MICROSIMULATION OF DEMAND AND SUPPLY OF AUTONOMOUS MOBILITY ON-DEMAND

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ABSTRACT

Agent-based models have gained wide acceptance in transportation planning as, with increasing computational power, it allows for large-scale people-centric mobility simulations. Several modeling efforts have been reported in the literature both on the demand side (with sophisticated activity-based models that focus on individual's day activity patterns) and on the supply side (with detailed representation of network dynamics through simulation based dynamic traffic assignment models). This paper proposes an extension to a state-of-the-art integrated agent-based demand and supply model, SimMobility, for the design and evaluation of autonomous vehicle systems. SimMobility integrates various mobility-sensitive behavioral models within a multiple time-scale structure, comprised of three simulation levels: (i) a long-term level that captures land use and economic activity, with special emphasis on accessibility, (ii) a mid-term level that handles agents' activities and travel patterns, and (iii) a short-term level, that simulates movement of agents, operational systems and decisions at a microscopic granularity. Within this context, this paper proposes several extensions at the short-term and mid-term level to model and simulate autonomous vehicle systems and its impacts on travel behavior. To showcase these features we present the first-cut results of a hypothetical on-demand service with autonomous vehicles in a car-restricted zone of Singapore. SimMobility was successfully used in an integrated manner to test and assess the performance of different autonomous vehicle fleet sizes and parking stations configurations and to uncover changes in individual mobility patterns specifically in terms of modal shares, routes and destinations.

1 INTRODUCTION

Although the initial developments of autonomous vehicles (AV) technologies were carried out during the 80's (*1*), vehicle automation technology has been under the spotlight since the 2005 DARPA's Grand Challenge (*2*). It is currently considered a key research effort in many car manufacturer and mobility/robotics research centers (*3*) and has recently started to be marketed for personal use (*4*, *5*, *6*). AVs rely on extensive technological developments in terms of software and hardware integration, high-level control design, sensor technology and data fusion techniques, motion control algorithms, and vehicle communication tasks (*7*). All these components keep evolving and being rethought for particular deployments, such as new fault-tolerance sensing frameworks (*8*), first- and last-mile targeted systems (*9*) or innovative communications for vehicular networks design (*10*). These developments target the change in terms of efficiency, safety and cost of vehicular systems. Yet, aspirations for its contributions in solving large scale transportation problems such as pollution, road congestion and land use are also high, but are still to be clarified, as they may rely on the design of the integrated service itself and the environment where it will be deployed (*3*).

Recent studies have focused on the design and operation of specific AV systems beyond the private use, such as on-demand services (Autonomous Mobility on-Demand - AMOD) (*11*, *12*, *13*, *14*, *15*). Zachariah and Mufti (*14*) modeled the implementation of a fleet of autonomous taxis in New Jersey, based on origin-destination trips derived from travel surveys and focusing on vehicle occupancy rates. The studies of Pavone *et al*. (*11*) and Smith *et al*. (*12*) show a theoretical solution to fleet sizing by introducing rebalancing assignments that minimize the number of empty vehicles traveling in the network. The introduced rebalancing policy (based on a fluidic model) has been tested in a low-fidelity simulation developed in Matlab and, using both theoretical and simulation results, it is possible to determine the minimum number of vehicles required to maintain the systems' stability. Note that in case of AMOD systems, fleet sizing is similar to fleet sizing of Mobility On-Demand (MOD) systems with human-driven vehicles, but with the advantage that the vehicles can redistribute themselves. Barrios and Godier (*16*), for example, evaluated three different rebalancing strategies (zero, periodic and continuous redistribution) for MOD systems. This evaluation was performed for both station-based (i.e. vehicles can be picked-up and dropped-off only at predefined stations) and free-floating (i.e. vehicle can be picked up and dropped off anywhere within an operating zone) system. Analysis was performed using an agent-based simulation approach and tested on a square grid with a random demand. Similarly, Brownell and Kornhauser (*13*) evaluated the necessary AV fleet size for two scenarios: (i) personal rapid transit, and (ii) smart paratransit. While the models did not account for rebalancing, they do give insight into the upper and lower bounds of the fleet size required for both models.

Only recently the mobility impacts of these systems have started to be analyzed. In (*15*) the impacts on car fleet size, volume of travel and parking requirements of shared and non-shared AMOD configurations are analyzed in an agent-based simulated scenario for Lisbon, Portugal. The study points a potential reduction of 9 out of every 10 existing cars, but noticing the increased fleet millage. However, the analysis did not include a dynamic traffic model which would simulate vehicle-level interactions (and therefore congestion) nor the impacts on individual choices. Fagnant and Kockelman (*17*) turned the spotlight to the analysis of impacts of a shared non-electric AMOD fleet in a simulated grid-like city with size of Austin, Texas, with around 1,700 trip requests per day (3.5% of the original private vehicle trips), where intermediate stops for pick up and drop off of additional passengers are not allowed. Each vehicle would serve 31 to 41 persons a day and would replace nearly 12 conventional vehicles; only less than 0.5% of travelers waited more than five minutes; 11 parking spaces per AMOD vehicle would also be freed. The overall distance traveled increased by 11% compared to a traditional human-driven self-owned fleet. Yet, the scenario analyzed does not rely on a real urban network, ignoring heterogeneous patterns. Burns *et al*. (*18*) focuses on the impacts of network configuration and service cost of shared AMOD fleets. Three different network environments are analyzed: a mid-sized city (Ann Arbor, Michigan, US), a low-density suburban development (Babcock Ranch, Florida, US) and a large and densely-populated urban context (Manhattan, New York, US). Using queuing theory and network models, travel patterns, cost estimates and vehicle requirements are computed for each scenario. For Manhattan, for example, where the demand considered was the one for the existing taxicab service, a significant reduction of average waiting time (from 5 to less than a minute) and fleet size (from 13,000+ to 9,000) was estimated.

In terms of simulation tools, agent-based approaches have shown to capture and reproduce different transportation-related phenomena, at different levels of details (from traffic micro-simulation to long-term land use models) (*19*). Using agent-based models for decision-making offers many advantages: agents (individuals, households, vehicles, etc) can be modeled in detail, with heterogeneous characteristics and preferences and their behavior can be validated at the individual level, leading to new possibilities for studying and evaluation policies, including AV. In (*15*, *17*), the benefits of using agent-based approaches were demonstrated, in terms of the flexibility in assessing different AV scenarios, the potential comprehensiveness in the assessment of different impacts and the detailed level of the outputs obtained. Agent-based models have reached a level of integration and complexity that elevate the potential of such methods for the analysis of mobility-targeted disruptive technologies.

It is clear that the first steps in simulating AV have been successfully carried out and provided important insights on which research, modeling and simulation efforts must be taken. The extension of impact assessment to individual behavioral decision making is necessary. The design and optimization of AV solutions should be carried out together with integrated behavioral simulation models to account for more realistic changes in demand and supply of the overall transportation system. In this paper we present our most recent efforts in using an integrated simulation framework for the analysis of AV systems in urban environments. As a pioneer exercise we showcase the capabilities of using both state-of-the-art behavioral and mobility models to investigate the impacts of AV scenarios. In Section 2 we describe how integrated and multi-level demand and supply can be modeled together. In Section 3 the set-up and the results of the specific simulation scenario of an AMOD service in Singapore are presented. Finally in the last Section, we describe the main conclusions and limitations of our study, list the on-going work and point to future research directions.

2 INTEGRATED SIMULATION OF AMOD DEMAND AND SUPPLY

The generic approach to model multi-level demand and supply is through loose coupling of different simulators, each one specialized on a specific component (*20*). The typical interface between models consists of exchanging files or API (Application Programming Interface) calls. For example, travel simulators such as Transcad (*21*), which runs a 4-step model, or TRANSIMS (*22*) and MATSim (*23*), which run an activity-based models, can generate vehicle and passenger trips that can be loaded in microscopic simulators for the computation of accurate network performance measures. In (*24*) MATSim and SUMO were combined by means of file exchange and a SUMO call from MATSim API to account for detailed traffic light control in agent's travel plans for a toy network. Yet, the consistency in terms of agents characteristics (e.g. individual preferences), model formulation (e.g. consistent route-choice models) and time resolution (e.g.

trip time attributes) remained at stake. A similar reasoning can be established between land use models and travel simulators, for accessibility computation.

To tackle these challenges SimMobility, a new simulation platform that integrates various mobility-sensitive behavioral models within a multi-scale framework that considers land-use, transportation and communication interactions, was recently proposed (*20*, *25*).

2.1 SimMobility

The high-level architecture of SimMobility is shown in Figure 1 (*20*). SimMobility is composed of three main modules differentiated by the time-frame in which we model the behavior of an urban system. The Short-Term (ST) simulator works at the operational level: it simulates movement of agents at a microscopic granularity (i.e. less than a second). It synthesizes driving and travel behavior in detail. The Mid-Term (MT) simulator handles transportation demand and supply at the day level; it simulates agents' behavior in terms of their activities and daily travel patterns. The MT represents moving vehicles at an aggregate level, and routes are generated by behavior-based demand models. The Long-Term (LT) simulator captures land use and economic activity on a year-to-year scale, with special emphasis on accessibility. It predicts the evolution of land use, models property development, determines the associated life cycle decisions of agents, and accounts for interactions among individuals and firms. Roughly speaking, SimMobility Short-, Mid- and Long-Term correspond to the traditional micro and meson of transportation modeling and land-use analysis.

SimMobility's framework is fully modular such that each level can run independently and only interact with the other level when necessary. The key to multi-scale integration in SimMobility is a single database model and a single code base that is shared across all levels. Every agent exists and is recognized by all levels, and information is used according to each level's needs. In this way, an agent's behavior and characteristics will remain consistent in the three simulators. Similarly, the code structure and functions are shared by the three levels, assuring consistency among sub-models. Further details on SimMobility, in terms of modeling details, consistency and integration, can be found in (*20*, *25*). In the next section we describe the proposed extensions to the ST and MT level for simulating AVs. Impacts at LT level were not considered in the present study as AV-related behavioral aspects such as car-ownership and individual/firm location decisions are still being integrated.

2.2 Integrating Autonomous Mobility On-Demand in SimMobility

To analyze the impacts of specific AV technologies on travel patterns, SimMobility demand and supply simulation components were extended to account for dedicated AMOD service and vehicle access restrictions. For this case study, we limit the analysis to the ST and MT simulators; the inclusion of LT (both by using a LT-generated synthetic population and analyzing the LT effects of AMOD) is still in progress.

Short-Term Model

SimMobility ST is responsible for advancing agents on the transportation network according to their respective behavioral and decision models. It is based on the open-source microscopic traffic simulation application MITSIM (*26*). In MITSIM, a probabilistic model is used to capture drivers' route choice decisions and driving behavior parameters and vehicle characteristics are randomly assigned to each driver-vehicle unit. Vehicles are moved according to route choice, acceleration and lane changing models. The acceleration model captures drivers' response to neighboring conditions as a function of surrounding vehicles motion parameters. The lane changing model integrates mandatory and discretionary lane-changes in a single structure. MITSIM includes also merging behavior through courtesy and yielding, and drivers' responses to traffic signals, information, speed limits and incidents. The detailed driving behavior model formulation and parameters implemented in SimMobility ST are those estimated and documented by Yang and Koutsopoulos (*26*), Ahmed (*27*) and Toledo *et al*. (*28*) for MITSIM. Additional enhancements were then made in SimMobility ST, such as: an enhanced reaction and perception time formulation (*29*), the lateral movement during lane-change and an intersection behavior driving based on the conflicts technique.

While MITSIM includes a well-defined structure for simulating traffic management (*26*), a more flexible Control and Operation system module that can also simulate fleet control was implemented in SimMobility. For this study, we extended the Control and Operation system module with a dedicated AMOD controller for managing AV operation. This is a comprehensive change on the supply capabilities of SimMobility ST. Our AMOD Controller is an integrated, but detachable, module composed of: an initialization, a fleet management and a vehicle tracking component (see Figure 2). The detailed description of its components can be found in (*30*).

The fleet management module is responsible for facility location, vehicle assignment and routing and vehicle rebalancing. The facility location model estimates the best locations to place distribution centers (parking stations) of AMOD vehicles. Stations aim to provide charging and maintenance facilities for vehicles, assuming an electric mobility solution and stand-by space when on-street parking is not available. The vehicle assignment and routing model decides how vehicles should be assigned to customers and routed to their destinations, minimizing distance traveled on the network. The rebalancing aims to move vehicles to where they are (or will be) needed. Due to asymmetries in travel patterns the AMOD system tends to become unbalanced mainly due to home-work commuting patterns. Rebalancing mechanisms are therefore required to realign the supply of vehicles with the expected demand (*12*, *31*). The AMOD Controller uses a Gaussian process to predict the demand for each station that is then fed to rebalancing model (*30*).

Finally, the AV decision making models should, preferably, be based on the motion control algorithms used by the AV manufacturers. For this first-cut implementation, the existing acceleration and lane-changing models in the vehicle flow model of SimMobility ST (see Figure 2) were adjusted to exclude human (driver's) heterogeneity factors and individual behavior stochasticity. All AV behave the same way, and the safety margins in terms of gap acceptance, safety headway and reaction time were reduced (to 1.0s, 1.0s and 0.5s, respectively).

Mid-Term Model

SimMobility MT simulates daily activities and travels at the individual level. It combines activity-based microscopic simulation on the demand side with mesoscopic simulation on the supply side (*25*). The demand side comprises two groups of behavioral models: pre-day models and within-day models. The pre-day models follow an enhanced version of econometric *Day Activity Schedule* approach that has been evolved from (*32*), predicting: (i) the activity sequence (including home-based tours, work-based sub-tours, and intermediate stops), (ii) the trip destinations and modes, and (iii) the departure times (on half-hour slots). This is based on a sequential application of hierarchical discrete choice models using a Monte Carlo simulation. Readers are directed to (*25*) to get details of the pre-day modeling framework.

At the pre-day level, an implementation of a car-restricted area with AMOD service was assumed to affect directly the destination and mode choice. Mode availability for trips involving origins and/or destinations within this area changed, leading to multimodal trips that combine private vehicles (in the case those are the modes restricted) outside the implementation area, and AMOD inside the implementation area. As transferring between modes is forced for these trips, it is necessary to properly model the agents' behavioral response. Transfers were therefore considered and the utility specification of the AMOD mode was based on the individual preferences towards taxi due to the lack of AMOD-specific data for model estimation. For mandatory activities with fixed destination (such as going to work or school) the agents were only able to change modes, while for non-mandatory activities (such as shopping) they also had the possibility of changing destination. The structure of the pre-day is such that mode choice (for mandatory activities) and mode/destination choice (for non-mandatory activities) models passes accessibility measures to the day pattern model. For the AMOD scenario, accessibility measures may change, which in turn may induce changes in day pattern choices for an individual (i.e. 2nd order effect of the AMOD). For example, an agent may select a more complex tour pattern, skipping shopping or including a shopping stop within a home-based tour instead of performing two separate tours, one for work and another for shopping.

Once the daily activity schedules are obtained for all agents, the within-day models predict the routes for planned trips, transforming the activity schedule into actual trips. Depending on the traffic conditions and effective travel times, the agents could reschedule the remainder of the day, cancel an activity, re-route while traveling (including alighting a bus to change route), or run an opportunistic activity, like shopping while waiting (*25*). On the within-day level, the implementation of the restricted area with AMOD service affected the route choice, i.e., private vehicles had a smaller number of available paths which may lead to a change in congestion on alternative paths.

The supply simulator follows the dynamic traffic assignment (DTA) paradigm as in (*33*). The DTA is run for private and public transport modes. Public transportation supply in MT model allows bus lines to follow headway based operations. On-road bus stops and bus bays with appropriate estimated average dwell and clearance time are also modeled. Furthermore, it also allows for the accurate estimation of impacts of the bus operations on the road traffic. The updated network performance measures were then transferred back to pre-day as a learning mechanism, for the individual choices re-estimation. Through an iterative process, consistency can be achieved between the demand and supply models of MT simulator.

The MT simulator takes as input a multimodal network and a population (which may come from the LT simulator or other population data sets) that contains detailed characteristics of each agent. As an output, it passes accessibility measures (in the form of Logsums) from the pre-day component of MT simulator to the LT simulator. The MT simulator provides the ST simulator with trip chains as input demand to simulate smaller network regions in more detail.

3 CASE STUDY ON THE CENTRAL BUSINESS DISTRICT (CBD) IN SINGAPORE

To test the above implementation a case study of a specific AMOD system in Singapore is used. In our case study private vehicles are not allowed to access a 14 Km^2 restricted zone in the CBD (see green area in Figure 3) and a smart-phone based AMOD service is introduced as an alternative mode, which operates only within the zone. Access to this area was granted to the existing bus lines, Mass Rapid Transit (MRT) trains and taxis.

The AMOD system uses autonomous mid-size sedans without car-pooling services. The cost of the AMOD service was assumed as 40% less than the regular taxi service in Singapore, resulting in an average cost of about \$3 SGD within the CBD area. The other modes were assumed to remain unchanged (i.e. buses and MRT kept their frequencies, fares and capacities and the taxi fleet and cost remained the same) using the year 2012 configuration as reference. Similarly, no changes in the road network and traffic control systems were assumed for this case study.

The simulated population was the one estimated for 2012 (see section 3.1). The impacts of AMOD parking locations within the CDB on land-use were ignored and residents of the CBD area were not given any privilege of driving their own vehicle within the restricted area. These strong assumptions allowed us to test the models and prove that the simulator gives us expected results. As the simulator is still under development, we are planning to relax some of these assumptions in the future.

To showcase the framework capabilities, a set of performance measures for the AMOD and overall transportation systems were assessed and compared to the existing supply, namely: service performance levels (waiting and travel times), route choice indicators (path splits), and mode shares (Section 3.4).

3.1 Data

For the calibration of SimMobility the following data sets from Singapore were used:

1. Land-use data, including residential buildings, firm and school locations and its respective characteristics;
2. Household interview travel survey (HITS) for 2008 and 2012;
3. 4.5 months of detailed GPS traces from a taxi fleet of about 15,000 vehicles;
4. 3 months of public transport smart-card data (EZ-link card) with tap-ins and tap-outs for buses and MRT.
5. Google transit network data for the buses routes and schedules;
6. SCATS traffic light configuration data;
7. Detailed road network configuration from multiple sources.

A synthetic population of 4.06 million individual travelers was generated for the entire island and validated for the year 2012 (for further details on the population generation process see (*25*, *34*). The HITS data allowed the estimation and validation of all MT pre-day choice models, resulting in activity-schedules for the full synthetic population. On the supply side, the road and public transportation network were coded using information from the Land Transport Authority (LTA), the Google transit and the NAVTEQ databases. Despite the fact that all levels of SimMobility use the same network database, the level-specific supply models use it differently (e.g., while ST lane change models need detailed lane attributes, MT uses them to compute segment capacities for speed-density functions). The traffic lights used in SimMobility ST were simulated according to the specific configurations of each intersection using LTA's SCATS. Driver's route-choice was estimated using the taxi GPS data while public transit route-choice used the EZ-link card data set (*34*).

The results from (MT) pre-day validation for the population of the year 2012 are shown in Figure 4. These predicted results are based on model estimation using HITS 2008 and validation with HITS 2012. %validation is done for HITS 2012. They cover all levels of decisions modeled in pre-day: (i) daily activity patters in terms of tours and intermediate stops, (ii) mode choice for all tours, and (iii) time of the day for all individual trips in the entire Singapore. This population corresponds to the baseline simulation (i.e., without AMOD) of our study case, and reproduces the mobility and activity patterns observed in practice for most of the scheduling dimensions except in some instances on time-of-day model. A full and integrated demand-supply calibration of the MT model should ideally include multiple data sources of network performance (such as traffic volumes or public transportation ticketing data); however this was still not considered in this study. Our estimations are consistent with HITS showing that about 57% of the motorized trips are performed in public transport, while 41% correspond to private modes including walk and the remaining 3% to taxi.

3.2 Optimizing the AMOD system

The configuration of the AMOD system was carried out by defining individual optimization algorithms for the facility location, vehicle assignment, routing and rebalancing.

The algorithm solving *Facility Location Problem* is selected based on the literature review presented in (*35*) and is formulated as the classical covering problem in a graph. Facilities (or stations) can be understood as distribution centers of AV. The objective function is to minimize the number of required stations covering all demand points (Eq. 1).

$$\begin{aligned} \text{minimize} \quad & \sum_{j=1}^{n} x_j \\ \text{subject to} \quad & \sum_{j \in N_i} x_j \geq 1\,, i = 1, \dots, m \\ & x_j \in \{0,1\} \end{aligned} \qquad \text{(Eq. 1)}$$

The objective function minimizes over a binary variable x_j indicating whether a station should be located at j network node or not. The first constraint shows the service requirement for the node i in the network that has at least one trip request. We assumed that i is covered by station j if distance $d_{ij} \leq S = 1000$m, resulting eventually in a set of servicing nodes N_i. The second constraint is the integrity constraint.

There are two methods implemented for the *Vehicle-Passenger Assignment*: (i) a greedy assignment, and (ii) a minimum weight bipartite matching. In (i) for each new request we assign the nearest -in terms of the travel time- vehicle. In (ii) a cost-based matching is performed every time interval t (e.g., t = 30 secs). Let P and V define the number of passengers in the waiting queue (anywhere on the network) and the number of available vehicles (either parked or returning to stations), respectively. For every t we solve an optimization problem which minimizes the the cost of picking up passengers. The cost function includes the travel distance to picking up the passenger and the waiting time of the customer in the following way:

$$c_{pv} = f_d \cdot c_{pv}^d + f_t \cdot c_{pv}^t \qquad \text{(Eq. 2)}$$

where f_d is the distance-cost factor; c_{pv}^d is the distance from current position of the vehicle to the customer location, in meters; f_t is the waiting time cost factor; and c_{pv}^t is the expected waiting time of the customer, in seconds. Currently both f_d and f_t are set to 1.0. The binary variable x_{pv} describes whether or not vehicle v is assigned to passenger p; $x_{pv} = 1$ if vehicle v is assigned to passenger p, 0 otherwise. The maximization problem is formulated as follows:

$$
\begin{aligned}
\text{minimize} \quad & \textstyle\sum_{c,p} c_{pv} \cdot x_{pv} - R \\
\text{subject to} \quad & \textstyle\sum_{v} x_{pv} \leq 1\,,\ p \in P \\
& \textstyle\sum_{p} x_{pv} \leq 1\,,\ v \in V \\
& x_{pv} \geq 0, \text{integer}
\end{aligned}
\qquad \text{(Eq. 3)}
$$

where $R = max\ (c_{pv}) + 1$ is the maximum cost of assignment plus one. The first two constraints ensure that each passenger is assigned to at most one vehicle and each vehicle is assigned to at most one passenger, respectively. The third constraint is the integrity constraint. We state that the problem always terminates with the best solution, i.e., we always want to add another client in the objective function -which makes our objective function to decrease- and passengers and vehicles are restricted to single assignments.

Rebalancing decides when and where to move empty vehicles to by minimizing demand looses. However, we should avoid having too many empty trips, because they serve no customers, increase operating cost and contribute to congestion. It is implemented as a discrete-time function and different rebalancing scenarios were tested: every 0.5, 1, 2 and 3 hour(s). We found out that the best performance in term of the shortest average waiting time is every 1 hour rebalancing. Therefore, for the rest of this study we show the results for rebalancing every hour.

The problem of rebalancing is formulated as follows: Let V be a total number of vehicles in the system and v_i and d_i be the number of vehicles and anticipated demand at station i. Excess demand at each station is defined as the number of customers who cannot be serviced only by vehicles at station i, i.e., $d_i^e = v_i - d_i$. The cost of sending one vehicle from station i to station j is represented by d_{ij} and measured as a shortest travel time distance between i and j. Decision variable r_{ij} describes the number of vehicles to send from i to j. The objective is to minimize total cost of rebalancing trips.

$$
\begin{aligned}
\text{minimize} \quad & \sum_{ij} d_{ij} \cdot r_{ij} \\
\text{subject to} \quad & d_i^e \leq \sum_{j} \left(r_{ji} - r_{ij} \right), \forall i, j \\
& \sum_{j} r_{ij} \leq v_i\ , \forall i \\
& r_{ij} \geq 0
\end{aligned}
\qquad \text{(Eq. 4)}
$$

The first constraint is the flow conservation at each node. The second constraint prevents us from sending more vehicles than we have available. The third constraint is the integrity constraint.

3.3 Assessing the impacts of the AMOD system

For the assessment of the AMOD system and its impacts on travel behavior, SimMobility ST and MT were used together, exchanging trip chains from the top-down and supply performance measures bottom-up. SimMobility MT simulated the entire island while ST simulated the CBD car-restricted area and the AMOD system operation in detail. The limitation of the AMOD case study to the small zone allowed for this initial tractable computational time in SimMobility ST. However, larger networks have already been successfully simulated (see red area in Figure 3).

SimMobility ST was used to test different fleet sizes of the AMOD system, different configurations of stations and different rebalancing policies. These simulations were run using the MT trip chains as demand. We classified the trips into 3 categories: (i) trips which had neither origin nor destination within the restricted zone, (ii) trips which had either origin or destination within the restricted zone, and (iii) trips which had both origin and destination within the restricted zone. Trips in (i) were simulated only within the within-day MT; trips in (ii) were divided into inside-CDB and outside-CBD sub-trips and the outside-CDB trips were simulated using MT only while the inside-CBD trips were simulated in both, ST and MT; trips in (iii) were simulated using both simulators. This allowed us to reach a high level of detail when simulating the operation of the AMOD system and its integration with the existing (and, eventually, future) control systems.

This process was carried out in an iterative fashion, with the trip chains generated first by MT and being passed to ST, where ST computed its performance measures (waiting times, travel times, costs, etc) and fed it back to MT. The feedback from ST was used again to generate a new set of individual choices. In the present case study, this loop was executed once.

3.4 Results

Figure 5 shows mean waiting times of customers across different AMOD fleet sizes for a 12 hours simulation (3am to 3pm) using 10 parking stations and with rebalancing. This half day simulation was carried out for fast computation within ST and when analyzing all considered AMOD configurations. For the characteristics (demand/network) of this case study, this configuration outperformed those with no rebalancing or with more stations. For simplicity, we present here the analysis for fleet size, but the reader may refer to (*30*) for the detailed rebalancing and stations analysis of the larger red area in Figure 3. It can be seen from Figure 5 that the average waiting time decreases when we increase the fleet size, and it is close to 5 minutes (including boarding) when AMOD fleet size is around 2400 vehicles. Further increase in the fleet size is not able to significantly decrease the waiting time (average and variance). A similar finding was obtained for an increasing number of stations. Furthermore, each vehicle serves in average 16.7 requests during the 12 hour simulation, which, although close to the lower values obtained by Fagnant and Kockelman (*17*) for different scenarios, is sensitive to the detailed traffic representation (including congestion and traffic lights which increase travel times) and the case-specific increased number of requests to the CBD during the morning peak hour when compared to the off-peak period.

The ST obtained performance measures for the 2400 vehicles, were fed back to SimMobility MT. Within SimMobility MT, the travel times, waiting times and cost for all sub-trips performed inside CBD were combined with outside CBD sub-trip attributes (from the supply of SimMobility MT). The combined performance measures were used in the re-simulation of individual choices for the entire population, within the pre-day of SimMobility MT. The implementation of the AMOD system affects agents' behavior in several ways: as the mode availability for trips to/through the CBD changes, travelers (mainly those choosing private modes in the base case) can change their travel modes, either transferring to AMOD in the periphery or changing to public transport, taxi or walking. Within the framework of activity-based simulation, the change in accessibility can affect other travel decisions, such as destination, time-of-day, or the decision to travel itself. For the simulated AMOD implementation, trips going into CBD decrease 1.5% (mostly for non-mandatory purposes, such as shopping), while the overall trips remain almost unchanged.

In Figure 6 the combined effect of the restricted zone and the changes in the transportation system performance on route choice decisions is shown for the agents driving a specific origin-destination pair. This impact on through traffic will inevitably affect the performance of the road network in terms of travel times and congestion levels in the periphery of the CBD. However, within the CBD, private trips (either by private cars, taxis or AV) are reduced by 7%.

In Figure 7 the changes in mode shares re-computed by the pre-day model are represented for all the trips having the origin and/or the destination within the CBD. AMOD incentivized the use of public transport, taxi and walking. Such analysis allows the assessment of increased demand for the other modes, and eventually test potential measures to mitigate undesirable impacts. Trips going into CBD in 7AM and 9AM increased 8.2%, which can have an impact on comfort levels and increase the number of denied boardings due to crowdedness.

Some of the above mentioned scenario assumptions are being relaxed in on-going simulations. Indeed, testing the proposed framework in other settings will most likely pose different challenges. Larger areas, such as area in red in Figure 3, have already been simulated and computational times were tested successfully.

4 DISCUSSION AND CONCLUSIONS

In this paper, we presented an extension to SimMobility for modeling and simulating AMOD systems. The benefits of using an integrated agent-based simulator in both demand and supply, for the design and assessment of disruptive technologies, was shown through a specific case study. The modular approach allows for different models to be integrated and evaluated within the SimMobility framework. As shown in this paper, AV systems features can be optimized and assessed together with other transportation related policies, having in mind changes in individual choices. The considered AMOD scenario was only optimized in terms of fleet size, stations locations and rebalancing strategy. Within this study, we did not target the full system design optimization nor the recommendation of specific operational details. Instead, we turned the spotlight to multiple capabilities of integrated microscopic simulation models for the analysis of AV technologies. The flexibility of using such framework will allow for integrating AV-specific solutions that may improve significantly the systems' performance (such as intersection management for AV or V2X communications).

Similarly, additional behaviors such as ride-sharing, need to be integrated in the simulation platform for its consideration in shared AMOD system design. Stated preferences surveys are typically used to collect such behavioral data, as revealed preferences for AMOD are not yet feasible. However, one must not ignore the possibility of biased results from such data collection procedure, as the AMOD experience might be totally different from the expectations that a respondent might currently have. This issue can be minimized by collecting stated preferences in simulator or pilot experiments. In fact, our research center in Singapore will continue to carry out public (controlled) experiments with a small fleet of AV, forming an excellent environment for such data collection.

We are currently working on extending our calibration framework using other existing data sources. It is known that the outputs of both ST and MT supply simulators can be improved using additional detailed traffic datasets.

Finally, the on-going work on extending the research to SimMobility LT will bring another set of powerful instruments and it will allow for the integrated simulation of the three levels of decision making. AMOD impacts on car-ownership decisions, land pricing and individual and firm location decisions along with its combined effects with long-term targeted policies represent our main on-going research effort.

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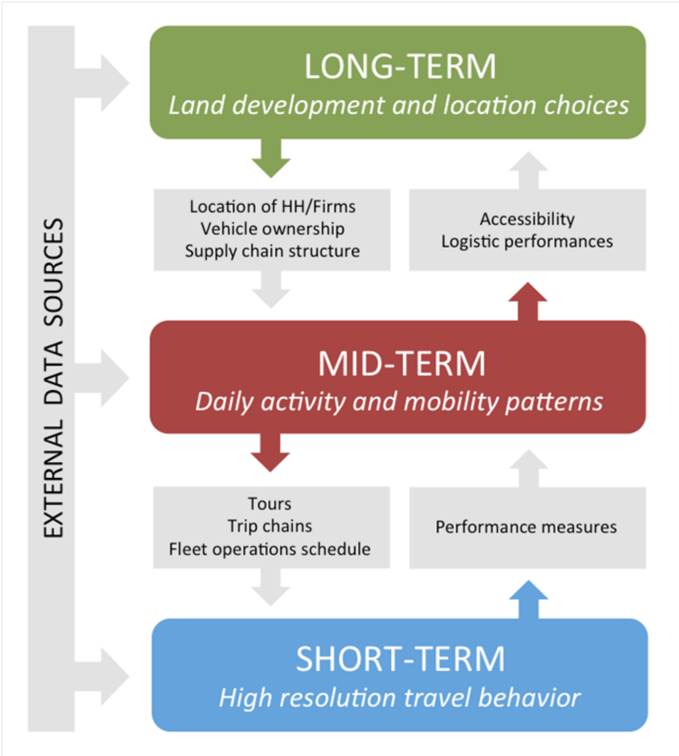

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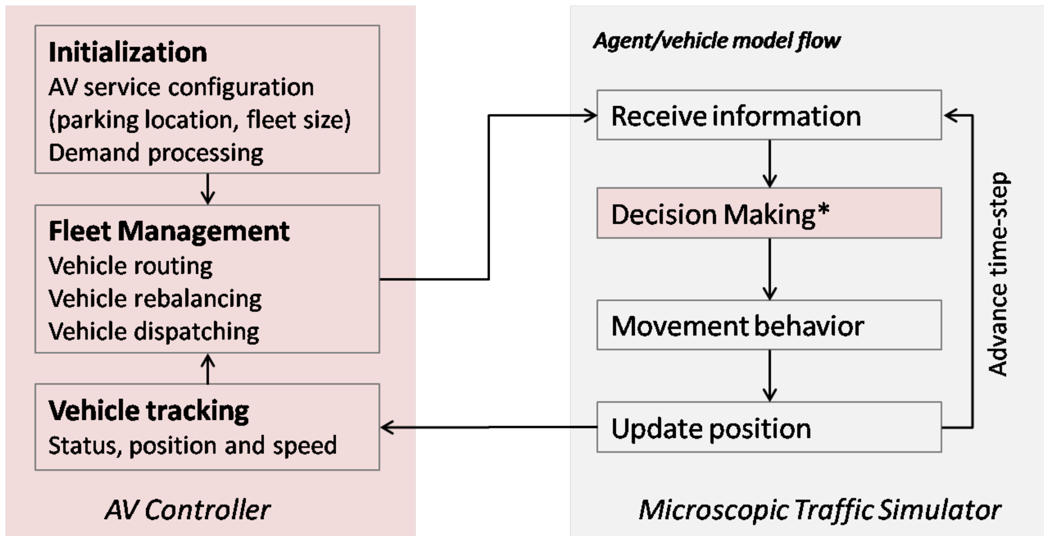


FIGURE 2 AMOD controller integration in SimMobility

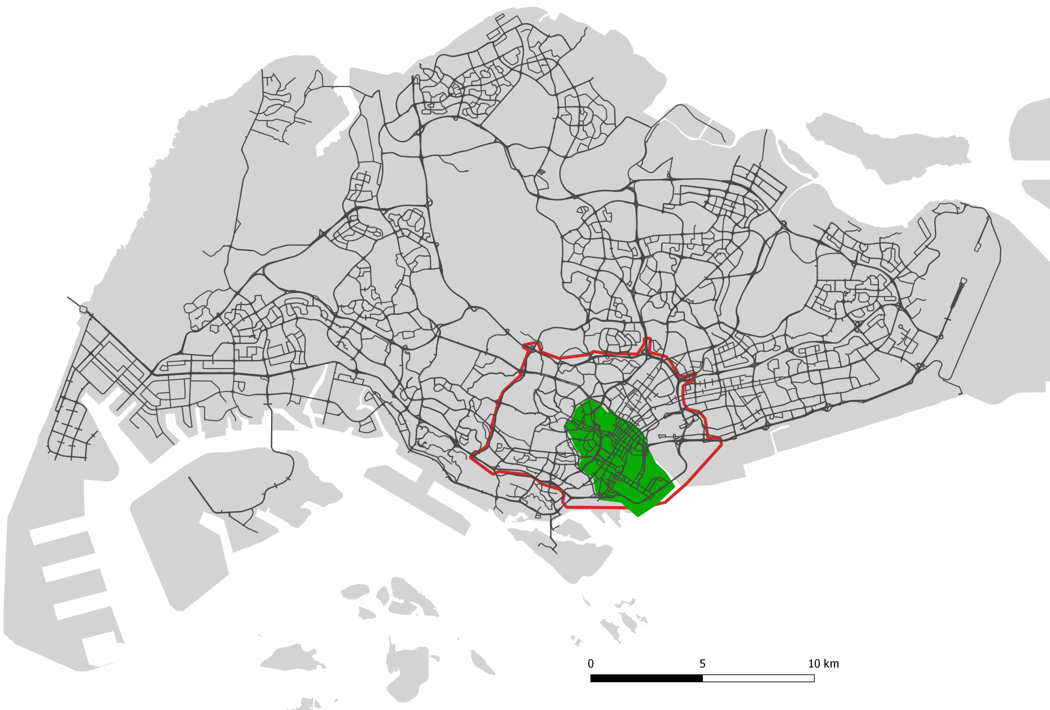
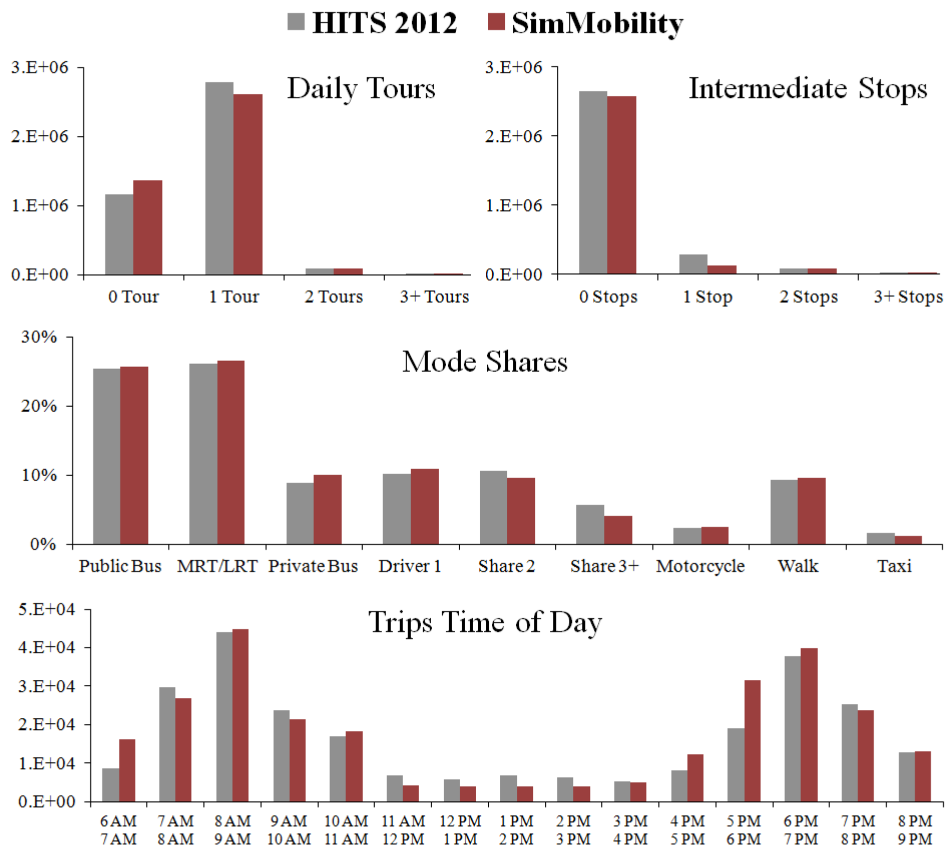


FIGURE 3 Singapore network and the car-restricted area with AMOD system (in green)



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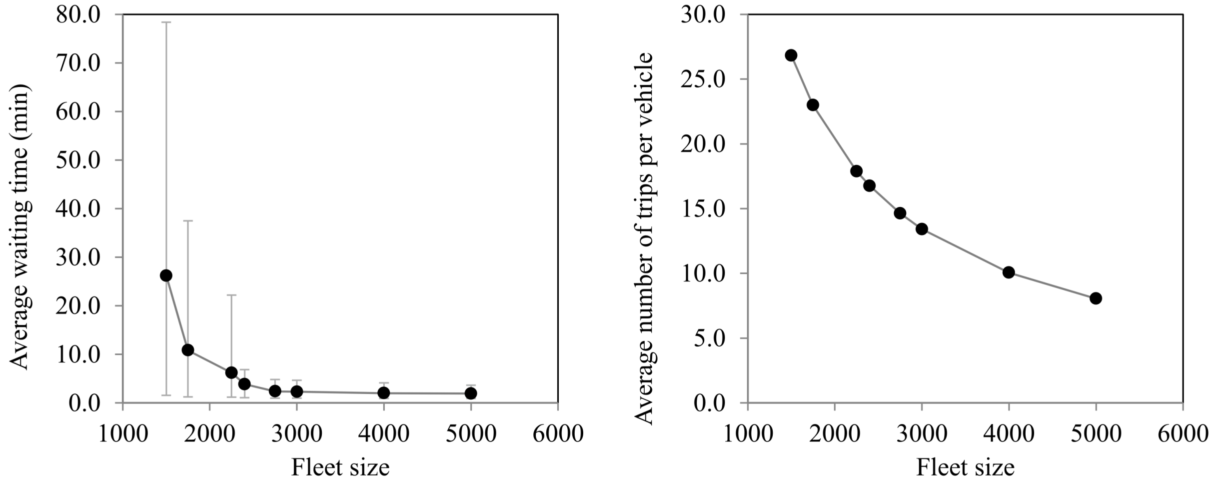

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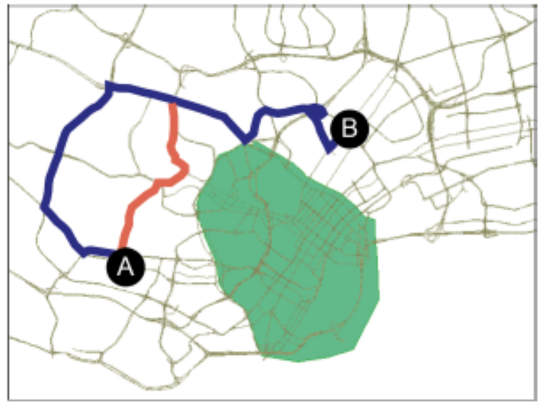

Path	Length	Travel Time	Split
1	10.6 km	17 min	13.0%
2	10.1 km	14 min	32.4%

Path	Length	Travel Time	Split
1	18.7 km	32 min	10.1%
2	15.4 km	29 min	25.3%

FIGURE 6 Effects on through traffic: path attributes for the two most selected paths from A to B, without (left) and with (right) the car-restricted area with AMOD

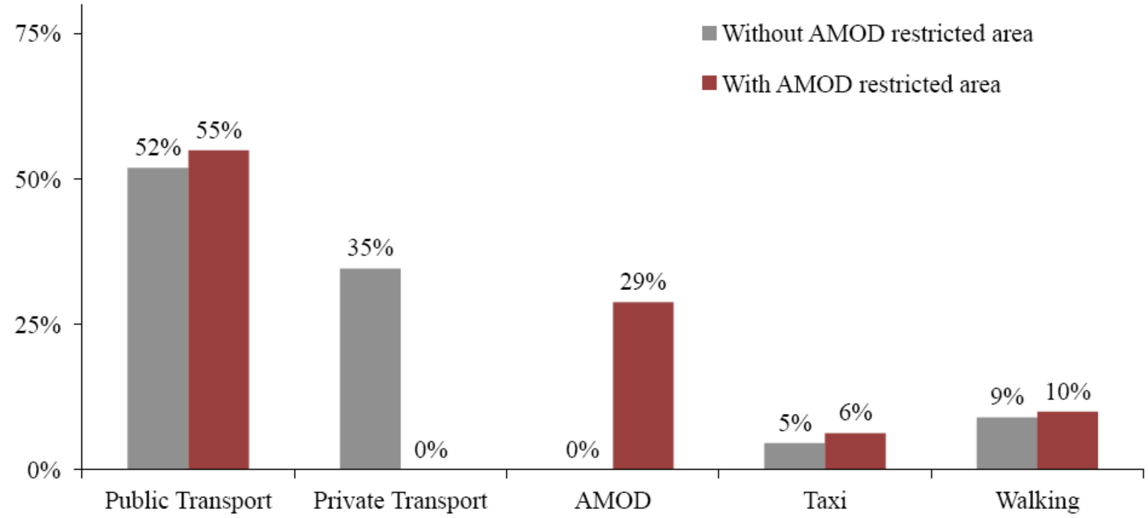

FIGURE 7 Car-restricted area with AMOD impact on mode choice