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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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1 **FROM TRADITIONAL TO AUTOMATED MOBILITY ON DEMAND:**
2 **A COMPREHENSIVE FRAMEWORK FOR MODELLING ON DEMAND SERVICES**
3 **IN SIMMOBILITY**

4
5 **Bat Hen Nahmias-Biran** ^{1,2}, **Corresponding Author**

6 E-mail: bathennb@ariel.ac.il; bathen@mit.edu

7
8 **Jimi B. Oke** ³

9 E-mail: oke@mit.edu

10
11 **Nishant Kumar** ²

12 E-mail: nishant@smart.mit.edu

13
14 **Kakali Basak** ²

15 E-mail: kakali@smart.mit.edu

16
17 **Andrea Araldo** ^{4,3}

18 E-mail: araldo@mit.edu

19
20 **Ravi Seshadri** ²

21 E-mail: ravi@smart.mit.edu

22
23 **Arun Akkinapally** ³

24 E-mail: arunprak@mit.edu

25
26 **Carlos Lima Azevedo** ⁵

27 E-mail: climaz@dtu.dk

28
29 **Moshe Ben-Akiva** ^{2,3}

30 E-mail: mba@mit.edu

31
32 ¹ **Department of Civil Engineering, Faculty of Engineering, Ariel University, Ariel 40700,**
33 **Israel**

34
35 ² **Singapore-MIT Alliance for Research and Technology, 1 Create Way, 138602, Singapore**

36
37 ³ **Intelligent Transportation Systems Lab, Massachusetts Institute of Technology,**
38 **Cambridge, MA 02139**

39
40 ⁴ **SAMOVAR, CNRS, Télécom SudParis, Institut Polytechnique de Paris**

41
42 ⁵ **Department of Management Engineering, Technical University of Denmark, 2800 Kgs.**
43 **Lyngby, Denmark**

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1 ABSTRACT

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

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21

1 1 INTRODUCTION

2 A majority of past research efforts have been devoted to modelling and optimizing Mobility on
3 Demand (MoD) fleet operations (1). Much less attention has been made to the decentralized
4 nature of MoD decision making process (2). Such nature arises from the dependency of current
5 MoD systems on drivers and their decision power. In the context of multi-agent simulation
6 technology, although some facets of centralized MoD operations —such as street pick-ups,
7 queueing, routing, and fleet dispatch—have been modelled, there is no platform that captures the
8 dynamics between decentralized driver’s decision-making and the centralized decision making.
9 Such decentralized perspective is critical in modeling MoD systems and the potential impacts of
10 automation, as drivers can only be informed, incentivized or coordinated but not centrally
11 controlled (3).
12

13 This work aims to fill this gap by introducing a comprehensive framework that models various
14 facets of MoD driver’s behavior along with a decentralized fleet management system within an
15 agent-based demand-supply simulator, SimMobility Mid-Term. SimMobility Mid-Term (MT)
16 simulator is an agent- and activity-based demand model integrated with a dynamic multimodal
17 network assignment model (4). The traffic dynamics are simulated using a multi-modal
18 mesoscopic simulator (supply simulator). MT is part of a much larger simulation platform that
19 also contains long term and short-term models. Simulating MoD services is extremely
20 challenging because of complex interactions between independent drivers, the central controller,
21 and travelers' decision processes. To facilitate the study of such a complex and partially
22 decentralized system, we propose an event-based modelling framework. In this framework, the
23 drivers, the controllers, and the travelers are represented as separate decision agents making
24 plans and event-triggered actions. Behavioral models were estimated to characterize decision
25 making of drivers using a GPS dataset from a major MoD fleet operator in Singapore in 2013,
26 containing position and service status data over 30 days. A unified framework was developed to
27 model the operation of both traditional MoD fleets and emerging ride-hailing services such as
28 Uber, and Lyft-like services. The specific behaviors of MoD service drivers are modelled within
29 a discrete-choice framework. Specifically, the following models are proposed: (i) Break, (ii)
30 Cruise/ Not to Cruise, (iii) Stand Choice (choice among the available MoD stand), (iv) Zone
31 Choice during cruising Model and (v) Route Choice. The suggested models can reflect strategic
32 decisions made by the driver.

33 While traditional MoD actions are made by the driver, some MoD services can coordinate some
34 of the processes above. Ultimately, automated MoD (AMoD) services could fully control and
35 optimize all decisions making processes. The AMoD controller would for example process
36 traveler’s service requests and assign them to a given vehicle after considering its current
37 occupancy (and potential route), whether the passenger is willing to share the ride or not, time to
38 reach to the pick-up location and the travel time to final destination. Thus, an MoD controller
39 agent in simulation should capture MoD service status, updated vehicle locations and monitor
40 vehicle movement through the network, reacting to incoming requests and changes on network
41 and fleet performance accordingly. A framework to handle MoD controllers in SimMobility was
42 presented in (4) and integrated within the calibrated SimMobility model of Singapore [for details
43 on the estimation, implementation and validation of the Singapore model, the reader is referred
44 to (4). In this paper, we have extended the MoD controller framework with several features for
45 service driver behavior modelling and simulation, and demonstrate it through a case study of

1 Singapore, where different MoD services are been modeled. Specifically, traditional MoD is
2 simulated and compared to AMoD. The current work has five major contributions: (1)
3 development of a comprehensive event-based framework that addresses complex behaviors and
4 interactions of service drivers, MoD centralized operation, and travelers; (2) incorporation of the
5 proposed framework within a highly realistic agent-based simulation platform, SimMobility; (3)
6 evaluation of the suggested framework against real-world data; (4) demonstration of the
7 proposed framework through a case study of Singapore; and (5) showcase the use of the
8 proposed framework in the evaluation of potential mechanisms and policies when deploying
9 MoD services.

10
11 The rest of the paper is structured as follows. Section 2 provides a literature review on recent
12 MoD and MoD services modeling and simulation. Section 3 introduces the MoD framework,
13 including the behavioral models and the MoD controller. Section 4 includes a case study
14 demonstrating the use of the MoD framework for modeling traditional MoD vs AMoD services
15 in Singapore. Finally, Section 5 presents the main conclusions and findings of this work.

16 **2 LITERATURE REVIEW**

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

22
23
24 Within the context of large-scale simulation of MoD services, majority of past research used
25 microscopic simulation. (6) used MATSim for the modeling of MoD services in Barcelona and
26 Berlin and focused on assessing the performance of two MoD dispatching strategies in balancing
27 supply and demand. The first strategy always serves awaiting requests by dispatching the nearest
28 idle MoD, but this method has poor performance under high demand. The second strategy is a
29 balancing strategy that minimizes pickup trip times instead of serving requests in the FIFO order.
30 However, neither strategy simulated real MoD behavior. (7) also used MATSim to simulate the
31 interaction between newly introduced autonomous vehicle MoD services with the existing means
32 of transport. They used a simplified version of a greedy controller in a MATSim scenario of the
33 city of Sioux Falls, South Dakota, USA. Both efforts using MATSim did not model the behavior
34 of the MoD driver but used random choices. (8) studied booking strategies for a MoD
35 dispatching system. The study identifies two types of booking: Current Booking (CBK), where
36 the customers makes a booking call for a MoD to arrive as soon as possible, and Advance
37 Booking (ABK), where customers indicate a pickup time which is at least in half an hour later. In
38 the simulation model, the central region of Singapore was chosen as the study area. The results
39 of the study show that advanced booking benefits small MoD operators with comparatively low
40 booking demands but is ineffective for larger MoD operators with high booking demands. (2)
41 used MoDSim to model MoD behavior at the macro-level. MoDSim is designed to be a
42 decentralized discrete event simulation; it models MoD drivers' cruising/roaming behavior while
43 treating the traffic condition in the network as exogenous. Singapore was used as the study area.
44 (9) developed a mathematical model for real-time high-capacity ride-sharing. The model was
45 experimentally validated with New York City MoD data, and results showed that 98% of MoD

1 rides currently served by over 13,000 MoD drivers could be served with just 3,000 MoD vehicles
2 via automation and sharing.

3
4 The second stream of research focuses on small scale optimization problems and empirical
5 models used to describe the different aspects of MoD services. (10) studied the MoD dispatching
6 system in Singapore and proposed a method where the MoD assigned a booking job is the one
7 with the shortest time path, reaching the customer in the shortest time determined by real-time
8 traffic conditions. The microscopic simulation was performed in a small toy network. (1)
9 proposed and tested an agent-based simulation model focused on a shared-MoD service. The
10 proposed system optimizes fares and travel time savings for passengers. The simulation did not
11 include a dynamic traffic model or a dynamic demand model. (11) focused on e-hailing,
12 proposing a spatial equilibrium model to balance supply and demand of MoD services.

13
14 (12) explored the market demand potential of a Shared-Ride MoD. They presented an integrated
15 choice and latent variable modeling framework for modeling the number of times per week a
16 Shared-Ride MoD would be used if it were implemented at the American University of Beirut
17 campus. A series of studies by Wong et al. (see for example 13) extensively details the customer-
18 searching behavior of MoD drivers over different periods of time. (14) explored methods of
19 optimizing mobility on demand personalized services. However, this simulation ignores actual
20 traffic conditions on the network.

21
22 The third stream of research consists of data driven studies that were used to draw insight into
23 the behavior of MoD drivers. (15) used a stated preference survey of 400 MoD drivers conducted
24 in 2000 in Hong Kong to estimate a multinomial logit choice model for MoD customer-searching
25 behavior and discovered that the journey time, toll, and waiting time were found to be significant
26 factors in the choices drivers made at the 1% level. (16) used the complete trace information
27 from 3590 MoD drivers in Beijing to understand passenger denial behavior of MoD drivers. (17)
28 focused on the willingness of MoD drivers to drive to the airport empty and used AVL data from
29 8,954 MoD drivers during a period of five weekdays in Shanghai. Their analysis revealed that
30 airport-serving MoD drivers earn significantly less in most time periods during the day, but
31 vacant-MoD drivers are still more likely to serve the airport if they have relatively higher profits
32 in airport-originated trips. (18) investigated the factors contributing to single-trip MoD
33 efficiency. By evaluating MoD performance using GPS data from 2000 MoD drivers in Wuhan
34 in 2013, they found that high-performing, efficient drivers operate further away from downtown
35 areas and navigate through the whole city, changing locations consistently to obtain the best
36 traffic conditions.

37
38 Methodologies used so far in the literature focused mainly on MoD dispatching algorithms with
39 very limited large-scale applications. Others used a real-world data to understand a specific MoD
40 driver behavior, but none of them tried to capture the full set of behavior of the MoD driver, or
41 combine all the pieces into one comprehensive framework that can address the complex
42 behaviors and interactions of MoD drivers, fleet controllers, travelers, congestion and other
43 modes. In this study we intend to fill this gap by developing a comprehensive tool to predict and
44 evaluate the impact of the transformation of on demand services using SimMobility simulator.

45
46

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 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 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, 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, 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 or (2) request an MoD and wait for pick-up. 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 her home or activity location. The Uber, and Lyft-like traveler cannot be picked up at the MoD stand.

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

1 choice. For the traditional MoD driver, we embed in the drivers the knowledge about the
 2 historical space and time distribution of the clients, based on historical demand data. The
 3 information is then used by MoD drivers to choose the most adequate MoD stands to stop at
 4 different hours of the day and choose the most attractive routes for finding clients in the street.

6 **3.4.1 State Vector of the MoD Driver**

7 An MoD driver is at any moment in one state of the state vector. To allow for different MoD
 8 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. |

9 **3.4.2 Events influencing the MoD driver agent**

10 The designed framework is event driven and there are seven major event types that influence the
 11 MoD driver agent as follows:

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

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

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

19 **Controller request event:** This event describes the messages the controller sends to the MoD
 20 driver regarding the pick-up request. This event can occur at any time.

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

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

26
 27 Figure 2 describes the traditional MoD driver behavior framework, showing the decision models
 28 and choices. The simulation starts by loading the agents at their home location as defined in the
 29 synthetic population. The MoD driver's initial decision will be to work or to take a break; if the
 30 driver decides to take a break, her state will change to break activity whose duration is pre-
 31 determined. Location and time information will be kept in the simulation.

32

1
2 ****Figure 2: Traditional MoD driver behavior framework****
3

4
5 If the MoD driver chooses to cruise, she will search the streets to find a client. She can do so by
6 moving towards a predetermined zone, then the zone-based cruising model will be activated first
7 and the route choice model will be activated second. After reaching the desired zone, the MoD
8 driver will cruise randomly from link to link with no specific target. The MoD will choose the
9 desirable zone according to the historical demand. If a client is found, the MoD driver will pick
10 her up; the route choice model will be activated, and the MoD will move towards the client
11 destination. If the MoD driver is cruising for too long, she will change her state to “do not
12 cruise,” else, she will go to her initial decision of whether to take a break.
13

14 In the case of a coordinated ride-hailing driver behavior framework, majority of the decisions are
15 taken out so that the driver cannot: (1) choose whether to cruise or not to cruise (2) choose to go
16 to a MoD stand, queue, and pick up a passenger there (3) choose to pick up passengers on the
17 street, or (4) choose her next zone to in which to cruise. On the interaction between the driver
18 and the MoD controller see Section 3.5. Note that traveler’s choices are not modeled in detail
19 and will be incorporated in future research.
20

21 **3.5 MoD Controller: the case of Automated MoD**

22 The model of Automated Mobility on Demand (AMoD) builds upon our previous work (5),
23 extended to handle new capabilities, for instance parking, handling single or shareable ride
24 requests, etc. An AMoD service consists of a fleet of *vehicles* and a *controller*. The interactions
25 between the user, the controller and the vehicles are depicted in Fig. 3. Users send *trip requests*
26 to the controller, which assigns them to vehicles in the form of *schedules*. The controller
27 computes and continuously updates a schedule for each vehicle, which dictates the sequence of
28 operations, i.e., pick-up, drop-off, etc., that the vehicle will perform. It is worth emphasizing the
29 main difference between MoD and AMoD services: the former are driven by the choices and the
30 experience of the drivers, while the latter are fully determined by a centralized controller and
31 vehicles follow the instructions given in the schedule.
32

33 **User requirements**

34 In the trip request, the user specifies *pick-up* and *drop-off* locations, *shareability*, indicating
35 whether the user is willing to share her ride with other users or not, *maximum waiting time* she is
36 willing to accept and the tolerated *delay* at arrival, i.e., the amount of additional delay she can
37 accept with respect to the minimum travel time possible. With the *tolerated delay*, the user
38 declares an upper bound of the delay she is willing to accept. In brief, we call *time constraints* of
39 a trip request its maximum waiting time and tolerated extra delay.
40

41 ****Figure 3: Interactions between agents in the model of AMoD service****
42
43

44 **Controller-Vehicle interaction**

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

- 1 • *Pick-up* a user; it includes the user-ID and the related trip-request containing all the user
- 2 requirements.
- 3 • *Drop-off* a user: similar to the pick-up command.
- 4 • *Cruise* to a certain zone.
- 5 • *Go to park* at a certain node.

6
7 The commands in a schedule can be arranged in any plausible order ensuring, for example, that a
8 drop-off for any user comes after the respective pick-up and that the number of passengers never
9 exceeds the number of seats available in the vehicle

10 **Schedule Computation**

11 The controller continuously collects request from users and periodically, i.e., every 10 seconds,
12 computes or updates vehicle schedules in order to match them. The controller computes feasible
13 schedules. A schedule is *feasible* if (i) all its pick-ups can be performed respecting the maximum
14 waiting time specified in the respective trip request and (ii) all its drop-offs can be performed
15 respecting the tolerated extra-time specified in the respective trip request. Note that if a feasible
16 schedule is updated inserting the pick-up and the drop-off of a new user, in order to ensure that
17 the new schedule is still feasible, not only we have to check that the time constraints of new user
18 are met, but we have also to consider that the insertion of the new pick-ups and drop-offs may
19 imply a detour for the vehicle that can delay the pick-up of the drop-offs of the passengers
20 previously inserted in the schedule, possibly violating their time constraints. If a modified
21 schedule is unfeasible, the modification is not accepted, i.e., the new passenger cannot be served
22 by that vehicle and the controller will attempt to match her to another vehicle. The controller is
23 able to handle both shareable and non-shareable requests. To do so, first the shareable requests
24 are matched to the available vehicles with some available seats, using the insertion heuristic
25 detailed in (5). Then, the controller matches the non-shareable requests with the closest empty
26 vehicles. Finally, updated schedules are sent to the vehicles.

27 28 29 30 **4 CASE STUDY: FROM TRADITIONAL TO AUTOMATED MOBILITY ON**

31 **DEMAND IN SINGAPORE**

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

41 **4.1 Model Estimation**

42 For the estimation of each of the driver decision dimensions, a GPS dataset collected from a
43 major MoD fleet operator in Singapore in 2013 was used. This data set contains more 25 million
44 records each day for a period of 30 days, and containing vehicle number, time, position and
45 service status data. MoD fleet size was fixed according to the information provided by the Land
46

1 Transport Authority in Singapore (19). The simulation is focused in reproducing MoD driver's
 2 behaviors in a typical working day in a city. MoD driver agents are identified by synthetic
 3 population generated for Singapore for 2012. Their start time of work and shift duration was
 4 modeled by fitting a distribution based on MoD GPS data, which was then used to determine
 5 each driver's starting time and shift duration. In Figure 4 (a) and (b) the distribution of shift
 6 duration and shift starting time, as obtained using the GPS traces, is presented (in blue).
 7 The specific behaviors of the traditional MoD drivers are modelled using a discrete-choice
 8 framework. Five are estimated, namely: (i) *Break Model*; (ii) *Cruising Model*; (iii) *Stand Choice*
 9 *Model*; (iv) *Zone Based Cruising Model*; and (v) *Route Choice Model*.

10
 11
 12 ****Figure 4: The distribution of (a) shift duration and (b) shift starting time****

13 14 15 ***Break Model***

16 The break model was estimated as a binary logit model estimating the probability of a MoD
 17 driver to take a break. A subsample of 39,831 observations taken from the GPS dataset were
 18 used for the model estimation. Table 1 shows the estimation results of the break model. The
 19 directions of the effects of all variables are theoretically consistent. 86% of breaks take place
 20 outside the CBD and 50% of the drivers take a break within 5 hours from their previous one.

21 22 ***Spatial Choice Model: Stand Choice***

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

29 30 ***Integrated Spatial Choice: Zone Based Cruising and Route Choice Model***

31 We estimated a multi-level decision model for the cruising zone selection and the route selection
 32 to reach the zone, using the nested logit formulation. The model was estimated by the sequential
 33 estimation procedure. At the upper level of this model, the probability to choose a specific zone
 34 to cruise in among all 1169 traffic zones, is estimated while at the lower level, a specific route to
 35 reach this zone is chosen. The data used were a subsample of 4000 observations taken from the
 36 GPS dataset. As the number of alternatives is very large, the ρ^2 is small as expected.
 37 Surprisingly, many highly visited cruise zones are not in the CBD. In fact, the most visited zone
 38 is outside the CBD with more than 1,580 pickups.

39 40 ***Cruise Choice Model***

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

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2 ****Table 1: The MoD driver behavior model estimates****

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

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10

11 ****Figure 5: The distribution of (a) cruising duration, and (b) queuing duration****

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14 **4.2 Study Area**

15 Our study was conducted using a representative synthetic population and network of Singapore.
 16 The total area of Singapore is 721.5 km² with a population of 5.3 million individuals in 2012
 17 (20). In Singapore, passengers make over 8 million trips on a daily basis with an average stop
 18 rate of 1.5 per individual. Singapore has a developed transportation system covering 3,356 km of
 19 roads which includes 10 expressways. The public transportation system consists of 15 MRT and
 20 LRT lines with a total of 124 subway stations (92 MRT stops and 32 LRT stops) and 728 bus
 21 lines spanning the island with a total of 4607 bus stops. The road network consists of 6220 nodes
 22 (intersections), 30585 segments (road sections with homogeneous geometry) and 14799 links
 23 (groups of one or more segments with similar properties). Singapore Island is divided into 1169
 24 Traffic Analysis Zones (TAZs).

25

26

27 **4.3 Experimental Design**

28 Two different scenarios are designed and simulated. We consider a “traditional MoD only”
 29 scenario where traditional MoD is operated for on-demand service delivery. The available modes
 30 are single occupancy car (Car), sharing with one extra passenger (Car Sharing 2), sharing with
 31 two extra passengers (Car Sharing 3), Private Bus, public Bus, Mass Rapid Transit (MRT),
 32 Motorcycle, Walk and traditional MoD. The modal availabilities are in accordance with our
 33 study area, which we describe in the following section. In the second scenario we introduce
 34 automated MoD, replacing traditional MoD service with two new modes: AMoD as a non-
 35 shared, driverless ride (AMoD), and AMoD as a shared ride (AMoD Pool), while the availability
 36 of all other modes from the base case scenario stays the same. We refer to this scenario as
 37 “AMoD only” scenario. In order to generate the demand for AMoD modes, given the absence of
 38 appropriate data, we assumed that individual preference towards AMoD is similar to that of
 39 MoD with some modifications. The first set of assumptions is that a single AMoD ride will be
 40 50% cheaper compared to MoD, and that a shared ride will be 30% cheaper than a single ride
 41 (21). We also implemented a distance-based additional in-vehicle travel time for the passengers
 42 who share the vehicle with other passengers (based on current Uber data). Furthermore, we have
 43 added the expected additional waiting time for the AMoD Pool rider. We conduct morning peak
 44 (6-10 am) simulations for each scenario in SimMobility using the Singapore network. The results
 45 are summarized in the following section. We also compare the impacts of fleet size and parking
 46 strategies for AMoD on network performance.

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5 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 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 other 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 significant reduction in PT mode share of more than 6%, with a shift towards 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 Car mode share.

****Figure 6: Mode share and demand profile during morning peak for (a) Traditional MOD and (b) Automated Mobility on Demand services****

Fig. 6 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 minutes cruising and 2 minutes queueing during the morning peak.

****Figure 7: MoD driver behavior during simulation****

In Fig. 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 10, 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. Comparing Figures 7c and 7d, 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 Fig 7c and 7d. Note that Fig. 7 counts the requests, pick-ups and drop-offs observed in each 5-minute interval. Obviously, not all the requests sent in a certain 5-minute interval are picked up and dropped off in the same interval, as they will be served later. The request-to-dropoff ratio is highest at about 8:00am and narrows down toward the end of the observed scenario. When the service is not well configured, e.g. with 36,000 vehicles and no parking, the number of requests served do not recover the number of requests sent, while using parking solves this problem.

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

1 In Figure 8 we compare driver behavior and fleet management between the “Traditional MoD
 2 only” and the “AMoD only” scenarios. Note that MoD vehicles are not parked or driven to a pre-
 3 specified location to pick up. Instead, passengers are picked up while hailing or waiting at the
 4 taxi stand. In the AMoD case, the fleet is more efficiently managed, as they are introduced
 5 incrementally, while MoD drivers are introduced according to their shift starting time. As the
 6 MoD shifts are set inefficiently, they spend a lot of time cruising. However, this inefficiency is
 7 greatly reduced towards the end of peak period.

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 10 ****Figure 9: Vehicle utilization profiles for “Traditional MoD only” (20,000 vehicles) and best-case
 11 “AMoD only” (45,000 vehicles) scenarios****

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 15 ****Figure 10: Waiting time (W) across automated on-demand modes for the different scenarios (in
 16 minutes). Avg Network-Wide W is the average W over buses, trains and MoD. Journey Time
 17 captures average travel time across all modes****

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 20 In Fig. 9 we report the impact on user-metrics of the different services, under different settings.
 21 Journey times (JT) do not include waiting times (W), which are represented separately. As
 22 expected, the shared requests experience higher waiting times. The increase in fleet size is
 23 clearly beneficial for non-shared requests, while its impact is less pronounced for the shared.
 24 This can be explained by the interest of the operator in decreasing the miles traveled: even if a
 25 large fleet is available, it will try to serve the shared requests with as few active vehicles as
 26 possible, as long as the user requirements are satisfied. This is reflected in the matching
 27 algorithm we have used (5). It is clear from Fig. 9 that the 45,000 AMoD fleet case is user-
 28 optimal. A limitation of the simulation framework at the time this experiment was carried out is
 29 that taxi waiting times are not given explicitly. However, as can be seen from the average
 30 journey times, similar levels of service are provided by both the AMoD and the traditional MoD
 31 cases. In Table 2, we compare average travel times and distances for passenger-vehicle trips for
 32 the two scenarios. These indicate that the overall patterns for single-passenger trips are largely
 33 unchanged. As expected, travel times for AMoD Pool are about 50% greater on average.

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 35
 36 ****Table 2: Average travel times and distances for passenger-vehicle trips in both scenarios****

37 38 39 **6 CONCLUSIONS**

40 We have demonstrated an agent-based simulation of daily activity patterns and movements in a
 41 dense urban network, using Singapore as a case study. Importantly, we have modeled in
 42 adequate fashion the behavior and movement of traditional mobility on demand services and
 43 compared comprehensively how this performs relative to the near-futuristic automated mobility
 44 on demand service. Our simulator – SimMobility – has enabled us to test the impacts on network
 45 performance of the user optimal automated case to the traditional case.

46

1 A key finding of this research is that a significant reduction in PT modes (12%) and a dramatic
 2 increase in mobility on-demand share (four times greater) are observed when AMoD services are
 3 offered as a substitute for traditional MoD services. Additionally, while demand for AMoD is
 4 over four times greater than that of traditional MoD, only about twice as many fleet are required
 5 to satisfy the increased demand levels. In the “traditional MoD only” case, there are 20,000 taxis
 6 available during the morning peak. For the “AMoD only” case, we employed simulation tests to
 7 obtain the user optimal fleet size of 45,000 for the same period, servicing 0.2 million trips (over
 8 5 times those of traditional MoD). This demonstrates that AMoD fleet are more efficiently
 9 managed compared to MoD fleet, and have the potential to improve urban mobility outcomes
 10 with the same level of service, at likely lower costs. We also show that when ridesharing is
 11 predominant, then fewer fleet can serve the demand just as efficiently.

12
 13 Our further avenues of research include quantifying the cost implications of AMoD
 14 implementation strategies and comparing their respective benefits. Given our capabilities to
 15 sufficiently model current Uber-like mobility-on-demand systems, we would like to further
 16 investigate driver behavior under today’s MoD frameworks.

17
 18 The differences in urban form and rates of technological and infrastructural development indicate
 19 that the introduction of AMoD services will have widely varying impacts. There are critical
 20 questions to be answered regarding its effects on congestion, parking and public transportation
 21 ridership. In order to better understand these future patterns, we are currently developing
 22 prototype cities representing distinct urban typologies. By simulating relevant scenarios in these
 23 prototype cities, we can further obtain insights into policy intersections for the best outcomes for
 24 AMoD service implementation.

25 26 **7 AUTHOR CONTRIBUTION STATEMENT**

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

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 41 anonymous reviewers for their time and attention in helping us to improve the quality of this
 42 manuscript.

43 44 **DISCLAIMER**

45 The contents of this report reflect the views of the authors who are responsible for the facts and
 46 accuracy of the data presented herein. The contents do not necessarily reflect the official views

1 or policies of Ministry of Transport (MoT), Land Transport Authority (LTA), Urban
 2 Redevelopment Authority (URA) and Housing Development Board (HDB) in Singapore.

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5 **Figure 2: Traditional MoD driver behavior framework**

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

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11 **Figure 5: The distribution of (a) cruising duration, and (b) queuing duration**

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13 **Figure 6: Mode share and demand profile during morning peak for (a) Traditional MOD and (b)**
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29 **List of table titles:**

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31 **Table 1: The MoD driver behavior model estimates**

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33 **Table 2: Average travel times and distances for passenger-vehicle trips in both scenarios**

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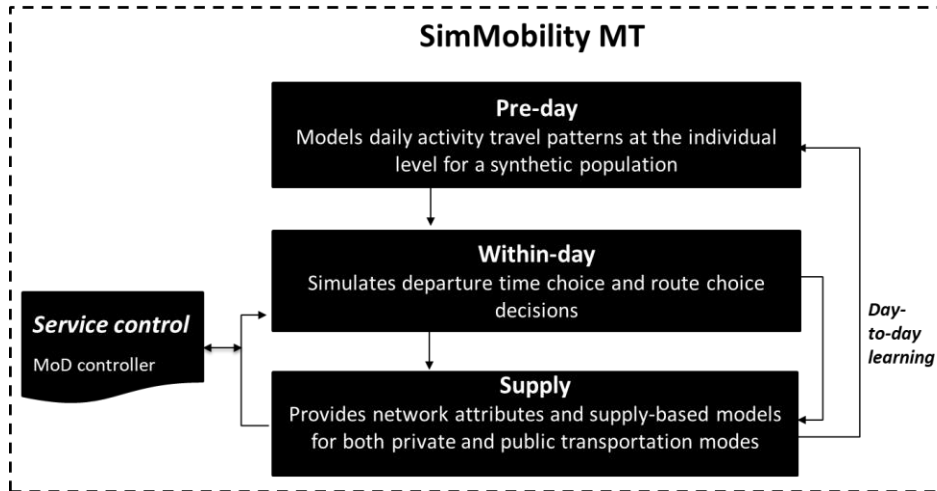


Figure 1: SimMobility MidTerm (MT) structure

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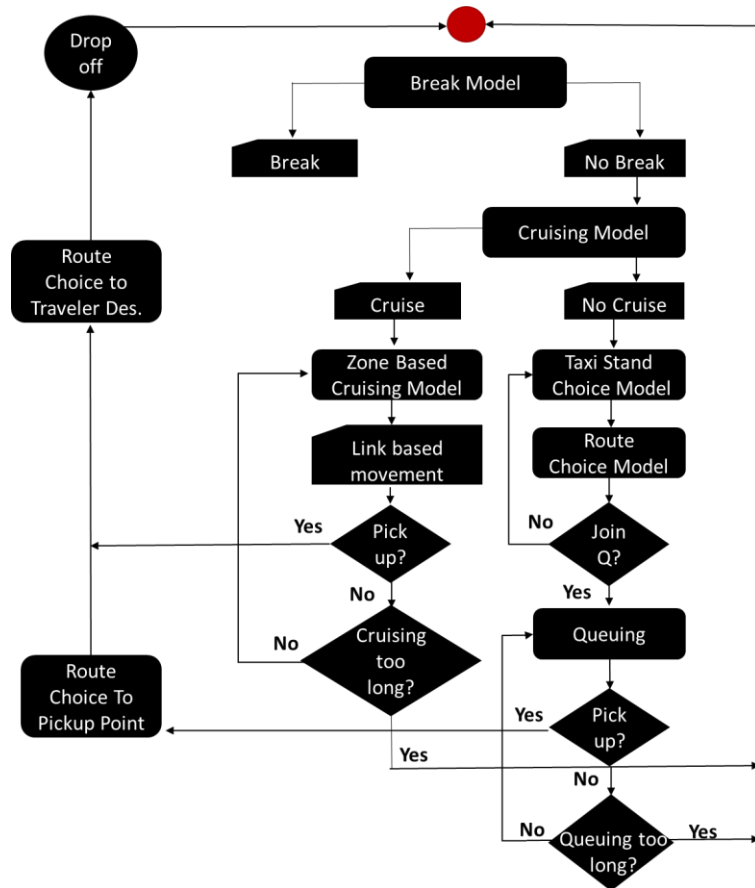
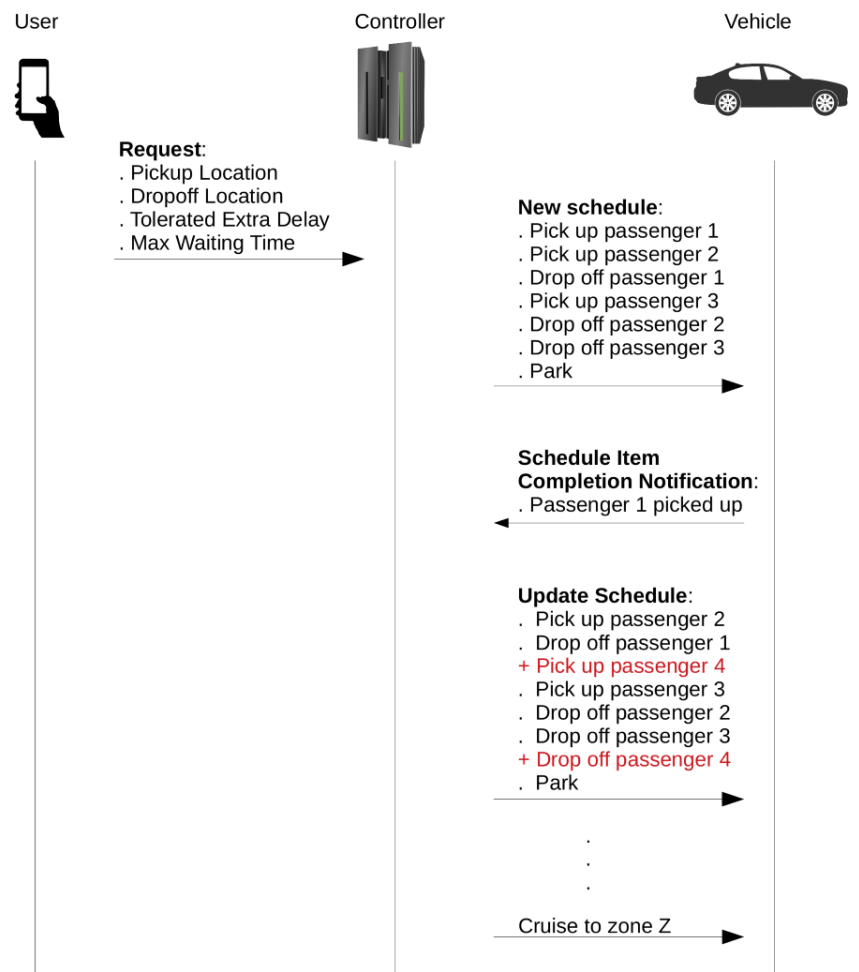


Figure 2: Traditional MoD driver behavior framework

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

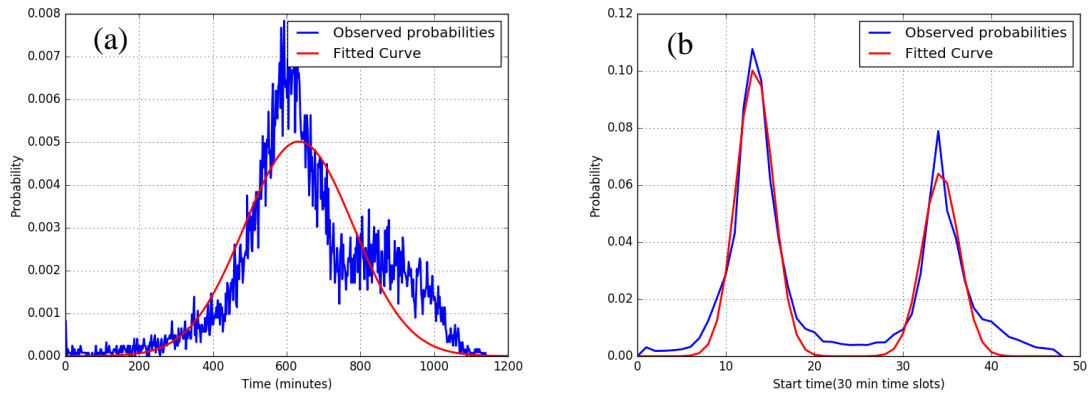


Figure 4: The distribution of (a) shift duration and (b) shift starting time

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1 **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 | $\mathcal{L}(0) = -27608.74$ |
| Travel cost to the nearest stand (SGD) | -0.473 | 0.0744 | -6.36 | $\mathcal{L}(\beta) = -14377.43$ |
| Time passed from the last break (hr) | 0.0633 | 0.00343 | 18.44 | $\rho^2 = 0.479$ |
| 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 | $\mathcal{L}(0) = -12254.165$ |
| Travel cost to the nearest stand (SGD) | -5.02 | 0.432 | -11.88 | $\mathcal{L}(\beta) = -5720.485$ |
| Time passed from the last break (hr) | 1.08 | 0.188 | -5.72 | $\rho^2 = 0.533$ |
| 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 | $\mathcal{L}(0) = -34924.773$ |
| Log scale parameter | 0.799 | 0.0102 | 78.6 | $\mathcal{L}(\beta) = -31192.34$ |
| Zone's area (km ²) | 2.38 | 0.175 | 13.59 | $\rho^2 = 0.107$ |
| Cruise choice model | | | | |
| Variable | Coefficient | Asymptotic st. error | t statistic | Summary statistics |
| Cruise constant | 0.639 | 0.0468 | 13.65 | Num. of observations = 13742 |
| Time left to the end of the shift (hr) | 0.0144 | 0.00436 | 3.31 | |
| In CBD dummy | -0.354 | 0.0541 | -6.53 | $\mathcal{L}(0) = -9525.229$ |
| Total pick up at the stand | -0.147 | 0.0403 | -3.64 | $\mathcal{L}(\beta) = -7624.537$ |
| 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 | |

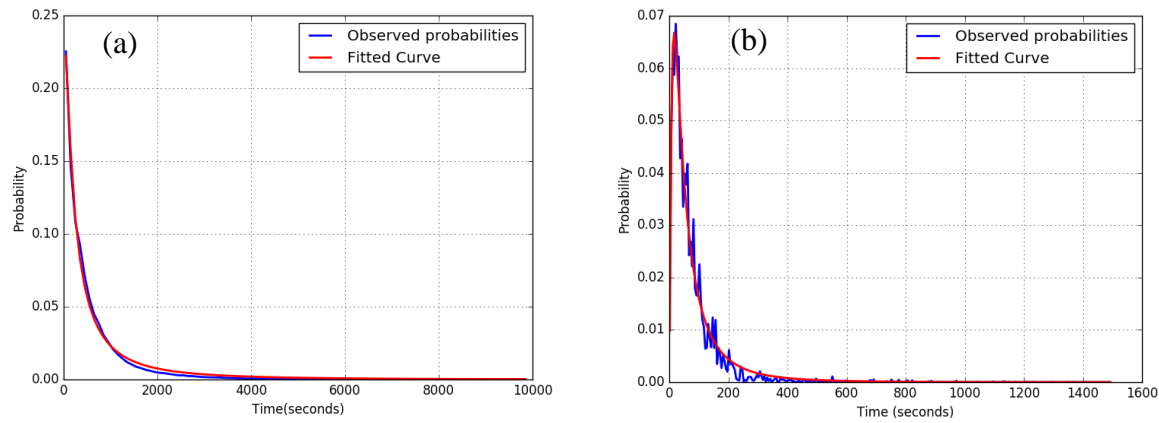


Figure 5: The distribution of (a) cruising duration, and (b) queuing duration

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1 **Figure 6: Mode share and demand profile during morning peak for (a) Traditional MOD and (b)**
 2 **Automated Mobility on Demand services**
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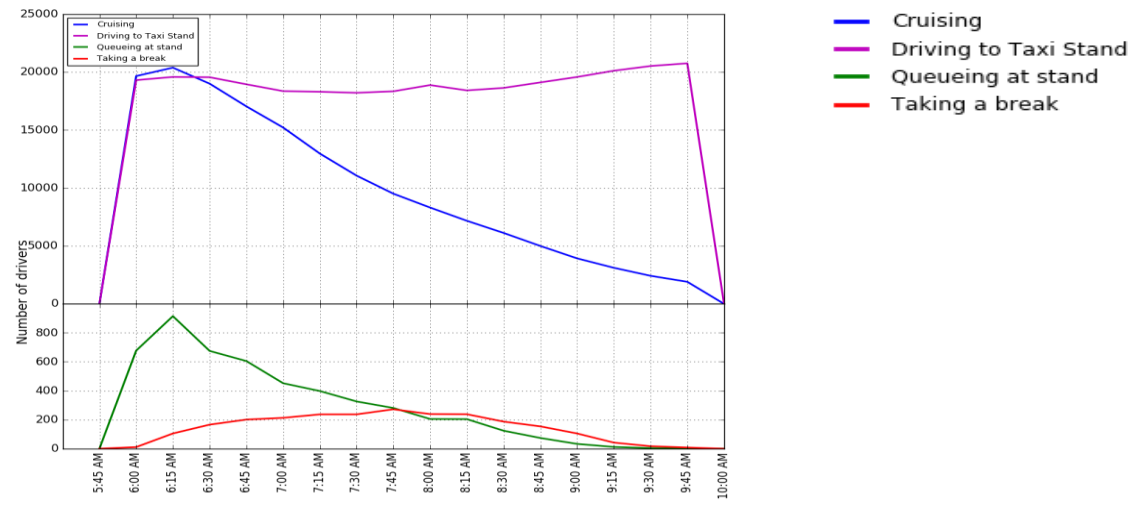
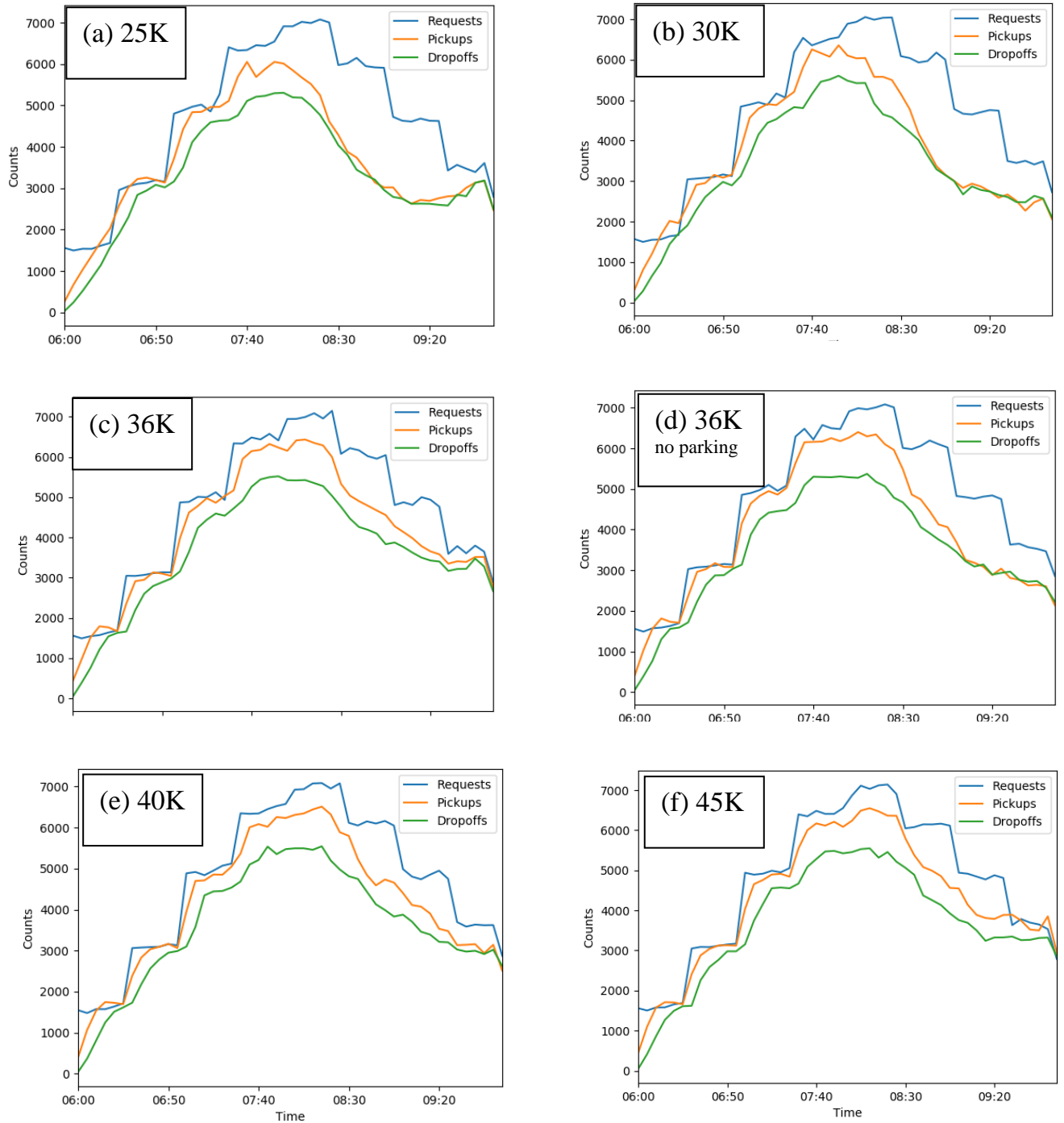


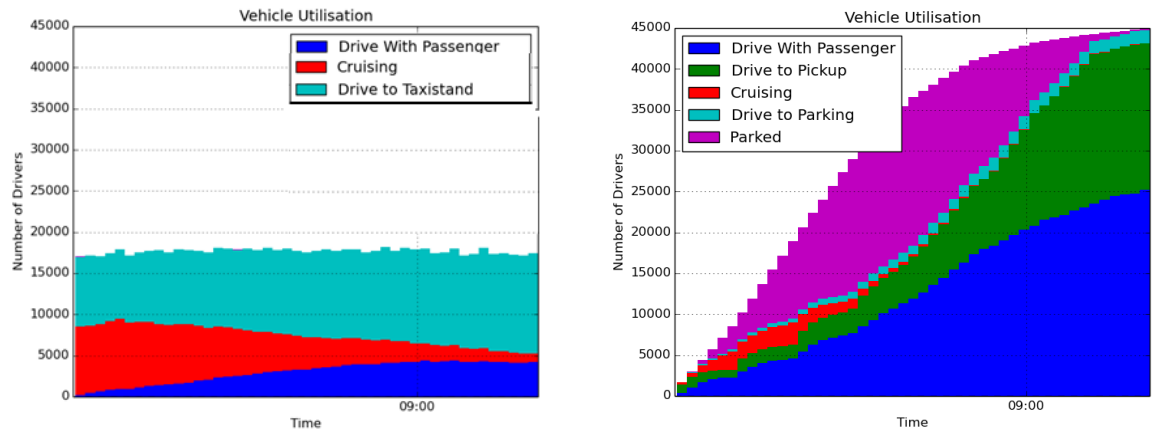
Figure 7: MoD driver behavior during simulation

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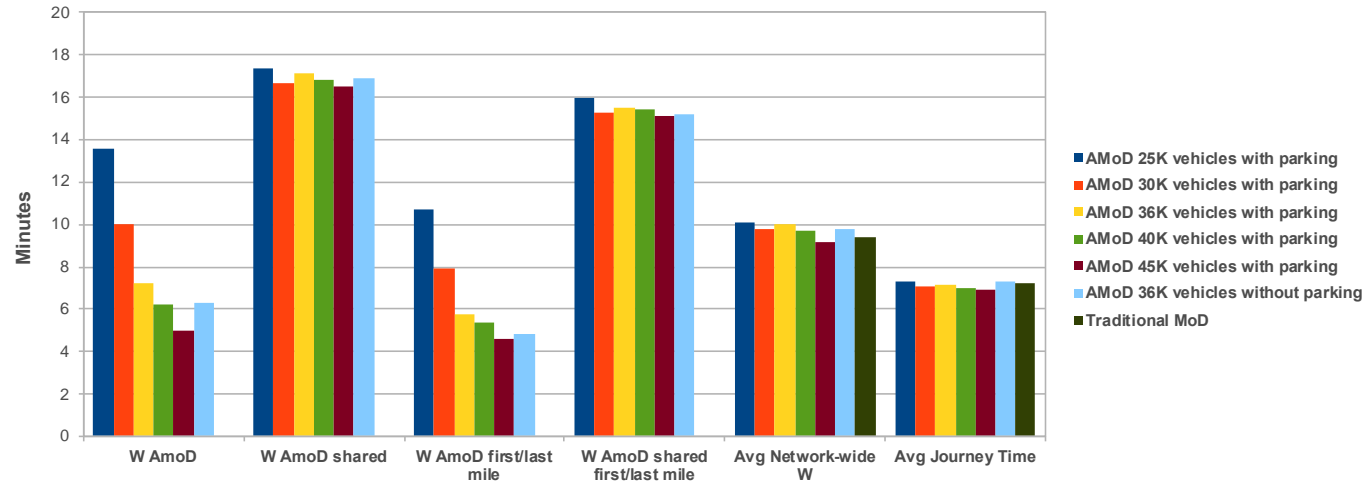
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Figure 8: Controller performance for AMOD service under various fleet size scenarios, all implemented with parking except (d).



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Figure 9: Vehicle utilization profiles for “Traditional MoD only” (20,000 vehicles) and best-case “AMoD only” (45,000 vehicles) scenarios



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Figure 10: Waiting time (W) across automated on-demand modes for the different scenarios (in minutes). Avg Network-Wide W is the average W over buses, trains and MoD. Journey Time captures average travel time across all modes.

1 **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 | - | - | - | - | 14.6 | 9.4 |
| AMoD | | | 13.2 | 8.0 | 20.3 | 13.7 | 15.6 | 10.0 |

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