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Assessing the Impacts of Automated Mobility-on-Demand through Agent-based Simulation: A Study of Singapore

Simon Oh\textsuperscript{a}, Ravi Seshadri\textsuperscript{a}, Carlos Lima Azevedo\textsuperscript{b}, Nishant Kumar\textsuperscript{a}, Kakali Basak\textsuperscript{a}, Moshe Ben-Akiva\textsuperscript{c}

\textsuperscript{a}Singapore-MIT Alliance for Research and Technology (SMART) 1 CREATE Way, #09-02 CREATE Tower, Singapore 138602
\textsuperscript{b}Department of Management Engineering, Technical University of Denmark, Kgs. Lyngby, 2800, Denmark
\textsuperscript{c}Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, Cambridge, MA 02139, United States

Abstract

The advent of autonomous vehicle technologies and the emergence of new ride-sourcing business models has spurred interest in Automated Mobility-on-Demand (AMOD) as a prospective solution to meet the challenges of urbanization. AMOD has the potential of providing a convenient, reliable and affordable mobility service through more competitive cost structures enabled by autonomy (relative to existing services) and more efficient centralized fleet operations. However, the short and medium-term impacts of AMOD are as yet uncertain. On the one hand, it has the potential to alleviate congestion through increased ride-sharing and reduced car-ownership, complementing mass-transit, etc. Conversely, AMOD may in fact worsen congestion due to induced demand, the cannibalization of public transit shares, and an increase in Vehicle-Kilometers Traveled because of rebalancing and empty trips. This study attempts to systematically examine the impacts of AMOD on transportation in Singapore through agent-based simulation, modeling demand, supply and their interactions explicitly. On the demand side, we utilize an activity-based model system, that draws on data from a novel smartphone-based stated preferences survey conducted in Singapore. On the supply side, we model the operations of the AMOD fleet (including the assignment of requests to vehicles and rebalancing) which are integrated within a multimodal mesoscopic traffic simulator. Comprehensive simulations are conducted using a model of Singapore for the year 2030 and yield insights into the impacts of AMOD in dense transit-dependent cities from the perspective of the transportation planner, fleet operator, and user. The findings have important policy implications that could potentially inform future deployments of AMOD.

Keywords: Automated Mobility-on-Demand (AMOD), Smart Mobility, Agent-based simulation, Activity-based model

1. Introduction

Urban mobility is in the midst of widespread changes, catalyzed by new business models of transportation networking companies (TNCs), electrification, connectivity, sharing and autonomy. The ride-sourcing mobility market has grown rapidly, penetrating 7-8% of the worldwide market while generating an estimated 44 billion USD in revenue in 2017 (OECD \textsuperscript{2018}, and is projected to double within the next five years (Statista \textsuperscript{2017}). This growth has
been attributed in part to low waiting and travel times, ease-of-use and convenience (Rayle et al., 2016; SFMTA, 2017). Concurrently, automated vehicle (AV) technology has been developing at breakneck speed with Waymo’s (formerly the Google self driving project) AVs clocking more than 10 million miles from 2008 to 2019, and numerous other car manufacturers also involved (Audi, BMW, Cadillac, Ford, GM, Mercedes-Benz, Nissan, Toyota, Volkswagen, and Volvo; Fagnant and Kockelman (2015)). Following the state of Nevada in 2011, more than 20 states have either passed legislation or authorized the testing of AVs on public roads (Shabanpour et al., 2018). Singapore, notably, has been at the forefront of AV deployment and the Ministry of Transport (MOT) and Land Transport Authority (LTA) have announced the introduction of pilot services of autonomous buses and on-demand shuttles in three districts by 2022. Moreover, the interest in studying the potential of AV solutions for Singapore was formalized by the MOT with the creation of the Committee on Autonomous Road Transport for Singapore (CARTS) in August 2014.

The convergence of these developments in the form of a system of on-demand shared driver-less taxis (hereafter Automated Mobility on Demand or AMOD) is likely to play a significant role in the future of urban mobility, in one way or another. Despite the plethora of foreseeable benefits that have been advocated —convenient, reliable and affordable mobility services through more competitive cost structures, improved efficiency through centralized fleet operations, improved safety and throughput, reduced parking, integration with transit— there is a large degree of uncertainty on the short, medium and long-term impacts of AMOD which could also lead to induced demand, the cannibalization of transit, increased Vehicle-Kilometers-Traveled (VKT) and dead heading. As a case in point, a recent white paper (Katherine Kortum, 2018) on preparing for automated vehicles and shared mobility identified critical research needs on the (unknown) impacts of AVs and shared mobility on transportation systems (including VKT, system capacity, transit, travel behaviour, and land use) as well as the requirements (infrastructure, operational configurations involving fleet management, AV deployment policy) to help inform policy makers.

In this context, the broad objective of this study is to examine the impacts of AMOD on transportation in Singapore, and contributes to the existing literature in the following respects. First, a systematic methodology is proposed to assess the future impacts of AMOD using activity– and agent– based simulation. It includes a) on the demand side, the use of data from a novel context-aware stated preferences survey on AMOD, b) on the supply side, modelling of the operations of the AMOD fleet including assignment of requests and re-balancing, and c) explicit modeling of demand and supply interactions. Second, comprehensive simulations are conducted using a model of Singapore in the year 2030 and yield insights into the impacts of AMOD in dense transit-dependent cities from the perspective of the transportation planner, fleet operator, and user.

2. Background

There is a growing body of research that focuses on behavioral preferences towards autonomous vehicles and AMOD, and assessment of impacts and potential of AMOD using agent-based simulation and optimization. In this review, we largely focus on the latter.

Early studies examined the potential of AMOD solutions to meet existing travel demand served by private vehicles. Burns et al. (2015) assessed a shared and driverless mobility system over different network configurations, including a mid-sized city (Ann Arbor, MI), a
low-density suburban development (Babcock Ranch, FL), and a large and densely-populated urban context (Manhattan, NY). The authors showed that fewer vehicles are required to accommodate existing private vehicle demand using AMOD. Spieser et al. (2014) reached similar conclusions by modeling the AMOD system using a spatial queuing theoretic network model to capture dynamic customer demand. They determined that a fleet size of around 300,000 vehicles (roughly one-third of the vehicle population) suffices to serve existing private vehicle demand in Singapore (in 2012) with maximum waiting times of less than 15 min.

Several studies have addressed operational problems pertaining to the deployment of AMOD and on-demand services, including the online and offline assignment of requests to vehicles and rebalancing. Santi et al. (2014) propose a method of shareability networks, which formulates the spatio-temporal sharing problem using a graph-theoretic framework. Simulations on a data set of New York city taxi trips indicate that the cumulative trip length can be reduced by 40% thorough ride-sharing. Vazifeh et al. (2018) build on the concept of shareability networks to address the minimum fleet problem, proposing a graph-theoretic solution approach. They show that a 30% reduction in fleet size can be achieved relative to existing taxi operations in New York city. Other approaches using linear and integer programming (Zhang and Pavone, 2016; Marczuk et al., 2016), graph theory (Alonso-Mora et al., 2017), and heuristics (Hyland and Mahmassani, 2018) have also been proposed for the assignment and re-balancing problems. The aforementioned studies do not consider behavioral impacts, network congestion and their interactions.

A second stream of work examines the impacts of AMOD in several different settings using agent-based simulation. Fagnant and Kockelman (2014) analysed the impacts of a shared non-electric AMOD fleet in a synthetic grid-type city roughly twice the size of Austin, Texas with an assumed AMOD mode share of 3.5% and temporal distribution of trips based on the NHTS, 2009. Simulation results suggest that each shared AV (SAV) has the ability to replace nearly 12 privately owned vehicles, serving between 31 and 41 travelers per day and eliminating up to 11 parking spaces per AMOD vehicle. Despite showing the potential benefits of the AMOD system, the study considers a stylized urban area, and does not model network congestion effects and demand-supply interactions. Boesch et al. (2016) determined the AV fleet sizes required to serve different levels of private vehicle demand in the greater Zurich region using the agent-based simulator MATSim (Horni et al., 2016). They found that the relationship between served demand and required fleet size is non-linear and the ratio increases as demand increases. Further, assuming waiting times of up to 10 minutes are acceptable, a reduction of up to 90% of the total vehicle fleet is possible even without rebalancing. Along similar lines, by extending MATSim with the dynamic vehicle routing problem (DVRP), Bischoff and Maciejewski (2016) indicate that 90000 to 100000 of autonomous taxis are required to serve 2.5 million inner-city trips to replace the 1.1 million private cars in Berlin. Maciejewski and Bischoff (2016) investigate congestion effects of autonomous taxis for the scaled-down scenarios over the different replacement rates of car trips (55K to 278K), fleet sizes (2.2K to 11K), and road capacity levels. More recently, Hörl et al. (2019) studied the performance of different fleet sizes and operational policies using demand for a synthetic Swiss population from the Zurich service region. The authors concluded that a fleet size of 7000 vehicles operating with a feed forward fluidic rebalancing algorithm is able to serve 90% of requests within a waiting time of 5 minutes.

In contrast with all of the aforementioned studies which ignore demand and supply inter-
action—network and service performance affect demand and vice-versa—a few researchers have attempted to model these interactions explicitly. Azevedo et al. (2016) assessed the sensitivity of AMoD fleet sizes and parking station configurations on individual mobility patterns, specifically with regard to modal shares, routes, and destinations. Basu et al. (2018) examine the potential of AMoD to replace mass transit on a synthetic city using agent- and activity-based simulation.

Several studies, again within the broad framework of agent-based simulation, have examined the integration of AVs with public transit (PT). Shen et al. (2018) design an integrated AV-PT system by re-purposing low-demand bus routes using the shared AV service while retaining the high-demand bus routes. Through the agent-based simulations, the authors conclude that only 17 (shared) and 22 (single) vehicles are required to replace 11 bus routes and that the integrated system would benefit both AV and PT operators. Wen et al. (2018) develop an agent-based simulation platform of the AMOD service and a discrete choice model of demand as two subproblems. An iterative feedback process is used to capture the interaction between the decisions of the service operator and those of the travelers.

In summary, despite the large body of work on the impacts of AVs and AMOD, several limitations remain in the literature. First, many studies make use of simplified abstractions of the urban region and network including grid type cities (Fagnant and Kockelman, 2014), Euclidean planes (Spieser et al., 2014), quasi-dynamic grid-based networks/roads (Zhang et al., 2015; Martinez and Viegas, 2017; Fagnant and Kockelman, 2018), synthetic grids (Hyland and Mahmassani, 2018), and synthetic cities (Basu et al., 2018). As noted by Boesch et al. (2016), this may be restrictive and insufficient in capturing the complex spatio-temporal characteristics of real transport demand. Second, almost all studies (with the exception of Boesch et al. (2016); Basu et al. (2018)) assume fixed network travel times (Spieser et al., 2014; Alonso-Mora et al., 2017; Fagnant and Kockelman, 2015; Burns et al., 2015; Zhang and Pavone, 2016; Boesch et al., 2016; Farhan and Chen, 2013) and do not explicitly model network congestion effects. This is crucial in accurately determining the impacts on network performance as well as the interactions with demand. Third, most studies do not explicitly capture behavioral responses to AMOD and assume that existing private vehicle demand is completely or partially substituted by AMOD (Burns et al., 2015; Boesch et al., 2016; Zhang and Pavone, 2016; Maciejewski and Bischoff, 2016; Bischoff and Maciejewski, 2016; Hori et al., 2019). Finally, only a few studies explicitly capture demand-supply interactions taking into account the complex relationship between travel times and waiting times, demand for AMOD, and fleet supply and operations.

This study attempts to address these gaps and derive insights into the impact of AMOD on transit dependent cities (in contrast with the auto dependent contexts typically studied in the literature) by explicitly modeling the demand for AMOD within an activity based framework that uses data from an SP survey on AMOD, and capturing demand-supply interactions.

3. Methodology

The systematic assessment of the impacts of AMOD necessitates a high-fidelity simulation environment with the capability of modeling individual decision making at a disaggregate level (activity participation, mode/departure-time/route choices), multimodal network performance, and operations of the new mobility services (such as existing mobility-on-demand (MOD) and future AMOD) including fleet management, assignment of requests to vehicles,
rebalancing, etc. For this, we employ SimMobility, an integrated agent- and activity-based simulation platform (Adnan et al., 2016).

SimMobility is comprised of three primary components operating at different temporal scales (Figure 1a), each consisting of numerous sub-models to simulate interactively the behavior within an urban system including passenger and freight transport. The Short-term model functions at the operational level: it simulates the movement of agents at a microscopic granularity of milliseconds. It synthesizes driving and travel behavior models, traffic control and management systems and also interacts with a communication simulator that models the impact of device-to-device communication (Azevedo et al., 2017). The Mid-term (day-to-day) simulator models daily transportation demand and supply for passengers and goods: it simulates agents behavior including their activity and travel patterns, and the movement of vehicles at a mesoscopic level (Lu et al., 2015). The Long-term (year-to-year) model captures land use and economic activity, with special emphasis on accessibility. It predicts the evolution of land use and property development and use, determines the associated life cycle decisions of agents, and accounts for interactions among individuals and firms (Zhu et al., 2018; Le et al., 2016; Zhu and Ferreira Jr., 2014).

In the simulation scenarios carried out as part of this study, we employ the SimMobility Mid-term simulator which takes as an input a synthetic population of individuals/households, land-use characteristics and road/public transit networks. SimMobility Mid-term models daily activity and mobility patterns through an activity-based demand model combined with a multimodal dynamic traffic assignment system. It consists of three modules: the Pre-day,
Within-day and Supply (see Figure 1b). The Pre-day module generates or simulates travel demand in the form of daily activity schedules for each individual in the population and is described in detail in Section 3.1. The Within-day module transforms the pre-day plans into actions and includes models of departure time choice, route choice and within-day re-scheduling. Finally, the Supply module simulates multimodal network performance including the operation of mobility-on-demand services. The network simulator is a mesoscopic traffic simulator that combines macroscopic traffic flow models with deterministic queuing theory. The simulation of on-demand services utilizes a smart mobility controller which is described in more detail in Section 3.2. Supply-demand interactions are modeled through the iterative day-to-day and within-day learning processes that are described in Section 3.3.

3.1. Demand

The Pre-day module is an activity-based model (ABM) system that adopts the Daily Activity Schedule approach [Ben-Akiva et al., 1996] to predict agents activity-travel schedule (plan) including: (1) Activity types and number, (2) Activity durations and time-of-day, (3) Activity locations, and (4) Modes. The Pre-day ABM is a system of hierarchical discrete choice models (logit and nested-logit) organized into three levels: the day-pattern level, the
tour level and the intermediate stop level, as shown in Figure 2. Bottom-level decisions are conditional on upper-level decisions and the levels are related through inclusive values (logsum or expected maximum utility) indicated by dashed lines. The inclusive values capture the sensitivity of activity and travel decisions modeled in higher levels of the hierarchy to the utility associated with conditional and as yet undetermined outcomes from lower level models.

The day pattern level (see Figure 2) includes models that predict the occurrence of tours and availability of intermediate stops for various purposes (work, education, shopping, and others). Primary activities are the anchors (e.g., home to work and work to home trips represent a tour with work as primary activity) of tours, and secondary activities are intermediate stops within a particular tour. The day pattern level generates a list of tours and availability of intermediate stops for each individual in the population. The models at the tour level add detailed information for each predicted tour including destination, travel mode, and time of day (arrival time and departure time). It also includes a model to predict the occurrence and characteristics of work-based sub-tours. Finally, the models at the intermediate stop level generate intermediate stops for each tour and then predict the destination, travel mode and timing of the stops for these secondary activities. A simulation of the ABM yields activity schedules for each individual in the population, including the timing (arrival time and departure time) of each activity at a resolution of 30 min, the destination at zonal level and the travel mode for each trip/tour.

Figure 3: Smart Mobility Service Controller

3.2. Supply

The Pre-day simulation, as described previously, generates activity schedules for each individual in the population. In the Within-day module, route choice, departure time choice and re-scheduling decisions in response to information or control are simulated based on the
plan-action framework (Ben-Akiva 2010). This yields trip-chains for each individual which are simulated on a multimodal network using the Supply module, which is a mesoscopic traffic simulator. The Supply module includes bus and rail controllers to manage public transit operations including the frequency/headway-based dispatching of vehicles, monitoring of occupancy, dwelling at stops and so on.

The Supply module is integrated with a Smart-Mobility Service Controller (SMS Controller hereafter) that models all aspects of on-demand services (including MOD, AMOD). The integrated framework allows for the definition of multiple instances of the SMS controller, each representing a specific operator that offers on-demand services of varying characteristics. The key features of the controller involve receiving ride-requests for single or shared taxi rides, assignment of vehicles to requests, dispatching and routing of vehicles, and rebalancing of vehicles when idle.

The concept of the SMS Controller is shown in Figure 3. The passenger sends a request to a specific on-demand service, specifying the intended pick-up and drop-off locations. The controller receives requests continuously, periodically processes these requests and assigns vehicles to them. In addition, the controller performs rebalancing actions for idle vehicles which could involve directing them to a parking location, or to cruise to a specified zone (such as a high demand area). The actions of the SMS Controller are relayed to the service vehicles in the form of updates to a schedule, which is maintained for each vehicle in the fleet at any point in time and consists of a sequence of schedule items. The schedule item could be one of the following types: pick-up, drop-off, cruise, park. Each schedule item contains relevant information such as locations for pick-ups, drop-offs, cruising and parking.

The assignment of requests to vehicles is performed using a simple heuristic. In order to maximize the extent of ride-sharing, the controller attempts to match shared-ride requests to vehicles that are already serving one or more requests and then to idle vehicles. This involves iterating through each of these vehicles and finding the first vehicle that can satisfy the incoming request while meeting certain constraints on waiting time and travel time of both the incoming request and existing requests that are being served by the vehicle. More specifically, for each vehicle, candidate schedules are created by inserting the pick-up and drop-off items of the incoming request within the existing schedule. If a candidate schedule is found that meets waiting time and travel time constraints of the incoming passenger and existing passenger(s), the schedule is deemed feasible and the request is assigned to the vehicle. The constraints are the following:

- The waiting time of all passengers already included in the schedule, as well as of the new passenger, must be below a certain threshold.
- For each passenger, we first estimate the minimum time that the passenger would spend for their trip if served as a single-ride. Next, we compute the estimate of their travel time as determined by the current schedule, which we call service time. The difference between service time and minimum time is the additional delay, which accounts for detours made for ride-sharing. The additional delay must be within a specified threshold.

Note that during the assignment process, candidate schedules are created considering vehicle capacity. The controller described in this section is an enhanced version of that presented in
3.3. Demand-Supply Interactions

As noted previously, demand supply interactions are explicitly modeled through the day-to-day and within-day learning mechanisms. The within-day learning component involves a feedback of time-dependent link travel times and public transit waiting times resulting in an iterative adjustment of route choice decisions until an equilibrium is attained. The day-to-day learning component involves a feedback of aggregate zone to zone travel times and waiting times (of both public transit and on-demand services) resulting in an iterative adjustment of travel and activity decisions of individuals until consistency is achieved.

4. Scenarios and Experimental Design

This section defines the simulation scenarios of interest and the performance measures for evaluation. The broad research focus is to examine the impacts of AMOD in Singapore in 2030. Performing scenario simulations for the year 2030 involves two key steps. First, a calibrated/validated base-year model is developed for Singapore in 2012. The parameters of interest to be calibrated include Pre-day model parameters on the demand side and traffic dynamics parameters, segment capacities on the supply side. The base year model is intended to reproduce travel and activity patterns, and network performance measures in Singapore for the year 2012 (refer Section 4.1). Second, a synthetic population, road and transit networks are developed for Singapore 2030. The Pre-day demand model for Singapore 2030 will be based on the calibrated model of 2012 which is extended to include the new modes of AMOD. The specification of the new modes in the mode and mode-destination choice models draws on data from a novel context-aware SP survey conducted on AMOD (refer Seshadri et al. (2019) for more details) involving 350 respondents and 2500 SP observations. The supply parameters of existing road segments from the calibrated 2012 model is utilized and suitable assumptions are made for the additional road segments (refer Section 4.2).

Following this, for each specific AMOD scenario, the simulation methodology involves two steps that utilize the SimMobility Mid-term model for Singapore 2030:

1. Generation of Daily Activity Schedule (DAS): The first step involves the generation of a detailed travel and activity pattern for each agent in the synthetic population using the Pre-day module. The set of patterns for the entire population is termed the daily activity schedule.

2. Simulation of Network and Fleet Performance: The second step is the simulation of network performance given the input DAS using the Within-day and Supply modules. Several iterations of Within-day and Supply are performed to obtain consistency in link travel times. As discussed in Section 3.3, performance measures (such as network travel times, public transit travel, and waiting times for on-demand services) will impact the travel/activity patterns computed at Pre-day level and hence several iterations (Day-to-day learning in Figure 1b) are performed between step 1 and 2 until consistency is achieved. Further, the fleet size for AMOD and on-demand modes (MOD services) are not assumed to be exogenous but are determined for each scenario by suitable trading off vehicle utilization during the peak period with average waiting times (refer Section 4.3.3).
4.1. Singapore 2012 Model

The Singapore 2012 model was developed using several data sources that include: (1) Land-use data, including residential buildings, firm and school locations and associated characteristics, (2) Household Interview Travel Survey (HITS) for 2008 and 2012 (from the Land Transport Authority or LTA), (3) Three months of detailed GPS traces from a taxi fleet of 15,000 vehicles (ComfortDelGro), (4) Three months of public transport smart-card data (called EZ-link) with tap-ins/outs for buses and rail (called MRT), (5) Google transit network data for the bus routes and schedules (LTA), (6) Road network data (LTA), and (7) Traffic count data from 54 screenlines/cordons across the island.

A synthetic population of 5.2 million individual travelers was generated for the entire island using a hierarchical iterative proportional fitting method (for further details on the population generation process, see Zhu and Ferreira Jr (2014)). HITS data of 2008 was used for Pre-day model estimation (refer SIYU (2015) for more details) and the estimated model was calibrated and validated using the HITS 2012 dataset. The number of tours performed, aggregate trip mode shares and trips by time of day are compared against the observed values from HITS 2012 in Figure 4 and indicate that the model replicates well existing travel patterns in terms of number of tours, mode shares and time-of-day patterns.

Parameters on the supply side including segment capacities and traffic dynamics parameters were also calibrated using screen-line count data across 50 locations provided by LTA and zone-to-zone travel times obtained from taxi GPS data. The daily total simulated counts are compared against observed values for different periods in Figure 5.
4.2. Singapore 2030 Model

In order to simulate future scenarios for the year 2030, a synthetic population of around 6.7 million was generated for the year 2030 using aggregate control totals (dwelling units, jobs, and educational enrollment) at the zonal (TAZ) level provided by the LTA. A Bayesian network approach was used for the population synthesis (Sun and Erath, 2015). The spatial distribution of population and employment are shown in Figure 6 and the distribution of income, age and demographic category are summarized in Figure 7.

As noted previously, for the estimation of 2030 scenarios, on the demand side, the cali-
brated/validated \textit{Pre-day} model for the year 2012 needs to be modified to reflect the availability of the new AMOD modes, specifically in the mode-choice and mode-destination choice models. For this, we start by assuming a similar specification for AMOD modes as that of the on-demand modes. The alternative specific constants (ASCs) and willingness-to-pay of AMOD modes are then tuned so that the proportion of AMOD mode shares to Rail shares is similar to that predicted by the estimated mode choice model on the weighted SP sample \cite{Seshadri2019} under different pricing assumptions (along the lines of \cite{Glerum2013}). The resulting mode shares under the different pricing scenarios are discussed in Section \ref{sec:results}. The SP model suggests a higher inclination to use AMOD than existing on-demand services/taxis, other factors being the same. Hence, we refer to this scenario as a \textit{high adoption} scenario. We also consider a second scenario, termed \textit{moderate adoption}, where the ASCs of the AMOD modes are in-between that of the previously determined values (high adoption case) and those of the on-demand modes (MOD).

The Singapore 2030 road and transit networks were provided by the LTA and are shown in Figure \ref{fig:network}; highways are indicated in black, urban arterials and local roads in grey, and transit lines for the rail system (MRT) in different colors. The entire network consists of 1,169 traffic analysis zones, 6,375 nodes, 15,128 links, 730 bus lines (both directions), 4,813

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig7.png}
\caption{Demographic Characteristics of the Singapore 2030 Synthetic Population}
\end{figure}
stops, 26 MRT lines (both directions) and 186 stations (429 platforms), and 2,205 parking facilities. Segment capacities and traffic dynamics parameters were set using the calibrated 2012 model for existing road and HCM values (Manual, 2000) were adopted for new roads. Finally, background freight traffic from a detailed freight model were used in all simulations (Sakai et al., 2019).

4.3. Scenarios and Performance Measures

The overall framework of the scenario simulations are depicted in Figure 9. We consider a baseline scenario which represents Singapore 2030 with existing modes and a series AMOD scenarios where AMOD is introduced both to serve door-to-door trips and public...
transit access/egress trips (refer Section 4.3.1). The AMOD scenarios include high and moderate adoption cases and each of these is considered under three different AMOD pricing assumptions (refer Section 4.3.2). Fleet definition and sizing is discussed in Section 4.3.3.

### 4.3.1. Mode Availability

The baseline scenario consists of all existing modes which are Car, Car-pooling (within a household with occupancy of 2 and 3), Bus (access/egress by walk), Rail (access/egress by walk), Private bus, Taxi, MOD Single/Shared, and Walk. In addition to the existing modes, AMOD scenarios include the four AMOD modes which provide both point-to-point services and first/last-mile connectivity to public transport. Table 1 summarizes the mode availability over the different scenarios.

**Table 1: Mode Availabilities**

<table>
<thead>
<tr>
<th>Mode</th>
<th>Access/egress</th>
<th>Baseline</th>
<th>AMOD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private</td>
<td>Car (Drive alone)</td>
<td>-</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Carpool (2)</td>
<td>-</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>Carpool (3)</td>
<td>-</td>
<td>✓</td>
</tr>
<tr>
<td>Public Transit (PT)</td>
<td>Bus</td>
<td>Walk</td>
<td>✓</td>
</tr>
<tr>
<td>Rail (MRT)</td>
<td>Walk</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>MOD Single</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>MOD Shared</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>AMOD Single</td>
<td>X</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>AMOD Shared</td>
<td>X</td>
<td>✓</td>
</tr>
<tr>
<td>Taxi</td>
<td>-</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>On-demand</td>
<td>MOD Single</td>
<td>-</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>MOD Shared</td>
<td>-</td>
<td>✓</td>
</tr>
<tr>
<td></td>
<td>AMOD Single</td>
<td>-</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>AMOD Shared</td>
<td>-</td>
<td>X</td>
</tr>
<tr>
<td>Walk</td>
<td>-</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Others</td>
<td>Private bus</td>
<td>-</td>
<td>✓</td>
</tr>
</tbody>
</table>

### 4.3.2. Pricing

A key factor that affects the uptake of AMOD is price; we consider three pricing scenarios where the AMOD single-ride fare is 75%, 100% and 125% that of existing taxis [Spieser et al. (2014) suggest costs could be up to 50%, although we adopt more conservative estimates]. The price of a shared AMOD taxi is assumed to be 75% that of a single-ride AMOD taxi. The fares of the traditional taxis and on-demand services are summarized in Table 2.

**Table 2: Taxi and MOD Fares**

<table>
<thead>
<tr>
<th>Fare Type</th>
<th>Taxi</th>
<th>Mobility On Demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Fare (SGD)</td>
<td>3.20</td>
<td>2.50</td>
</tr>
<tr>
<td>Per-km fare (SGD)</td>
<td>0.55 (&lt;10 km)</td>
<td>0.63 (&gt;10 km)</td>
</tr>
<tr>
<td>Per-min fare (SGD)</td>
<td>0.29</td>
<td></td>
</tr>
</tbody>
</table>
4.3.3. Fleet Sizing

The fleet size and composition are important characteristics that affect performance of the AMOD service (in terms of waiting times and travel times, request satisfaction rates etc.) as well as demand for AMOD. In order to determine an appropriate fleet size for each scenario, we first determine a candidate set of fleet sizes (procedure discussed subsequently) and then select a suitable value from this candidate set by examining average waiting times and fleet utilization from the simulations (note that for each scenario and candidate fleet size several day-to-day and within-day iterations have to be carried out as described in Section 3.3). More specifically, we attempt to ensure that utilization is close to 100% during the peak period, request satisfaction rates are close to 100% and waiting times are sufficiently low (see Section 5.3). The determination of candidate fleet sizes is discussed next. The fleet of AMOD vehicles is assumed to consist of a combination of 4-seaters and 6-seaters.

Recall that the demand from the pre-day module is in the form of a daily-activity schedule which includes spatio-temporal details of the demand pattern at a resolution of 30 minutes, including the origin/destination/mode for each trips, tour/stop type, expected departure/arrival time, activity start/end time. In order to obtain a preliminary estimate of required fleet size, first, we extract demand specific to the AMOD modes (denoted by $m$) along with the associated trip lengths (denoted by $D_{m,t,k}$, where $t$ denotes the time interval and $k$ denotes the trip index). The total distance of all trips by AMOD mode $m$ in interval $t$ is simply,

$$TD_{m,t} = \sum_{k} D_{m,t,k}, m \in M, t \in T$$

(1)

Assuming that each AMOD vehicle serves $s$ trips during the day with an average distance of $d$ km, an initial estimate ($FS$) of the required fleet size is expressed as:

$$FS(\alpha_m, \beta_m) = \sum_{t}^{T} \sum_{m}^{M} \frac{TD_{m,t} \ast \frac{1}{\alpha_m \ast \beta_m}}, 1 \leq \alpha_m \leq C_v, 1 \leq \beta_m \leq 1.5$$

(2)

where $\alpha_m$ represents the average occupancy and $\beta_m$ is a factor that captures the reduction in vehicle kilometres travelled due to sharing, $C_v$ is the maximum vehicle capacity. Using estimates of $d$ and $s$ based on the operations of existing taxis in Singapore, $s = 17$, $d = 10km$ (Land Transport Authority), preliminary simulations indicated that values of $\alpha_m^* = 2.9$, $\beta_m^* = 1.25$ yield a high request satisfaction rate and utilization. The corresponding fleet size (with $\alpha_m^* = 2.9$, $\beta_m^* = 1.25$) is termed $FS_0$ which is scenario specific and a function of the demand for the AMOD modes. Four candidate fleet sizes are considered for each scenario which are set as $1.3FS_0, FS_0, 0.7FS_0$ and $FS(C_v, 1.5)$.

4.3.4. Performance Measures

The various simulation scenarios are evaluated using several performance measures classified into: (1) Demand patterns, (2) Network performance, and (3) AMOD Service metrics. Demand patterns are characterized in terms of mode shares and mode shifts (between baseline and AMOD scenarios). Network performance is characterized using vehicle-kilometers traveled (VKT), average trip speeds, and a distance weighted travel time index or TTI (the ratio of congested to free-flow travel times). The AMOD service metrics include request satisfaction rates, vehicle utilization (measured as the percentage of occupied, idled vehicles), and average waiting times.
5. Results and Discussion

The results from the simulation of the various scenarios are discussed in three parts, demand patterns, network performance and AMOD service metrics.

5.1. Demand Patterns

The overall trip mode shares are summarized in Figure 10 for the two adoption scenarios. In the case of moderate adoption, the results indicate that the mode share of AMOD (single-ride and shared) varies from 5.8% to 8.9% as the price reduces from 125% to 75% of taxis. The extent of shared rides compared to single rides for the AMOD modes is significantly higher than that of MOD (existing on-demand services). Further, the shares of transit with AMOD access/egress ranges from 1.6 to 2.3% which is in-line with current figures from ride-hailing services which suggest that around 25% of all on-demand trips begin or end at an MRT station in Singapore. Figure 11b shows the mode shifts from the base scenario to the AMOD scenario (for the 75% pricing case) and suggests that a large proportion of trips made by AMOD are shifts from transit (both bus and rail (MRT)). This implies that the cannibalization of transit, as is already being observed in several cities worldwide, is a likely outcome with the introduction of AMOD too. Overall, transit trips decrease by around 7.9% (percentage change in the mode share) and on-demand trips increase by a massive 83% with the introduction of AMOD. The extent of shifts from private vehicle modes to AMOD are significantly smaller although car trips do decrease by around 8%. The amount of induced demand due to the introduction of AMOD is quite small (< 0.1%) which is surprising, suggesting that the latent demand that can be served by AMOD is minimal.

Figure 10: Mode Shares: (a) High Adoption (left), (b) Moderate Adoption (right)
The results in terms of mode shares and shifts for the high adoption case are shown in Figures 10a and 11a respectively and are even starker with regard to the cannibalization of transit. AMOD modes shares are significantly higher than existing taxi/on-demand services and range from 11.9% to 18.8% as the price reduces from 125% to 75% of taxi. Transit trips decrease by around 24.8% and on-demand trips increase by 183%. The reduction in car trips is higher than the moderate adoption scenario at 20.2%, although it should be pointed out that in terms of absolute number of trips, the shifts from transit are far higher. The results also suggest that the shifts from transit occur across the island and can be observed in both zones with relatively lower transit accessibility and zones with higher transit accessibility. This suggests that the shifts to AMOD are likely due to the convenience offered by a door-to-door services and potentially the high inclination towards trying new technologies such as AVs.

![Figure 11: Mode Shifts](image)

(a) High Adoption  
(b) Moderate Adoption

In summary, a key finding from the analysis of demand patterns is that the unrestricted introduction of AMOD is likely to cause a significant cannibalization of public transit demand, which potentially can be mitigated through policies to improve AMOD transit integration such as discounts for trips that end in rail stations, pricing and more limited area-wide deployments. We would like to also point out two caveats to these findings. First, surge pricing is not modelled, and it is assumed that there is a sufficient fleet to meet the demand for AMOD. As described in Section 5.3 an optimal fleet size is computed that suitably trades off vehicle utilization with passenger waiting times. If the AMOD fleet is exogenously capped and surge pricing is introduced, this will naturally reduce the demand for AMOD during the peak periods. Second, there are no limits imposed on the overall vehicle population which is allowed to increase from the baseline to the AMOD scenarios. An additional scenario is therefore simulated where the vehicle population is capped and hence, the number of private vehicles is reduced by an amount equal to the AMOD fleet size required for the specific
scenario (results from this scenario are discussed in the next subsection). This is in line with the zero-vehicle growth policy of the Singapore government enforced through the COEs (Certificate of Entitlement).

5.2. Network Performance

The impacts on demand patterns suggest that the number of vehicle trips or vehicle mileage increases considerably. This is corroborated by results from the Supply module which yields detailed information of individual vehicle trajectories as well as segment level speeds, flows and densities. Figure 12 shows the total vehicle-kilometers traveled (VKT) by private and on-demand service vehicles for the three pricing scenarios in the moderate and high adoption cases. The results indicate a significant increase in VKT between 11 and 17% even in the moderate adoption scenario. A significant proportion of AMOD VKT (around 20%) is due to the empty trips that are required for AMOD operations (labelled AMOD_OP). This is despite the fact that AMOD vehicles are assumed to be directed to the nearest parking station after completing a trip. However, it should be noted that AMOD VKT does depend on fleet operational algorithms which can potentially improve the extent of sharing and reduce VKT. The increase in VKT is even more severe in the high adoption case as expected and ranges between 25 and 42%. The decrease in private car VKT is 8.8% and 20.2% in the two scenarios for the 75% pricing case.

The significant increase in VKT, as expected, results in an increase in network congestion and is reflected in the travel time index (distance weighted) which is plotted in Figure 13. In the moderate adoption case, the average TTI in the morning peak increases significantly by around 14% (for the 75% pricing scenario) over the base scenarios. Over the entire day (Figure 14), the average TTI increases by around 5.7% (from 1.41 to 1.49) which is partially mitigated at higher AMOD prices. In the high adoption scenario, the congestion impacts are
far more severe with an increase of almost 28% in the morning peak (75% pricing). Moreover, the significant gridlock results in an increase in the duration of peak period congestion which does not completely dissipate even in the off-peak.

![Figure 13: Distance Weighted Travel Time Index (TTI) by time of day](image)

Figure 13: Distance Weighted Travel Time Index (TTI) by time of day

![Figure 14: Average Distance Weighted Travel Time Index (TTI)](image)

Figure 14: Average Distance Weighted Travel Time Index (TTI)

Similar patterns of network congestion are observed in the average trip speeds (Figure 15), which decrease by almost 10% from the baseline to the AMOD scenario (75% pricing in the moderate adoption case). As mentioned with TTI, in the high adoption case, the increase in duration of peak period congestion is observed which does not dissipate in the off-peak period.

As noted previously, the above scenarios assume that the overall vehicle population is not capped. In line with current Singapore policy, we re-simulate the 125% pricing and moderate adoption scenario, assuming that the private vehicle population is reduced by 27000 vehicles (which is the optimal AMOD fleet size determined for this scenario). This ensures that the total vehicle population does not increase with the introduction of AMOD. The results show that the VKT increase is in fact mitigated (11% to 7.75%; Figure 16a), although there is still an increase in VKT relative to the base scenario. However, clearly, the COEs can be
effectively used to curb the increases in VKT observed with the introduction of AMOD. Comparing the with and without COE cases in terms of TTI and trip speed (Figures 16b and 16c), we observe that the decrease in VKT with COE contributes towards mitigating congestion (7.6% increase in TTI; 5.5% decrease in trip speed during the peak).

5.3. Service Metrics
This section focuses on performance metrics from the operator and user standpoints. We first describe the approach adopted to determine AMOD fleet sizes for each simulation scenario. This involves first identifying several candidate fleet sizes based on the scenario specific demand for AMOD (refer Section 4.3.3). For each candidate fleet size, after consistency has been achieved by through several iterations of the demand and supply, we examine vehicle utilization rates, request satisfaction rates and average waiting times.
The average wait times and vehicle utilization rates are shown in Figure 17 for an arbitrary scenario (100% pricing in the moderate adoption case). In this case, the four fleet sizes are considered (FS1=43,800, FS2=33,700, FS3=23,600, FS4=20,200) based on our initial estimates derived from Eq. (2) (refer Section 4.3.3). As can be seen, the smaller fleet sizes (FS3, FS4) yield large average wait times and completely utilized fleet during the morning and evening peak periods. On the other hands, the largest fleet size (FS1) shows a very low utilization rate (75%) even during the morning peak and moreover, does not yield a significant improvement in average wait times compared to FS2. Thus, in this scenario, the fleet size is set to be FS2 (33,700) which shows sufficiently low waiting times while maintaining a reasonably high fleet utilization. It is noted that in all cases the request satisfaction rate is close to 100%.

![Figure 17: Fleet Sizing](image)

(a) Average Waiting Times  
(b) Fleet Utilization

The approach described previously is applied to determine the fleet sizes for each simulation scenario. These fleet sizes are summarized in Table 3 for the MA case and indicates that the fleet sizes are required to satisfy AMOD demand range from 27,500 to 43,200 as the price varies from 125% to 75%. The request satisfaction rates are close to 100% and the small percentage of un-served demand arise from the waiting time constraints. In addition, it is noted that the existing MOD fleet size varies from 20,000 to 22,000 for the three scenarios, implying that the total size of the on-demand fleet exceeds that of the existing Private Hire Car (PHC) fleet in Singapore. In the high adoption scenario, the corresponding fleet sizes range from 48,000 to 80,000 although the number of un-served requests is larger due to network congestion.

<table>
<thead>
<tr>
<th>Price</th>
<th>Fleet Size</th>
<th>Requests</th>
<th>Assignments</th>
<th>Satisfaction Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>75%</td>
<td>43,200</td>
<td>891,135</td>
<td>883,882</td>
<td>99.01</td>
</tr>
<tr>
<td>100%</td>
<td>33,700</td>
<td>708,997</td>
<td>704,291</td>
<td>99.21</td>
</tr>
<tr>
<td>125%</td>
<td>27,500</td>
<td>584,548</td>
<td>580,645</td>
<td>99.21</td>
</tr>
</tbody>
</table>

The fleet utilization rates for the moderate adoption scenarios are summarized in Figure 21.
and show that in all cases a utilization of close to 100% is achieved during the morning peak period.

Figure 18: Fleet Utilization: Moderate Adoption

As noted previously, the AMOD fleet is assumed to be composed of 4- and 6-seaters implying that up to six rides can be matched in a single vehicle. Table 4 summarizes the extent of sharing achieved in the moderate adoption case. For example, under the 75% pricing case 41,147 trips have a sharing of 3, which implies that for 41,147 shared AMOD trips, the maximum vehicle occupancy at any point during these trips was 3. The results show that around 35-42.4% of all shared rides are served by a single vehicle with no matching possible. This is an outcome of both the matching heuristic, the rebalancing strategy (both of which can be potentially improved) and the spatiotemporal distribution of demand. At higher demand levels (75% pricing) the extent of sharing achieved is larger as expected. Moreover, the percentage of trips wherein a sharing of 4 is achieved is the highest, likely due to the fleet composition mix (70% of 4-seaters) and an increase in the fleet of 6-seater AVs potentially would increase the percentage of trips where a sharing of 5 and 6 is achieved. In summary, the extent of sharing does appear promising and underscores the potential of ride-sharing with up to 65% of the AMOD shared demand being shared in actuality.

Finally, from the standpoint of the user, the average waiting times for single and shared ride of AMOD service by time of day are shown in Figure 19; the average over the entire 24 hours ranges between 5.3-5.5 min and 5.8-6.2 min respectively for the different pricing
<table>
<thead>
<tr>
<th>Price</th>
<th>Single rides</th>
<th>Shared rides and %</th>
</tr>
</thead>
<tbody>
<tr>
<td>75%</td>
<td>434,565</td>
<td>152,084 31,144 41,147 152,994 19,163 38,477</td>
</tr>
<tr>
<td></td>
<td></td>
<td>35.00% 7.20% 9.50% 35.20% 4.40% 8.80%</td>
</tr>
<tr>
<td>100%</td>
<td>347,221</td>
<td>136,335 27,643 34,962 111,407 14,800 23,524</td>
</tr>
<tr>
<td></td>
<td></td>
<td>39.10% 7.90% 10.00% 32.00% 4.20% 6.70%</td>
</tr>
<tr>
<td>125%</td>
<td>284,377</td>
<td>122,998 24,366 30,098 84,882 11,306 16,636</td>
</tr>
<tr>
<td></td>
<td></td>
<td>42.40% 8.40% 10.40% 29.20% 3.90% 5.70</td>
</tr>
</tbody>
</table>

(a) AMOD Single rides
(b) AMOD Shared rides

Figure 19: Average Waiting Times

strategies in the moderation adoption case.

6. Conclusions

This paper assessed the impacts of AMOD on the transportation system in Singapore using activity- and agent-based simulation. The microsimulation platform included activity-based model which incorporated data from a novel SP survey on AMOD, a detailed model of the operations of the on-demand services and demand-supply interactions. Comprehensive simulations over a range of scenarios for the year 2030 (involving up to 9 million daily trips and over 1 million on-demand trips) yielded the following insights:

- AMOD use is likely to be higher than that of existing taxi/MOD services (even at comparable prices) with a substantial proportion of users (using the new modes) shifting from public transit. In the moderate adoption scenario, public transit ridership declines by roughly 8%. The cannibalization of transit can be mitigated partially by pricing and measures of integration of transit with AMOD such as discounts, incentives, etc.
• In the case that total vehicle ownership is not capped, the introduction of AMOD causes a significant increase in VKT of up to 17% in the moderate adoption case and an increase in TTI during the peak by up to 14%. The increase in network congestion can be mitigated by caps on vehicle ownership; the VKT increase is mitigated, reducing from 11% to 7.7% when the total vehicle population is fixed. Additional measures such as policies to improve vehicle occupancy and incentives may be necessary to mitigate the impacts on network congestion.

• The fleet sizes required to serve AMOD demand in an island-wide deployment range from 27,500 to 43,200 in the moderate adoption scenario, over and above an on-demand and taxi fleet of around 20,000 each.

It should be pointed out that the current modeling framework did not consider surge pricing (furthermore, the fleet size was endogenously determined by trading off waiting times and utilization) which constitutes an important avenue for future research. Further, through the use of a microscopic supply model, it would be interesting to examine in more detail vehicle interactions and conflicts near intersections, queues induced by pick-up/drop-off activities curbside, and access/egress behavior to/from parking infrastructure, etc. Finally, analyzing the long-term impacts of AMOD on residential location, job location and vehicle ownership are also interesting and important directions for future research.

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