Implementation and Policy Applications of AMoD in multi-modal activity-driven agent-based urban simulator SimMobility

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ABSTRACT

Among the new transportation services made possible by the introduction of Automated Vehicles (AVs), Automated Mobility on Demand (AMoD) has attracted a lot of attention from both the research community and the industry. AMoD provides a service similar to taxi or ride-sharing services, while being driver-less. It is expected to attract a huge fraction of travelers currently using mass transit or private vehicles and will have a disruptive effect on urban transportation. While most studies have focused on the operational efficiency of the technology itself, our work aims to investigate its *impact*.

Our contribution is two-fold. First, we present the AMoD framework that we developed in SimMobility. The framework's novelty lies in allowing simulation of AMoD operations, along with providing flexibility to evaluate how AMoD availability will impact an individual's choices and activities, as well as how the overall system will adapt to these new services. This marks a clear difference with current approaches, which assume the demand for new services as fixed and does not capture user preferences.

Second, we present a case study that investigates the role of mass transit in an urban system, where AMoD is widely available. Mass transit is already challenged by current ride-sharing services, e.g., Uber and Lyft, which provide comparatively better and cheaper service. This trend will plausibly be exacerbated with the introduction of AMoD, which may indirectly act as a replacement to mass transit. Our simulation results show that mass transit is irreplaceable, despite the high efficiency of AMoD, in order to avoid congestion and maintain a sustainable urban transportation system with acceptable level of service.

INTRODUCTION

Various patterns of motorization development have evolved over the years in different regions of the world according to specific transportation cultures. New technologies and the ubiquitous use of smartphones have opened the possibilities for more convenient, affordable, fast and safe options in urban transportation. This has led to the emergence of mobility-on-demand (MoD) systems, such as Uber and Lyft, which aim to provide fast and reliable mobility that is catered to the needs of the individual. At the same time, Automated Vehicle (AV) technology has advanced at an impressive pace. Research corporations, like Google and Tesla, have been in a race for developing a fully automated vehicle, with Tesla (*1*) recently showcasing the first production model of *Tesla 3*. The combination of these two promising technologies, known as Automated Mobility on Demand (AMoD), has recently attracted interest in the research community and investment in the industry (for example, Uber (*2*) has started testing AV programs in several states in the US).

The term AMoD, coined by Kornhauser et al. (*3*), designates a service similar to MoD or taxi, with the difference that vehicle operations are now driver-less. AMoD combines the benefits of MoD and AVs in several aspects. First, operational cost is drastically reduced, given that the labor cost of drivers is completely removed and the energy efficiency of AVs. Furthermore, negative externalities, such as emissions, travel time uncertainty and accidents, will also reduce, as already observed for MoD by Martin and Shaheen (*4*) and for AVs by Milakis et al. (*5*). The latter also observes that AMoD will increase road network utilization, making it possible to transport more passengers with less congestion, with respect to privately owned cars. Fagnant and Kockelman (*6*) found that the AV benefits would amount to between USD 2,690 and USD 3,900 per year per vehicle incorporating decreases in insurance, parking costs and traffic congestion.

It is clear that AMoD is a disruptive technology that will deeply impact the transportation system. Most of the literature (see Fernandes and Nunes (*7*), Santi et al. (*8*), Fagnant et al. (*9*), Alonso-Mora et al. (*10*)) till date has focused on the efficiency of AMoD and AVs, in terms of road movement and fleet management. We claim that, besides this research direction, it is also crucial to answer the following question: *How will AMoD impact the urban transportation system?* Studying the efficiency of AMoD alone is not sufficient to address this question. The aforementioned advantages of AMoD are expected to attract many travelers, switching from private automobile usage or public transit to these new services. Will there be too many AVs circulating on the road network, thereby leading to extreme congestion? Will the revenue of mass transit organizations decrease and, as a consequence, result in a downward spiral of reduced investment and level of service? How should urban policy-makers regulate AMoD services?

To answer questions like these, we need an *integrated* approach, which embraces the operational aspects of the new technology and also considers the response of individuals to their availability. To that effect, this work provides a two-fold contribution. First, we introduce a framework, developed in SimMobility, which allows to integrate the simulation of traveler choices with the operation of AMoD services. Second, we apply this framework to a case study, where we investigate the role of mass transit in future urban transportation systems when AMoD will widely available. The framework is slated to be released as an open-source project. Designed to be modular and easily extensible, we expect the research community to greatly benefit through rapid development, testing and comparison of results. Current research works focusing on AMoD simulations lack in this aspect, which makes repeatability of experiments and verification of results almost impossible.

Questioning the role of mass transit in the future thus becomes increasingly relevant. Debates are ongoing on whether current MoD will replace mass transit (see Rayle et al. (*11*), Hall et al. (*12*)). Researchers and transit authorities indicate ride-sharing as one of the possible causes for the decline in mass transit ridership, as reported by Fitzsimmons (*13*), Lazo (*14*) and Sadowsky and Nelson (*15*). Polzin (*16*) warns that the loss in revenue resulting from this decline would create a vicious cycle of decreased investment in public transport, which would in turn slow down infrastructure improvement and hamper the quality of service. As a result, mass transit would experience an even larger decline in ridership. If these concerns are relevant now, with MoD, they will be even more so with the introduction of AMoD as rapid improvements in performance and user convenience occur. These concerns have been confirmed in the literature as well (see Litman (*17*)).

Will mass transit have the same vital importance as it currently does in the future when AMoD will be easily implementable? Should policy-makers implement regulations to protect it? Considering both greenfield and brownfield urban developments, should mass transit still receive investment or be forced into oblivion with the deployment of a fully efficient AMoD service? Using a simulation-based approach to demonstrate a case study of our proposed framework, we show that mass transit is irreplaceable even when AMoD is available. In dense urban environments with infrastructural constraints, mass transit remains the best way to cope with high mobility demand. However, AMoD can also contribute greatly in improving urban mobility if regulations shape an integration with mass transit.

The remainder of the paper is organized as follows. The following section provides a brief overview of the SimMobility simulation framework and expands upon the methodology used to include AMoD services in the simulator. The next section includes the experimental scenario design along with a brief description of the study area and results from our simulations. The final section of the paper provides concluding remarks along with directions for future research.

METHODOLOGY AND FRAMEWORK

Along with a brief introduction to SimMobility, we provide an outline for the design and implementation of AMoD services in our simulation framework.

Overview of SimMobility

SimMobility is a multi-scale agent-based simulation platform that incorporates time-scale dependent behavior modeling through activity-based frameworks (refer to Adnan et al. (*18*)). Considering land-use, transportation and communication interactions, SimMobility can be used for a variety of applications ranging from implementation of intelligent transportation systems and estimating vehicular emissions to evaluation of alternative future scenarios and generation of innovative policy and investment strategies. SimMobility encompasses three major components:

1. *Long-Term (LT):* A macroscopic land use-transport simulator that involves creation of a synthetic population along with housing location choice, job location choice and car ownership choice at the temporal scale of days to months to years (refer to Zhu and Ferreira (*19*) and Le et al. (*20*));

2. *Medium-Term (MT):* A mesoscopic supply simulator coupled with a microscopic demand (daily activity) simulator that involves mode choice, route choice, activity pattern and incident-sensitive (re)scheduling at the temporal scale of seconds to minutes (refer to Lu et al. (*21*));

3. *Short-Term (ST):* A microscopic traffic simulator that involves lane changing, gap acceptance, route choice and acceleration-braking behavior at the temporal scale of a fraction of a second (refer to Azevedo et al. (*22*)).

This paper will focus on the Medium-Term (MT) simulator only since the AMoD framework has been designed for MT-level decisions. While it would be interesting to observe the effect of inclusion of such services on LT decisions, it serves as a direction for future research. The MT modeling framework is an integration of activity-based demand modeling systems with dynamic traffic assignment for modeling supply decisions. There are three components in the MT framework that interact with each other leading to feedback mechanisms for agent decisions:

1. *Pre-day* models daily activity travel patterns at the individual level for a synthetic population;
2. *Within-day* simulates departure time choice and route choice decisions incorporating en-route decisions such as re-scheduling;
3. *Supply* provides network attributes and supply-based models for both private and public transportation modes.

AMoD Framework

After providing a brief overview of how AMoD fits into SimMobility, we proceed to explain the design and implementation in further detail.

Overview

The AMoD service is first made available in the pre-day, i.e. individuals from the synthetic population have access to it in their choice set while constructing their activity schedules. At the pre-day level, each individual makes a mode choice which is modeled using the random utility framework. The systematic utility of each mode is computed as a weighted sum of parameters like the cost, the travel time, the waiting time, etc. We make assumptions on the cost of AMoD based on literature since existing data is not available. Other parameters like the travel time and the waiting time are provided a-priori values initially, which are corrected later with the use of a *feedback loop* which is shown in Figure 1. A probability is computed for each mode depending on their utility, assuming a known distribution for the error term. Then, each individual makes mode choices based on these probabilities and constructs an activity schedule for the day, including the movement between locations as well as their preferred mode. The supply simulation is then launched, in which the individual performs the activities and trips specified in the day activity schedule. After the simulation is complete, the actual waiting and travel times are recorded and *fed back* to the pre-day module, i.e., these new values are used to replace the a-priori values that we assigned for the computation of the perceived utility. The entire process (construction of the day activity schedule and supply simulator) is then repeated with these values.

Before expanding on the implementation, it is worth emphasizing the power of this approach. In most of the literature (Santi et al. (*8*), Alonso-Mora et al. (*10*)), we find that traveler choice has been neglected. The evaluation of AMoD systems has been based on simplistic assumptions, such as *all taxi riders or all private automobile owners would switch to AMoD*. However, in

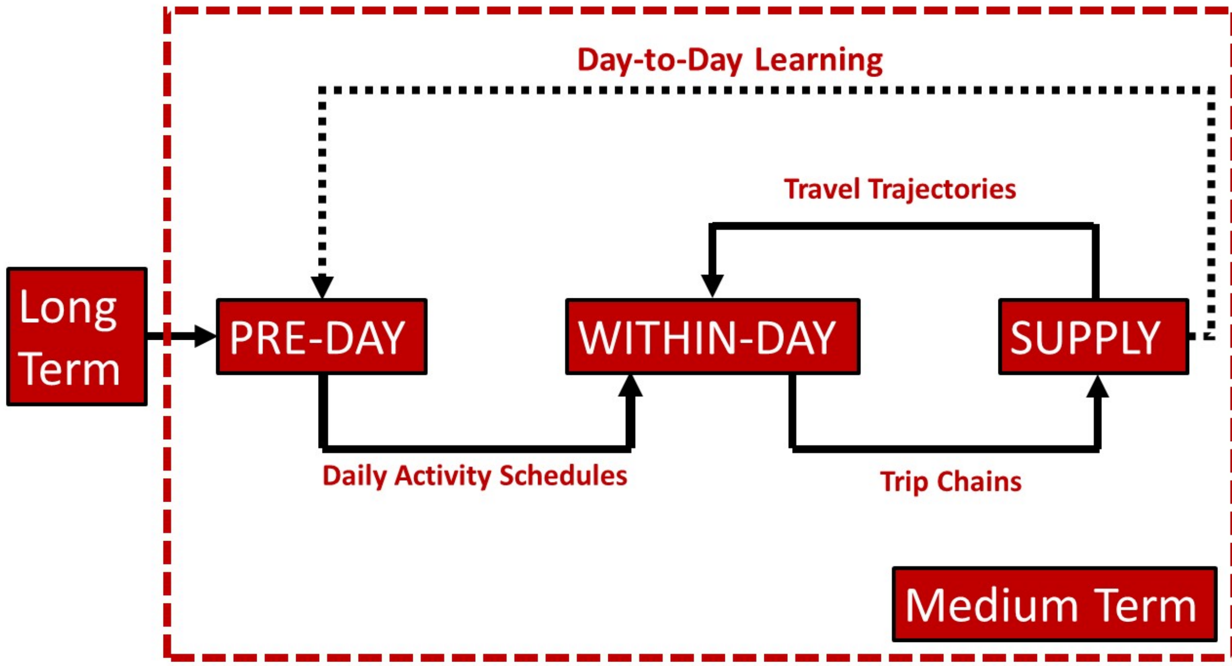

FIGURE 1 Feedback loop mechanism in SimMobility Medium Term (adapted from Lu et al. (*21*))

a multi-modal urban transportation system, such dramatic shifts are hardly observed. It is crucial to consider only a partial shift (based on differential utility), as our approach does, to provide a more realistic approach for studying the adoption and impact of AMoD at the system level. Furthermore, our framework is flexible enough to allow investigations under different hypotheses. We can determine a feasible cost for AMoD operators by testing scenarios with different levels of cost. The major contribution of our framework is to allow for evaluation of the impact of performance metrics on user adoption and vice-versa. For example, a certain strategy may be widely accepted leading to large demand but is only able to maintain a required level of service till a certain level of demand. Therefore, the cost to target can be adjusted accordingly through experiments.

Model and Design of AMoD in the Supply Simulator

In the supply simulator, the AMoD framework is composed of three components: the *user*, the *vehicle* and the *controller*. The different interactions between them are shown in Figure 2 through a control flow diagram. Our framework allows for simulating different AMoD services, each controlled by a separate controller, at the same time. The user sends a request to an AMoD service, specifying the intended pick-up and drop-off locations. The requests directed to an AMoD service are periodically processed by the relative controller. The processing consists in the creation of a *schedule* for each vehicle subscribed to that service. A schedule is a sequence of commands to instruct the vehicle. They can be of type *pick-up a user*, *drop-off a user*, *cruise in a certain zone*, *park*. Each schedule is then sent to the intended vehicle, which will just execute the sequence of commands. It is noteworthy that this mechanism is naturally suited to implement ride-sharing, i.e. serving two or more users with the same vehicle at the same time. For example, if we want user

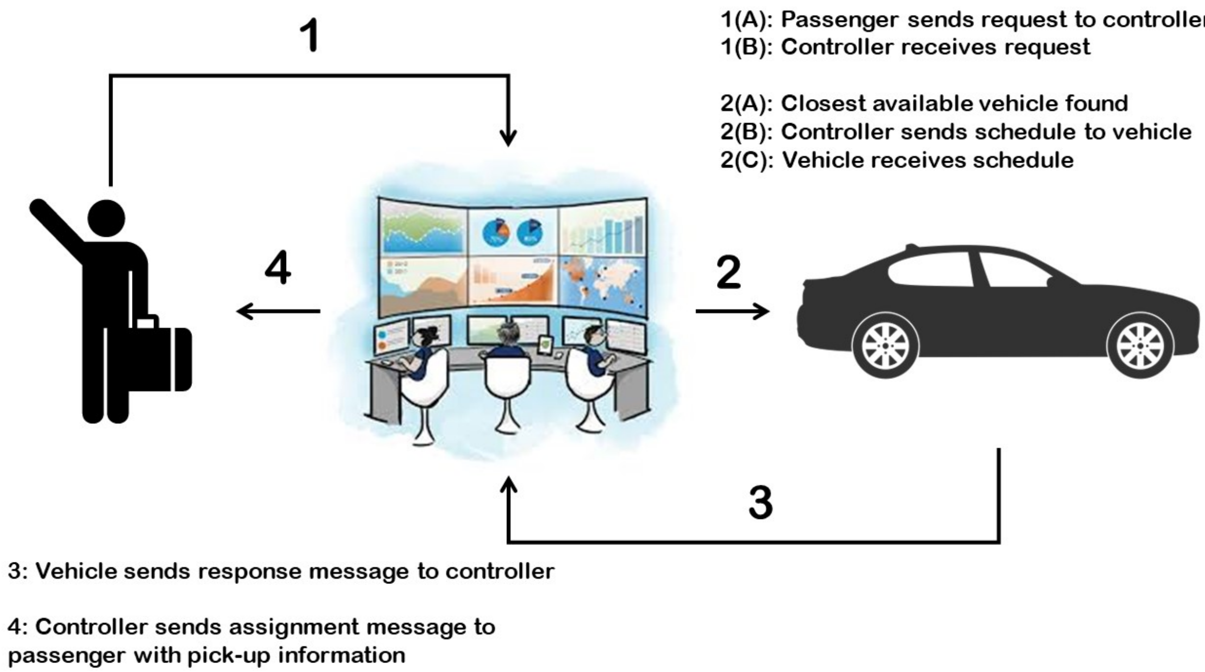

FIGURE 2 Control flow diagram for the AMoD framework

1 to share a ride with user 2, it suffices to send to a vehicle a schedule containing the following commands: *pick-up user 1*, *pick-up user 2*, *drop-off user 1*, *drop-off user 2*. Since the users, vehicles and the controller are interacting asynchronously through messages, the simulation is made fully parallelizable leading to significant savings in computation time.

The algorithm of the AMoD controller tries to assign each incoming request to an available driver in a greedy fashion. The match is feasible if adding the pick-up and the drop-off of the new user to the schedule of the driver satisfies the following constraints. First of all, the waiting time of all the passengers already included in the schedule, as well as of the new user, must be below a certain threshold. Moreover, for each of them we first estimate the *minimum time* that the user would spent for her trip if the vehicle was only serving her, going from her origin to her destination directly. Then, we compute the estimate of the time between her pick up and her drop off, as specified in the schedule, which we call *serving time*. The difference between serving time and minimum time is the *additional delay*, which accounts for the detours made by the AMoD due to the fact that the trip is not exclusively serving a single user, but is shared with others. Along with the aforementioned constraint on the waiting time, we also impose that the additional delay be below a certain threshold. Both the thresholds are specified as 10 minutes.

CASE STUDY: AMOD & MASS TRANSIT

We now apply the framework described above to consider the role of mass transit in future urban mobility. *Will mass transit be remain as relevant when AMoD is widely available?* The answer to this question will drive future investment in transportation infrastructure, which is the major motivation behind this case study.

Experimental Design

To evaluate the importance of the role of mass transit in future urban systems with AMoD, we designed three different scenarios which are separately simulated and subsequently compared. We consider a *Base Case* scenario where smart mobility services have not been introduced yet. The available modes are single occupancy car (*Car*), sharing with one extra passenger (*Car Sharing 2*), sharing with two extra passengers (*Car Sharing 3*), public bus (*Bus*), Mass Rail Transit (*MRT*), traditional taxis (*Taxi*), motor-cycle (*Motorcycle*) and walking (*Walk*). The modal availabilities are in accordance with our study area, which we describe in the following section.

In the *Without Public Transit* scenario we introduce AMoD in lieu of mass transit modes like Bus and MRT. We assume that the behavioral preferences towards AMoD are the same as that of taxi and that the AMoD cost is reduced by 40% (w.r.t. taxi) based on the literature (see Spieser et al. (*23*)). Network performance in the form of travel times were passed to the day-to-day learning module, which feeds back to the pre-day model to update individual choices.

A final scenario, termed *With AMoD*, is constructed with the inclusion of AMoD along with availability of all modes from the base case scenario. Apart from the traditional on-demand door-to-door service, AMoD can also augment the rail service by providing first-last mile connectivity. This would cater only to trips that have either the origin or the destination as an MRT station, due to which ride-sharing is also heavily encouraged. The initial parameter values for AMoD remain the same; however, the waiting time is increased by 5 minutes for each leg of a trip compared to walking to reflect the delay passengers would experience while waiting for the vehicle to arrive. Overall travel time for the first and last mile of the trip will be reduced by 87.5% as compared to walk, which is due to our modification of the access/egress time value in the utility equation for MRT from a generic walking speed (4 kmph) to an average AMoD speed (40 kmph). The feedback methodology described earlier is utilized in this scenario as well.

We conducted 24 hour simulations for each scenario in SimMobility using the study area mentioned in the subsequent sub-section. The initial simulation was used to generate real-time parameter estimates such as travel times for different modes, which were then used as feedback for the choice models in the pre-day component (we called this process *feedback loop* in one of the previous sections). The results of further simulations, which represent the actual experiments, are summarized in the following sub-sections.

Study Area

This case study was tested using a prototypical city - *Virtual City*, which consists of a moderately sized network and population, generated so as to resemble land use patterns, travel behavior, and activity patterns observed in Singapore. The total population in our Virtual City is 351,000 (~10% of Singapore) with an average tour rate of 1.14 per individual. The road network consists of 95 nodes (intersections), 286 segments (road sections with homogeneous geometry) and 254 links (groups of one or more segments with similar properties). There are 12 bus lines, each having a constant service headway that ranges from 3 minutes to 9 minutes, spanning the region with 86 bus stops. Virtual City also has 4 MRT lines with a total of 20 subway stations, and 24 Traffic Analysis Zones (TAZs) overall.

Results for Virtual City

As mentioned in previous sections, a strong suit of SimMobility is the flexibility to adapt demand models as a part of the pre-day simulation component (that generates the day activity schedule).

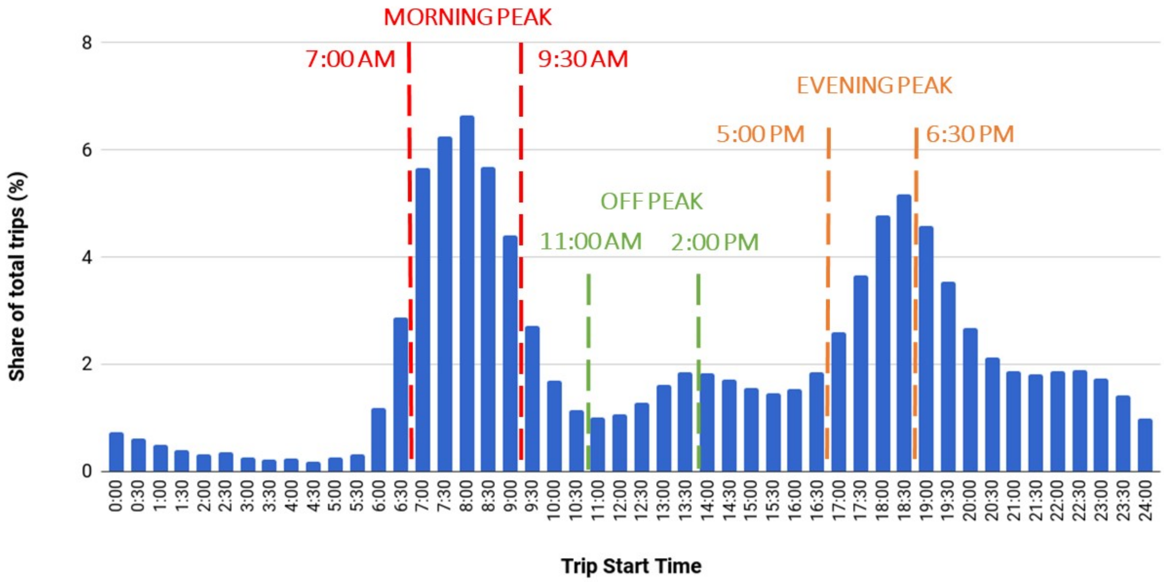

FIGURE 3 Temporal trip distribution

Therefore, we are able to observe the changes in mode choice while comparing the pre-day simulation results for the three scenarios. The temporal distribution of trips, obtained through the time-of-day (TOD) choice model is shown in Figure 3. Since the TOD model considers only individual socio-economic characteristics as independent variables, the same temporal distribution of trips is obtained for the other two scenarios.

From Figure 4, we can see that the demand for Taxi and AMoD during both morning and evening peak periods is significantly higher compared to the remainder of the day. Therefore, we adopt a dynamic fleet sizing strategy, whereby the fleet size is selected to match or be slightly higher than the demand for the remainder of the day but will only match about 10 - 15% of the demand during peak periods. Despite this seemingly low fleet size, the network experiences considerable levels of congestion as we discuss in the following sub-sections making addition of further vehicles to the fleet counter-productive.

We observe from Figure 5 that the sharpest increase in mode share for the *Without Mass Transit* scenario occurs in the case of AMoD. AMoD is also found to be more preferable to Taxi due to lower costs for both the futuristic scenarios. The consistently high Walk share is in agreement with a study by the Land Use Transport Authority (LTA) in Singapore that reported several South-East Asian hubs like Bangalore, Delhi, Mumbai, Beijing, Osaka, Shanghai, Tokyo and Singapore itself witnessing high mode shares for walking, ranging from 20% to 30% (refer to LTA (*24*)). Considering the *With AMoD* scenario, it is clear that the drop in Bus share is compensated by AMoD. An interesting point of note is a rise in the choice of MRT with the introduction of AMoD, thereby indicating that availability of first-last mile connectivity does play a role in enhancing the choice of mass transit.

To evaluate the performance of the whole transportation system on a typical day, three

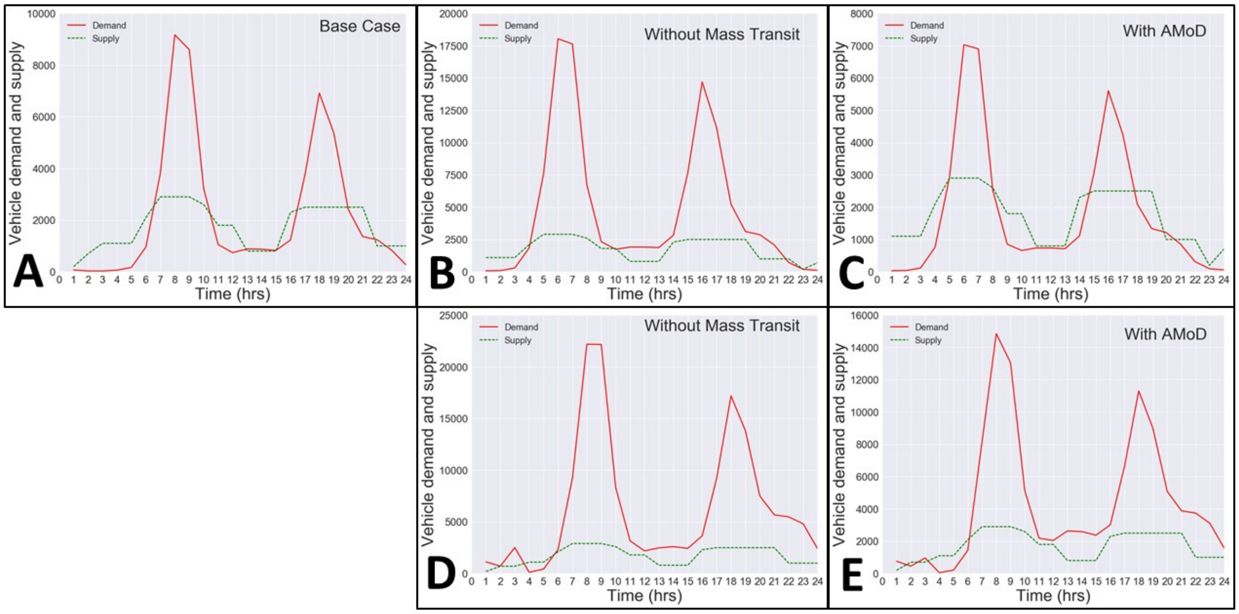

FIGURE 4 Temporal distribution of Taxi (A, B, C) and AMoD (D, E) demand and supply across scenarios

categories of metrics are defined:

- *System performance metrics* reflect the system's overall behavior for a particular scenario. We are specifically interested in identifying the levels of congestion. To this aim, we compute segment density and queuing. Segment density is defined as the number of aggregated vehicles on a road segment over its length, which can be expressed in veh/lane/km. As indicators of queuing in the network, we investigate proportion of segments experiencing queuing along with their average queue lengths.

- *User experience metrics* reflect an individual's quality of travel in the network. We compute parameters of interest such mode-specific In-Vehicle Travel Times (IVTTs) and Waiting Times (WTs) at the trip level. Longer IVTTs might point towards high levels of congestion in the network, while longer WTs would indicate that the current supply parameters such as fleet size are not adequate for the existing demand. The total Travel Time (TT) is also computed as the sum of IVTT and WT, except for Car which does not have WT due to which TT is equal to IVTT.

- *AMoD performance metrics*: Introduction of AMoD warrants a separate examination of its performance. A preliminary evaluation of the ride-sharing algorithm can be made through observing the average vehicle occupancy and the proportion of shared trips. We would also like to explore the Vehicle Kilometers of Travel (VKT) (which acts as a proxy indicator of emissions) by AMoD vehicles while in different states.

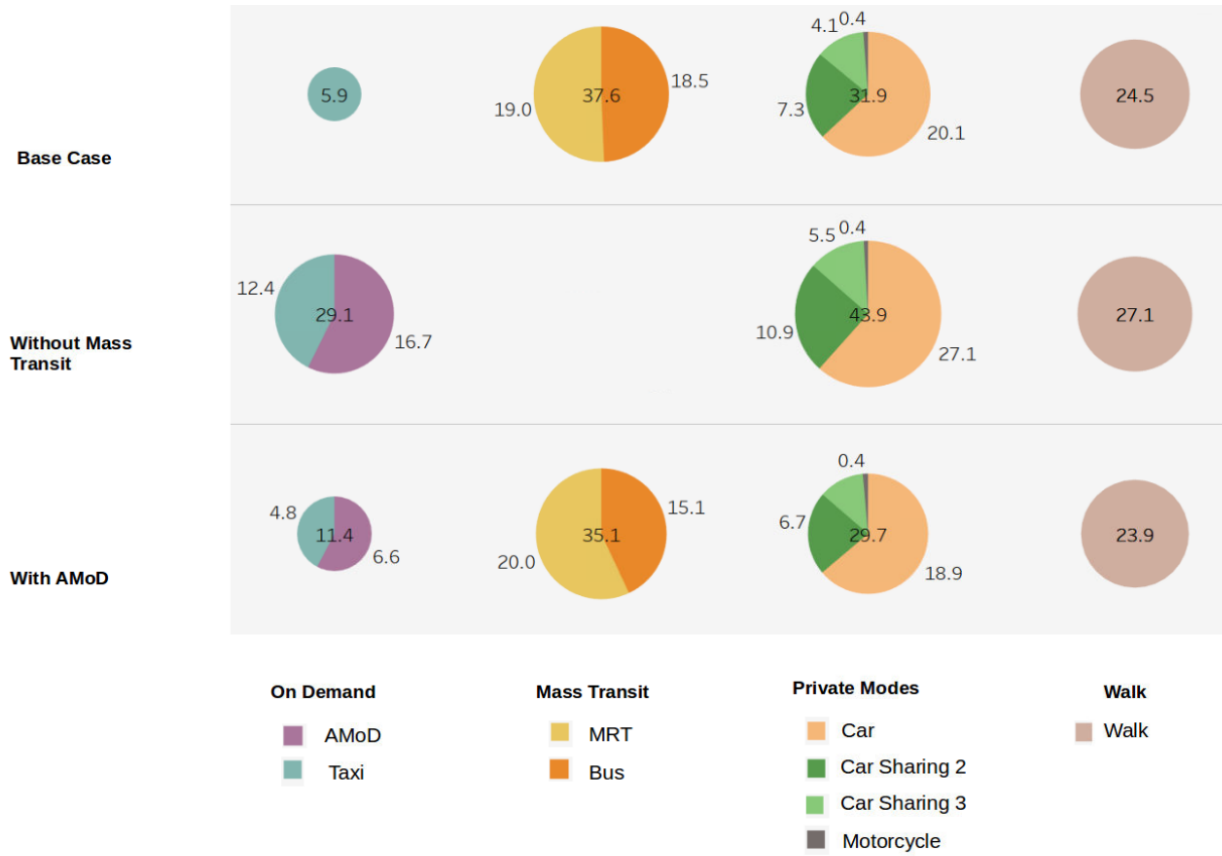

FIGURE 5 Varying mode choices across the three scenarios

System Performance Metrics

Since the morning peak has a higher trip volume than the evening peak (Figure 3) and we wish to examine the overall system in its most critical state, we drop the evening peak period from further analysis. Figure 6 shows segment density maps for Virtual City during the morning peak period and the off-peak period across the three scenarios. It is easy to observe that congestion for *With AMoD* scenario is comparatively higher than the base case, while the *Without Mass Transit* scenario experiences extremely high levels of congestion. It is interesting to note in the *Base Case* and *With AMoD* scenarios that congestion drains away during the off-peak period, as one would expect. However, in the *Without Mass Transit* scenario, congestion deteriorates considerably.

To examine the queuing patterns, the number of queued vehicles and total queue length were averaged over the morning peak and off-peak periods, following which we focused only on the segments which had a queue. For the morning peak period, 64% of segments experienced queuing with an average queue length of 6.6 meters in *Base Case*. This increased to 69% with a massive jump in queue length to 229 meters for *Without Mass Transit*, while *With AMoD* had a queuing rate of 67% with an average queue length of 49 meters.

Similar trends, although of lower magnitudes, were observed for the off-peak period as well. *Base Case* had 28% segments with 0.1 meter as the average queue length, indicating minimal levels of congestion. As observed from the congestion maps, *With AMoD* also experienced minimal congestion with 49% of segments experiencing queuing but with an average queue length of only

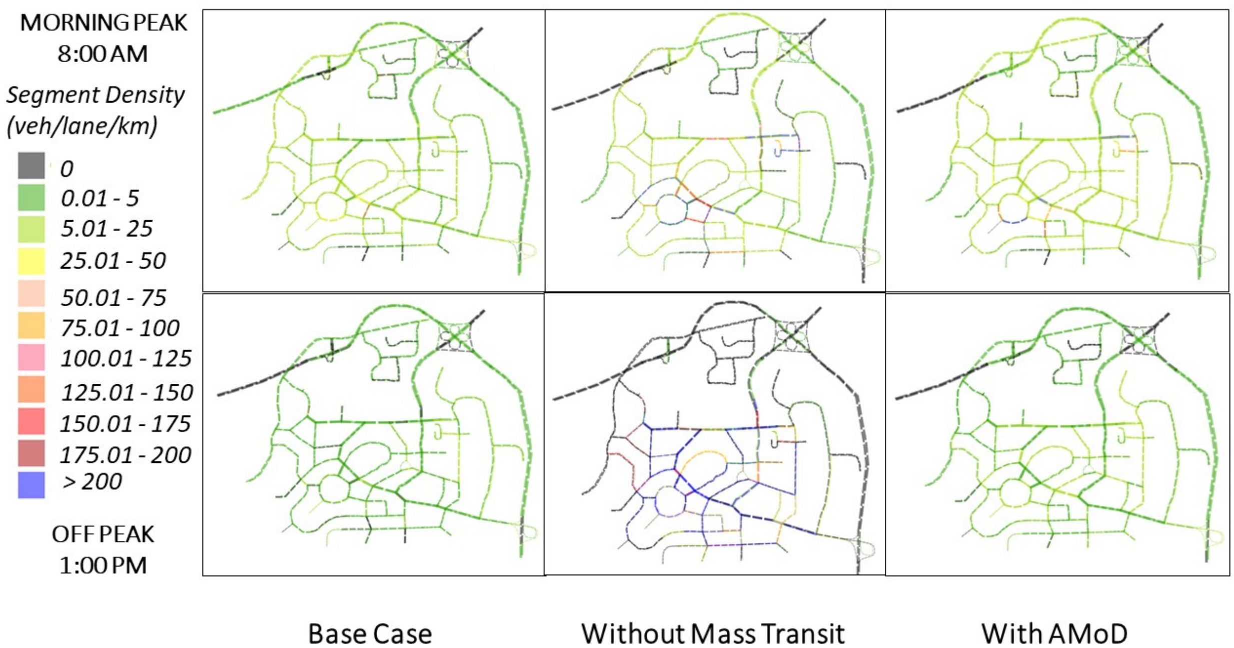

FIGURE 6 Congestion maps for peak and off-peak periods

0.2 meters. The extent of unexpectedly high congestion in the off-peak period for *Without Mass Transit* can be witnessed through a queuing rate of 41% with a staggeringly large average queue length of 1100 meters.

User Experience Metrics

An important parameter that define a user's travel experience is travel time, which has two components - IVTT and WT. We present cumulative distribution functions for mode-specific travel times in Figure 7. We keep MRT out of this analysis, since it operates on a fixed schedule-based service and its user experience is not affected by on-road congestion. Although increased demand would require an increase in train capacity or a more frequent service, this investigation is an avenue for future research.

Bus users have almost similar waiting experiences in both the *Base Case* and *With AMoD* scenarios due to the constant headway-based bus service. However, users in the *With AMoD* scenario have a higher IVTT due to more on-street congestion. While 65% of Taxi users have to wait for less than 15 minutes in *Base Case*, the same is experienced by 80% in the other two scenarios indicating a good level of service. However, due to congestion, the IVTT increases considerably with the 95th percentile being around 15, 45 and 30 minutes respectively for the three scenarios. Car users experience a similar trend in IVTT as well. The dynamic fleet sizing strategy provides a lower WT for AMoD users in the *With AMoD* case. This scenario also witnesses lower IVTT and hence, lower total travel time. The higher congestion in the *Without Mass Transit* scenario has resulted in the comparatively largest travel times for AMoD users, leading to the most unfavorable travel experience.

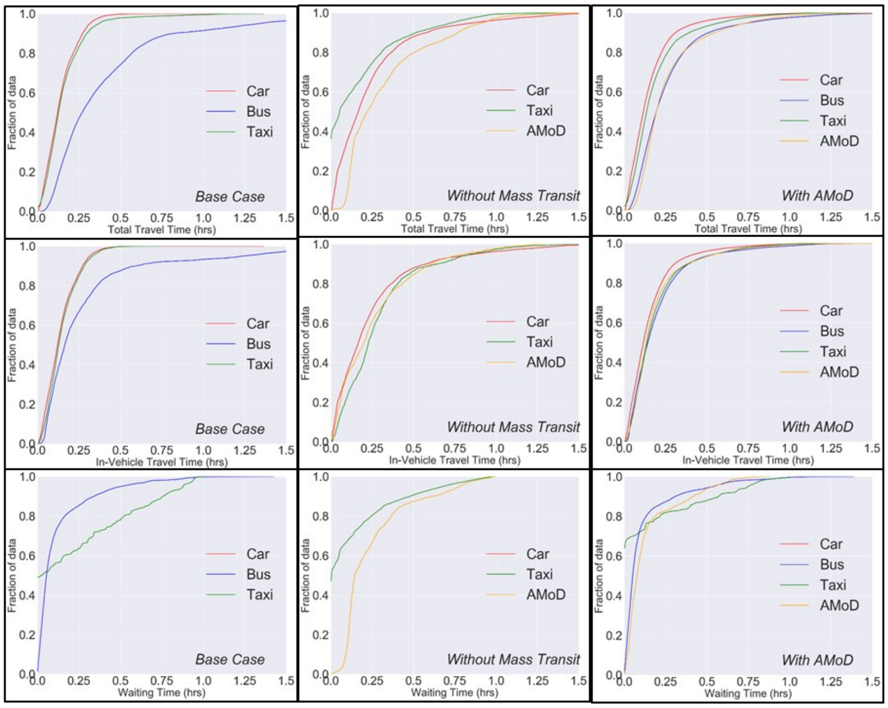

FIGURE 7 Overall user experience metrics for different modes across scenarios

AMoD Performance Metrics
We now examine the performance of AMoD specifically to gain deeper insights into their impact on the system as a whole. Considering the considerably higher demand for AMoD in the *Without Mass Transit* scenario, we observe the average vehicle occupancy to decrease from 1.80 to 1.47 in the *With AMoD* scenario. The proportion of shared trips also decreases by around 30%, thereby indicating that AMoD adjusts to incorporate more ride-sharing as demand increases.

For the *With AMoD* scenario, around 60% of total VKT is spent while traveling with a passenger, 35% while going for pick-up or parking, and 5% for empty vehicle cruising. The same observations for the *Without Mass Transit* scenario are 55%, 40% and 5% respectively. The considerably high non-trip contribution to VKT has been pointed out earlier in our discussions, which can be decreased through future explorations of better ride-matching and routing algorithms. However, an interesting observation is that higher demand will lead to an increased contribution to VKT while going for a pick-up.

Discussion

Advancements in AV technology and MoD transportation services herald the arrival of smart urban mobility in the next decade. In the light of concerns about what this might bode for the future of mass transit, it is important to investigate the impact of AMoD on an urban multi-modal transportation system. We undertake a simulation-based approach to examine hypothetical scenarios for different policy implementations with regard to the role of AMoD. While *With AMoD* encourages the introduction of AMoD and suggests that it might be useful for boosting mass transit ridership by providing first-last mile connectivity, *Without Mass Transit* paints a picture of a future where mass transit has been completely replaced by AMoD. While we obtain mode-specific insights about individual travel experience, all three categories of scenario evaluation metrics point out that *completely replacing mass transit with AMoD might not be possible without adversely affecting user experience and level of service*. Making mass transit unavailable would indeed force a modal shift to on-road modes like cars, taxis and AMoD. However, the resulting congestion would make for a terrible travel experience and lead to a complete breakdown of the system due extremely heavy congestion. Mass transit would be irreplaceable in areas with dense demand due to its high passenger/space ratio: one bus equals about 30 cars in terms of capacity, whether the car is automated or not. A key contribution of this research has been to clearly identify how policy-makers should encourage the growth of AMoD and attempt to incorporate it in the existing transportation system. Results from *With AMoD* look promising enough to perhaps consider providing subsidies to services that encourage use of mass transit, such as provision of access/egress connectivity. Therefore, we expect future urban mobility to shape AMoD not as a competitive but complementary service to mass transit.

Acknowledging that this is a preliminary investigation, we also outline directions of future research efforts. Supply decisions such as optimal fleet sizing and more refined algorithms for rebalancing and ride-sharing would be important contributions. Further scenarios can be designed to test different policy implementations of AMoD, such as modifying the *With AMoD* scenario with a subsidized cost for AMoD services providing connectivity to mass transit. Finally, the next step would be to test these scenarios on different urban regions, perhaps contrasting a transit-friendly city like Singapore with automobile-dependent regions such as Boston. The authors do not expect AMoD to be a panacea for either case; we rather reinforce that urban policies must be driven by inherent transportation cultures.

CONCLUSION

AMoD is unanimously considered as a game-changer in urban transportation. In order to fully exploit the benefits and limit the potential negative effect, systematic investigation is needed. Focusing on the performance of the operations of AMoD only is not sufficient. To correctly capture its *impact* on future urban transportation, an integrated approach is needed, which also encompasses how travelers will respond to the availability of this technology. To this aim, we developed an *AMoD* framework in SimMobility, that allows us to evaluate the adoption of the new service by the travelers, as well as its operations. Furthermore, we apply the framework to a case study that shows that mass transit will still play an irreplaceable role in urban transportation, even after the wide adoption of AMoD. The case study shows the potential of the framework to provide useful results for policy-makers.

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