Autonomous Mobility on Demand in SimMobility: Case Study of the Central Business District in Singapore

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***Abstract*—Autonomous mobility on demand (AMOD) has emerged as a promising solution for urban transportation. Compared to prevailing systems, AMOD promises sustainable, affordable personal mobility through the use of self-driving shared vehicles. Our ongoing research seeks to design AMOD systems that maximize the demand level that can be satisfactorily served with a reasonable fleet size. In this paper, we introduce an extension for SimMobility—a high-fidelity agent-based simulation platform—for simulating and evaluating models for AMOD systems. As a demonstration case study, we use this extension to explore the effect of different fleet sizes and stations locations for a station-based model (where cars self-return to stations) and a free-floating model (where cars self-park anywhere). Simulation results for evening peak hours in the Singapore Central Business District show that the free-floating model performed better than the station-based model with a "small number" of stations; this occurred primarily because return legs comprised "empty" trips that did not serve customers but contributed to road congestion. These results suggest that making use of distributed parking facilities to prevent congestion can improve the overall performance of an AMOD system during peak periods.**

Keywords*—Automated mobility on demand, agent-based simulation, fleet-sizing, facility location.

I. Introduction

According to the most recent estimates, over 7.27 billion people inhabit the Earth [1] with more than half of the population living in the urban areas [2]. The urban population is expected to double by 2050 [3], tripling expected number of cars [4], which already exceeds 1 billion [1]. This increase will further exacerbate current problems such as road congestion, parking availability and pollution. Currently, public transportation does not allow door-to-door service and lack schedule flexibility and personalization. Public transport, when provisioned for peak hour demand, may result in low efficiency as vehicles become idle in off-peak hours.

An alternative solution is Mobility on Demand (MOD) system, which can be classified as public transportation with flexibility of privately owned vehicles. A MOD system is a fleet of shared vehicles that can be accessed (picked-up or dropped-off) at specific locations in a city. A key difference factor of MOD systems, when compared to existing transportation modes, is demand-responsiveness. Unlike scheduled systems like buses and trains, MOD vehicles only operate when there is demand for the service. As such, it promises to be an sustainable, affordable system for personal mobility in densely populated urban environments [5], [6].

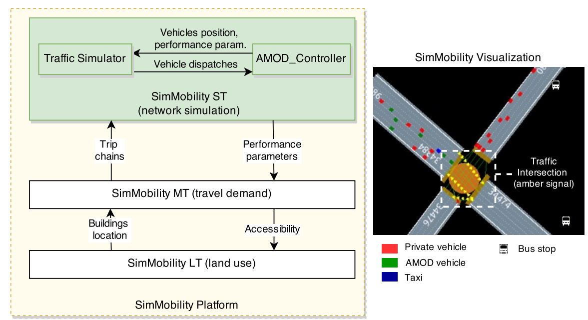


Fig. 1: The AMOD_Controller is a component linked to the SimMobility simulator that enables the platform to simulate an AMOD service running on the transportation network. The AMOD service can be simulated alongside regular taxis, private vehicles and public transportation.

Since vehicles are shared, MOD systems typically require smaller fleet sizes and have lower static land consumption in comparison with systems utilizing privately owned, individually operated vehicles [5], [7], [8]. Vehicle sharing also implies higher vehicle utilization, which increases the replacement rate. This hastens the adoption of newer, more fuel-efficient vehicles and results in lower vehicle emissions [5]. First attempts at introducing an MOD system can be traced back to 1948 in Switzerland [9]. After initial failures (mainly due to the available technology at the time), MOD was successfully launched in Switzerland in 1987, and Germany in 1988 [9].

Despite these prominent advantages, an unbalanced MOD fleet can result in service availability problems for consumers, particularly during periods of high demand. One potential solution for this issue is to leverage on recent developments in robotics technology and use vehicles with self-driving capabilities. Through automated rebalancing, Autonomous Mobility on Demand (AMOD) systems can redistribute cars to better meet demand. Furthermore, through system-level coordination, autonomous vehicles can use existing road infrastructure more efficiently, for example, by reducing the distance headway and by routing vehicles though less-congested roads [7]. In addition, AMOD systems can provide mobility for people who may be otherwise unable to drive, such as disabled individuals.

Although ongoing research in the areas of autonomous vehicles is very active, the transportation research community has shifted its attention to AMOD systems only recently. Important questions related to the design of AMOD systems still remain open. For example, what fleet sizes are required to ensure a satisfactory level of service? What are the trade-offs between different rebalancing and parking location policies?

This paper presents AMOD Controller developed as an extension of SimMobility (Fig. 1), a micro-simulation platform that allows users to test models and hypotheses related to the management and deployment of AMOD systems. Current research on mobility on demand systems often relies on coarse-grained simulators where gross approximations are made, e.g., vehicles are "teleported" between different locations [6], [10], [11] or, due to computational reasons, scenarios are run using scaled samples [8]. This work builds on and extends SimMobility [12], a high-fidelity agent-based simulator, which scales to millions of agents and can provide fine-grained metrics such as individual car locations and road-segment congestion throughout the simulation.

We demonstrate the utility of our platform by evaluating a policy where private cars are restricted from entering the high-traffic Central Business District of Singapore. Instead, travelers have access to an AMOD system (in addition to taxis and public transport). We study the effects of different fleet sizes on customer waiting times for two models: (1) a station-based where cars self-drive back to stations and (2) a free-floating model where cars self-park at drop-off locations.

The reminder of this paper is organized as follows. In Section II the literature review on recent work on studies related to fleet sizing for autonomous mobility on demand systems is presented. Section III describes our methodology and the proposed AMOD controller. Our case study is presented in Section IV, with simulation results in Section V. Finally, we conclude this work with a summary and a description of future work in Section VI.

II. Background and Related Work

In this section, we review recent work related to fleet-sizing for MOD systems. From an operational perspective, MOD can be implemented in three ways: (a) station-based, (b) free-floating and (c) peer-to-peer system (also known as a person-to-person system). In (a) and (b), vehicles are owned by a company, while in (c) existing car owners make their vehicles available to others. Furthermore, in (a) and (c) customer can pick-up/return vehicle only at designated stations (also called distribution centers or car parks), while in (b) there is no stations and users can pick-up and drop off vehicles freely within an operating area [8], [9].

In this study we focus on station-based and free-floating models for an AMOD system. The flexibility of MOD and AMOD systems comes at a cost of having no guarantee to find a car resulting in longer waiting time when a vehicle is not yet available. To maximize the likelihood of finding a car, the fleet of AMOD vehicles should be appropriately sized and managed. The problem of fleet sizing of mobility on demand systems is an actively researched topic [6], [8], [13]–[15], with several studies assessing optimal fleet sizes for AMOD systems [7], [10], [16]. In brief, fleet size largely depends on five crucial factors: (a) the size and configuration of operating network (which is related to the distance of trips), (b) the average demand for service, (c) the level of service that the system provider wants to achieve, (d) the routing policy, (e) the rebalancing policy and (f) the facility (car distribution centres/parking) locations. When designing MOD systems, (a), (b) and (c) are very often fixed in our model, while (d), (e) and (f) can be selected in different ways, what can influence the fleet size and waiting times of passengers.

To estimate the minimum required fleet size, many researchers have focused on rebalancing strategies for both station-based and free-floating carsharing system [6], [8]–[11], [16]. One of these studies [11] shows 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. In case of AMOD systems, fleet sizing is similar to fleet sizing of MOD systems with human-driven vehicles, but with the advantage that the vehicles can redistribute themselves. The introduced rebalancing policy (based on a fluidic model) was tested in a low-fidelity simulation developed in Matlab. Using both theoretical and simulation results, the authors determined the minimum number of vehicles required to maintain system stability.

In [6], three different redistribution strategies (zero, periodic and continuous redistribution) for station-based and free-floating carsharing were analysed. Analysis was performed using an agent-based simulation approach and tested on a square grid with a random demand. The authors showed that without changes in percentage of satisfactorily served demand, continuous redistribution of vehicles results in a reduction in the required fleet size as compared to zero-redistribution and periodical redistribution strategies.

Another recent study [16] evaluated fleet sizing for an autonomous Taxi (*aTaxi*) system. The paper evaluated two models: (a) personal rapid transit, in which customers were served by the same vehicle if they arrived at a station within a time window and their origin and destination stations were the same, and (b) smart paratransit, where vehicles were re-routed to pick-up additional customers. For both models, stations were established in a grid. The authors presented upper and lower bounds for the fleet size required for both models.

An important factor in the overall performance of MOD and AMOD systems is facility location. Intuitively, the spatial distribution of demand in a city is non-uniform and hence, strategically placed facilities can reduce customer waiting times and required fleet size. In traditional MOD systems, accessibility to the stations (in terms of distance from your location to the station) is a critical factor, because people must walk to get a vehicle. In station-based AMOD systems, customers do not have to walk, however proper car park locations can influence the waiting time of passengers.

Strategically locating stations for AMOD systems is intimately related to the problem of optimally placing stations in bike-sharing programs [17]–[19], charging stations for electric vehicles [20]–[22] and bus stops for public transportation [23]. It is also closely related to similar problems in communication networks, logistics and distribution systems [23]. Unfortunately, the facility location problem is NP-hard and most existing work rely on approximation algorithms [24]. In the related problems [17]–[21], [23], [25], facility locations are optimized based on the expected demand for the service. Two of the most common approaches are: (1) minimizing impedance and (2) maximizing coverage. The first approach allocates stations such that the sum of all of the weighted costs between demand points and stations is minimized. The

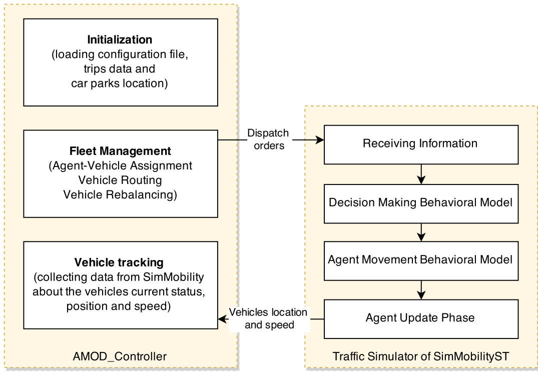


Fig. 2: The AMOD_Controller consists of three main components which handle initialization, fleet management and vehicle tracking. In particular, the fleet management module is responsible for assigning, routing and rebalancing. It dispatches orders to SimMobilityST, which performs a 0.1 second scale simulation of the vehicles and returns vehicular information (e.g., speed and location) to the vehicle tracking component that captures and logs the results.

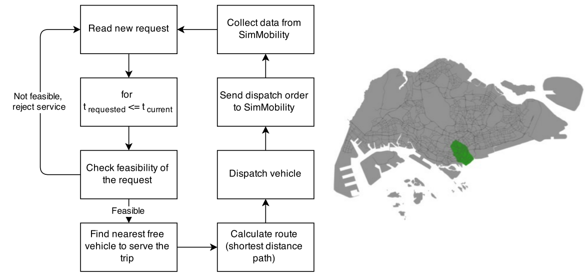


Fig. 3: Left: Implementation of a FIFO-based service in the AMOD_Controller (t represents the time). In this model, new requests are first tested for feasibility (if a path exists from any vehicle to the request pick-up point and from the source to the destination nodes). Feasible requests are then serviced by assigning a free vehicle to service the trip. The vehicle is dispatched with a pre-defined route (the shortest driving path). As the vehicle is in service, data is continually collected and logged by AMOD_Controller for later analysis. Right: The case study area in Singapore (highlighted in green), encompassing the Central Business District (CBD).

second approach allocates stations such that as many demand points as possible is within the impedance cut-off (e.g., time, distance) from stations. Based on the results shown in [17], [19] the maximum coverage approach shows a better efficiency in terms of minimizing waiting time of customers.

III. Methodology

A long-term goal of our research is to determine how different fleet sizes and facility locations influence the performance of an AMOD system. To better capture the behavior and dynamics of travel patterns, we used a multi-agent modeling approach in a microscopic simulation framework. In contrast to fluid-dynamic and queuing theory models, multi-agent simulation allows for more detailed and complex behaviors to be represented. In this work, we extended SimMobility—an agent-based simulation platform—with a dedicated controller for managing autonomous vehicles.

A. Extending SimMobility with the AMOD Controller

SimMobility is a multi-scale simulator that considers land-use, transportation and communication networks along with individual choices and decisions at different levels of resolutions: from detailed traveler movements to day-to-day and year-to-year travel decisions. It handles transportation demand for passengers and goods, simulates agents' activity and travel patterns and captures land-use and economic activity, with special emphasis on accessibility. The individual travel behavior is modeled under an activity-based formulation, where each agent's daily activities and its impact on the transportation systems are simulated [12]. The core traffic simulation model of SimMobilityST is based on the microscopic simulation tool MITSIM [26]. SimMobility is under ongoing development and it is an open-source software based on a distributed C++ implementation. As mentioned, its behavioral models rely in different temporal resolutions and, for the purposes of this study, we focus primarily on the SimMobility Short-Term (SimMobility ST) simulator, which simulates the individual decisions and the transportation network at the sub-second level.

Our AMOD_Controller is an integrated, but detachable, component that imbues SimMobilityST with the capability to simulate an AMOD system (Fig. 1 and 2). The AMOD_Controller was implemented in C++ for fast execution, however there are plans for Python and Julia plugins to enable rapid prototyping.

In essence, the AMOD_Controller (together with Simmobility) is an experimental research tool to test hypothesized models and algorithms for autonomous vehicle routing, dispatching and scheduling. The models and algorithms are organized into three main components: initialization, fleet management and vehicle tracking modules (Fig. 2). The principal component is fleet management, which assigns, dispatches and routes vehicles. This component is typically reconfigured depending on the model being evaluated. As a simple example that has been implemented, consider a first-in-first-out (FIFO) service that assigns to each customer the nearest available vehicle (in terms of shortest-path distance). The AMOD vehicles are routed with the least cost path between two different locations, where the cost is proportional to the traversed distance. After dropping off passengers, vehicles can either return to the originating station, the closest station or simply wait at the drop-off location for a service request. The implemented model of AMOD_Controller is summarized in Fig. 3.

More complex assignment and routing mechanisms can be accommodated within the existing controller framework by substituting the relevant sub-components; this allows for proposed algorithms to be quickly prototyped, incorporated and tested within SimMobilityST. Throughout the simulation, the fleet is monitored by the vehicle-tracking component, which also records relevant information (vehicle positions and events such as customer pick-ups) for later analysis. For example, in our preliminary experiments, the obtained logs were post-processed to obtain distributions of customer waiting and travel durations.

B. AMOD Post-Service Routing Models

In this study, we evaluated two post-service routing alternatives, that is, how the autonomous vehicles behaved after

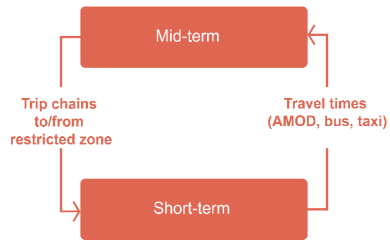


Fig. 5: Case-study modeling framework. The demand generation process of AMOD is based on integration of SimMobility Mid-Term (MT) simulator with SimMobility Short-Term (ST) simulator. The mid-term (day-to-day) simulator handles transportation demand for passengers and goods, while SimMobility ST simulates network on the operational level.

dropping-off passengers:

1) In *station-based model*, after servicing a trip, AMOD vehicles always drove back to the nearest station and waited for new requests (and re-charge if necessary).
2) In *free-floating model*, AMOD vehicles self-parked at drop-off locations, where they waited for new requests. It is assumed that all drop-off locations contained parking facilities where the vehicles could wait and optionally recharge.

Both models assume that customers make reservations in real time (no advance booking is allowed) and that AMOD vehicles pick up and drop off passengers at any node in the road network. We also only considered individual rides, where each trip was served by a single vehicle.

For *non-autonomous* MOD systems, the free-floating scheme is arguably more preferable for the consumer since it alleviates him/her from the costs associated with returning the vehicle. For autonomous systems, vehicles can self-return to station, but this return leg constitutes an empty trip (which may increase road congestion and fuel-use). Furthermore, if the station is further away from the next requested service, the vehicle would be making an unnecessary trip. On the other hand, in the free-floating model, vehicles can become severely unbalanced leading to longer waiting times for consumers. The station-based model requires use of car-parks, which contributes to increased land-use. Our study seeks to evaluate the effects of both models in the densely-population island nation of Singapore during a peak travel period.

IV. Case study – Central Business District in Singapore

In this section, we describe preliminary case-study simulations designed to evaluate the effect of a new policy restricting private vehicle usage within in the high-traffic Central Business District (CBD) in Singapore (Fig. 3). In this scenario, private vehicles were not allowed to access a 14km^2 restricted zone in the CBD and AMOD was introduced as an alternative mode of transport. In other words, only taxis, public transportation and AMOD vehicles were permitted to enter the analysed area. The simulations were run for the period of 2 hours during evening peak (5:00PM to 7:00PM).

A. Demand Generation

The demand generation process of AMOD is based on integration of SimMobility MT simulator with SimMobility ST simulator. Description on midterm simulator can be found in [12], in general it simulate agents mobility decisions that includes their activity and travel patterns along with mode, time-of-day and route choices. For this study the SimMobility MT model assumes all private vehicle trips as a combined modal trip (i.e., Private vehicle + AMOD) if part of the trip is inside CBD. The mode choice model in SimMobilityMT is modified by making it sensitive to AMOD waiting time and additional cost terms, which actually fed back by SimMobility ST in an iterative framework to bring consistency. Further parking prices for private vehicle is reduced as now they have been parked outside the CBD region. For the base case, the total number of AMOD trips for the simulated period was 28,525 trips.

B. Facility Location and Fleet Sizes

In the station-based model, 4 different sets of facility locations were analyzed (Fig. 4). The first set consisted of 10 nodes, which were selected based on the highest frequency of originating trips (*high-demand* nodes). The remaining three sets consisted of the top 20, 30 and 40 high-demand nodes, respectively. There was no capacity constraint on the facilities, i.e., the facility could hold as many cars as required. In the free-floating model, *initial stations* were assumed in the same manner as for the station-based model; however, in the free-floating model, cars were not required to return to these stations. Twelve different fleet sizes were simulated, i.e., from 2000 to 7500 AMOD vehicles in the system. At the beginning of the simulation, vehicles were uniformly distributed over the facilities.

V. Results

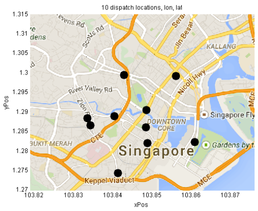
This section discusses the outcomes of our simulations, specifically number of customers served and customer waiting times for each of the different scenarios. We compared the free-floating model against the station-based model with a varying number of facilities and assessed effect of different fleet sizes on the performance of AMOD system.

A. Number of Customers Served

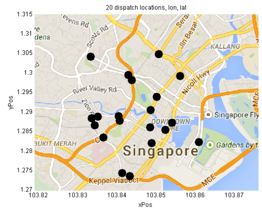
Figure 6 shows the percentage of customers served versus the AMOD fleet size in the system under (a) free-floating and (b) station-based models. Note that not all the generated trips were served because a proportion of the passengers had not yet arrived by the end of the simulation.

In both models, increasing the vehicle fleet size resulted in a linear increase in the number of passengers served, with gradient coefficients of 0.037 for the free-floating model and 0.022 for the station-based model. In other words, every additional 100 cars provisioned increased the average demand served by 3.7 percent (1055 people-trips) in the free floating scheme. For the station-based model, this increase was smaller at 2.2 percent (627.55 people-trips).

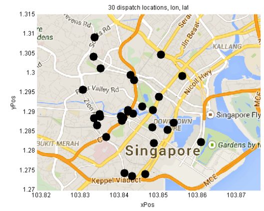
The free-floating model was able to serve 90% of the demand, significantly more than the station-based model (68% of the requested trips). The low service rate in station-based model was likely caused by heavier traffic due to empty vehicle rides. This is consistent with the average travel time (which can be seen as a proxy metric for road congestion) of both models. The average travel time in the station-based model was higher on average, e.g., with 40 stations and 7500 vehicles the average travel time for the station-based model was 14.17



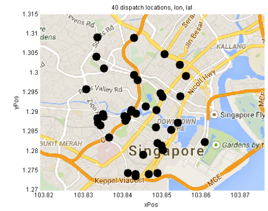
(a) 10 facilities.



(b) 20 facilities.

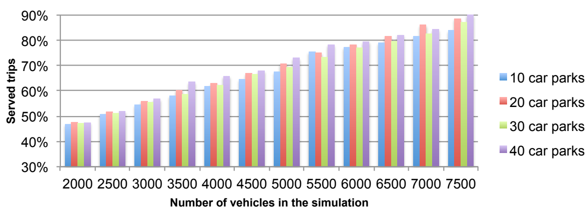


(c) 30 facilities.

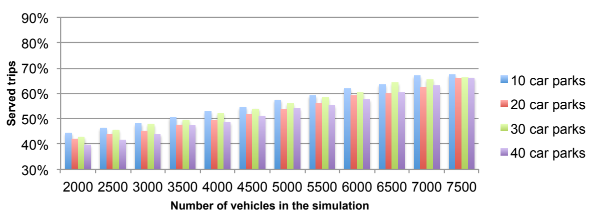


(d) 40 facilities.

Fig. 4: Car parks locations: a) 10 facilities at the most frequent origins of the trips, b) 20 facilities at the most frequent origins of the trips, c) 30 facilities at the most frequent origins of the trips, d) 40 facilities at the most frequent origins of the trips. Background map is generated from Google Maps.

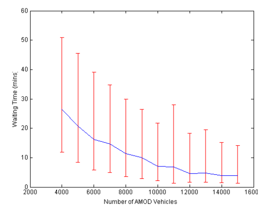


(a) Free-floating model.

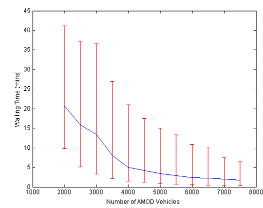


(b) Station-based model.

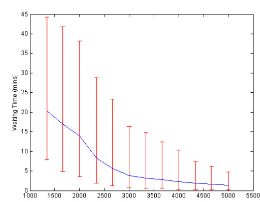
Fig. 6: Percentage of customers served versus the AMOD fleet size in the system for: a) Free-floating model, b) Station-based model. Using the free-floating model we could serve as much as 90% of the demand (with 7000 vehicles and more), while using station-based model we could only serve up to 68% of the demand.



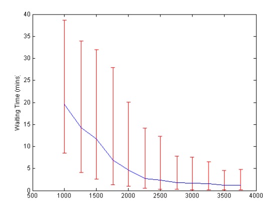
(a) 10 initial stations.



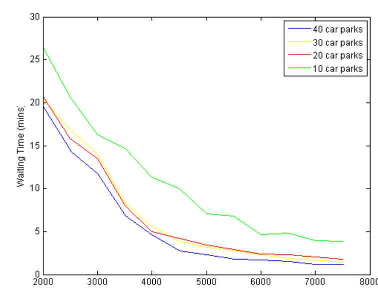
(b) 20 initial stations.



(c) 30 initial stations.



(d) 40 initial stations.



(e) 10, 20, 30 and 40 initial stations.

Fig. 7: Average customer waiting time (minutes) versus the AMOD fleet size for the free-floating model with: a) 10 initial stations, b) 20 initial stations, c) 30 initial stations, and d) 40 initial stations, e) 10, 20, 30 and 40 initial stations. All sets of stations were located at high-demand nodes.

minutes, $\approx 30\%$ higher than in the free-floating model (10.59 minutes).

B. Customer Waiting Time Analysis

In this section, we analyze the waiting times, defined as the time difference between the trip request time and the pick-up time (the time taken to pick-up the customer was not included). Figure 7 shows the median customer waiting times (with upper and lower quartiles) versus the number of AMOD vehicles under the free-floating model.

As expected, increasing the AMOD fleet size resulted in a fall in waiting times, since more vehicles were available to service the requested trips. For example, with 20 initial stations, the median waiting time decreased from 20.74 to 1.80 minutes as the fleet size grew from 2000 to 7500 (similarly, the variance in the waiting times decreased from 31.38 to 6.09). Unlike the effect on total demand served, this waiting time change is non-linear and shows diminishing returns—the rate of improvement decreases with increasing fleet size and appears minimal beyond 6000 vehicles.

The initial distribution of vehicles (i.e. at the beginning of the day) also influenced the performance of the system; increasing the number of initial stations decreased passenger waiting times. The biggest difference is between 10 and 20 stations, where we observed an average improvement of approximately 4 minutes across fleet sizes. However, further increases in the number of stations resulted in only minimal decreases in waiting times (< 1.5 minutes).

VI. Conclusion and Future Work

In this paper, we presented an extension to SimMobility, a multi-agent micro-simulator, for modeling and simulating AMOD systems. The modular approach taken in our extension allows for different models to be integrated and evaluated within the SimMobility framework. As a demonstration, we used this extension to evaluate a policy restricting the use of private vehicles in the Central Business District in Singapore. Our preliminary results show that unnecessary (empty) trips contribute to congestion and therefore they should be minimised and performed only when necessarily.

This work sets the stage for future research in AMOD systems. We are currently developing the AMOD Controller to encompass more sophisticated models, particularly for routing and rebalancing vehicles. Indeed, proper rebalancing has been shown to have a positive effect on system performance, resulting in smaller fleet sizes [10]. However, our work suggests that rebalancing has to be done at minimum required level as empty vehicle trips increase road congestion. In addition, parking facilities can be placed strategically to reduce the number of on-road vehicles, at the cost of additional land use.

Taking a broader outlook, we believe that SimMobility, coupled with the AMOD controller, is a valuable tool for studying the effects of introducing autonomous vehicles on city streets. As shown in this paper, policies incorporating a mix of transportation modes and models can be evaluated to better design and engineer future urban mobility systems.

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