handling single or shareable ride requests, etc. 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 Fig. 3. Users send *trip requests* to the controller, which associates them to vehicles in the form of *schedules*. The controller computes and continuously updates a schedule per each vehicle, which dictates the sequence of operations, i.e., pick-up, drop-off, etc., that the vehicle will perform. It is worth emphasizing the main difference between MoD and AMoD services: the former are driven by the choices and the experience of the drivers, the latter are fully determined by a centralized controller and vehicles just obey to the instructions written in the schedule.

User requirements

In the trip request, the user specifies *pick-up* and *drop-off* location, *shareability*, indicating whether the user is willing to share her ride with other users or not, *maximum waiting time* she is willing to accept and the tolerated *delay* at arrival, i.e., 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 *time constraints* of a trip request its maximum waiting time and tolerated extra delay.

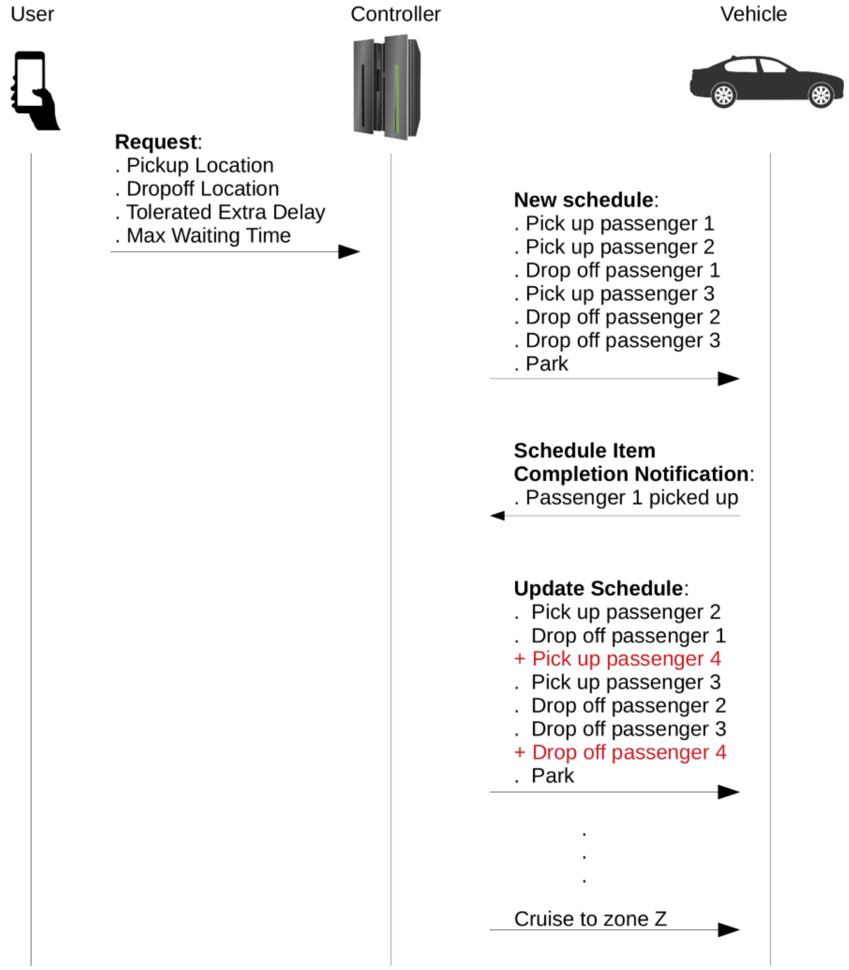

Figure 3: Interactions between agents in the model of AMoD service

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* associated, which is a sequence of *commands*. Commands can be of the following types:

- *Pick-up* a user; it includes the user-id and the related trip-request containing all the user requirements.
- *Drop-off* a user: similar to the pick-up 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 pick-up 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, i.e., every 10 seconds, computes or updates vehicle schedules in order to match them. The controller computes feasible schedules. A schedule is *feasible* if (i) all its pick-ups 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 pick-up and the drop-off of a new user, in order to ensure that the new schedule is still feasible, not only we have to check that the time constraints of new user are met, but we have also to consider that the insertion of the new pick-ups and drop-offs may imply a detour for the vehicle that can delay the pick-up 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, i.e., 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 *(29)*. Then, the controller matches the non-shareable requests with the closest empty vehicles. Finally, updated schedules are sent to the vehicles.

4 CASE STUDY: FROM TRADITIONAL TO AUTOMATED MOBILITY ON DEMAND IN SINGAPORE

Researchers who have focused on the algorithms to optimize fleet operation, have claimed the superiority of AMoD over MoDs 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 really understand the impact of shifting from current human-driven MoD to future Automated MoD, we claim it is necessary to accurately model drivers' behavior, which has been overlooked in current studies on AMoD. We showcase this claim in this section by comparing accurately traditional MoD service and future AMoD in Singapore.

4.1 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 data set contains more 25 million records each day for a period of 30 days, and containing vehicle number, time, position and service status data. MoD fleet size was fixed according to the information provided by the Land Transport Authority in Singapore *(28)*. The simulation is focused in reproducing MoD driver’s behaviors in a typical working day in a city. MoD driver agents are identified by synthetic population generated for Singapore for 2012. Their start time of work and shift duration was modeled by fiting a distribution based on MoD GPS data, which then was used to determine each drivers starting time and shift duration. In Figure 2 (a) and (b) the distribution of shift duration and shift starting time, as obtained using the GPS traces, is presented (in blue).

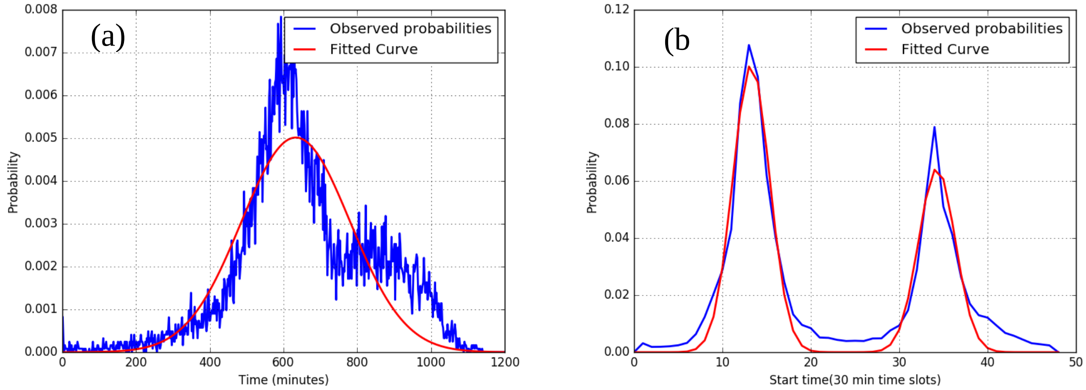

Figure 2: The distribution of (a) shift duration and (b) shift starting time

The specific behaviors of the traditional MoD drivers are modelled using a discrete-choice modeling framework. Specifically, we estimate five models, each of which focuses on one of the typical behaviors of the drivers, including: (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, which estimates the probability of a MoD driver to take a break (the base category) or not. A subsample of 39,831 observations taken from a full GPS data set were 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 CBD and 50% of the drivers take a break within 5 hours from their last break.

Spatial Choice Model: Stand Choice

The second model is for simulating the choice of a stand. The model is estimated as a location choice model using the multinomial logit formulation. The model estimates the probability of a MoD driver to choose a specific stand from 214 alternative stations scattered around in the network. We used a subsample of 2,324 observations trips taken from the full GPS data set. Table 1 presents the parameter estimates for the stand choice model. The directions of the effects of all variables are theoretically reasonable, with the estimated marginal effect of travel cost per kilometer of around 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 was estimated by the sequential estimation procedure. At the upper level of this model, the probability to choose a specific zone to cruise in among all 1169 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 4000 observations taken from full GPS data set. As the number of alternatives is very big, the ρ^2 is small as expected. Surprisingly, many high visited cruise zones are not in the CBD, in fact, the most visited zone is outside the CBD with more than 1580 pickups.

Cruise Choice Model

The cruise/no cruise choice model was estimated as a binary logit model, which estimates the probability of a MoD driver to to cruise (the base category) or not. The data used were a subsample of 13742 observations taken from the full GPS data set. 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 area are also characterized by a large number of 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.

Table 1: The MoD driver behavior model estimates

Break model				
Variable	**Coefficient**	**Asymptotic st. error**	***t* statistic**	**Summary statistics**
Break constant	-3.03	0.0457	-66.28	Num. of observations = 39,831
In CBD dummy	-0.47	0.0451	10.43	
Log employment	0.19	0.0165	11.5	$\mathscr{L}(0)$ = -27608.74
Travel cost to the nearest stand (SGD)	-0.473	0.0744	-6.36	$\mathscr{L}(\beta)$ = -14377.43
Time passed from the last break (hr)	0.0633	0.00343	18.44	ρ^2 = 0.479
Time left to the end of the shift (hr)	0.0557	0.00402	13.84	
Number of previous breaks	-0.365	0.00787	46.32	
Stand choice model				
Variable	**Coefficient**	**Asymptotic st. error**	***t* statistic**	**Summary statistics**
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	$\mathscr{L}(0)$ = -12254.165
Travel cost to the nearest stand (SGD)	-5.02	0.432	-11.88	$\mathscr{L}(\beta)$ = -5720.485
Time passed from the last break (hr)	1.08	0.188	-5.72	ρ^2 = 0.533
Time left to the end of the shift (hr)	1.75	0.0674	25.94	
Number of previous breaks	2.31	0.0792	29.16	
Integrated spatial choice and route choice model				
Variable	**Coefficient**	**Asymptotic st. error**	***t* statistic**	**Summary statistics**
In CBD dummy	1.38	0.0748	18.41	Num. of observations = 4999
Stand dummy	0.633	0.0427	14.81	
Route choice logsum	0.00313	0.000452	6.93	$\mathscr{L}(0)$ = −34924.773
Log scale parameter	0.799	0.0102	78.6	$\mathscr{L}(\beta)$ = -31192.34
Zone’s area (km^2)	2.38	0.175	13.59	ρ^2 = 0.107
Cruise choice model				
Variable	**Coefficient**	**Asymptotic st. error**	***t* statistic**	**Summary statistics**
Cruise constant	0.639	0.0468	13.65	

Time left to the end of the shift (hr)	0.0144	0.00436	3.31	Num. of observations = 13742
In CBD dummy	-0.354	0.0541	-6.53	$\mathscr{L}(0) = -9525.229$
Total pick up at the stand	-0.147	0.0403	-3.64	$\mathscr{L}(\beta) = -7624.537$
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	

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

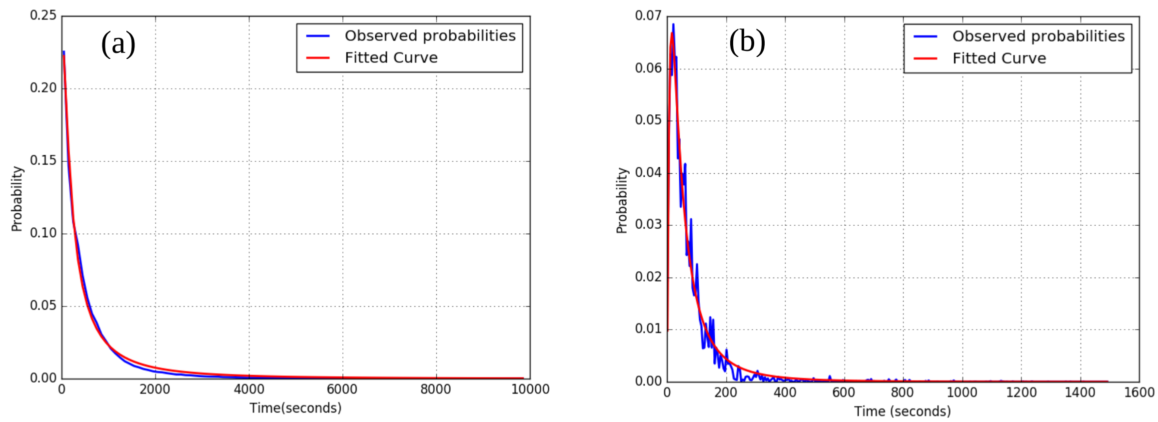

Figure 4: The distribution of (a) cruising duration, and (b) queuing duration

4.2 Study Area

Our study was conducted using Singapore synthetic population and network. The total area of Singapore is 721.5 km^2 with a population of 5.3 Million individuals in 2012 *(30)*. 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 covering 3,356 kilometers of roads which includes 10 expressways. The public transportation system consists of 15 MRT and 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 4607 bus stops. The road network consists of 6220 nodes (intersections), 30585 segments (road sections with homogeneous geometry) and 14799 links (groups of one or more segments with similar properties). Singapore Island is divided into 1169 Traffic Analysis Zones (TAZs).

4.3 Experimental Design

Two different scenarios are designed and simulated. We consider a 'traditional MoD only' scenario where traditional MoD are operated for on-demand service delivery. The available modes are single occupancy car (Car), sharing with one extra passenger (Car Sharing 2), sharing with two extra passengers (Car Sharing 3), private bus (Private Bus), public bus (Bus), Mass Rail Transit (MRT), motor-cycle (Motorcycle) walking (Walk) and traditional MoD (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 and replace regular 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. We assumed that individual’s preferences towards AMoD is similar to MoD with some modifications. In order to generate the demand for AMoD modes, given the absence of appropriate data, we assumed that individual’s preferences towards AMoD is similar to MoD with some modifications. The first set of assumptions is that a single AMoD ride will be 50% cheaper as compared to MoD , and that a shared ride will be 30% cheaper than a single ride *(31)*. We also implemented a distance based additional in-vehicle travel time for the passengers who share the vehicle with other passengers (based on Uber app). Furthermore, we have added the expected additional waiting time for the share rider. We conduct morning peak (6-10 am) simulations for each scenario in SimMobility using Singapore network. The results summarized in the following subsections. We also compare the impacts of fleet size and parking strategies for AMoD on network performance.

5 RESULTS AND DISCUSSION

Mode share distribution for each scenario is shown in Figure X. In the ‘traditional MoD only’ case, MRT and Public Bus accounts for 48.6% of the share, while Walk is taking a bit more than 20% of the share, and Private Bus a little more than 10%. Private car accounts for a little more that 12% of the share and additional 4.3% will share the Car with other passengers. The traditional MoD service consist of 3% of the share. In ‘AMoD only’ scenario, where AMoD services are offered as a substitute for traditional MoD services, we see significant reduction in PT mode shares of more than 6% towards AMoD, which consist of 13.2% in total. We also observe a small reduction in Walk and Private Bus as well as in Car sharing modes in favor of AMoD, while no change in Car mode share.

Figure 5: Demand profile during morning peak for (a) Traditional MOD and (b) Automated Mobility on Demand services

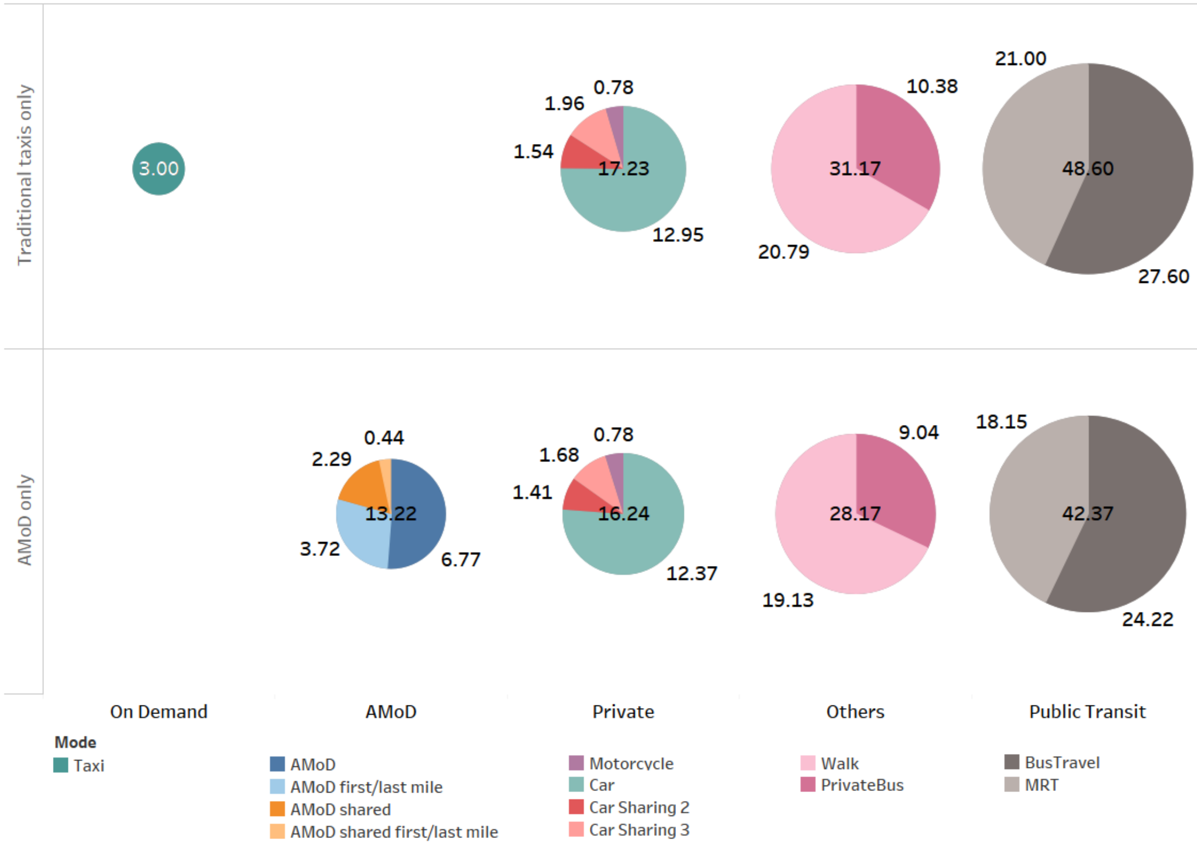

Figure 6: Mode share distributions for the given scenarios

Fig. 7 shows the activity of the traditional MoD drivers under the model of Sec. 4. As expected, the number of drivers queueing at the MoD stands and cruising reduces during peak hours. On average, drivers spend 80 minutes cruising and 2 seconds queueing during the morning peak.

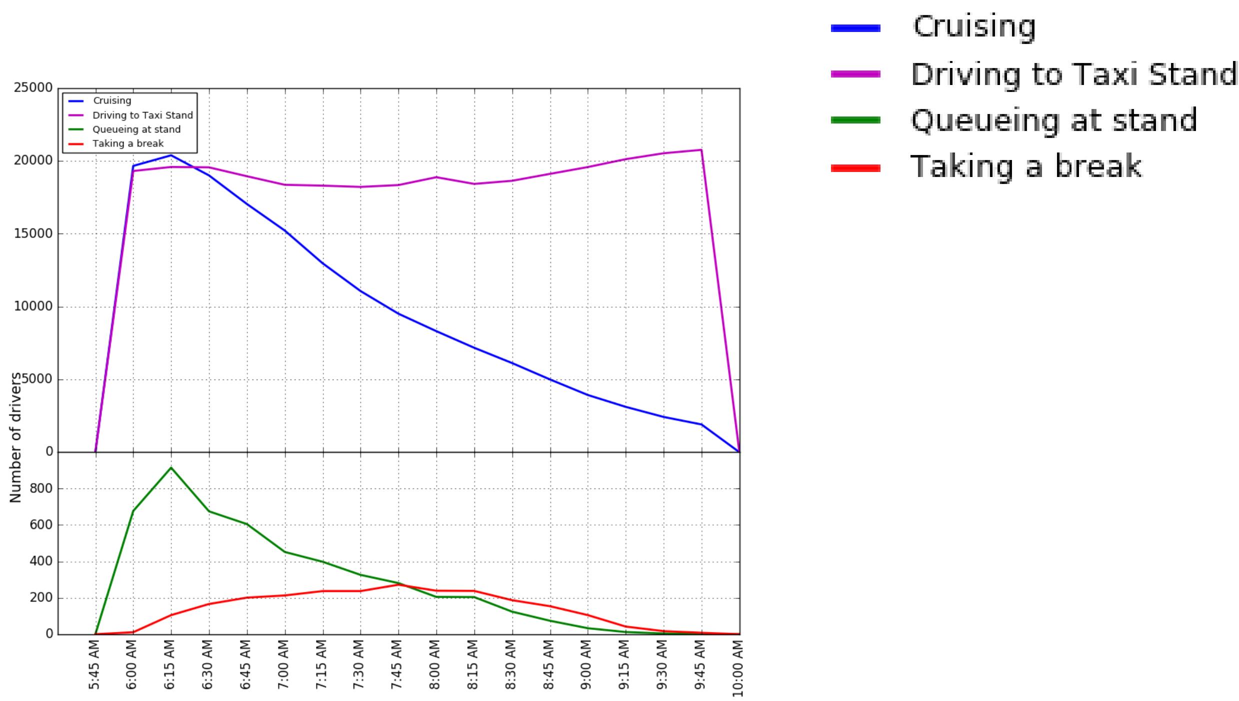

Figure 7: MoD driver behavior during simulation

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. In order to compare to the alternate strategy wherein vehicles are cruising, instead of parked, we compare the 36,000 fleet case under both conditions. From Figures 8c and 8d, we see that waiting time are slightly lower. Overall, however, parking ensures that demand is ultimately met, as can be seen toward the end of the curves in both figures.

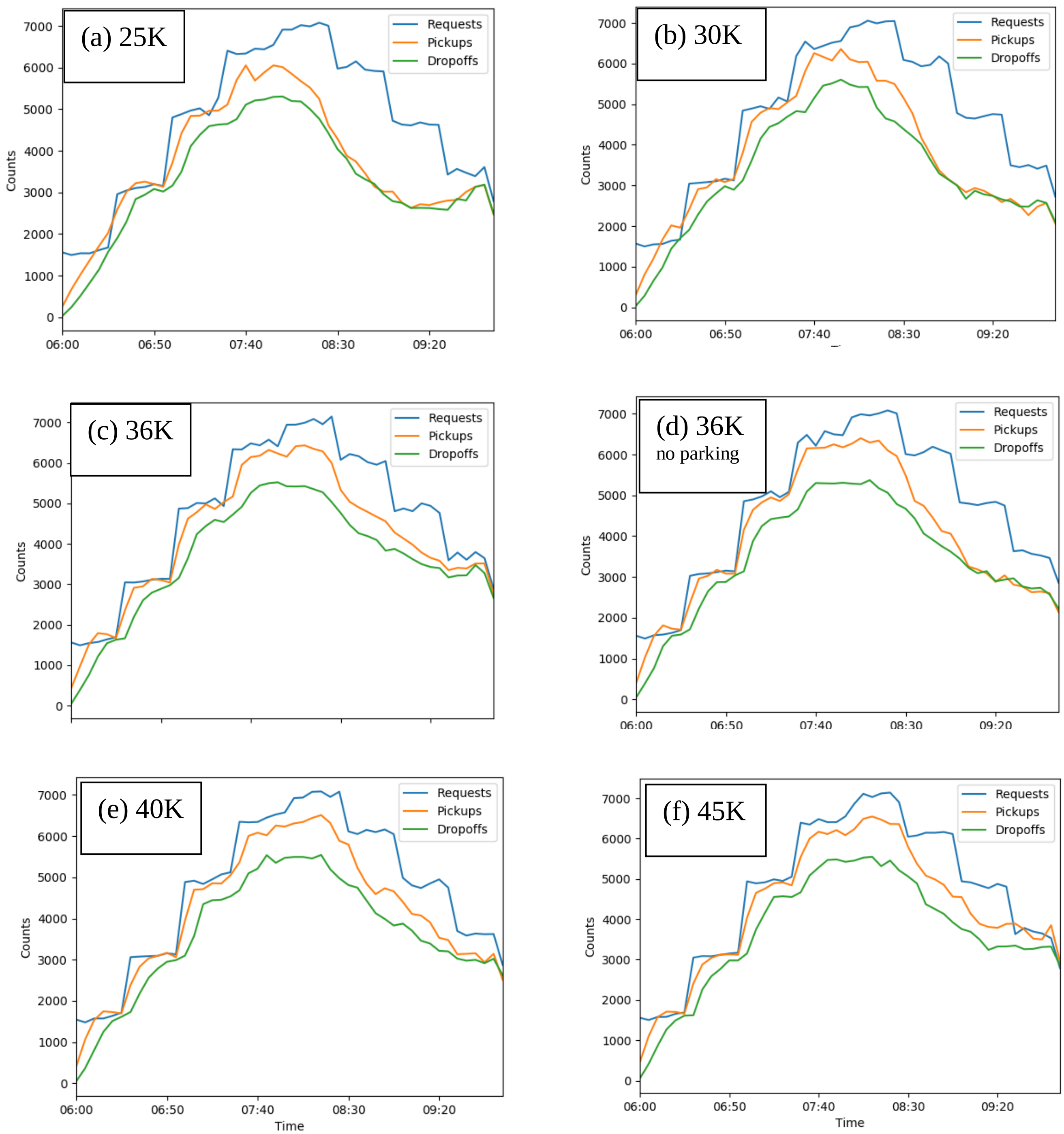

Figure 8: Controller performance for AMOD service under various fleet size scenarios, all implemented with parking except (d)

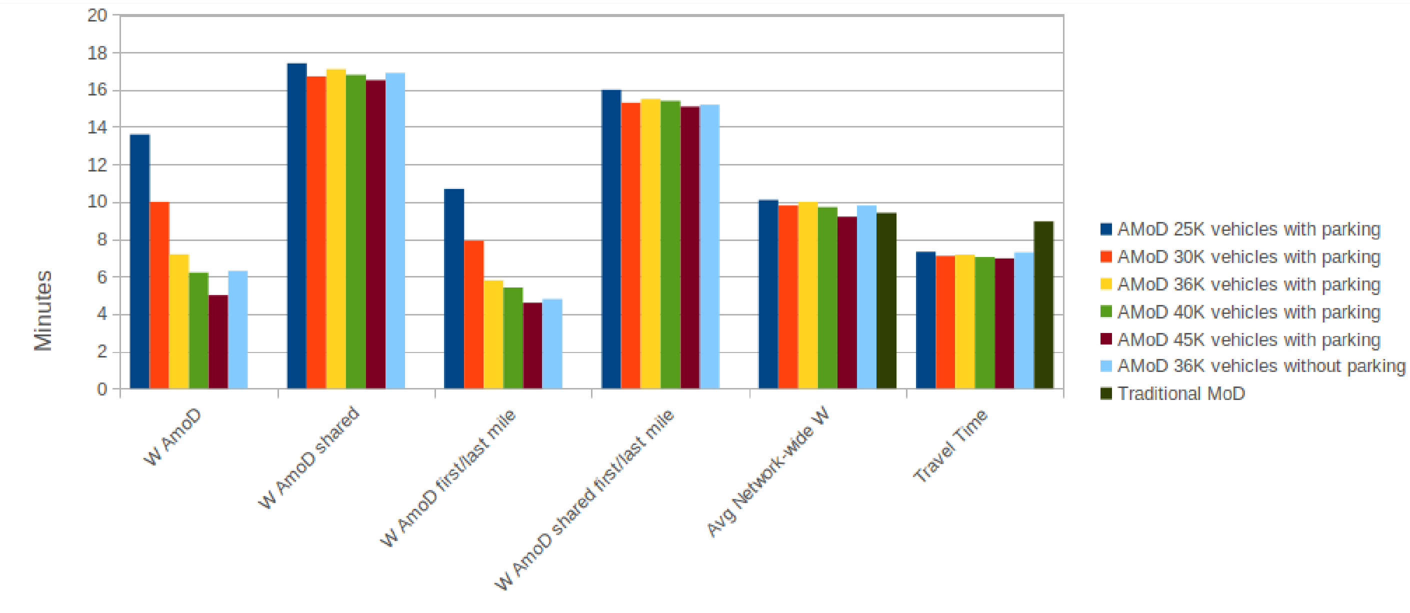

Figure 9: Waiting time (W) and Travel time (TT) for the different scenarios (in minutes).

In Fig. 9 we report the impact on user-metrics of the different services, under different settings. Travel times (TT) do not include waiting times (W), represented separately. As expected, the shared requests experience higher W. 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 use.

6 CONCLUSIONS

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

A key finding is that while demand for AMoD is over four times greater than that of traditional MoD, only about twice as many fleet are required to satisfy the increased demand levels. This demonstrates the potential of AMoD to improve urban mobility outcomes at likely lower costs. We also show that when ridesharing is predominant, then fewer fleet can serve the demand just as efficiently.

Our ongoing research includes quantifying the cost implications of these strategies and comparing their respective benefits. We also have the capabilities to sufficiently model today's Uber-like mobility-on-demand systems, and we would like to further investigate driver behavior under today's MoD frameworks.

7 AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: B. Nahmias-Biran, J. Oke, A. Araldo, K. Basak, R. Seshadri, C. Azevedo: Study conception and design, Analysis and interpretation of results and Manuscript preparation. M. Ben-Akiva: Study conception and design.

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