Evaluating Automated Demand Responsive Transit Using Microsimulation

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ABSTRACT Recent advancements in automated vehicle technology and the concurrent emergence of ride-hailing services have focused increasing attention on Automated Mobility-on-Demand (AMOD; a system of shared driverless taxis) as a potential solution for sustainable future urban mobility. However, the impacts of an unrestricted deployment of AMOD are as yet uncertain and likely to be context-specific; evidence with existing on-demand services suggests that they may lead to the cannibalization of mass-transit and increased traffic congestion. In this context, automated demand-responsive transit (also termed microtransit), which provides similar on-demand services (stop-to-stop or curbside) through higher capacity vehicles, may prove to be a promising substitute and/or complement. In this study, we evaluate the performance of such an automated demand response transit system (hereafter AMOD minibus) through agent-based simulations of the Singapore network. Towards this end, we extend SimMobility (an agent-and activity-based microsimulation laboratory) with the capability of modeling an AMOD minibus service including demand, supply and their interactions. On the demand side, we use an activity-based model system that draws on data from a stated-preferences survey conducted in Singapore. On the supply side, an insertion heuristic is applied to dynamically perform both the assignment of requests to vehicles and vehicle routing. Scenario simulations on the Singapore network (with an area-wide deployment of the AMOD services) indicate the potential benefits of an automated demand responsive transit service for local circulation, which can result in a reduction of Vehicle Kilometres Traveled of up to 50% (compared to the AMOD shared taxis) whilst satisfying the same demand, with a modest increase in average travel times.

INDEX TERMS Agent-based simulation, automated mobility-on-demand (AMOD), high-capacity ride-sharing, shareability.

I. INTRODUCTION

Sustainability of future urban mobility is a key concern for transportation planners, regulators and policy makers worldwide, prompting the need for solutions to improve mobility, accessibility, and livability in urban areas. Automated Mobility-on-Demand (AMOD) – a one-way ride-sharing system with self-driving robotic vehicles – is one such innova-
the need for research on the economic implications, transportation network efficiency effects, behavioral shifts and broader land-use impacts of AMOD systems, which are as yet uncertain. Moreover, the pioneering nature of the technology driving AMOD systems allows for many possible configurations and service designs, namely: fleet sizes, pick-up and drop-off stations, booking schemes, car-sharing criteria and operational set-ups, routing and rebalancing strategies and so on. In fact, AMOD design is also influenced by the size and configuration of the operating area, resulting in a clear need to develop context-specific models and assessment methods. With this background, the broad objective of this study is to use agent-based simulation to evaluate the performance of an automated demand response transit system (hereafter AMOD minibus), which provides stop-to-stop on-demand mobility services through higher capacity vehicles) vis-à-vis a system of AMOD taxis and shared taxis.

In order to understand the potential benefits of AMOD systems, researchers have conducted extensive studies to evaluate the impact of AMOD on transportation (including VKT, system capacity, transit, traveler behavior, and land use) as well as the requirements for AVs and shared mobility (including infrastructure, operational configuration and fleet management, AV deployment policy, etc.) to help inform policy makers.

Initial studies examined the capability of shared and driverless mobility systems in satisfying existing or prevailing demand, and determined the required fleet sizes relative to existing vehicle populations [1], [2]. An important aspect of these on-demand systems is the dynamically changing distributions of demand and supply across locations. To mitigate the effect of this problem, researchers have focused on sharing and rebalancing strategies for MOD and AMOD systems [3]–[9]. For instance, in Pavone et al. [3] and Smith et al. [5], the authors propose a theoretical solution to fleet sizing by introducing rebalancing assignments that minimize the number of empty vehicles traveling in the network and the number of rebalancing drivers needed, while ensuring stability. In contrast, Zachariah et al. [8] modeled a fleet of autonomous taxis in New Jersey based on origin-destination trips derived from travel surveys, and focused on vehicle occupancy rates. Note that in case of AMOD systems, fleet sizing is similar to fleet sizing of MOD systems with human-driven vehicles, but with the advantage that the vehicles can be controlled in a more centralized manner and redistribute themselves more efficiently compared to decentralized human-driven taxis. In an OECD report [9], the impact on car fleet size, volume of travel and parking requirements over two different time scales (24-hour average and peak hour period) for shared and non-shared AMOD taxi configurations are analyzed in an agent-based simulation scenario for Lisbon, Portugal. The study points to a potential reduction of 9 out of every 10 existing cars but suggests increased fleet mileage. However, the analysis did not include a dynamic traffic model which could simulate vehicle-level interactions (and therefore congestion effects). Also, mid- and long-term impacts on individual choices were not considered.

Fagnant and Kockelman [10] examined the impacts of a shared non-electric AMOD fleet in a simulated city with a size of Austin, Texas (see also [11] and [12] for more on safety, behavior and congestion implications of AVs). A mode share of 3.5% is assumed and simulated for the AMOD system, where intermediate stops for pick up and drop off of additional passengers are not allowed. The results suggest that each shared AV could serve 31 to 41 persons a day, and would replace nearly 12 conventional vehicles. 11 parking spaces per AMOD vehicle would also be freed. The overall distance travelled increased by 11% compared to a traditional human-driven self-owned fleet. However, the scenarios analyzed do not rely on a real urban network, and ignore heterogeneous land use and travel patterns, and long-term behavioral shifts. Burns [2] focuses on the impacts of network configuration and service cost of shared AMOD fleets. Three different network environments are analyzed: a mid-sized city (Ann Arbor, Michigan, US), a low-density suburban development (Babcock Ranch, Florida, US) and a large and densely-populated urban context (Manhattan, New York, US). Using queuing theory and network models, travel patterns, cost estimates and vehicle requirements are computed for each scenario. Some studies have also examined in detail the cost implications of autonomous vehicle services [13].

Researchers have also examined the problem of assignment and rebalancing of on-demand services from the perspective of a vehicle routing problem having multiple pick-up and delivery schedules [14], [15] using various optimization methods including clustering and nearest neighborhood search [16], graph theory [17]–[19], heuristics [20]–[24], and a linear assignment problem with a federated optimization architecture [25].

Some studies have observed an increase in congestion with AMOD due to additional vehicle-kilometres-traveled (VKT) generated by dead heading and rebalancing [26], [27]. This is of all the more relevance, given a recent Stated Preferences survey [28] which suggests that a significant portion of AMOD trips are likely to be shifts from public transit. Partly for this reason, many transportation authorities (such as the LTA in Singapore) are attempting to explore the potential of higher capacity stop-to-stop on-demand services in dense urban areas, also termed on-demand responsive transit or micro-transit (the automated DRT system is referred to as AMOD minibus) [29]. However, the required service configurations of these AMOD minibus services to accommodate demand, and their performance in real networks is still unknown and warrants systematic investigation. A few studies have examined such services, albeit in a limited perspective using simplistic simulation models [23], demand models and networks, while some studies have examined their feasibility under different operating practices [30], vehicle dispatching strategies [31], and first/last-mile strategies [32], [33]. Finally, a recent review study examines various aspects related to the deployment of autonomous buses [34].
The primary contributions of this paper are twofold. First, we propose an agent- and activity- based simulation framework to evaluate demand responsive transit services including the modeling of demand, supply and their interactions. On the demand side, we use an activity-based model system that draws on data from a stated-preferences survey conducted in Singapore. On the supply side, an insertion heuristic is applied to dynamically perform both the assignment of requests to vehicles and vehicle routing. Second, the framework is then applied to examine the potential of such an automated demand response transit system through simulations of the Singapore network. The remainder of this paper is organized as follows. Section II describes the agent-based simulation platform (called SimMobility) integrated with a Smart Mobility Service controller and presents the modeling of the AMOD minibus service. Section III outlines the experimental design and the simulation scenarios for a case study in Singapore. Following this, Section IV evaluates the performance of the AMOD minibus service and finally, Section V summarizes the key findings and provides concluding remarks.

II. METHODOLOGY

A. SIMULATION FRAMEWORK

SimMobility is a high-fidelity agent-based microsimulation laboratory, which coherently integrates individuals’ choices and travel behavior emphasizing the principle of activity-based accessibility across different timescales represented by three core models: the Long-term model that captures year-to-year evolution of land use and agents’ socio-economic activities [35], the Mid-term model, which predicts day-to-day individual activity patterns and travel behavior, and network dynamics at a mesoscopic level [36], and the Short-term model that simulates agents’ movements at the microscopic granularity [37], [38]. The overall structure and information flow across models are depicted in Figure 1. Recently, this framework has been extended with a Smart Mobility Service (SMS) controller that replicates all aspects of the service management and fleet operation of on-demand taxi and shared taxi services [39], [40].

In this paper, we utilize SimMobility Mid-term, which consists of three component modules (Pre-day, Within-day, and Supply) as shown in Figure 2.

The Pre-day module is an activity-based model (ABM) system that determines each individual’s daily activity pattern using a hierarchical set of discrete choice models (based on random utility maximization) organized into three different levels: day pattern, tour and intermediate stop level [36]. It takes as an input, individuals and households from a synthetic population, land-use and network details. The new AMOD (including AMOD minibus) services are included in the choice set of individuals in the mode and mode/destination choice models. More details of the pre-day model system can be found in [36].

In the Within-day module, individuals perform departure time choice, route choice and within-day rescheduling. In this stage, the individuals who intend to use an on-demand mobility service (such as AMOD) send a ride request to the SMS controller. The controller is a detachable module that is responsible for real-time service and fleet management as noted previously. For each ride request, the controller finds a suitable vehicle to assign, given constraints on maximum waiting time, and tolerated extra travel time (a detailed description may be found in [40]). The controller has the capability to assign multiple passengers to a single vehicle for ride-sharing by incorporating a vehicle seat capacity constraint in the assignment algorithm (e.g. 4 to 6-sharing).

The individual travel and vehicle movements are captured by the Supply module that simulates network performance and dynamics at a mesoscopic level using a combination of macroscopic traffic flow models (speed-density relationships) and deterministic queueing theory. After performing the trips (i.e. drop-off of all passengers), the service vehicles are controlled by the rebalancer which either directs the vehicle to a parking location, or to cruise to a specific high demand zone. The performance measures (such as travel times) in the Supply level can impact the demand pattern (at the Pre-day and Within-day level) through the iterative processes termed day-to-day and within-day learning.
B. ASSIGNMENT AND ROUTING HEURISTIC FOR AMOD MINIBUS SERVICE

The SMS controller described previously handles door-to-door requests through smaller capacity single-ride and shared taxis. This section extends the controller to model the stop-to-stop AMOD minibus service and proposes a heuristic to assign vehicles to requests and determine routes dynamically online. The heuristic involves two steps. Step 1 searches candidate service vehicles and uses a matching algorithm to identify a vehicle whose current route is as ‘similar’ as possible (in terms of spatial characteristics) to the current request. Step 2 finds the optimal position to insert the origin and destination of the incoming request within the existing route of the vehicle to minimize the total travel cost of all passengers within the vehicle. This is described more formally next.

Consider a hypothetical incoming request from individual $i$ (denoted $IR(i)$) who wishes to board and alight at the stops $B_i$ and $A_i$ respectively (the stops could be bus stops or designated curbside locations). Let $ER_r$ denote the existing route of service vehicle $r$ ($r \in \mathcal{R}$, where $\mathcal{R}$ denotes the set of service vehicles with cardinality $R$) consisting of a set of stops given by $ER_r = [S_{1} = i_{1}, \ldots, S_{j} = i_{j}]$. The stop points in the route of vehicle $r$ closest to $B_i$ and $A_i$ (in terms of shortest path distance) are denoted by $(S^*_{j_{mb}, j_{ma}})$ and are computed for each vehicle $r \in \mathcal{R}$. Further, define a vector $Z$ containing the sum of the shortest path distances from the stop points $(S^*_{j_{mb}, j_{ma}})$ to $B_i$ and $A_i$ respectively, for all vehicles $r \in \mathcal{R}$.

\[
Z = [(d^*_{j_{mb}} + d^*_{j_{ma}}), \ldots, (d^*_{j_{mb}} + d^*_{j_{ma}})]^T
\]

Next, we identify a subset of candidate vehicles $\mathcal{R}_1 \subset \mathcal{R}$, which satisfy certain distance constraints, $d^*_{j_{mb}} < d_{max}$, $d^*_{j_{ma}} < d_{max}$ (where $d_{max}$ is a parameter of the heuristic). Let $|\mathcal{R}_1|$ be denoted by $K_1$. For each vehicle in this subset of candidates $r \in \mathcal{R}_1$, we compute the direction (or slope) of the incoming request and that of the existing route of the vehicle (measured based on the points $(S^*_{j_{mb}, j_{ma}})$ as:

\[
g_i = \left(\frac{y_{B_i} - y_{B_j}}{x_{B_i} - x_{B_j}}\right); \quad g_r = \left(\frac{y_{S^*_{j_{ma}}} - y_{S^*_{j_{mb}}}}{x_{S^*_{j_{ma}}} - x_{S^*_{j_{mb}}}}\right)
\]

where $x$ and $y$ denote the geographical $X$ and $Y$ co-ordinates respectively. Based on $g_i$ and $g_r$, we next select a subset of $K_2(\leq K_1)$ candidates $\mathcal{R}_2 \subset \mathcal{R}_1$ of vehicles, whose existing route is closest in direction to the incoming request. From these $K_2$ candidates, we simply select $K \leq K_2$ candidates ($K$ is a parameter of the heuristic) with the largest occupancy (to maximize the extent of sharing). This final set of $K$ vehicles is denoted by $\mathcal{R}$.

Now, in Step 2, our objective is to select the vehicle from this set of $K$ candidates, which will incur minimum additional total cost (in terms of waiting time and travel time of all passengers in the vehicle), if the incoming request is accepted, subject to constraints on the maximum allowable waiting time and travel time for each passenger. Thus, for a given candidate vehicle $r \in \mathcal{R}$, the cost $C_r$ is defined as:

\[
C_r = \alpha \sum_{p \in P_r} WT_p + \beta \sum_{p \in P_r} TT_p
\]

where, $\alpha$ and $\beta$ represent the values of waiting time and travel time respectively (in $\$$ per unit time), $P_r$ denotes the set of passengers in vehicle $r$, $WT_p$ is the individual waiting time for passenger $p$ (difference between the request time and boarding time, $t^*_{p} - t^*_{p(request)}$), and $TT_p$ is the travel time or time between boarding and alighting, $(t^*_{p(alight)} - t^*_{p(board)})$. Note that $t^*_{p(board)}$ and $t^*_{p(alight)}$ are determined based on congested travel time on the shortest path, computed when the controller received the request.

For each route, we now evaluate the additional costs incurred by inserting the new request or schedule items ($B_i$ and $A_i$) into the existing route in four possible ways (recall that we have already identified the stops on the existing route closest to the boarding and alighting stops of the incoming request, denoted by $S^*_{j_{mb}}, S^*_{j_{ma}}$):

\[
HR^1 = [S_{j=1}, \ldots, B_i, S^*_{j_{mb}}, A_i, S^*_{j_{ma}}, \ldots, S_{j=R}] \quad (4)
\]
\[
HR^2 = [S_{j=1}, \ldots, S^*_{j_{mb}}, B_i, A_i, S^*_{j_{ma}}, \ldots, S_{j=R}] \quad (5)
\]
\[
HR^3 = [S_{j=1}, \ldots, S^*_{j_{mb}}, B_i, S^*_{j_{ma}}, A_i, S^*_{j=R}] \quad (6)
\]
\[
HR^4 = [S_{j=1}, \ldots, B_i, S^*_{j_{mb}}, \ldots, S^*_{j_{ma}}, A_i, S^*_{j=R}] \quad (7)
\]

The travel cost in now recomputed for these four hypothetical routes using Equation (3) and an ‘optimal’ vehicle $r^*$ with route $p^*$ is selected that incurs minimum additional cost ($AC_m$), given by,

\[
AC_m = C_r(HR^p_r) - C_r(ER_r), \quad r \in \mathcal{R}, \quad n = 1, 2, 3, 4 \quad (8)
\]

where, $C_r(ER_r)$ is the original cost of the existing route $ER_r$ of vehicle $r$, and $C_r(HR^p_r)$ is the new cost of the $n$th alternative route $HR^p_r$.

Finally, the controller dispatches the chosen vehicle ($r^*, p^*$) if the following constraints are satisfied: the waiting time ($WT_p \leq WT_{max}, \forall p \in P_r$); the additional tolerated delays on travel time ($TT_p \leq TT_{max}, \forall p \in P_r$); the available seat constraint ($|P_{r^*}| < C_{max}$). The procedure is summarized in Figure 3.

III. SIMULATION SCENARIO AND EVALUATION

In order to evaluate the performance of the AMOD minibus service vis-a-vis AMOD taxis, we use a model of Singapore in 2030. The synthetic population for 2030 was generated using a Bayesian approach [44] based on land-use data, socio-economic data and other control totals (see also [35] for more details on the population synthesis). The demand model for 2012 (that matches observed modes shares, activity details on the population synthesis). The demand model for using a Bayesian approach [44] based on land-use data, socio-economic data and other control totals (see also [35] for more details on the population synthesis). The demand model for 2012 (that matches observed modes shares, activity details on the population synthesis). The demand model for using a Bayesian approach [44] based on land-use data, socio-economic data and other control totals (see also [35] for more details on the population synthesis). The demand model for using a Bayesian approach [44] based on land-use data, socio-economic data and other control totals (see also [35] for more details on the population synthesis).
preferences (SP) survey on AMOD conducted in Singapore (see [28] for more details). The calibration and validation of the 2012 model also included matching simulated outputs to observed screen-line counts, public transit smart card data and network travel times [36].

The road and transit networks of the year 2030 in Singapore consist of 1,169 zones, 6,375 nodes, 15,128 links, 730 bus lines over 4,813 bus stops, 26 MRT lines over 186 stations (Figure 5). The overall approach and scenario design is summarized in Figure 4.

The baseline model of Singapore 2030 (SC0) includes all existing modes, namely private car, car-pooling with 2 to 3 people within a household, private bus, walk, taxi, MOD (Uber-like ride-sourcing services), and public transit (bus, rail) with access and egress by walk (Table 1).

In the AMOD scenarios SC1 and SC2, we introduce the AMOD (Single/Shared) mode in addition to the existing modes; AMOD trips are served by different types of AMOD fleets in the two scenarios: AMOD taxi (in SC1) and minibus (in SC2). The modes in scenarios SC1 and SC2 are shown in Table 1. The AMOD services are assumed to operate within a restricted geo-fenced area in the western part of the island shown in Figures 5 and 6. This service area consists of 153 traffic analysis zones over an area of 74.36 km² that includes residential, commercial, business, and industrial zones. The road network in this region consists of 715 nodes, 1,768 links, and 753 bus stops. We note that the stops (pick-up/drop-off) locations for the AMOD minibus service are assumed to be pre-specified and same as the existing bus-stops in the study area. Further, we assume a ‘station-based’ fleet operation that directs the service vehicles after a drop-off (when empty) to the parking facilities (marked with green and red nodes for AMOD taxi and minibus respectively).

As noted previously, on the demand side, the Activity-based model includes the new AMOD modes in the mode-choice and mode-destination choice models, with suitable constraints to ensure that they can only be used within the designated zones in the western region. The AMOD fares or prices are assumed to be lower than human-driven taxi
services at 50% and 75% of taxi price for the shared ride and single ride respectively (see [1], [2], [41], [42]; note that although the operating costs have been estimated to be lower by as much as 80% in the literature, we adopt a more conservative estimate of fare reduction of 50%). The constraints in the matching heuristic described in the previous section are set to 15min for both $WT_{\text{max}}$ and $TT_{\text{max}}$ and 3km for $d_{\text{max}}$. The performance of the AMOD minibus relative to the single-ride/shared AMOD taxis is evaluated based on several evaluation criteria including service metrics (request satisfaction rate, fleet utilization, vehicle occupancy), network performance (vehicle-km traveled or VKT, energy consumption) and user metrics (passenger waiting and travel time).

For all the three scenarios, several iterations of the day-to-day and within-day learning processes are performed. The day to day learning process (which involves an iterative update of the zone to zone travel times and waiting times) ensures that the travel times and waiting times used in the pre-day models are consistent within 15% on average with the actual travel and waiting times that are an outcome of the supply simulations. In practice, around 10 iterations of the day to day learning process are sufficient to attain consistency. The initial iteration uses an apriori estimate of the travel times and waiting times and these are updated with the values from the supply simulation with each subsequent iteration.

### IV. SIMULATION RESULTS

#### A. DEMAND PATTERNS

The Pre-day module predicts demand patterns (in terms of a detailed daily activity schedule) for the 6.7 million agents in the synthetic population of Singapore 2030. Once AMOD is introduced in the service area, it results in a slight increase in total trips within the study area (origin or destination within the study area) of around 2% from 1,003,985 to 1,027,141. Table 3 compares the mode shares within the study area for the two scenarios. The share of AMOD taxis/shares taxis is 8.03%, with the majority of shifts to AMOD coming from public transit (Table 4 and Figure 7b). Figure 7a shows the detailed temporal demand pattern of AMOD over the time-of-day, which shows distinct morning and evening peaks due to commuting trips. Note also that, in addition to the passenger travel modes defined in Table 3, every scenario has been simulated with background freight traffic generated by SimMobility Freight [43]. Given these demand patterns (note that these shares are in fact obtained after several iterations of the day to day learning process to ensure demand supply equilibrium), the supply simulation results for the scenarios (SC1, SC2) are presented in the following sections. Further, in the simulation of SC2, the AMOD (Single/Shared) and Rail (AMOD) trips are served by the AMOD minibus service.

#### B. SYSTEM PERFORMANCE

We first present performance measures of the AMOD service from the operator’s perspective. The fleet sizes shown

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**TABLE 2. AMOD fleet definition.**

| Fleet | AMOD Taxi | AMOD Minibus |
|-------|-----------|--------------|
| Scenario | SC1 | SC2 |
| Capacity (Seat) | 4 | 6 | 10 |
| PCT | 1 | 1 |
| Service Type | Door-to-door | Stop-to-stop |
| Fleet Size (FS) | 2000 | 1200 |
| Parking location | Public housing | Depot |

---

| Mode | Baseline | Intro of AMOD* |
|------|----------|----------------|
| Car  | 93235 (9.29%) | 89630 (8.73%) |
| Carpool | 99973 (9.56%) | 91274 (9.18%) |
| Bus  | 229803 (22.89%) | 215510 (20.98%) |
| Rail (Walk)* | 224239 (22.33%) | 205448 (20%) |
| Rail (MOD)* | 3790 (0.38%) | 3494 (0.34%) |
| Private bus | 88386 (8.8%) | 81458 (7.93%) |
| Taxi  | 20348 (2.03%) | 17866 (1.74%) |
| AMOD (Single/Shared) | 64572 (6.44%) | 57080 (5.58%) |
| Walk | 175541 (17.88%) | 172089 (16.75%) |

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**TABLE 3. Estimated trips and mode share.**

| Mode | Baseline |
|------|----------|
| Car  | 93235 (9.29%) |
| Carpool | 99973 (9.56%) |
| Bus  | 229803 (22.89%) |
| Rail (Walk)* | 224239 (22.33%) |
| Rail (MOD)* | 3790 (0.38%) |
| Private bus | 88386 (8.8%) |
| Taxi  | 20348 (2.03%) |
| AMOD (Single/Shared) | 64572 (6.44%) |
| Walk | 175541 (17.88%) |

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**TABLE 4. Shift rate to AMOD from EM within service area.**

| Mode | AMOD | Rail (AMOD) |
|------|------|-------------|
| Car  | 5.81% | 5.01% |
| Car-pooling | 9.65% | 10.28% |
| MOD, Taxi | 10.44% | 10.89% |
| Public transit | 52.2% | 54.01% |
| Walk | 9.14% | 11.15% |
| Other (Private bus) | 12.77% | 8.69% |

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* AMOD defined in the service area.
* Accounts with walk, MOD, and AMOD.

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FIGURE 6. AMOD service area in SC1 and SC2.
in Table 2 for the SC1 and SC2 scenarios were determined through several simulations with varying fleet sizes, and are the minimum required to ensure a request satisfaction rate close to 100% (Table 5 summarizes the service statistics and satisfaction rate) with reasonable waiting times (discussed later). The average time taken for an AMOD minibus request to be accepted (matched to a vehicle) in the peak period was 17.5 seconds (maximum of 30 seconds). We note however that the response time is affected significantly by the waiting time and travel time constraints, and the response time would increase if these are made more stringent. Note also that a request may not be served if a vehicle is not found that meets the constraints on waiting time and travel time. In this case, the traveler switches mode if his/her request is not satisfied within a pre-specified time interval of 10 minutes. The number of AMOD requests (86,443 trips in SC1) differs slightly from the pre-day demand (82,472 trips in Table 3) because we allow agents to change their mode during the

**FIGURE 7. Demand pattern.**

**FIGURE 8. Fleet utilization.**

**TABLE 5. Service statistics and satisfaction rate.**

| Scenarios    | Request | Pick-up | Drop-off | Satisfaction (%) |
|--------------|---------|---------|----------|------------------|
| SC1 (AMOD Taxi) | 86443   | 86009   | 85920    | 99.5%            |
| SC2 (AMOD Minibus) | 80501   | 80139   | 79752    | 99.5%            |

*Within-day* simulation before performing their actual trips (e.g. convert from AMOD to Walk if the trip distance is walkable). In addition, the number of requests in SC2 is less than SC1 because only the AMOD (Single/Shared) trips (82,472 trips in Table 3) in SC1 are assumed to be served by the AMOD minibus service in SC2. Also note that the MOD fleet size was fixed to 19,000 for all scenarios for the island-wide service based on preliminary simulations (to ensure that all requests are satisfied with reasonable average waiting times).

The status of each AMOD vehicle during operation can be classified into utilized (i.e. vehicles driving with (or to) the passengers) and idled (i.e. vehicles cruising, parked or en-route to parking). Figure 8 shows the fleet utilization patterns of the AMOD taxis (in SC1) and AMOD minibuses (in SC2) over the time of day. As expected, in the early morning hours, almost all vehicles are idled at parking locations (ratio of utilized fleet close to 0). As the demand surges during the onset of the morning peak, the utilization rate quickly reaches close to 100%. Overall, the vehicle utilization rates are relatively low (on average 22% and 14% for SC1 and SC2 respectively) due to a low utilization during the off peak.

Figure 9 illustrates the extent of sharing and vehicle occupancy over the time of day. As noted in Table 2, the AMOD taxi fleet accommodates four to six passengers within a single
vehicle, while the AMOD minibus fleet handles up to ten passengers. The average vehicle occupancy of the AMOD vehicles during the peak period for the two scenarios are also computed by calculating the average of maximum vehicle occupancies of utilized vehicles (vehicles that are not idle) during each five second interval, and then averaging these occupancies for the period of interest (e.g., peak period). The values are found to be 1.4 and 5.1 (pax/veh) for the AMOD taxis (SC1) and AMOD minibus (SC2) respectively, indicating a significantly higher extent of ride-sharing in SC2 (seat utilization of close to 50% in SC2 versus around 20% for SC1).

In order to estimate impacts on network congestion, we examine the vehicle kilometres-traveled (VKT) of the AMOD service vehicles during pickup and dropoff operations (drive with passenger(s) between pick-up and drop-off point(s)) and during dead heading (empty trips including driving to the passenger, parking, and cruising). Figure 10 illustrates the total travel distance of service vehicles over the time-of-day. Overall, the AMOD taxis (715,266 km in SC1) travel a significantly larger distance compared to the AMOD minibus (303,808 km in SC2). Table 6 shows the total travel distances (for the entire day) for each operational status. The results indicate that the VKT of the AMOD minibus is 2.3 to 2.5 times less than that of the AMOD taxis in both categories (service and operational distance). This is likely due to the smaller fleet size, larger extent of sharing (higher vehicle occupancy) and the change from a door-to-door to stop-to-stop service.

The energy consumption of the AMOD fleets are another important measure of performance in regard to sustainability. Table 7 reports the primary energy consumption for the AMOD fleets in the Scenarios SC1 and SC2. This is calculated using an average energy consumption rate (ECR), which decreases with travel distance (233, 183, 166 Wh/km for short (less than 2km), medium (between 2 and 10km), and long distance (more than 10km) trips) and is based on the assumption that the AMOD fleet is composed of battery electric vehicles (BEV) [46], [47]. Moreover, in order to account for transmission and distribution losses of electric vehicles (so called well-to-wheels effects), we multiply the energy consumption with the production factor of 2.99 (US average energy-to-fuel ratio). The results indicate that the total energy consumption of AMOD minibus service (189,769 kWh) is around 57% less than that of the AMOD taxi (441,257 kWh).

In terms of user metrics, we first examine the waiting time of passengers for the two scenarios (Figure 11). It should be...
noted that in case of the AMOD minibus, it is assumed that the user makes a request at the origin node before starting the access leg of the trip, and the waiting time reported here is the waiting time of the traveler after reaching the pickup stop. Access and egress walk times are reported separately in Table 8. Thus, in some periods of the off-peak, the AMOD minibus shows slightly lower waiting times than the AMOD taxi, whereas during the peak, the AMOD minibus (SC2) shows higher waiting times than the AMOD taxis (SC1) even after exclusion of walking time. This may be due in part to the higher number of stops and longer detours in case of the minibus. The average waiting time of the AMOD minibus increases from around 4.4 minutes (in the off-peak) to 9.2 minutes (in the peak periods). The waiting time of AMOD taxis also shows a similar trend, yielding low waiting times of 4.6 min in the off-peak and increased waiting time of 6.2 min in the peak periods (see Table 8). The longer detours due to a higher number of stops along the route also yields a higher average travel time for the AMOD minibus service compared to the AMOD taxi service (9.4 minutes versus around 12 minutes).

### C. DISCUSSION

By design, the AMOD minibus service allows for a greater extent of sharing and higher vehicle occupancy, leading to longer waiting and travel times than the AMOD taxi because of detouring and a higher number of stops. The results indicate that average additional delay (the gap between total journey times) is around 6.5 minutes per passenger, which may be acceptable given the stop-to-stop nature of the service. On the other hand, from the service operator’s standpoint, the AMOD minibus service requires a smaller fleet size and results in less empty miles traveled.

Notwithstanding the additional delays in journey time, the simulation results suggest that for certain types of geofenced regions, demand responsive transit may be a feasible alternative to shared/single ride taxis, leading to a significant reduction in VKT whilst serving roughly the same levels of demand. This may in part be due to the specific spatiotemporal distribution of demand in the study area considered, which contains distinct residential and commercial areas leading to a large number of trips generated from the residential area to business areas (and also to the MRT stations) in the morning peak (and vice versa in the evening peak). This allows for the effective aggregation of demand, and consequently, leads to improved performance of the matching algorithm and operations of demand responsive transit. In this regard, further research is warranted to investigate how scalable such a service is, and its performance for larger geographical areas such as for instance, an island-wide deployment in Singapore.

### V. CONCLUSION

This paper presented an agent-based simulation framework to evaluate the performance of automated demand responsive transit (AMOD minibus) including the explicit modeling of demand, supply and their interactions. On the supply side, the AMOD minibus service is modeled using a matching and routing algorithm that can cluster the incoming ride requests and match them to existing service routes so as to minimize additional travel costs incurred. The AMOD minibus service is implemented within the agent-based simulation platform SimMobility. Further, simulations from a case study in Singapore indicate that the AMOD minibus service can lead to a substantial reduction in VKT (up to 50%) compared to single/shared AMOD taxis with a larger extent of sharing (3 times larger than AMOD taxi during the peak periods), while resulting in modest increases in travel time.

Further research is required to examine the performance and viability of such demand responsive transit services for larger geographical areas and more complex spatio-temporal distributions of demand.

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