# Simulation Framework for Rebalancing of Autonomous Mobility on Demand Systems

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**Abstract.** We are observing a disruption in the urban transportation worldwide. The number of cities offering shared-use on-demand mobility services is increasing rapidly. They promise sustainable and affordable personal mobility without a burden of owning a vehicle. Despite growing popularity, on-demand services, such as carsharing, remain niche products due to small scale and rebalancing issues. We are proposing an extension to the traditional carsharing, which is Autonomous Mobility on Demand (AMOD). AMOD provides a one-way carsharing with self-driving electric vehicles. Autonomous vehicles can make the carsharing more attractive to customers as they (i) reduce the operating cost, which is incurred when a manually driven system is unbalanced, and (ii) release people from the burden of driving.

This study is built upon our previous work on Autonomous Mobility on Demand (AMOD) systems. Our methodology is simulation-based and we make use of SimMobility, an agent-based microscopic simulation platform. In the current work we focus on the framework for testing different rebalancing policies for the AMOD systems. We compare three different rebalancing methods: (i) no rebalancing, (ii) offline rebalancing, and (iii) online rebalancing. Simulation results indicate that rebalancing reduces the required fleet size and shortens the customers' wait time.

## 1 Introduction

During the post-World War II period automobiles became more widespread, especially in the US. With large-scale suburban areas, the commuting trend accelerated and people became car-dependent [1]. The mass use of motor vehicles led to some unforeseen consequences in terms of congestion, pollution, safety and climate change. This has spurred a growing interest in shared-use mobility—particularly a one-way vehicle sharing—as a sustainable alternative to privately owned vehicles. The challenge is to ensure flexibility of private vehicles while removing the need of car ownership. It is commonly known that most of the vehicles used in urban areas are heavily *underutilized*, i.e., private vehicles are parked around 22 hours daily and their driving speed is usually five to ten times slower than their design speed [2]. One of the hopes for shared-use mobility is that it will reduce congestion and costly parking requirements. Despite these prominent advantages, an inadequate and unbalanced fleet of shared vehicles can result in service unavailability problems, 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) can redistribute cars to better meet demand. Autonomous vehicles can make the carsharing more attractive to customers as they can (i) reduce the operating cost, which is incurred when a manually driven system is unbalanced, and (ii) release people from the burden of driving.
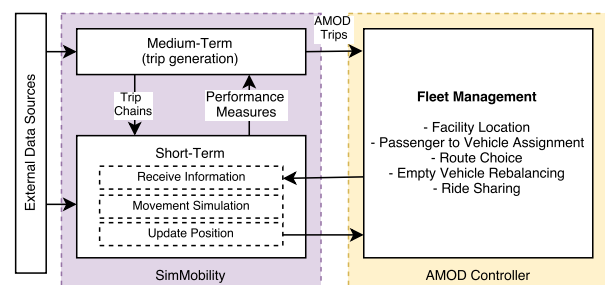


**Figure 1.** The AMOD Controller handles fleet management of autonomous vehicles and consists of five main components responsible for: (i) facility location, (ii) passenger to vehicle assignment, (iii) routing, (iv) empty vehicle rebalancing and (v) ridesharing. AMOD Controller dispatches orders to SimMobilityST, which performs a 0.1 second scale simulation of the vehicles and returns vehicular information (e.g., speed and location) back to the fleet management module. The AMOD trips are generated in SimMobilityMD.

A main motivation for the development of AMOD systems is sustainable transportation, yet no standard methodology has been established to accurately and consistently design and evaluate this new service. Existing methods for operating as well as modeling urban transport require extensions to credibly incorporate AMOD systems as benefits analysis requires controlled experiments that compare transportation behavior with and without the new mode. Breakthroughs in real-time management of the entire transportation system can lead to transit models that better optimize resources and improve efficiency.

This work is built upon our work presented in [3, 4] and sets out to highlight importance of rebalancing for autonomous mobility on demand system. In our previous studies, we presented the AMOD Controller, which handles fleet management of autonomous vehicles, specifically facility location, passenger to vehicle assignment, vehicle routing, empty vehicle rebalancing and ridesharing. The AMOD Controller is developed as an extension of SimMobility—an agent-based microscopic simulation platform—to model and evaluate different scenarios of AMOD systems (Fig. 1). In the current work we focus on the framework for evaluating the impact of different rebalancing policies on the performance of the AMOD system. The system performance is measured in terms of the level of service, i.e., the customers' waiting time and travel time (travel time is understood as an indicator of road congestion).

The rest of this paper is structured as follows. Section 2 provides a literature review of fleet management of mobility on demand systems. Section 3 discusses our methodology to test different rebalancing policies. Results are presented in Section 4. Conclusion and future directions are highlighted in Section 5.

## 2 Background and literature review

Automated mobility on demand systems attempt to provide a one-way carsharing with self-driving electric vehicles. AMOD vehicles hold great promise for mobility on demand systems because they can cooperate with each other and rebalance themselves. Through the system-level coordination, autonomous vehicles can use existing roads more efficiently i.e. by reducing the distance headway to the autonomous vehicle in front or by routing vehicles via not heavily congested roads [5]. To the consumer, AMOD offers an alternative transportation mode to the private vehicles. AMOD vehicles are demand-responsive, which means that they do not operate on a regular schedule like buses or trains, but rather only run when there is a request for the service. This allows for a long- term environmental sustainability and potential cost savings for customers, while relieving people from the burden of driving. Autonomy could also potentially increase safety as the road accidents are mainly caused by the human errors.

The system of autonomous shared vehicles combines benefits of both, standard carsharing systems and taxis. In general, carsharing system might be seen as not as attractive as taxis because the customers might not be able to find a free vehicle close to their position. On the contrary, taxi can pick them up from any location, but with the cost of hiring people to drive the vehicles. AMOD reduces the need of hiring drivers while ensuring vehicles' availability not only within a walking distance to parking lots. Despite these advantages, an unbalanced and inappropriately sized fleet of AMOD vehicles can result in service unavailability problems, particularly during periods of high demand. To address these problems, a few directions in the literature have been established.

To estimate the minimum required fleet size of shared-use vehicles, many researchers have focused on rebalancing strategies for both station-based and free-floating carsharing system [6–8]. Some studies attempt to estimate the fleet size of autonomous shared-use vehicles [3–5, 9–11].

[9] 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. The introduced rebalancing policy (based on a fluid model) was tested in a simulation framework developed in Matlab. Following on this work, [5] discusses a thought experiment of replacing all vehicles in Singapore with a fleet of autonomous and on demand cars to serve for the personal mobility of the entire population. The authors investigate the potential benefits of the AMOD system. Their work shows that the AMOD system requires a number of robotic vehicles equal about 1/3 of the current number of passenger vehicles in Singapore. [11] proposes a queuing-theoretical model for autonomous mobility on demand systems, which minimizes the number of rebalancing vehicles by solving a linear program. The model is applied to the New York City. Their case study shows that the current taxi demand in Manhattan can be met with about 60% of the size of the current taxi fleet.

[12] presents algorithms for dynamic vehicle routing (DVR) for autonomous transportation-on-demand. In each specific DVR scenario the author adopts the methods from queuing theory, combinatorial optimization, and stochastic geometry for the automatic planning of optimal multi-vehicle routes to provide service to demands. Similarly, [13] and [14] consider routing of shared-use autonomous vehicles. The authors design a routing policy that minimizes the average steady-state time delay between the generation of an origin-destination pair and the time the trip is completed. [2] reviews modeling, control and evaluation of AMOD systems presented in [5, 11–14].

An overview of the modeling, control and evaluation of AMOD systems is presented in [2]. The review is built upon work discussed in [5, 11–14].

[3, 4] is published in continuance of [2, 5, 9, 11]. These two studies make use of SimMobility, a microscopic simulation tool, which allows mode choice and congestion to be taken into account while performing evaluation of the AMOD system. One of their findings for a specific policy indicates that introducing the AMOD impacts the mode choice of commuters as some of them switch to the new service. The authors also show that the rebalancing has a positive effect on system performance (when com-

pared to the system without rebalancing model), however, the empty vehicle trips increased vehicle miles traveled (VMT) and road congestion. In this paper we extend the work on rebalancing by introducing the model which directly estimates the fleet size of AMOD system.

# 3 Methodology

This work is built upon the studies presented in [3, 4]. A long-term goal of our analysis is to establish a complete and comprehensive research that compares transportation efficiency with and without autonomous mobility system. The research seeks to answer the following questions: (i) What fleet sizes and vehicles distribution are necessary to serve a given demand? (ii) What vehicles assignment and route choice policies are likely to improve system performance? (iii) How to perform rebalancing of the vehicles? (iv) How the ride-sharing should be incorporated into the system?

To better capture the behavior and dynamics of travel patterns, we use a multi-agent modeling approach in a microscopic simulation framework (Fig. 1). We extended SimMobility with a dedicated controller for managing autonomous vehicles. As shown in Figure 1, SimMobility is made up of three pillars: (i) the Short-Term (ST) simulator, which simulates movement of agents at a microscopic granularity, (ii) the Mid-Term (MT) simulator, which simulates agents' behavior in terms of their activities and travel patterns, and (iii) the Long-Term (LT) simulator, which captures land use and economic activity on a year-to-year scale. SimMobility's framework is fully modular in a way that each level can run independently and only interact with the other level when necessary. Every agent exists and at all levels and in this way agent's behavior and characteristics are consistent across the three pillars. More details on SimMobility can be found in [15].

As presented in our previous papers, the fleet management problem is divided into five sub-problems: (i) facility location, which attempts to find the best locations of the stations to park and recharge the vehicles, (ii) passenger to vehicle assignment, which is to find the best vehicle for each customer, (iii) routing, which aims to find an optimal assignment of a vehicle to the route between the origin and destination, (iv) empty vehicles rebalancing, which is to redistribute vehicles to better meet the demand, and (v) ride-sharing, which attempts to match more than one passenger to one vehicle.

The current work sets out to highlight the importance of rebalancing for autonomous mobility on demand system. In our methodology we distinguish three rebalancing methods: (i) no rebalancing, (ii) offline, and (iii) online rebalancing. In (i) vehicles are only moved when assigned to customers and parked at the destination of the trip. This is our baseline scenario for the analysis. (ii) is run based on the historical data and the rebalancing counts are decided before starting the simulation, while (iii) is run during the simulation time and the rebalancing counts are optimized based on the predicted requests at the time of invoking the rebalancing function. From the perspective of system manager, the offline model solves problem of strategic

planning and long-term operation, specifically what is the number of vehicles needed and how to distribute them between stations. The online model solves for the short-term operating decisions, specificalljmy how to move vehicles based on the current situation on the network. This study aims to analyze and compare the three models.

## 3.1 Offline rebalancing

The offline rebalancing model developed in this study extends the linear program introduced in [9]. The objective of our model is to find the minimum number of vehicles at each station at the beginning of the day (Fig. 2). As proven in [9] this is equivalent to minimizing the rebalancing effort. This policy requires a priori knowledge of the demand $d_{ij}(t)$. We assume that this knowledge is available through the historical data and we obtained it from the simulation in SimMobility MT.

The model is formulated as follows. Let $N_i(t)$ and $d_i^w(t)$ be the number of vehicles owned by station $i$ at time $t$ and anticipated number of customers waiting at station $i$ at time $t$ such that $d_i^w(t) = \sum_j [d_{ij}(t) - d_{ji}(t - \tau_{ji})]$. Two decision variables are the number of empty (rebalancing) vehicles to send from station $i$ to station $j$ at each rebalancing period, $r_{ij}(t)$, and the number of vehicles idling at station $i$ at time $t$, $v_i(t)$. Note, that $N_i(t)$ is the sum of vehicles departed for $i$ plus vehicles idling at $i$. Therefore, at any time $t$, $N_i(t) = v_i(t) + \sum_j [d_{ji}(t - \tau_{ji}) - d_{ij}(t)] + \sum_j [r_{ji}(t - \tau_{ji}) - r_{ij}(t)]$ for all $i,t$. The number of vehicles departed for station $i$, but not available for assignment yet, is $dep_i(t)$. Then, the total number of vehicles $N = \sum_i N_i(t) + \sum_i dep_i(t)$; $N$ is constant over time. We define $v_i^{reb}(t) = \sum_j [r_{ji}(t - \tau_{ji}) - r_{ij}(t)]$ and assume that the travel time from station $i$ to station $j$ is known and given as $\tau_{ij}$; $\tau_{ij}$ is constant over time for any $i$ and $j$, $i \neq j$. Length of the rebalancing interval is $\Delta t$; $\tau_{ij}$ is aggregated based on $\Delta t$.

The objective of this problem is to minimize the number of rebalancing trips at all times $t$.

$$
\begin{aligned}
\min \quad & \sum_i r_{ij}(t) \\
\text{s.t.} \quad & N(t) = N(t - \Delta t) && \forall t \\
& v_i(t) + v_i^{reb}(t) \geq d_i^w(t) && \forall i, t \\
& v_i(t + \Delta t) = v_i(t) + v_i^{reb}(t) - d_i^w(t) && \forall i, t \\
& v_i(t = 0) = v_i(t = T_p) && \forall i \\
& r_{ij}(t = 0) = r_{ij}(t = T_p) && \forall i, j \\
& r_{ij}(t), v_i(t) \geq 0 && \forall i, j, t
\end{aligned}
\tag{1}
$$

The first constraint is set to ensure that the number of vehicles in the system is constant over time. The second constraint tells us that the number of available vehicles at station $i$ has to be sufficient to serve the demand. The third constraint describes a flow conservation at each node. The fourth and fifth are the periodicity constraints. The sixth are the non-negativity constraints.

The model solves for the number of vehicles required to service given booking requests and the rebalancing
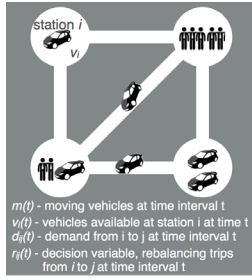
**Figure 2.** A simple example of an unbalanced AMOD system, i.e., we can observe that the top right station is heavily underserved, while there are vehicles available at the bottom right station. The rebalancing aims to align the demand with the supply.

counts between different intervals. The number of vehicles at the beginning of the simulation and the rebalancing counts resulted from the model were fed to the simulator and later compared against the solutions of the online model.

### 3.2 Online rebalancing

The online model used in this study is based on the fluid model first introduced in [5, 9]. The model repeatedly solves the optimization formulated in [4] and it finds the rebalancing counts to match the anticipated demand at all stations.

In the online model, the number of excess demand at station $i$, $\hat{d}_i$, is the number of customers that cannot be served using only the vehicles available at station $i$, i.e., $\hat{d}_i = v_i - d_i$. A negative $\hat{d}_i$ indicates that there are vehicles available to send. We assume that the cost of sending one vehicle from station $i$ to station $j$ is equivalent to the travel time between the $i$ and $j$ and given as $c_{ij}$, which is constantly being updated by SimMobility (travel time is time-varying). Our decision variable $r_{ij}$ is the number of empty (rebalancing) vehicles to send from station $i$ to station $j$. Note, that for simplification, $t$ is omitted in this formulation (the model can be understood as a time invariant model). The objective function minimizes the rebalancing effort.

$$\min \quad \sum_{ij} c_{ij} r_{ij}$$

$$\text{s.t.} \quad \sum_{j} (r_{ji} - r_{ij}) \geq \hat{d}_i \qquad \forall i, j$$

$$\sum_{j} r_{ij} \leq v_i \qquad \forall i \qquad (2)$$

$$r_{ij} \geq 0 \qquad \forall i, j$$

The first constraint ensures that the number of rebalancing counts is greater or equal to the excess demand. The second constraint prevents us from sending more vehicles than we have available in at station $i$. The third constraint is the non-negativity constraint.

The online model is implemented such that the AMOD controller executes it at every time $t = n\Delta t$, where $n$ is the number of intervals and $\Delta t$ is the length of the interval,

i.e., in this study we focus on online rebalancing every one hour, which is explained in Section 4.1.

## 4 Results

In this section we study the relation between the rebalancing models, number of vehicles in the simulation and customers' waiting times (Fig. 3). The waiting time is defined as the time difference between the trip request time and the pick-up time.

### 4.1 Simulation setup

To evaluate performance of the three rebalancing policies, we use a $56km^2$ network of the Central Business District in Singapore. The network consists on 1229 nodes, 14948 lanes and 313 traffic signals.

The demand generation process for AMOD is based on integration of SimMobility MT with SimMobility ST. The simulated population in SimMobility MT was estimated based on the Household Interview Travel Survey for 2012 (for more details please refer to [4]). Given the output from SimMobility MT, we replaced all transport modes except of the Mass Rapid Transit (subway) and public buses with the AMOD service. If only a part of the trip was inside CBD, then we cut the trip and simulated it from or to the border of the network. We run the simulation for the period of 3am-12pm. The total number of AMOD trips for this period was 363,859. Customers do not drop the booking requests and leave the system only when they finish their trips.

Locations of the stations are optimized based on the maximum coverage model (detailed description in [4]). In this study, we assumed that the coverage radius of a station is 1000 meters, which is equivalent to 2-3 minute ride at the average speed of 30 km/h (based on the Land Transport Authority's data, the average speed for arterial roads during peak hours in Singapore is 28.9 km/h [16]). Solution of the model is 34 stations within the analyzed zone. In the online model, we initialized stations with equal number of vehicles across the stations. We simulated fleet sizes of 10,000 to 40,000 vehicles. In the offline version the stations were initialized with the number of vehicles based on the optimization output (to recall, the offline model gives a unique solution for the fleet size, vehicle distribution between the stations and the number of rebalancing trips, while the online model is solved during the simulation for the rebalancing counts).

Both models are sensitive to the rebalancing interval. Therefore, the interval for the offline model is 15 minutes, while for the online model is 1 hour. The reason of this difference is the following: too long interval in the offline model results in overestimation of the fleet size (as the travel time is discretized based on the interval size); too short interval in the online model results in rebalancing during the peak period (especially if there is a booking queue).

All simulations were run in SimMobility ST, which simulates the individual decisions and the transportation
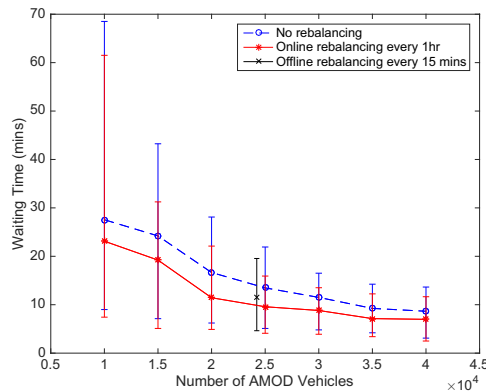
**Figure 3.** The performance of the three different rebalancing policies expressed in terms of the waiting time across different fleet sizes. The no-rebalancing policy (the blue line) performs quite poorly compared to the online and offline rebalancing methods. Both rebalancing methods help in reducing the fleet size, i.e., we need 35,000 vehicles without rebalancing for the average waiting time to be below 10 minutes and only 25,000 if we perform rebalancing. This finding translates to significant savings in the number of required parking lots.

network at the sub-second level (microscopic level). Our AMOD Controller is an integrated, but detachable, component that imbues SimMobilityST with the capability to simulate an AMOD system (Figure 1).

### 4.2 Policy comparison

Figure 3 summarizes the performance of the three rebalancing methods introduced in Section 3. It shows the average customer waiting time (with upper and lower quartiles) for different rebalancing policies as a function of the fleet size. We observe a decrease in waiting time with the increase in the fleet size. The trend lines for the no rebalancing model (the blue line) and the online rebalancing model (the red line) are nonlinear. The no rebalancing policy performs quite poorly in terms of the waiting time. Given the level of service we want to achieve, it requires the biggest fleet size for the AMOD operation, e.g., performance curve for the online model indicates that for the fleet size of 25,000 vehicles and more the average waiting time falls below 10 minutes. If we do not perform rebalancing we need as many as 35,000 vehicles, which translates to 28% increase in the required fleet size. Our finding that rebalancing reduces the fleet size is consistent with [2, 4, 5, 11].

The offline model (the grey cross) optimizes the fleet size and rebalancing effort by providing 24,216 vehicles. For this fleet size the average waiting time is 11.62 minutes, which is almost 2 minutes longer than for a similar fleet size under online rebalancing model. With the fleet size of 24,216 (offline model) and 25,000 (online model) we could serve 93% and 89% of the trips, respectively. 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.

The differences in the results can be explained as follows: (i) Time-invariant travel time in the offline model results in underestimation of the fleet size. The online model performs assignment and rebalancing based on the current travel time on the network (taken from Simmobility), while the offline model does it based on the average travel-time, which does not account for congestion. (ii) In the offline model all booking requests are served immediately causing overestimation of the fleet. In the online model the customers are waiting for service a queue. The queue is always taken into account during rebalancing. (iii) The simulation of the offline model accounts for the optimized initial vehicle distribution, while in the online model vehicles are distributed evenly across the stations.

## 5 Conclusion and future work

The work described in this paper has been concerned with the development of algorithms for rebalancing of mobility on demand systems in Singapore. Three rebalancing models were proposed: (i) no rebalancing, (ii) offline rebalancing, and (iii) online rebalancing; (i) is our baseline model. In this configuration, vehicles are only moved when assigned to customers and parked at the destination of the trip. The results show that this model requires the biggest fleet size for the average waiting time to fall below 10 minutes. In (ii) and (iii) for the same level of service, we need about 28% and 23% less vehicles, respectively. We observed that the offline model gives a reasonable estimation of the fleet size, however further analysis has to be done to reduce the gap between online and offline model. For the future work we are planning to enrich rebalancing by combining the benefits of both models into one robust rebalancing policy. We have also an interest in incorporating the demand management policies in our AMOD Controller, e.g., dynamic pricing.

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