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Automated Mobility-on-Demand vs. Mass Transit: A Multi-Modal Activity-Driven Agent-Based Simulation Approach

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Abstract

Among the new transportation services made possible by the introduction of automated vehicles, automated mobility-on-demand (AMoD) has attracted a lot of attention from both industry and researchers. AMoD provides a service similar to taxi or ride-sharing services, while being driverless. 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* on urban mobility. Our contribution is two-fold. First, we present a flexible AMoD modeling and simulation framework developed within a multi-modal agent-based urban simulation platform (SimMobility). The framework allows the detailed simulation and assessment of different AMoD operations together with an activity-based framework that accounts for changes in demand, such as activity participation, trip making, mode, destination, or route choice decisions. Second, we focus our attention on the role of mass transit in a futuristic urban system where AMoD is widely available. Mass transit is already challenged by current ride-sharing services, for example, Uber and Lyft, which provide comparatively better and cheaper services. 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 levels of service.

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 individualistic needs. At the same time, automated vehicle (AV) technology has advanced at an impressive pace. Corporations, such as Google and Tesla (*1*), have been in a race to develop a fully automated vehicle. The combination of these two promising technologies, known as automated mobility-on-demand (AMoD), has recently attracted interest among both researchers and industry (for example, Uber (*2*) has started testing AV programs in several states in the US).

The term AMoD (*3*) designates a service similar to MoD or taxi, with the difference that vehicle operations are driverless. AMoD combines the benefits of MoD and AVs in several aspects. First, operational cost is drastically reduced, given the complete removal of driver labor costs and superior energy efficiency of AVs. Furthermore, negative externalities, such as emissions, travel time uncertainty, and accidents, may also reduce, as already observed for MoD (*4*) and for AVs (*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 AV benefits would amount to between \$2,690 and \$3,900 annually 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 (*7–11*) has focused on the efficiency of AMoD and AVs, in terms of road movement and fleet management. However, only a handful of recent studies have shown the importance

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of considering changes in demand when designing such disruptive technologies. Azevedo et al. (*12*) assessed the sensitivity of AMoD fleet sizes and parking station configurations on individual mobility patterns, specifically with regard to modal shares, routes, and destinations. Martinez and Viegas (*13*) and ITF (*14*) focused on the mobility, mode performances, and environmental changes that might result from large-scale adoption of shared and self-driving vehicle fleets in Lisbon and Helsinki, respectively.

Cities are increasingly focused on developing sustainable urban transportation systems, with attempts to increase quality and access to public transport and non-motorized modes. In light of these initiatives, the question of the hour is: *How will AMoD impact an urban transportation system?* Merely studying efficiency of AMoD operations is not sufficient to answer this question. The demand for AMoD depends on both its attractiveness compared with other existing modes (such as private automobiles and mass transit) and on the creation of new trips due to enhanced accessibility. *Would AVs lead to extreme on-road congestion if mass transit were to be discarded?* The performance of the overall transportation supply system is of primary interest to urban policymakers. *Will the ridership (and therefore revenue) of mass transit services decrease and, as a consequence, potentially lead to a downward spiral of reduced investment and level of service?*

Questioning the role of mass transit in the future thus becomes increasingly relevant. Debates are ongoing on whether current MoD will replace mass transit (*15,16*). Researchers and transit authorities indicate ride-sharing as one of the possible causes for decline in transit ridership (*17–19*). Polzin (*20*) 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. Consequently, 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, which is expected to lead to a rapid improvement of service performance and user convenience. These concerns have been confirmed in the literature as well (*21*).

To answer questions like these, we follow an *integrated* approach, which embraces the operational aspects of the new technology while considering the response of individuals to their availability. To that effect, this work provides a twofold contribution. First, we introduce a flexible framework, developed in the open-source platform SimMobility (*22*), for the detailed simulation of the operation of AMoD services. 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.

Second, we apply this framework to a case study, where we investigate the role of mass transit in future urban transportation systems. *Will mass transit have the same vital importance as it currently does in the future when AMoD will be easily deployable?* Using our simulation framework in a case study, we show that, in dense urban environments with infrastructural constraints, a mass transit system is still necessary to cope with high mobility demand. However, AMoD can also contribute greatly in improving urban mobility if integrated with mass transit.

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. 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 (*23,24*);
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 (*25*);
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 (*26*).

This paper will focus on the MT simulator only, as 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.

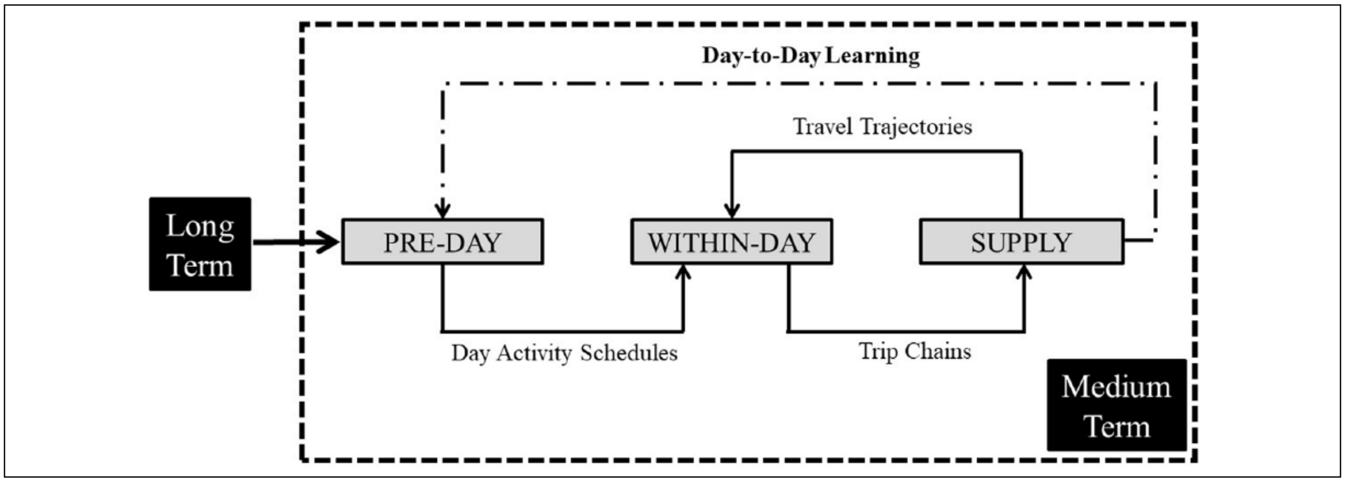

Figure 1. Feedback loop mechanism in SimMobility Medium-Term (adapted from Lu et al. [*25*]).

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, that is, 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 (*27*). The systematic utility of each mode is computed as a weighted sum of the following parameters: *total travel time*, which consist of in-vehicle travel time, waiting time, and walking time; *travel cost*, which consists of road tolls, ticket prices, service prices, and so forth; *number of transfers in public transport, a dummy variable for the CBD, vehicle ownership, age* and *gender*. 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. We make assumptions on the generalized travel cost of AMoD (see Experimental Design section) based on literature since relevant data are not available for this mode. The reader should refer to Li and Biran (*28*) for further details about the underlying behavioral models.

Travel times and waiting times are historical values, which are updated with the use of the day-to-day learning component shown in Figure 1, when "permanent or recurrent" changes on the system status quo are observed. This module feeds back supply outputs in the form of zone-to-zone travel times and costs to the pre-day level to update travelers' knowledge of the system. After a simulation is complete, the simulated costs, waiting, and travel times are recorded, aggregated at the zone-to-zone level and fed back to the pre-day module for its next run (day), that is, weighted averages of values from the previous and current iterations are used to update the historical values in the database. The pre-day simulation is then re-launched, in which the individual re-plans the activities and trips for the next simulation iteration (day). Assuming that there is indeed a change on travelers' knowledge of the system, multiple iterations of the day-to-day learning are expected until convergence of these transferred values is achieved.

Before expanding on the implementation, it is worth emphasizing the benefits of this approach. By using such a framework, we relax the common assumption that demand is fixed and pre-defined. In fact, in a multi-modal urban transportation system, such static conditions are hardly observed and it is crucial to consider partial behavioral shifts (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. For instance, we can determine a feasible price for AMoD operators by testing scenarios with different levels of price. The major contribution of our framework is to allow for the evaluation of impact of performance metrics on user adoption and vice-versa. For example, a certain AMoD operational 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 target price can be adjusted accordingly through experiments. We cannot

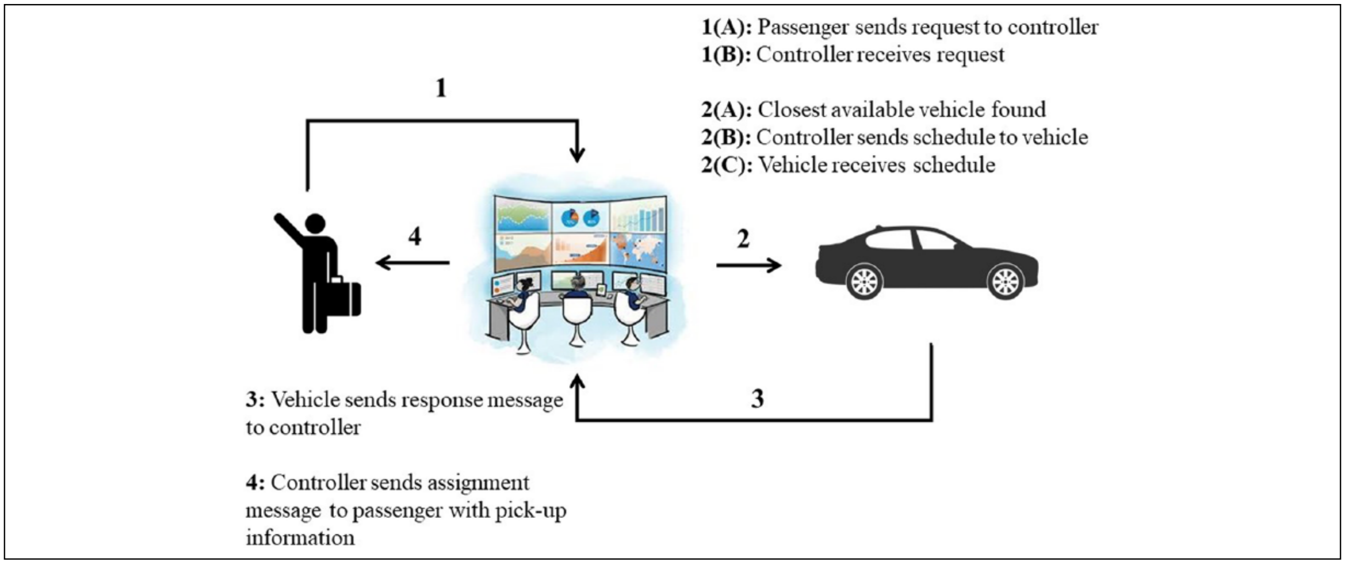

Figure 2. Control flow diagram for the AMoD framework.

present such analyses in this paper for brevity, but we emphasize that our framework enables this kind of research.

Model and Design of AMoD in the Supply Simulator. In the supply simulator, the AMoD framework is composed of three components: the *passenger*, 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 passenger 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 of 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 passenger*, *drop-off a passenger*, *cruise in a certain zone*, and *park*. Each schedule is then sent to the intended vehicle, which will execute the sequence of commands.

It is noteworthy that this mechanism is naturally suited to implement ride-sharing, that is, serving two or more users with the same vehicle at the same time. For example, if we want passenger 1 to share a ride with passenger 2, it suffices to send to a vehicle a schedule containing the following commands: *pick-up passenger 1*, *pick-up passenger 2*, *drop-off passenger 1*, *drop-off passenger 2*. Since the passengers, vehicles, and the controller are interacting asynchronously through messages, the simulation is made fully parallelizable, leading to significant savings in computation time.

While unable to include a detailed description of the ride-matching algorithm here for brevity, we refer the reader to Araldo et al. (*29*). The algorithm of the AMoD controller tries to assign each incoming request to an available vehicle periodically. The match is feasible if adding the pick-up and the drop-off of the new passenger to the schedule of the vehicle satisfies the following constraints.

1. The *waiting time* of all the passengers already included in the schedule, as well as of the new passenger, must be below a certain threshold.
2. For each passenger, we first estimate the *minimum time* that the passenger would spend for their trip if a vehicle were only serving them, going from their origin to their destination directly. Next, we compute the estimate of the time between their pick-up and 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 detours made due to the fact that the trip is not exclusively serving a single user, but is shared with others. We also impose that the additional delay be below a certain threshold.

We consider 10 minutes to be the threshold for both parameters and the sharing capacity to be 2 passengers in this study.

Case Study: AMoD and Mass Transit

We now apply the framework described above to consider the role of mass transit in future urban mobility. *Will mass transit 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

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*), pooling with one extra passenger (*Carpooling 2*), sharing with two extra passengers (*Carpooling 3*), public bus (*Bus*), Mass Rail Transit (*MRT*), traditional taxis (*Taxi*), motorcycle (*Motorcycle*), and walking (*Walk*). The modal availabilities are in accordance with our study area, which we describe in the following section.

In the *Without Mass Transit* scenario we introduce AMoD in lieu of mass transit modes such as Bus and MRT. We assume that the behavioral preferences toward AMoD are the same as that of taxi and that the AMoD price is reduced by 40% (w.r.t. taxi), based on the literature *(30)*. 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 trip legs that have trip-ends at MRT stations, in 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 trip leg compared with 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 with walk, which is as a result of our modification of the access/egress time value in the utility equation for MRT from a generic walking speed (4 km/hr) to an average AMoD speed (40 km/hr). Note that we use the average AMoD speed for the access/egress time in the utility equation only for the first run of the process (as an a-priori value). Subsequent runs have updated AMoD access/egress times obtained from the supply simulation. 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 following 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 (recall the *feedback loop* described earlier). The results of subsequent simulations, which represent the actual experiments, are summarized below.

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. Relevant maps are shown in Figure 3.

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). 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 total trips, obtained through the time-of-day (TOD) choice model is shown in Figure 4. Since the TOD model is largely dependent on individual socio-economic characteristics as independent variables, we do not witness significant changes in the pattern across the three scenarios, i.e., 4(*a*), 4(*b*), and 4(*c*).

From Figure 4, we can see that the demands for Taxi and AMoD during both morning and evening peak periods are significantly higher compared with 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 because of lower tariffs for both the futuristic scenarios. The consistently high Walk share is in agreement with a study by the Land 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% (*31*). 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.

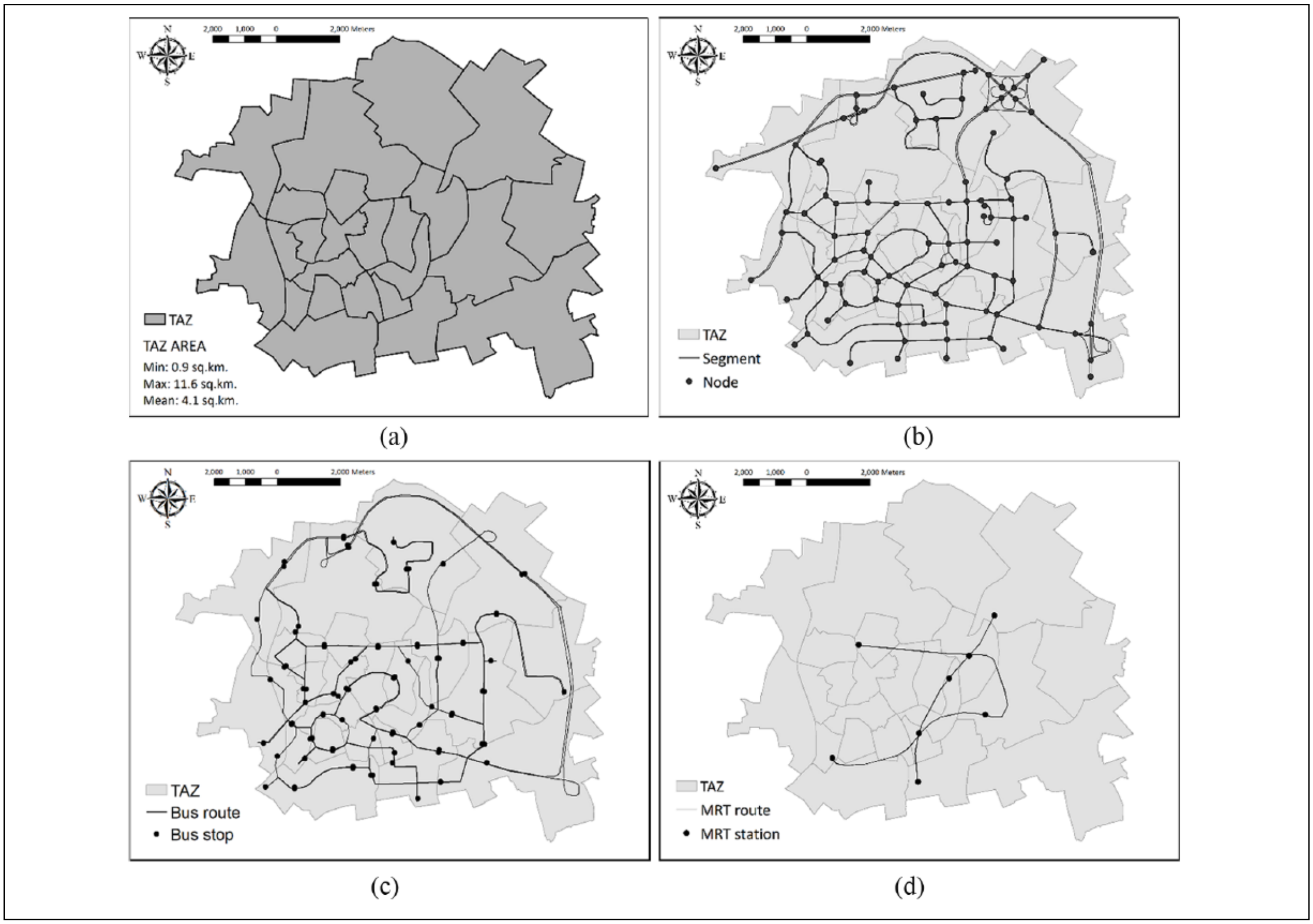

Figure 3. Maps of the Virtual City showing: (a) TAZ boundaries, (b) road network, (c) bus network, and (d) MRT network.

To evaluate the performance of the whole transportation system on a typical day, three categories of metrics are defined.

1. *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.
2. *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 toward high levels of congestion in the network, and 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, meaning that TT is equal to IVTT.
3. *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 AVs while in different states.

System Performance Metrics. As the morning peak has a higher trip volume than the evening peak (Figure 4) 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

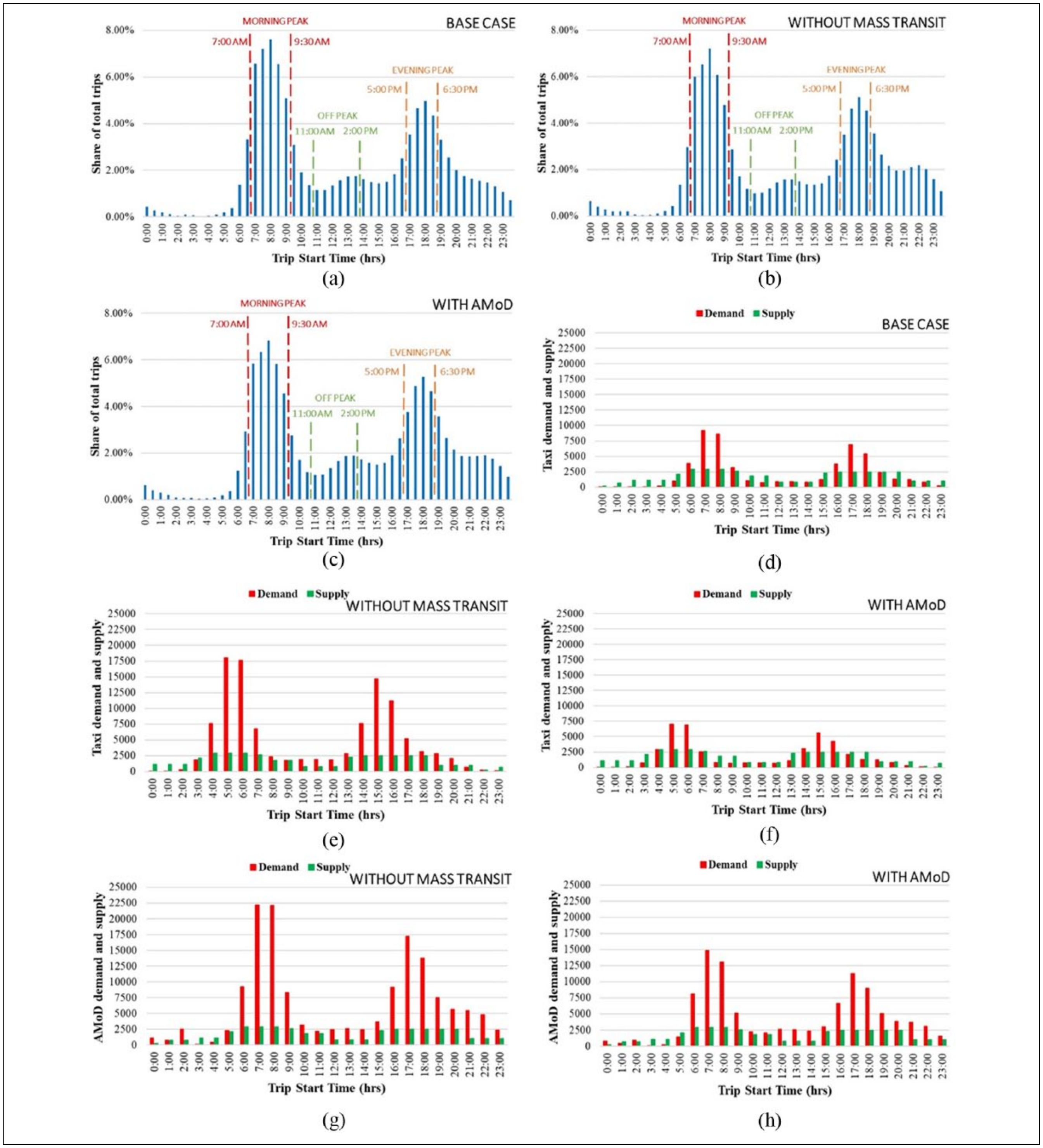

Figure 4. Temporal distribution of total trips (a, b, c), taxi demand and supply (d, e, f) and AMoD demand and supply (g, h) for all possible scenarios.

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 m in *Base Case*. This increased to 69% with a massive jump in queue length to 229 m for *Without Mass Transit*, while *With AMoD* had a queuing rate of 67% with an average queue length of 49 m.

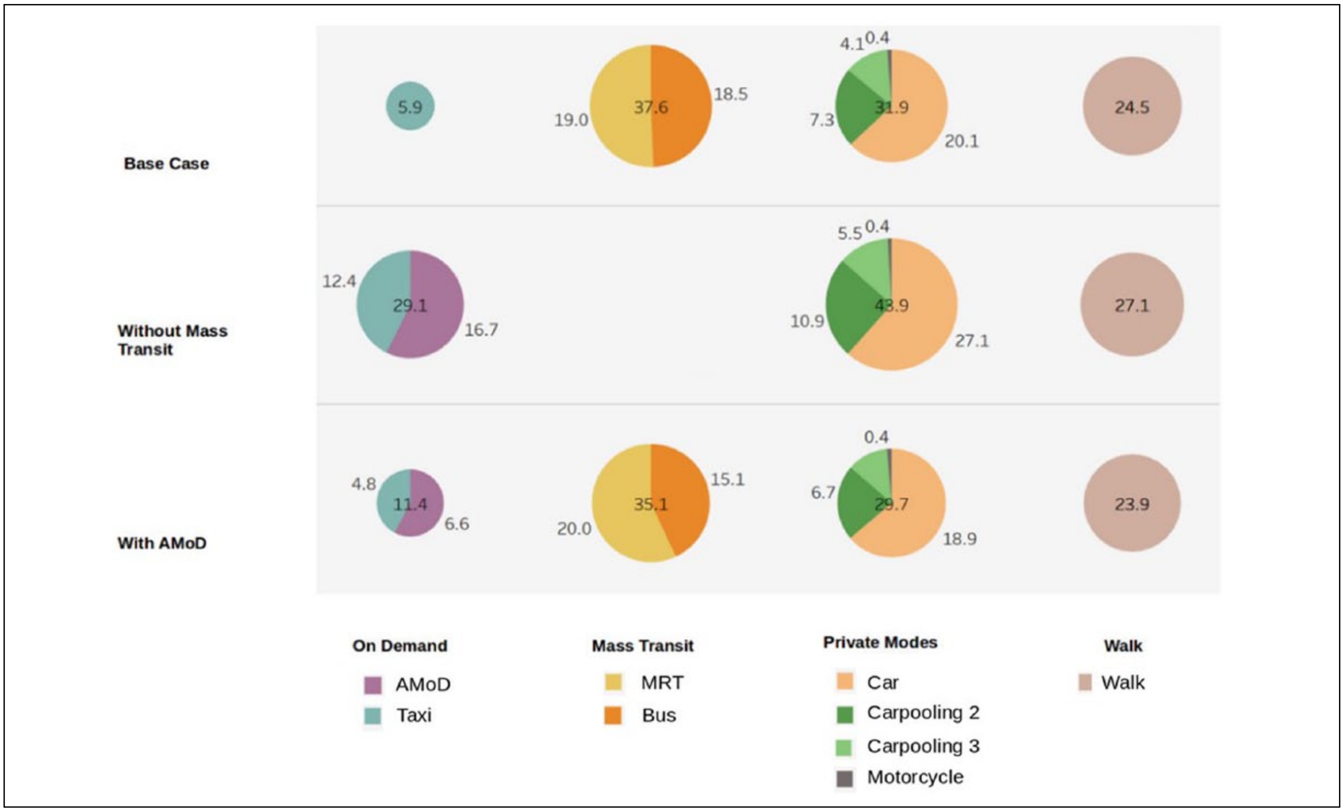

Figure 5. Changes in modal shares across the three scenarios.

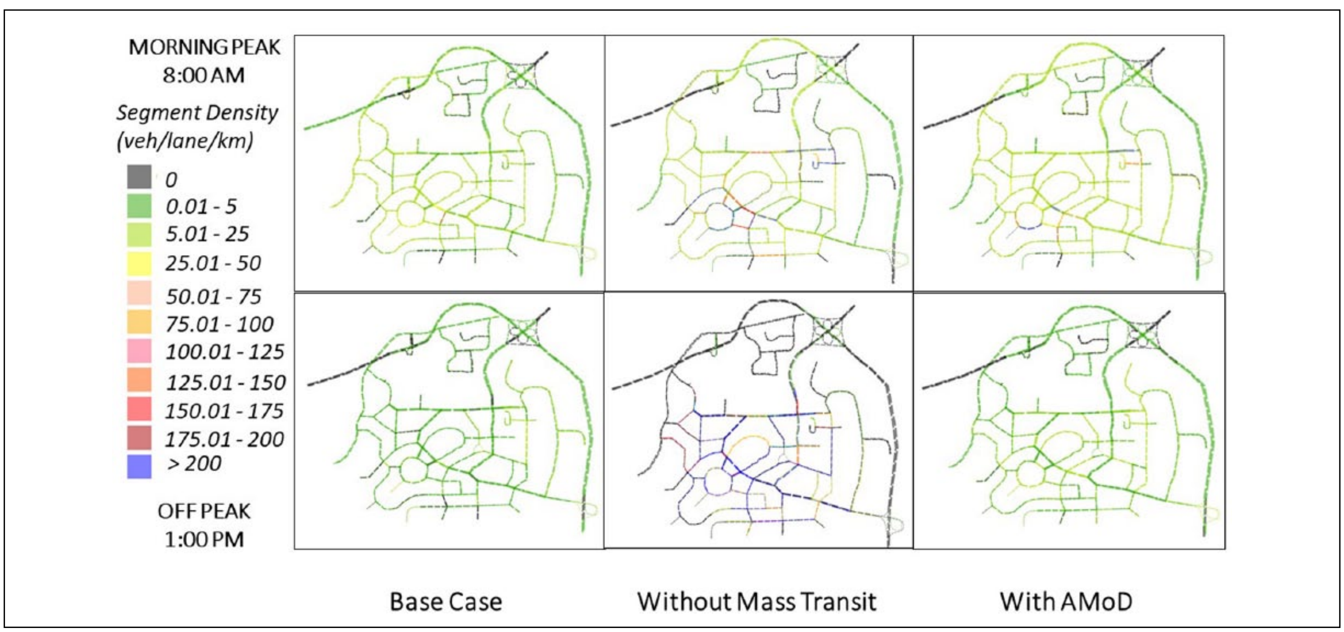

Figure 6. Congestion maps for peak and off-peak periods.

Similar trends, although of lower magnitudes, were observed for the off-peak period as well. *Base Case* had 28% segments with 0.1 m 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 0.2 m. 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 m.

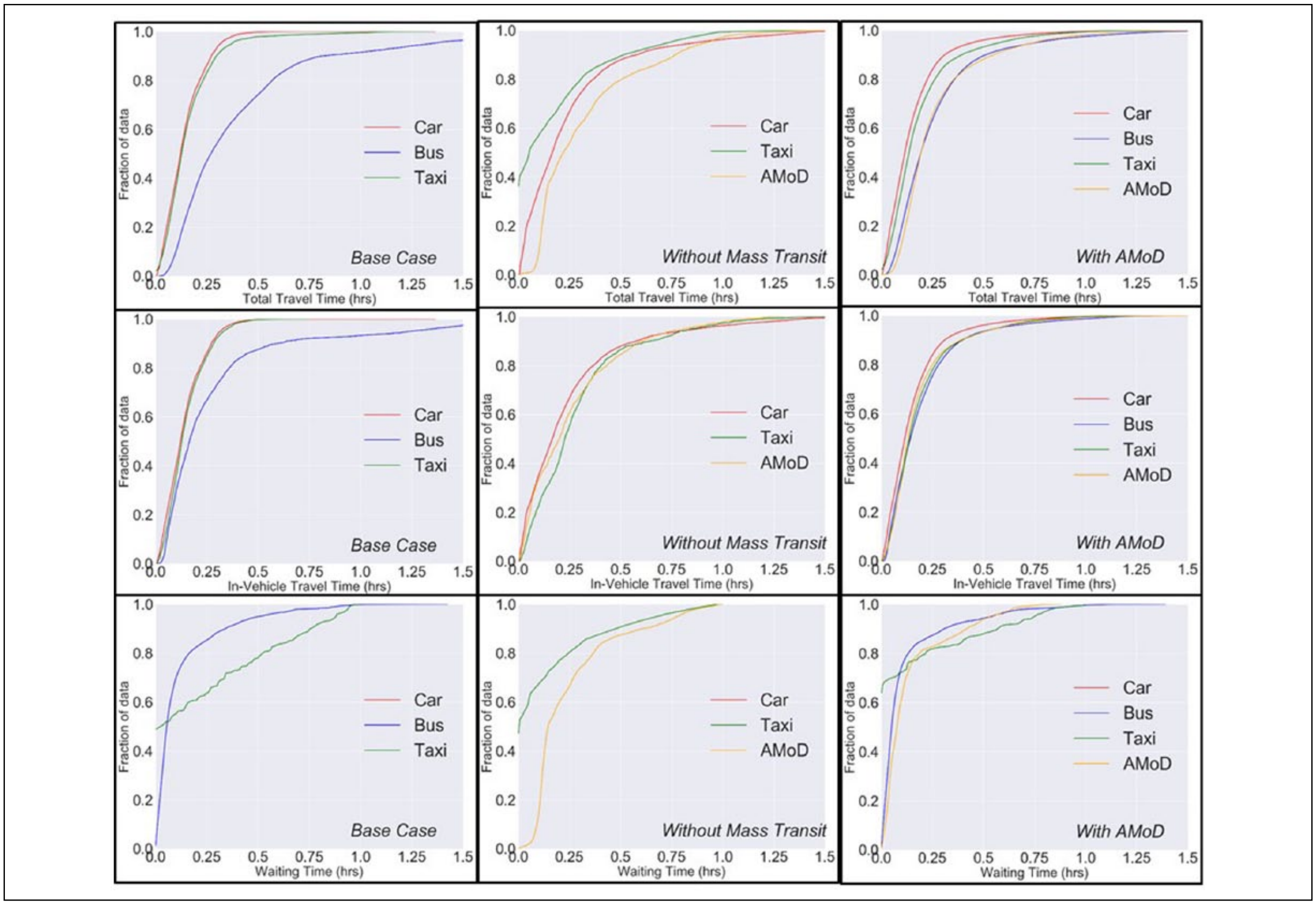

Figure 7. Overall user experience metrics for different modes across scenarios.

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 because of 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, because of 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, therefore, 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.

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 may lead to an increased contribution to VKT while going for a pick-up.

Discussion

Advancements in AV technology and MoD 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* represents a scenario where mass transit has been completely discarded. Although 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 such as cars, taxis, and AMoD. However, the resulting congestion would make for a terrible travel experience and lead to a complete breakdown of the system because of extremely heavy congestion. Mass transit would be irreplaceable in areas with dense demand because of 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, future research should focus on the scenarios in which future urban mobility shapes AMoD not as a competitive but complementary service to mass transit.

We acknowledge that this is a preliminary investigation and the trends we observe in our case study cannot be generalized. Therefore, several research avenues remain open for further exploration. Supply decisions such as optimal fleet sizing and more refined algorithms for re-balancing and ride-sharing would be important contributions. Further scenarios can be designed to test different policy implementations of AMoD, such as a modified AMoD price scenario for subsidized AMoD services providing connectivity to mass transit. The effects of preferential traffic treatments such as transit signal priority or high-occupancy vehicle lanes should be evaluated. The interplay between mass transit and AMoD deserves further investigation. Redesigning mass transit services (headways, routes, capacities, and so forth) based on changes in vehicle occupancies on different transit lines due to availability of AMoD is a particularly promising avenue.

Finally, the next step would be to test these scenarios on different urban scenarios, including mixed urban and suburban areas, contrasting a transit-friendly city like Singapore with automobile-dependent regions such as Boston, and different levels of car ownership and income. All these aspects are expected to impact the mode share and the performance of the transportation system. The authors do not expect AMoD to be a panacea for all the urban scenarios; 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 presented an AMoD framework in SimMobility that allows us to evaluate the adoption of the new service by travelers, as well as its operations. Furthermore, we apply the framework to a case study which shows that mass transit may play an irreplaceable role in urban transportation, especially under scenarios of wide adoption of AMoD. Having proposed a method to quantify the implications of discarding mass transit and demonstrated it in a specific AMoD-inclusive urban scenario, the next question we ask is: *When are we better off without mass transit, and when does mass transit complement AMoD?*

Acknowledgments

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