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Citation: Le, Diem-Trinh et al. "Simulating Multi-scaled Impacts of Automated Mobility-on-Demand Services" Paper presented at the 2019 IEEE Intelligent Transportation Systems Conference, ITSC 2019, Auckland, New Zealand, 27-30 Oct. 2019, IEEE © 2019 The Author(s)

As Published: https://dx.doi.org/10.1109/ITSC.2019.8917418

Publisher: IEEE

Persistent URL: https://hdl.handle.net/1721.1/125645

Version: Author's final manuscript: final author's manuscript post peer review, without publisher's formatting or copy editing

Simulating Multi-scaled Impacts of Automated Mobility-on-Demand Services

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***Abstract* – In this paper, we simulate the impacts of Automated Mobility-on-Demand (AMoD) using SimMobility, an integrated land-use transport micro-simulation platform. Using data for Singapore, we examined the future scenarios in which AMoD is added as an additional mode on top of existing modes, or as an exclusive one. We found that AMoD may lead to changes in accessibility, which will consequently affect people's behaviours. Our results show that a scenario in which AMoD is an additional mode is a preferred option, whereas the exclusion of AMoD will lead to lower accessibility for people in the study area.**

Keywords—Microsimulation, activity-based accessibility, autonomous vehicles

I. Introduction

Autonomous Vehicles (AVs) is by all means one of the most trending topics in transportation research. Researchers have explored several dimensions of AVs such as its potential impacts on traffic, policies, and people's travel preferences [1–5]. However, little is known about how Automated Mobility-on-Demand (AMoD)'s effects on accessibility can be quantified. Furthermore, to date, none has provided a complete overview of AMoD's impacts on multiple temporal and spatial levels. It is well-established that land use and transport interact with each other, that is, changes in land use affect transport performance and vice versa [6]. How does the interactive change look like when AMoD is introduced?

Many integrated land use transport models (LUT) connect a travel demand model with a land use model using an accessibility measure. Accessibility is the value of the connectivity provided by a given land use transport system at a specific location [7]. Among several accessibility measures, the activity-based accessibility (ABA), the expected maximum utility that a person gains from access to spatially distributed opportunities, has a high potential as an accessibility indicator and as an integration link between land use transport models [8,9]. How can ABA be used to measure the impacts of AMoD?

In this paper, we demonstrate how an integrated land-use transport micro-simulation platform simulates and reflects the impacts of AMoD in future scenarios. Specifically, we seek to answer three main questions:

(1) What are AMoD's impacts on accessibility?

(2) How will AMoD affect transport performance?

(3) How will changes in accessibility (resulting from AMoD) affect households and individuals' behaviors?

II. Methodology

A. Activity-based accessibility (ABA) measure

Based on the random utility theory, an individual's accessibility is measured as the expected maximum utility that can be achieved from the choice set, which in a nested logit model can be expressed as:

$$E(max\ U_{ik}) = \frac{1}{\lambda} ln \sum_{i \epsilon A_k} exp(\lambda . V_{ik})$$

where V_{ik} is the systematic component of utility U_{ik} for individual k selecting alternative i from the choice set A_k and λ is a scale parameter. This measure of accessibility is commonly referred to as the "*logsum*" i.e. the logarithm of the sum of the exponentiated utility among the available alternatives [8].

In a day activity schedule system, logsum is calculated from the lowest level to the top level of the nested logit of travel choices. Decisions on lower levels depend on those at higher levels. Higher level's decisions are linked to the lower ones through the use of the logsum, which reflects expected maximum composite utility of choices from lower levels. This logsum generated at the highest level of a day activity schedule system is an indicator of an individual's accessibility and is referred to as activity-based accessibility [8,9].

The ABA is similar to traditional utility-based accessibility measures, yet instead of focusing on a particular trip purpose, it incorporates the impacts of trip chaining, the full set of activities pursued in a day, and the scheduling of activities. This type of accessibility measure is generated from the day activity schedule model system, an activity-based travel demand model system, which can model the whole day's schedule of multiple activities and trips taken by an individual, using various modes, and joined together in a particular pattern. Total accessibilities generated from the transport components can then be passed into the land-use components as exploratory variables to predict long-term choices. In an integrated model where the travel demand is activity-based, individual accessibility or access to spatial opportunities is assumed to affect long-term decisions. Changes in travel behaviour lead to changes in accessibility, which influence location choices. Conversely, changes in land use patterns lead to changes in accessibility and then changes in travel demand such as the mode, amount, and timing of travel. For this reason, ABA was adopted as an integration link in the SimMobility microsimulation platform.

B. Simulation platform

SimMobility is a system of mobility-sensitive behavioural models integrated in a multi-scale activity-based simulation platform, which considers land-use, transport, and communication interactions [10,11]. In SimMobility, agent behaviours are modelled at multiple levels and in various timescales, which corresponds to three integrated simulators:

Short-term (ST) simulator is a traffic micro-simulator, extended with a communication simulator as well as pedestrian and public transport. The ST simulator represents events and decisions at a high spatial temporal resolution (i.e. on the order of tenths of a second), such as lane changing, braking, accelerating, individual and crowd pedestrian movement, and agent-to-agent cell-phone communications.

Mid-term (MT) simulator is a mesoscopic simulator designed for activity-based modelling, with explicit pre-day and within-day behaviour, including re-routing, re-scheduling, and multiple transport modes. Agent decisions such as route choice, mode choice, and activity pattern are modelled at the seconds to minutes timeframe. The pre-day models follow an econometric day activity schedule approach to decide an agent's initial overall daily activity schedule, particularly its activity sequence (including tours and sub-tours), with preferred modes, departure times by half-hour slots, and destinations. This is based on sequential application of hierarchical discrete choice models using a Monte Carlo simulation approach.

Long-term (LT) simulator is a land-use transport simulator with a market transaction bidding model. It models long-term choices such as house (re)location, job location, and car ownership by simulating day-to-day transactions in the real estate and job market.

Across these three levels, SimMobility implements the activity-based modelling paradigm i.e. all choices are ultimately tied to the agents' goal of performing activities on the corresponding time scale. Agents can be of different types such as households or firms, and can have varying roles including operators, bus drivers, or real-estate agents. SimMobility simultaneously simulates demand and supply at each level, as well as interactions between different levels. For example, the LT simulator provides an agent population and land-use configuration to the MT, which transmits trip-chains to the ST simulator. The ST provides performance measures to the MT, which then provides accessibility measures in the form of ABAs from the top-level model of pre-day component to the LT simulator.

C. Integrating SimMobility-MT and SimMobility-LT with ABA

SimMobility-MT consists of three main components: Pre-day, Within-day, and Supply models. The pre-day model is the highest level plan, including only important choices e.g. the activity schedule. The activity schedule defines an agent's planned activities and corresponding times, together with the main transport modes between activities. Following the Day Activity Schedule approach [11], MT Pre-day model consists of a system of interconnected discrete choice models representing choices at distinct dimensions.

The MT simulator receives the populations from the LT simulator that contains agents' characteristics, and processes the day activity schedule of each agent. It then passes the accessibility measure i.e. the ABA from the top-level model of the Pre-day component (the Day Pattern Binary Model) to the LT simulator. In SimMobility, the ABA measure reflects the range of choices in destinations and modes, the scarcity of time and money, and accounts for the heterogeneous preferences among agents. As a link between the MT and the LT simulator, it ensures the behavioural consistency of agents by encapsulating agents' day-to-day activity and travel considerations into their long-term location and vehicle ownership choices.

We expect that introducing AMoD will affect individuals' accessibility, which will subsequently affect their long-term and mid-term choices. We simulate the impacts of AMoD using the SimMobility simulation platform.

To simulate AMoD in SimMobility, we made it an available option for individuals in the synthetic population when using MT Pre-day to model their activity schedule. In the Supply simulator, the passenger sends a request for an AMoD service specifying the pick-up and drop-off locations. An AMoD controller processes the request and sends a vehicle to pick up the passenger. After dropping off the passenger, the vehicle can either cruise (free floating) or be sent to designated parking locations. Details for the AMoD framework are described in Basu et al. [12].

D. Scenario specifications

We simulated three transportation scenarios for the year 20XX: (1) Base case scenario refers to existing transport modes including car, ride-sharing, bus, train, and walk, but excluding cycling and PMDs, (2) Partial automation scenario refers to the case where AVs are introduced as an additional mode, and (3) Full automation scenario is where AV is the exclusive mode.

AV deployment scenario is specified as in Table I.

TABLE I. AV DEPLOYMENT SCENARIO

Dimension	Description
AV vehicle type	Varying fleet size and vehicle capacity
AV services	Point-to-point AV taxis & stop-to-stop AV mini-buses
Controller	MaaS-AMoD controller
Ride type	Single ride & Ride sharing
Parking	-Free floating/ always roaming -Central allocation (parking in assigned depots)

Synthetic populations and road networks for the simulation were generated considering forecasted future growth rate. We assumed that road capacity remains the same as for the base case. The activity-based models in MT were estimated using the Singapore Household Interview Travel Survey (HITS) 2012 and the same preferences were assumed to hold in 20XX. AV fleet size was estimated based on travel demand (Table II). We also assumed that cost for AMoD rides is 50% of taxi rides.

TABLE II. AV FLEET SIZE

Fleet	Base case	Partial automation	Full automation
AMoD	0	400	800
MOD	1900	2100	0
Taxi	550	450	0

E. Sample selection and study area

SimMobility was used to simulate AMoD impacts on accessibility in a selected planning area, which is located in central Singapore (black borders in Figure 2 and 3). The area covers 8.2km^2, with an estimated population of approximately 200,000 in 20XX. The area is one of the oldest residential towns in Singapore and includes a good mix of land uses. We assume AMoD is deployed only in the study area while the rest of Singapore remains unchanged.

III. RESULTS

A. Changes in accessibility

Figure 1 shows the changes in accessibility between various scenarios. From the figure, it is clear that the overall accessibility increases under the scenario of partial automation while decreases under the scenario of full automation, compared against baseline. For those living outside of the study area, changes are mostly nonexistent since most of their daily trips are not affected under different scenarios. For those living inside the study area, on the other hand, changes are more prominent.

Both car owners and those who do not own private vehicles see an increase in accessibility under the partial automation scenario where AMoD is added to the available modes. For car owners, full automation leads to a drastic decrease in accessibility because of the restriction of private car use. For non-owners, the addition of AMoD outweigh the loss of private cars and taxis since they mostly rely on public transit in the baseline scenario.

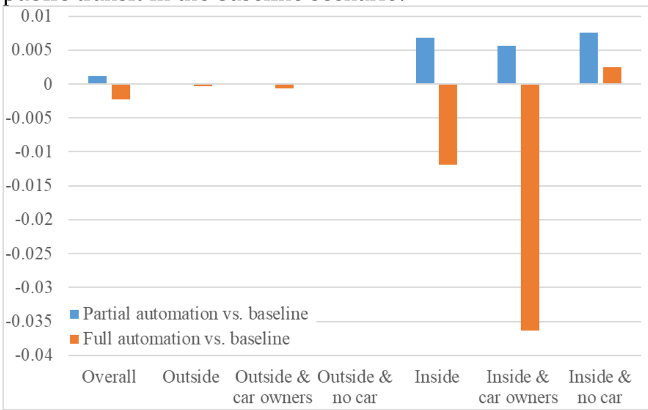

Fig. 1. Changes in accessibility

Figure 2 and 3 below demonstrates the spatial distribution of changes in accessibility. As shown in Figure 2, the most significant gain in accessibility occurs within the study area under the partial automation scenario. Figure 3, on the other hand, shows that the study area also sees the largest drop in accessibility under the full automation scenario. Results here suggest, under current specifications, the benefit of additional utility provided by AMoD could not compensate the complete loss of private vehicles.

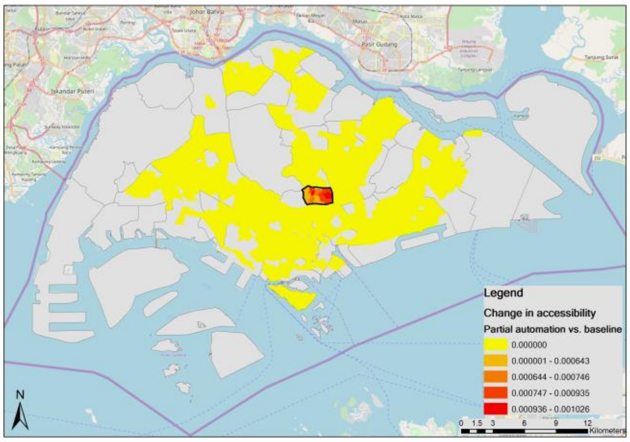

Fig. 2. Spatial distribution of accessibility changes (partial automation vs. baseline)

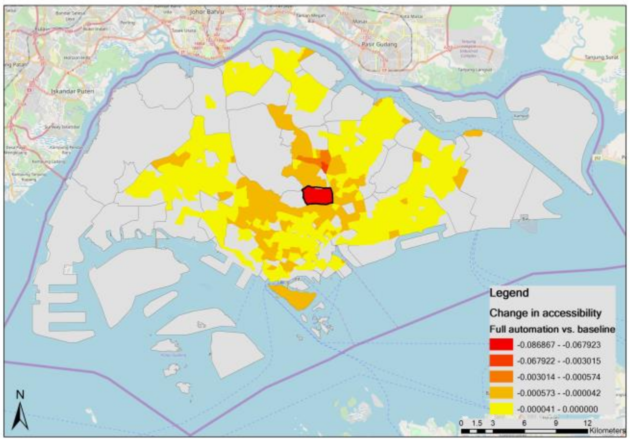

Fig. 3. Spatial distribution of accessibility changes (full automation vs. baseline)

B. *Short-term impacts*

The first immediate effects of AMoD will be on the transport network, which can be simulated at a microscopic level, e.g. SimMobility-ST. SimMobility-ST functions at the operational level; it simulates movement of agents at a microscopic granularity (within day). It synthesizes driving and travel behavior in detail and also interacts with a communication simulator that models the impact of device to device communication on these behaviors. The portfolios of AMoD under different scenarios can be compared in terms of following performance measures of urban mobility environment and help to set the key idea how to introduce and operate AMoD:

- Urban infrastructure usage, from lane structure (curbside) congestion, travel-times, connectivity, intermodal hubs capacity and parking and curb side usage
- Energy and fuel consumption to vehicle emission by travel, driving behavior changes as well as fleet management scenarios

This part, however, has not yet been completely implemented. Hence, we focus on demonstrating AMoD impacts at the long term and mid-term time scales only.

C. *Mid-term impacts*

To evaluate AMoD impacts, we use several scenario evaluation criteria. This section describes a few typical indicators produced by SimMobility-MT to demonstrate AMoD impacts at the mid-term level.

Having AMoD as a transport mode affects people's mode choice. Figure 4 shows the mode share among three scenarios: Base case, Partial automation and Full automation. In the Base case, trips by cars account for approximately 25%. This figure reduces to about 21% when AMoD is introduced in the scenario of Partial automation. In contrast, the share of public transport trips increases from around 60% in Base case and Partial automation scenario to more than 90% in Full automation scenario. In the Partial automation scenario, AMoD serves about 1% of total trips and this figure increases to 3% in Full automation scenario. In the other words, there is a shift to AMoD and PT in Partial and Full automation scenarios, at the expense of private vehicles.

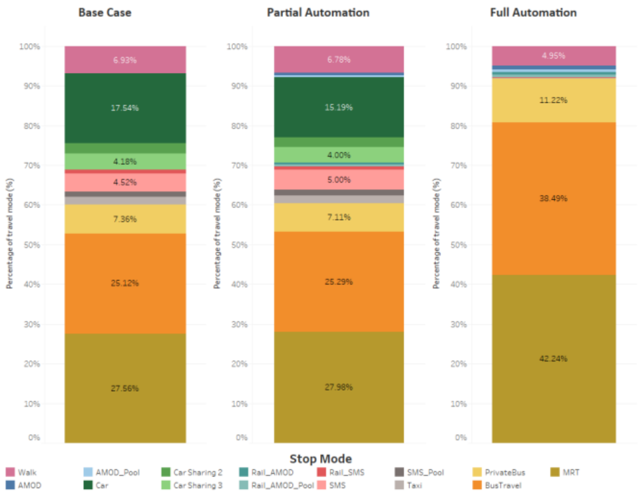

Fig. 4. Mode share among three scenarios

Figure 5 compares total travel time by transport mode among the three scenarios. It seems that travel time in Full automation scenario is the highest across all scenarios, for all activities. When looking at daily total travel time (figure not included), the numbers similar between two scenarios: Base case and Partial automation. However, in the scenario of Full automation, travel time by public transport increases considerably from around 40,000 hours to nearly 55,000 hours for buses and from about 12,000 hours to over 23,000 hours for MRT. This is probably due to the shift to public transport mentioned above. The fact that AMOD price is assumed to be higher than that of public transport might have contributed to the low take-up rate for AMOD and high take-up rate for bus and MRT.

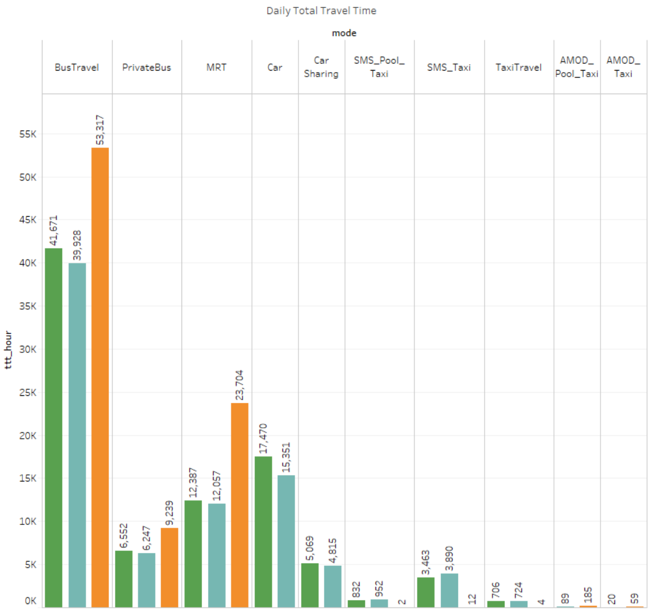

Fig. 5. Daily total travel time

Figure 6 shows the share of all trips by number of transfers. The share of trips without transfer is highest in Partial automation scenario, and lowest in Full automation scenario at all times. On the other hand, Full automation scenario has the largest share of transfer trips. Specifically, at peak hours, the number of trips with one transfer in this scenario increases by nearly 50% (from around 21% to around 33% in the morning peak hours), and similarly for trips with two or more transfers. It can be said that the Partial automation scenario tends to have the most efficient connection, followed by Base case and Full automation.

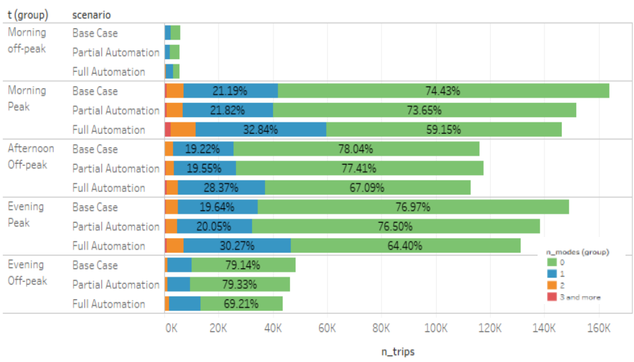

Fig. 6. Share of transfer trips

Figure 7 indicates the average number of passengers carried per vehicle across three scenarios. In the scenario of Base case and Partial automation, a human car carries around two people per hour. However, this figure increases to 10-12 people for AMoD vehicle at peak hours when it is introduced in the Partial and Full automation. During off-peak hours, an AMoD vehicle serves about 4 and 9 people in the scenario of Partial and Full Automation respectively. AMoD is therefore more efficient than private cars in terms of number of passengers carried per hour.

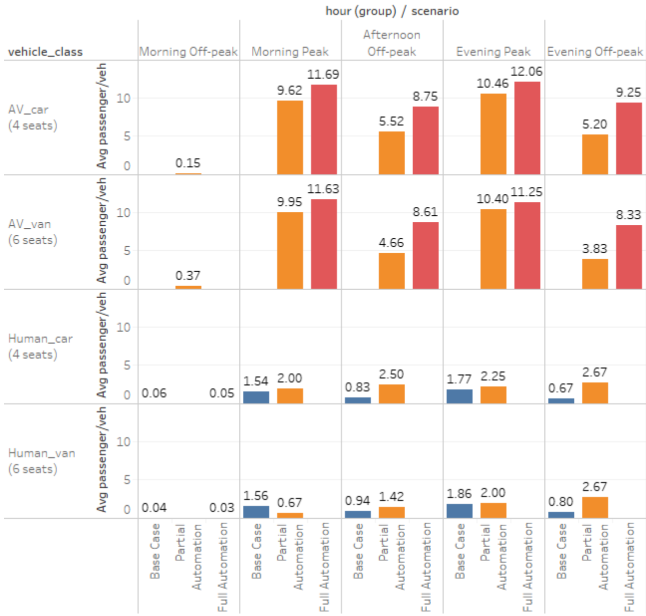

Fig. 7. Average number of passengers carried per vehicle

D. *Long-term impacts*

AMoD affects mode share, as described in the previous section. Under both partial and full automation, the car ownership rate is likely to decrease. The added accessibility originated from AMoD and also the decreased utility of private cars from restrictive measures would collectively contribute to the increased motivation of residents in the study area to give up car ownership.

On the other hand, since the accessibility measure increases under the partial automation scenario, residence in the study area would become more attractive. Therefore, housing prices in the study area are likely to increase along with the willingness-to-pay level of household buyers on these housing units. Under the full automation scenario, the attractiveness of living in the study area would mostly depend on the tradeoff between accessibility gains from AMoD and the loss of private cars and taxis. In the current setting, it seems that the housing inside the study area is more favorable under full automation than it is under other scenarios, as detailed in [13].

The impact of AMoD on job location choice may not be as obvious. Other factors including salary, promotion prospects, and other benefits may also affect the choice of job opportunities. Nonetheless, the increased accessibility by adding AMoD may attract more workers to work in the study area and encourage workers living in the study area to seek more distant jobs. Further information on long-term impacts will be detailed in our forthcoming paper [13].

IV. CONCLUSIONS

In this paper, we have examined a scenario in 20XX where AMoD is deployed in a relatively small area in Singapore, as either an additional mode on top of existing modes, or as an exclusive one. Using an integrated simulation approach, our results show that AMoD may have several effects on individual's accessibility, which will consequently influence their long-term and mid-term choices. Specifically, deployment of AMoD in the study area will lead to significant increase in accessibility for people who live in the area and do not own cars. For car-owners, however, restricting private vehicle ownership will result in a loss in accessibility. With increased accessibility in the Partial Automation scenario, houses and jobs in the area may become more attractive, resulting in more people willing to relocate to the area. Changes in accessibility will also affect mode share, including an increase in public transport usage (mode share and travel time) at the expense of private mode. The introduction of AMoD will also lead to higher transportation efficiency as on average shared AVs will carry more passengers per hour than human cars. Overall, we found that a scenario in which AMoD is an additional mode is a preferred option, whereas the exclusion of AMoD will lead to lower accessibility and reduced transportation performance. We have not carried out the microscopic simulation but expect that AMoD will also have significant short-term impacts.

Our paper demonstrates the potential of ABA as an integration indicator in integrated land-use transport models, which suggests important implications for micro-simulation approaches in LUT analysis. Our study is explorative in nature yet the preliminary results may provide some useful implications for urban and transport planners in their AVs policies decision-making process.

Acknowledgment

This research is supported by the Singapore Ministry of Transport, Urban Redevelopment Authority, Land Transport Authority, Ministry of National Development and the National Research Foundation, Prime Minister's Office under the Land and Liveability National Innovation Challenge (L2 NIC) Research Programme (L2 NIC Award No. L2NICTDF1-2016-3). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not reflect the views of the Singapore Ministry of Transport, Urban Redevelopment Authority, Land Transport Authority, Ministry of National Development and National Research Foundation, Prime Minister's Office, Singapore.

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