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Microsimulation of Demand and Supply of Autonomous Mobility On-Demand

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Agent-based models have gained wide acceptance in transportation planning, as with increasing computational power it is now possible to run 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 pattern) 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 presents a detailed framework for modeling and simulating autonomous vehicle supply models and its impacts on travel behavior. We showcase the features of this proposed framework with a pioneer case study on the potential impacts of introducing an Autonomous Mobility-on-Demand (AMOD) service in a car-restricted zone of Singapore. SimMobility was used in an integrated manner to determine the fleet size and parking stations requirements for the AMOD service and to uncover changes in agents’ activity travel patterns specifically in terms of modal shares, routes and activity destinations.
1 INTRODUCTION

Although the initial developments of autonomous vehicles (AV) technologies was carried out during the 80’s (1), vehicle automation technology has been under the spotlight since the 2014 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). AV 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 were it is deployed (3).

Recent studies have focused on the design and operation of specific AV systems beyond the private use, such as Autonomous Mobility on-Demand (AMOD) services (11, 12, 13, 14, 15). Zachariah and Mufti (14), for example, model 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 and the number of rebalancing drivers needed, while ensuring stability. 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 system 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) focused on analysis of an autonomous Taxi system. The authors evaluated the necessary fleet size for two models: (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 over two different time scales (24-hour average and peak hour period) for 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 effects). Also mid-term and long-term impacts on individual choices were not considered. Fagnant and Kockelman (17) turned the spotlight to the analysis of impacts of a shared non-electric AMOD fleet in a simulated city with size of Austin, Texas. A model share of 3.5% is assumed and simulated for the AMOD system, where intermediate stops for pick up and
drop off of additional passengers are not allowed. Each vehicle would serve 31 to 41 persons a day, with an average waiting time below 20 seconds, and would replace nearly 12 conventional vehicles. 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 land use and travel patterns, and does not consider long-term behavioral shifts. Burns et al. (18) focused on the impacts of network configuration and service cost of shared AMOD fleets. Three different network environments were 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.

Studies on the potential impacts of AVs on land use and long-term choices of urban residents and firms is limited. In a recent study on the potential impacts of autonomous vehicles and policy preparations, Fagnant and Kockelman (3) summarizes the anticipating effects may brought by autonomous vehicles, mostly focusing on the travel behaviors and safety (19). Using various simulation results, they found that each shared autonomous vehicle (SAV) "could serve the same number of trips as 10 household-owned vehicles", indicating the potential impact of autonomous vehicle on vehicle ownership. In addition, a number of studies mentioned urban form can be benefited from AVs by releasing part of lands in urban areas from parking areas. By one estimate, about 31% of the space in the central business districts of 41 major cities in the US was devoted to parking, and more space would be available for improving the built environment (20, 21). However, the effect of AVs on the spatial choices of urban residents and firms is less known and less studied. On the one side, AVs can provide safer and improved accessibility for the population (e.g. the disabled, the elderly and children) who cannot drive. Therefore, a place with SAVs service may become preferable for these people. On the other side, the AVs may also change the goods delivery system, which could have an impact of the location choice of those affected businesses.

In terms of simulation tools, agent-based approaches have been shown to capture and reproduce different transportation-related phenomena, at different levels of details (from traffic micro-simulation to long-term land use models) (22). Using agent-based models for decision-making offers many advantages. Agents (individuals, households, vehicles, or other relevant units of analysis) can be modeled in detail, with heterogeneous characteristics and preferences. Their behavior can be validated at 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 scenarios of AV, the potential comprehensiveness in the analysis of different impacts and the detailed level of the outputs obtained. Yet, agent-based models have reached a level of integration and complexity that elevate the potential of such methods in 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 modeling and simulation efforts must be taken and where further research is needed. 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 state-of-the-art simulation frameworks for the analysis of AV systems in urban environments. In the next Section we describe how integrated and multi-level demand and supply can be modeled.
together, having in mind the impact of AV technologies. In Section 3 the set-up and the results of a specific simulation scenario of an AMOD service in Singapore under the proposed framework is presented. Finally in the last Section, the main conclusions of our study and the on-going and future research are described.

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 (23). The typical interface between models consists of exchanging files or API (Application Programming Interface) calls. For example, Urbansim combines land-use, demographic and business establishment models, where agents make long-term decisions (e.g. home and job relocation) by considering, among others, transport accessibility (24). A common approach to obtain accessibility measures is by calling travel models, such as Transcad (25), which runs a 4-step model, TRANSIMS (26), or MATSim (27), the latter two following an activity-based paradigm. The challenge is then to make these models speak with each other and guaranteeing full consistency (e.g. same population in Urbansim and Transcad, same spatial and temporal resolution and references). A similar reasoning can be established when combining the above mentioned travel models with detailed control and motion simulation models, such as SUMO (28), VISSIM (29) and AIMSUN (30). In (31) for example, 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 again, 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.

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, has recently been proposed (23, 32).

2.1 SimMobility

The high-level architecture of SimMobility is shown in Figure 1. SimMobility is comprised by 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. 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 Mid-Term (MT) simulator handles transportation demand and supply on a day-to-day basis; it simulates agents’ behavior in terms of their activities and 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 and property development and use, determines the associated life cycle decisions of agents, and accounts for interactions among individuals and firms. Roughly speaking, SimMoobility Short-, Mid- and Long-Term correspond to the traditional micro, meso and macro levels of transportation analysis.

SimMobility’s framework is fully modular in a way that each level can run independently and only interact with the other level when necessary. The key to multi-scale integration in Sim-Mobility 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, and 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 and integration, can be found in (23, 32).

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 with dedicated AMOD service and vehicle access restrictions features.

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 (33). 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. SimMobility ST moves vehicles 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 model. Merging, drivers’ responses to traffic signals, speed limits and incidents. The generic driving behavior models and parameters implemented in SimMobility ST are those estimated by Yang and Koutsopoulos (33), Ahmed (34) and Toledo et al. (35). Several additional enhancements were recently made its original driving behavior such as: an enhanced reaction and perception time formulation, lateral movement during lane-change, within lane and also intersection behavior driving based on the conflicts technique.
A Control and Operation system module simulates control centers, such as traffic control, parking manager or bus control. We extended the Control and Operation system module with a dedicated AMOD controller for managing AV. 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). Detailed description of each component can be found in [36].

**FIGURE 2**: AMOD controller integration

The fleet management module is responsible for facility location, vehicle assignment and routing and vehicle rebalancing.

The facility location model estimates what are the best locations to place distribution centers (also called stations or car parks) of AMOD vehicles. Stations aim to provide charging and maintenance facilities for vehicles, assuming an electric mobility solution. Vehicles can also be parked there when waiting for future requests. The vehicle assignment and routing model decides how vehicles should be assigned to customers and routed to destinations while minimizing distance traveled on the network. The rebalancing aims to move vehicles to where they are/will be needed. Due to asymmetries in travel patterns the AMOD system—similarly to any one-way car-sharing system—tends to become unbalanced, i.e., during morning peak majority of people travel to work in downtown and leave their vehicles there. Vehicles build up at some stations, and become depleted at others. Rebalancing mechanisms are therefore required to realign the supply of vehicles with the future demand [12, 37]. Furthermore, AMOD Controller uses a Gaussian process to predict future demand for each station. The future demand is then fed to rebalancing model.

Finally, the decision making models for the AV should, preferably, be based on the motion control algorithms under development by the AV manufacturers. For this first-cut implementation, the existing acceleration and lane-changing models in SimMobility ST 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 an individual level. It combines activity-based microscopic simulation on the demand side with macroscopic simulation on the supply side [32]. The demand side comprises two groups of behavioral models: pre-day models and within-
day models. The pre-day models follow an econometric Day Activity Schedule approach (38) to predict a daily activity schedule for the agents, particularly in terms of: (i) activity sequence (including home-based tours, work-based sub-tours, and intermediate stops), (ii) trip destinations and modes, and (iii) departure times (on half-hour slots). This is based on a sequential application of hierarchical discrete choice models using a Monte Carlo simulation.

At the pre-day level, the implementation of a car-restricted area with AMOD services was assumed to affect directly the destination and mode choice models. Mode availability for trips involving origins and/or destinations within the restricted area will change, leading to multimodal trips that can 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 in terms of decisions. The utility specification of the combined mode and destination choice for the car-restricted area with AMOD service was based on the individual preferences towards taxi due to the lack of individual AMOD-specific data for estimation. For mandatory trips with fixed destination (such as going to work or school) the agents will only be able to change modes, but for non-mandatory trips (such as going shopping) the agents will have the possibility of changing mode and/or destination, as well as deciding to skip the trip.

Once the daily activity schedules are obtained for all agents, the within-day models predict the routes for their 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 (32). Furthermore, at the within-day level, the implementation of a restricted area with AMOD services affects the route choice, in terms of available alternatives. For trips outside the restricted area, all potential paths between origin and destination will have to go around, leading to a potential increase in travel times.

The supply simulator follows the dynamic traffic assignment (DTA) paradigm as used previously in (39), including both private and public transport modes. Particularly for public transport, MT model allows for bus line scheduling and headway based operations are currently being implemented. We also explicitly represent on-road bus stops and bus bays, which allows for accurate estimation of impacts of the bus operations on the road traffic.

Within the MT simulator, the interaction between the within-day and supply is responsible to bring the system to consistency. The MT simulator takes input in the form of a population (which could come from the LT simulator, if the integration is desired) that contains detailed characteristics of each agent, and a multimodal network. As an output, it can pass accessibility measure (in the form of Logsums) from pre-day models to the LT simulator. The MT simulator can also provide the ST simulator with trip chains as input demand to simulate smaller region traffic in more detail.

**Long-Term Model**

The LT simulator of SimMobility models the behavior of agents in the housing market, and ultimately the commercial real estate market and the job market. It simulates the year-to-year impacts of alternative future mobility scenarios on residential and workplace locations, vehicle ownership, land use distribution, and value of the built environment. The LT simulator is therefore responsible for the generation and updating of a population of agents and their corresponding demographic and spatial attributes.

A two-stage data synthesis methodology is employed for construction of a synthetic pop-
ulation of households and firm establishments at building scale (40). The approach is designed to accommodate the need for spatially disaggregated details in a manner that can be readily adjusted and rerun to incorporate new data sources, changed time frames, and updated relationships and hierarchies across overlapping datasets. Long-term behaviors of agents and their effects on urban form, markets and other agents are implemented by a group of behavioral models that are connected in a sequential/event-based framework.

These behavioral models take account of demographic and economic factors of agents, spatial amenities and the regulatory variables translated from exogenous policies. The LT simulator centers on a real estate market module, which emulates the dynamic interaction process between demand and supply in the market. The market module include a series of models that simulate (i) "awakening" of households who begin searching for new housing, (ii) eligibility, affordability, and screening constraints, (iii) daily housing market bidding, and (iv) modeling developer behavior regarding when, where, what type, and how much built space to construct by taking into account market cycle and uncertainty. Changes in residential location then trigger a household’s re-assessment of private vehicle ownership and possible re-assignment of workers (students) to jobs (schools).

As mentioned, the LT simulator is integrated with the MT simulator via built-in functions facilitating the exchanges of data related to land use and transportation performance. One set of functions computes accessibility measures (in the form of Logsums) for individuals considering alternative residential, work, or school locations, and alternative vehicle ownership conditions. On the other hand, another set of functions allows the LT simulator to pass to the MT simulator population information with updated residential and job locations as well as vehicle ownership. Currently this exchange is done for each simulated year.

At this stage all sub-models of the MT simulator are being calibrated, using different sources of information (including MT Logsums), in order to produce an appropriate synthetic population; the inclusion of long-term impacts in the present study (both by using their population and analyzing the effect of AMOD) is still in progress.

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. Firstly, private vehicles are not allowed to access a 14Km$^2$ restricted zone in the CBD in Singapore (see green area in Figure 3). A smart-phone based AMOD service was introduced as an alternative mode within the restricted area. Yet, the 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). Similarly, no changes in the road network and traffic control systems were assumed for this case study.

On the demand side, the population socio-demographic characteristics, individual preferences and the land use configuration was kept unchanged. The impacts of AMOD parking locations within the CDB on land-use were ignored and residents of the CBD area were not given the privilege of driving their own vehicle within the restricted area. It is worth noting that some of these assumptions will be relaxed and optimized in our future simulations of this and other simulation
A set of performance figures for the AMOD system and for the overall transportation system in Singapore (congestion levels, destination choice and mode shares) were assessed and compared to the existing supply.

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) collected in 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 timings;
7. Detailed road network configuration from multiple sources.

A synthetic population of 4.06 million agents was generated for the entire island (for further details on this process see 32, 40). 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 configuration of each intersection using LTA’s data and a SCATS-like algorithm. Driver’s route-choice was estimated using the taxi GPS data while public transit route-choice used the EZ-link card data set.

Calibration results for SimMobility MT pre-day models are shown in Figure 4. These results cover all levels of decisions modeled in pre-day: daily activity patterns (in terms of tours and intermediate stops), mode and destination choice for all tours, and time of day for all trips. These results correspond to the base case (i.e. without AMOD) of our study case, and reproduce the mobility and activity patterns observed in practice. It is interesting to notice that in Singapore about 57% of the motorized trips recorded in HITS (and therefore predicted by MT simulator) are performed in public transport, while 41% correspond to private modes and the remaining 3% to taxi.

![Graph showing calibration results for SimMobility MT pre-day models]

**FIGURE 4**: Base case validation
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 and routing and vehicle rebalancing, respectively.

The algorithm solving Facility Location Problem was selected based on the literature review presented in (41). It is formulated as the classical covering problem in a graph. The algorithm is run offline based on the historical demand. Vertices are generated at every location of the historical demand. Given demand nodes \( i \) and facility nodes \( j \), a set of the potential facility nodes \( N_i \), so that \( N_i = \{ j | d_{ij} \leq S \} \), a maximum acceptable service distance \( S \) (tested values between 850-1000m for our application) and a binary variable \( x_j \) indicating whether there should be a facility at \( j \) or not, the objective function of the model is to minimize number of required facilities covering all demand points (eq. 1).

\[
\begin{align*}
\text{minimize} & \quad \sum_{j=1}^{n} x_j \\
\text{subject to} & \quad \sum_{j \in N_i} x_j \geq 1, \quad i = 1, \ldots, m \\
& \quad x_j \in \{0, 1\}
\end{align*}
\]

The first constraint shows the service requirement for the demand node \( i \). The second constraint is the integrality constraint.

Passenger-to-Vehicle Assignment is formulated as the minimum weight bipartite matching problem. Given a list of passengers waiting to be served \( P \), where each passenger \( p_j \) is described by its current location \( (x, y) \), a list of available vehicles \( V \), where each vehicle \( v_i \) is described by its current location \( (x, y) \) and status, a cost of picking up passenger \( i \) by vehicle \( j \), \( c_{ij} \) and decision variable \( b_{ij} \) describing whether or not vehicle \( j \) is assigned to passenger \( i \); \( b_{ij} = 1 \) if vehicle \( j \) is assigned to passenger \( i \), 0 otherwise. The objective is to minimize the distance traveled by vehicles to pick up passengers (what is equivalent to maximization of the inverted cost).

\[
\begin{align*}
\text{maximize} & \quad \sum_{ij} \frac{1}{c_{ij}} b_{ij} \\
\text{subject to} & \quad \sum_{i} b_{ji} \leq 1 \quad j \in P \\
& \quad \sum_{j} b_{ji} \leq 1 \quad i \in V \\
& \quad b_{ij} \geq 0, \text{integer}
\end{align*}
\]

Meaning of the constraint 1 and 2: each passenger can be assigned to at most 1 vehicle and each vehicle can be assigned to at most 1 passenger, respectively. The cost is defined as follows:

\[
c_{ij} = f_d \cdot c^\text{dist}_{ij} + f_t \cdot c^\text{time}_{ij}
\]

where \( f_d \cdot c^\text{dist}_{ij} \) is the distance cost factor multiplied by the distance from current position of the vehicle to the customer location, in meters; \( f_t \cdot c^\text{time}_{ij} \) is the waiting time cost factor multiplied by the expected waiting time of the customer, in seconds; currently both factors are set to 1.0.
Rebalancing of the Vehicles Rebalancing was performed every hour to reduce customer waiting time during the high-demand periods, while ensuring that we rebalance a minimum required number of vehicles as empty vehicle trips contribute to congestion. The problem 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., \( d^e_i = v_i - d_i \). The cost of sending one vehicle from station \( i \) to station \( j \) is represented \( d_{ij} \) 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.

\[
\text{minimize} \quad \sum_i d_{ij} r_{ij} \\
\text{subject to} \quad d^e_i \leq \sum_j (r_{ji} - r_{ij}) \forall i, j \\
\sum_j r_{ij} \leq v_i \forall i \\
r_{ij} \geq 0
\]

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

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 simulators 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. In SimMobility ST different fleet sizes for the AMOD system, number of parking stations and configurations with and without rebalancing were tested. These simulations were ran using the demand in the form of trip chains from the SimMobility MT simulator. This was done by dividing the trips, which were destined or originated in the CBD region and have their origin and destination outside the CBD region into sub-trips. The inside CBD sub-trip is simulated using SimMobility ST, while the rest of the trip chains were simulated sing the within-day SimMobility MT simulator. Trips who have their origin and destination within the CBD region were also simulated at the ST level. 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 is carried out in an iterative fashion, with the trip chains generated by MT being passed to ST which computes itself performance measures (waiting times, travel times, costs, etc) that will be used again to generate a new set of individual choices.

3.4 Results

In Figure 5, different waiting time performances for different AMOD fleet sizes are presented for a 12 hours simulation (3am to 3pm) using 20 parking stations and with rebalancing. The rebalancing and the 20 parking stations were found to be optimal for the demand and area of this case-study. It can be seen from the figure that the average waiting time decreases with the increase in the fleet size, and it is equal to 5 minutes when AMOD fleet size is around 2200 vehicles. Further increase in the fleet size is not able to significantly decrease the waiting time. A similar finding was obtained
for an increasing number of parking stations.

The obtained performance measures for the above optimum scenario, were transferred back to the SimMobility MT simulator. Within the SimMobility MT simulator, the travel times, waiting times and cost for all sub-trips performed inside CBD were combined with outside CBD sub-trip attributes (obtained from the supply of SimMobility MT) and stored in a manner that it can be aggregated and feedback to the pre-day component of the SimMobility MT. The individual choices for the entire population can be re-simulated once again.

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.

In Figure 7 the changes in mode shares computed by the pre-day model are represented for all the trips having the origin and/or the destination within the CBD. Such analysis allows the assessment of increased demand for the other modes, and eventually test potential measures to mitigate undesirable impacts (crowdedness in buses).

These two example showcase the potential of using integrated agent-based simulation tools for the analysis of different impacts of AMOD systems, estimating the changes in the travel patterns and on the overall system performance.

Some of the above mentioned scenario assumptions are being relaxed in on-going simulation exercises. Indeed, testing the proposed framework in other settings will most likely pose different challenges presented here. Larger areas, such as area in red in Figure 3, have already been simulated. For this specific scenario, computational time of SimMobility ST was tested successfully and the benefits of using the proposed framework compared to less detailed simulators was also analyzed. In Figure 8, the AMOD system performance outputs in terms of travel time and waiting time for different fleet sizes are shown using SimMobility and a basic simulator (a
coarse simulator, without detailed rad network but using euclidean distances between origin and destination nodes and ignoring agent interactions and therefore congestion). As expected the more realistic representation of the supply in SimMobility has a clear impact on the results of the AMOD design and operation performance.

4 DISCUSSION AND CONCLUSIONS

In this paper, we presented an extension to SimMobility, a multi-agent micro-simulator, for modeling and simulating AMOD systems. The benefits of using integrated agent-based traffic simulator built on disaggregated behavior models in both demand and supply, in the design and assessment of disruptive technologies was shown through a specific AMOD case-study. The modular approach taken in our extension allows for different models to be integrated and evaluated within the SimMobility framework. As shown in this paper, technical design features can be optimized and policies incorporating a mix of transportation modes can be evaluated, having in mind individual choices and the environment affecting these choices.

We are currently working on extending our calibration framework using other existing databases. The outputs of the both the ST and MT supply simulators can be improved using traffic count and speed measurements on the network in Singapore. The on-going work on extending the impact assessment to SimMobility LT using the proposed integrated fashion is expected to bring another set of powerful analysis instruments. 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.

The flexibility of the proposed simulation framework to study complex scenarios also brings new possibilities to the detailed design of AMOD systems. SimMobility ST has a network communication simulator that will allow us to test alternative AV communication technologies and assess its impacts on its performance. Similarly, AV-specific solutions for intersection man-

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<th>Share</th>
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<table>
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<td>2</td>
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FIGURE 7: Car-restricted area with AMOD impact on mode choice

FIGURE 8: Comparison of travel time and waiting time for basic simulator and SimMobility.

Management can significantly improve an AMOD system performance. The first steps have already been made in testing AV-specific slot-based intelligent intersection algorithms within the Control and Operation module of SimMobility ST.

As future work, collecting useful data on individual preferences regarding AMOD is the main objective. Stated preferences surveys are typically used to collect such data, as revealed preferences 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 together with 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 the perfect environment for such data collection.

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References


[20] Folsom, t. j. i. p. a. c. y., Tyler C, ????


