

**TOWARD A SYSTEMATIC APPROACH TO  
THE FLEET SIZE ESTIMATION OF  
AUTONOMOUS MOBILITY-ON-DEMAND SYSTEMS**

A Thesis

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of Cornell University

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Master of Science

By

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## **ABSTRACT**

The objective of this study is to provide analytical guidelines for the design of shared-vehicle Autonomous Mobility-on-Demand (AMoD) systems. Specifically, we consider the fundamental issue of determining the appropriate fleet size from operational perspectives. In this study, we model and analyze the AMoD system, whereby all modes of personal transportation in a city are replaced by one centralized controlled fleet of automated vehicles. A framework which integrates traffic assignment, vehicles routing and automated vehicles rebalancing is provided to estimate fleet size. Experimental results, based on simulations, are provided using actual demand data obtained from NYC Taxi and Limousine Commission. Results reveal that in midtown Manhattan during weekday morning peak hours, an AMoD fleet whose size is 63% of that currently in operation can satisfy all travel demands with the passenger waiting time less than 6 minutes.

## **BIOGRAPHICAL SKETCH**

Tong Zhu is currently studying in the Civil and Environmental Engineering with a concentration in Transportation Systems Engineering at Cornell University. He is in the M.S. degree program beginning in Fall 2014. His research focus on Autonomous Mobility-on-Demand systems, utilizing machine learning, operations research and transportation engineering tools to improve urban mobility services and mitigate traffic congestions. During his Master's program, he also spent time with the Accenture IT consulting team in Shanghai, China. Prior to that, in 2014, Tong graduated from Beijing Jiaotong University, China where he received a B.S. in the School of Traffic and Transportation. As an undergraduate, Tong had been involved in many projects about Transportation Systems, including Transit signal priority control, OD matrix estimation and module development for transportation simulation platform.

## **ACKNOWLEDGMENTS**

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## Chapter 1 Introduction

1  
2 This study attempts to model and analyze the operational aspects of Autonomous Mobility-on-  
3 Demand (brief as AMoD) systems, a waiting to emerge mode of personal transportation wherein  
4 self-driving vehicles satisfy travel demands. Empirical and theoretical studies have been done on  
5 modeling and analyzing the AMoD system from various aspects, among which the fleet sizing  
6 estimation is a fundamental study.

7  
8 Concretely, this study tries to answer the fundamental question that how many self-drive vehicles  
9 would be needed to achieve a certain quality of service in different control and routing scenarios.  
10 In terms of traffic assignment and vehicles routing, primarily we assume that automated vehicles  
11 are rational and with internet-enabled GPS devices they have perfect knowledge of the current  
12 traffic network. Therefore, if all automated vehicles can fit in a centralized-control system, the  
13 system optimal traffic flow can be formed throughout the whole network. In this study, we first  
14 attempt to assign traffic in a system optimal approach, that is to minimize total travel time  
15 throughout the network. Besides, for propose of providing higher quality service so that  
16 passengers get more satisfied using AMoD systems, we attempt the passenger prior traffic  
17 assignment strategy where vehicles transporting passengers from origins to destinations are  
18 preferentially routed on the fastest path to achieve a system optimal flow pattern, while empty  
19 rebalancing vehicles are assigned onto the traffic network in a way that minimizes the  
20 rebalancing impact on the passenger vehicles. Practically, we measure the performance of both  
21 assignment strategies and observe the tradeoffs measured by various metrics of interest.

## Chapter 2 Background and Significance

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At the dawn of a revolution in urban transportation, ensuring sustainable access to mobility is a serious issue. Road networks and the supporting infrastructure are operating at or near capacity, however, the demand for transport continues to rise. Attempts to add parking spaces and expand roadways raise environmental concerns, threaten the livability of cities, and, in many cases, are prohibitively expensive. Fortunately, the emergence of shared-economy markets and ongoing advancements in autonomous vehicle technology may provide a novel option to alleviate the ensuing increase in the demand for personal mobility [1].

Various participants, including major car manufacturers, research universities, and even software companies have now demonstrated vehicles capable of performing almost all driving-related tasks autonomously [2]. As of June 2015, autonomous cars from Google have logged more than 1 million miles of unassisted driving [3]. Moreover, longstanding legal barriers that have limited the impact of self-driving vehicles are beginning to fall. Although most jurisdictions currently require autonomous vehicles to have a safety-driver onboard to intervene in the event of an emergency, impending legislation is likely to relax this requirement [4]. For AMoD systems, this freedom would allow vehicles to rebalance themselves to more effectively serve the travel demand by facilitating smaller fleet sizes, shortening expected wait times, etc.

Rapid advances in vehicle automation technologies coupled with the increased economic and social interest in MoD systems have brought debates regarding the viability of AMoD systems to front edges. Assessing the merits of AMoD systems raises certain key issues. How many robotic vehicles would be needed to achieve a certain quality of service? What would be the cost for



1 their operation? Would AMoD systems decrease congestion? In general, do AMoD systems  
2 represent an economically viable, sustainable, and societally-acceptable solution to the future of  
3 personal urban mobility? In 2015, the authors of [1] suggest that an AMoD system can meet the  
4 personal mobility needs of the entire population of Singapore with a number of robotic vehicles  
5 that is less than 40% of the current number of passenger vehicles. In 2016, the authors of [5]  
6 reveal that rebalancing can dramatically reduce the number of customer walk aways, even for  
7 relatively small fleet sizes.

# Chapter 3 Model Development

## HUB-BASED SPATIAL-QUEUEING MODEL OF AMoD SYSTEMS

### 1. The Hub-based Network

At a high level, an AMoD system can be mathematically modeled as follows. Consider a given environment, where a fleet of self-driving vehicles fulfills transportation requests. Transportation requests arrive according to an exogenous process with associated origin and destination locations within the environment. Transportation requests queue up within the environment, which gives rise to a network of spatially localized queues dynamically served by the self-driving vehicles. Such a network is referred to as a “spatial queueing system.”

The analytical space is formally represented by a graph  $G = (V_G, E_G)$  where  $V_G$  is a finite set of nodes such that each  $i \in V_G$  is a hub at which automated vehicles pick up and drop off passengers.

For the hub-based spatial queueing model, the key idea is that  $V_G = \{1, \dots, N\}$  is a collection of  $N$  hubs located in the plane and that arriving passengers can only be served at hubs.  $E_G \in V_G^2$  is a set of edges such that  $ij \in E_G$  if and only if there is a direct link between node  $i$  and node  $j$ . In a road network, passengers can arrive at any hub and being transported along edges of the network. In the simplest scenario, an arriving process generates spatially localized origin-destination requests in a geographical region  $Q \in R^2$ . The process that generates origin-

1 destination requests is modeled as a spatiotemporal arriving process. Trip requests are serviced  
 2 by vehicles that can transport at most one trip demand at a time.

3 Figure 1 illustrates that a self-driving vehicle successively alternates among three states when  
 4 completing trips: (1) transporting a passenger from an origin  $O_i$  to a destination point  $D_i$ , (2)  
 5 rebalancing (empty) from  $D_i$  to the origin point of the next trip  $O_i'$ , (3) parked at a destination  $D_i$ .

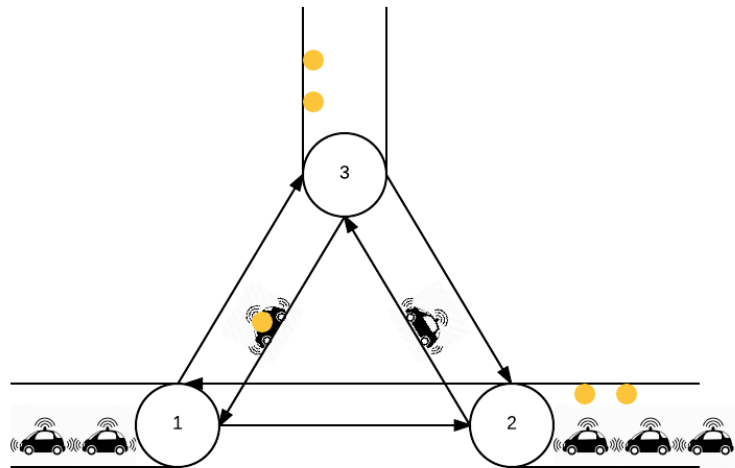


Figure 1 Hub-based Spatial Queueing Model

## 6 2. AMoD Systems Stability Function

7 In this section, a fleet size estimation framework for AMoD systems is proposed. Compared with  
 8 the framework in [1], this new framework take traffic assignment strategies and vehicles routing  
 9 into account. Instead of making routing decisions individually, AMOD systems have the  
 10 advantage of assigning all vehicles in one fleet centrally to achieve different operation goals.

11 We begin by summarizing the fleet size estimation framework originally reported in [1]. The  
 12 system stability equation given below was first developed by Rick Z, Kevin S, Emilio F, and

1 Marco P.

$$2 \quad \lambda(d_{OD} + EMD(\varphi_O, \varphi_D)) < mv \quad (1)$$

3 where  $d_{OD}$  denotes the inter-trip distance, that is the shortest distance from O to D;

4  $EMD(\varphi_O, \varphi_D)$  is the Earth Mover's Distance (Wasserstein Distance) between  $\varphi_O$  and  $\varphi_D$ , that is

5 the minimum amount of distance, on average, a vehicle must travel to realign itself with the

6 travel demand;  $m$  is the number of vehicles in the fleet;  $v$  is the travel speed.

7 One interpretation of equation (1) is that: a fleet of  $m$  vehicles, each capable of traveling at speed

8  $v$ , is able to, collectively, cover distance of the accumulation of all OD distance added with the

9 realignment distance between successive OD pairs.

10 Equation (1) measures system stability by total distance traveled and average velocity.

11 Concretely, (i) the distance  $d_{OD}$  is computed using Dijkstra's Shortest Path algorithm; and (ii) to

12 determine how fast, on average, an individual taxi travels, the total distance traveled by the taxi,

13 with a passenger on board, was divided by the total associated time during each hour of the day.

14 As a result, the estimated minimum fleet size provided by this model is a loose lower bound of

15 fleet size which may cause enormous queue length in the real-world traffic.

16 In this study, we choose total travel time as the measurement of system stability. Because travel

17 time is easier to obtain and can better represent traffic conditions. Thus, the new stability

18 equation can be depicted as follows:

$$\sum_{i,j} \lambda_{ij}^{OD} T_{ij}^{OD} + \sum_{i,j} \lambda_{ij}^R T_{ij}^R < M \quad (2)$$

where  $T_{ij}^{OD}$  denotes the travel time of loaded vehicles, that is the travel time from node  $i$  to node  $j$  under real-time traffic flow;  $T_{ij}^R(\varphi_O, \varphi_D)$  is the travel time of empty rebalancing vehicles under real-time traffic flow.  $\sum_{i,j} \lambda_{ij}^{OD} T_{ij}^{OD}$  can be seen as the service unit needed for passenger vehicles where as  $\sum_{i,j} \lambda_{ij}^R T_{ij}^R$  represents the service unit needed to cover rebalancing trips.  $M$  is the lower bound of fleet size.

In our model, we use the Bureau of Public Roads (BPR) volume-delay function as travel time function.

$$t_a(x_a) = t_{free} \left( 1 + \alpha \left( \frac{x_a}{c_a} \right)^\beta \right) \quad (3)$$

where  $t_{free}$  is the free flow travel time on a link per unit of time;

$x_a$  is the volume of traffic on link  $a$  per unit of time (flow attempting to use link  $a$ );

$c_a$  is the capacity of link  $a$  per unit of time;

$t_a(x_a)$  is the average travel time for a vehicle on link  $a$ .

### 3. Fleet Size Estimation for AMoD Systems

#### A. Fleet Sizing Model with System Optimal Traffic Assignment Approach

##### *i. Linear Programming: Compute Rebalancing Trip OD Table*

In 2012, the author of [6] proved mathematically that rebalancing is required in almost all MoD systems to avoid an infinity queuing of passengers. In order to address the imbalance AMoD system, where hubs with high pick-up demand run out of vehicles, and simultaneously others

1 with high drop-off demand will berth excess vehicles, AMoD system need to constantly  
2 rebalance fleets so that vehicle supply matches demand in a timely manner.

3 In 2016, the author of [5] introduced two rebalancing strategies of AMoD system, namely  
4 feedback and feedback + proportional predictive rebalancing. The author first proposed to take  
5 stock of the outstanding demands in the system, then send excess empty vehicles to match the  
6 demands along the most efficient route. Feedback rebalancing is performed to cater current  
7 demand and supply while feedback + proportional predictive rebalancing is performed in  
8 preparation of the upcoming travel demand.

9 We summarize and implement the feedback + proportional predictive rebalancing reported in [5]  
10 to compute the minimum amount of rebalancing work required to cater both current passenger  
11 demand and the passenger demand arriving in  $[t + \Delta\tau]$ .

12 As shown in Figure 2, at  $t_0$  available vehicles are uniformly distributed across all hubs. At time  
13  $t$ , available vehicles first pick up passengers waiting in the queue at hub  $i$  transporting them from  
14 origins to destinations via assigned routes. Simultaneously, if hubs have excess vehicles, these  
15 excess vehicles are ready to be preemptively dispatched to redirect themselves for meeting the  
16 near future needs if time  $t + \Delta\tau$ . The black solid lines indicate all possible passenger trips and  
17 the red dash lines indicate all possible rebalancing trips.

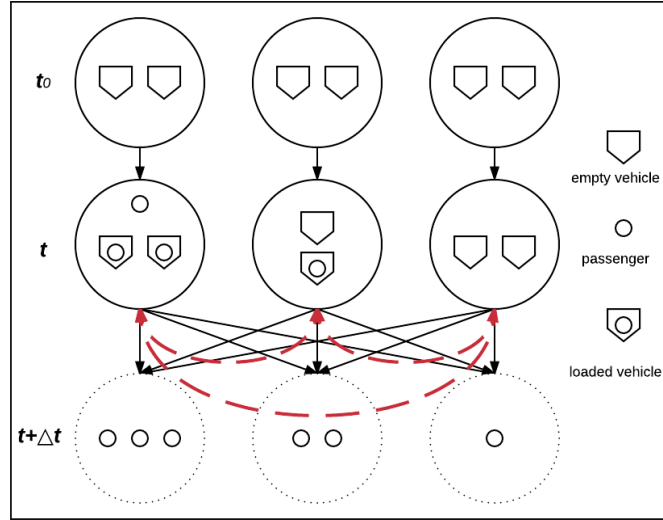


Figure 2 Hub-based Rebalancing Model

- 1 The objective function (4) represents the total amount of time traveled by empty vehicles to
- 2 realize desired fleet distribution. The constraint (5) ensures that after all rebalancing trips are
- 3 accounted for, each hub  $i$  has  $n_i^{des}$  vehicles.

$$4 \quad \min \sum_{ij \in E} T_{ij} n_{ij} \quad (4)$$

5 *s.t.*

$$6 \quad \sum_j n_{ji} - \sum_j n_{ij} \geq n_i^{des} - n_i^{exc}, i \in V \quad (5)$$

$$7 \quad n_{ij} \geq 0, ij \in E \quad (6)$$

- 8 where  $n_{ij}$  represents the number of rebalancing vehicles that fleet operators send from node  $i$  to
- 9 node  $j$ ;  $n_i^{des}(t)$  denotes the number of desired vehicles at  $i$  following rebalancing;  $n_i^{exc}(t)$
- 10 denotes the number of excess vehicles at  $i$ ;  $m$  is the total number of available vehicles;  $q_i(t)$  is

1 the number of outstanding demands at node  $i$  at time  $t$ ;  $Q(t)$  therefore denotes the total travel  
 2 demand in the system;

$$3 \quad \left\{ \begin{array}{l} n_i^{des}(t) = q_i(t) + \frac{\lambda_i(t + \tau)}{\sum_{j \in V} \lambda_j(t + \tau)} \cdot (m - Q(t)), \quad Q(t) < m \\ \frac{q_i(t)}{Q(t)} \cdot m, \quad otherwise \end{array} \right. \quad (7)$$

$$4 \quad n_i^{exc}(t) = v_i(t) \quad (8)$$

$$5 \quad m = \sum_{i \in V} n_i^{exc}(t) \quad (9)$$

$$6 \quad \sum_{i \in V} n_i^{des} \leq m \quad (10)$$

$$7 \quad Q(t) = \sum_{i \in V} q_i(t) \quad (11)$$

8 This feedback + proportional predictive rebalancing strategy moves excess empty vehicles  
 9 preemptively in preparation for demands arriving in time interval  $[t, t + \Delta\tau]$ .

## 10 *ii. System Optimal Traffic Assignment*

11 The following objective function minimizes the total vehicles travel cost.

$$12 \quad \min_{n_{ij}} \sum_{ij \in E} t_{ij}(x_{ij} + n_{ij}) \cdot (x_{ij} + n_{ij}) \quad (12)$$

13 *s.t.*



$$\sum_k f_k^{ij} = \lambda_{ij}^{OD} + \lambda_{ij}^R (\forall i, j) \quad (13)$$

$$\sum_k f_k^{ij} > 0 (\forall k, i, j) \quad (14)$$

$$x_{ij} + n_{ij} = \sum_{k,i,j} f_k^{ij} \sigma_{a,k}^{ij} \quad (15)$$

To provide an outline of fleet size estimation procedure with system optimal traffic assignment strategy, we divide the algorithm into four steps as shown below:

Step	Input	Algorithm to compute the lower bound of fleet size	Output
(1)	Initialization: $M_0 = \sum_{i \in V} \lambda_{ij}^{OD}(t_0)$	Feedback + proportional predictive rebalancing.	rebalancing trip OD data: $\lambda_{ij}^R$
(2)	$\lambda_{ij}^{OD}$ and $\lambda_{ij}^R$	SO traffic assignment for both passenger vehicles and rebalancing vehicles.	vehicles travel paths P
(3)	Path P and network information	Perform simulations.	loaded vehicles travel time: $T_{ij}^{OD}$ rebalancing vehicles travel time: $T_{ij}^R$
(4)	$\Delta m$	while $\sum_{i,j} \lambda_{ij}^{OD} T_{ij}^{OD} + \sum_{i,j} \lambda_{ij}^R T_{ij}^R > M$ : M = $M_0 + \Delta m$ ; redo (1); redo (2); redo (3); return M;	estimated fleet size: M (lower bound)

Table 1 Fleet Size Estimation Framework: System Optimal Approach

For each time step  $\Delta T$ , we first perform linear programming (4) – (6) with initial fleet size  $M_0 = \sum_{i \in V} \lambda_i^{OD}$  to compute the rebalance OD trip table; Secondly, we assign both the passenger trips and rebalancing trips onto the network in a system optimal fashion by solving (12) – (15); Step three, perform simulations which keep tracking positions of all vehicles in the fleet to get the loaded vehicles travel time  $T_{ij}^{OD}$  and the rebalancing vehicles travel time  $T_{ij}^R$ ; Step four, compute

1 total service units then plug the result into the system stability equation (2), if the total service  
 2 units is greater than current fleet size  $M$ , increase  $m$  by  $\Delta m$  then redo step(1) – step(3).

### 3 **B. Fleet Sizing Model with Passenger Prior Traffic Assignment Approach**

4 Besides system optimal traffic assignment, for propose of providing higher quality passenger-  
 5 oriented service where passengers get more satisfied using AMoD systems, we attempt the  
 6 passenger prior traffic assignment strategy where vehicles transporting passengers from origins  
 7 to destinations are preferentially routed on the fastest path to achieve a system optimal flow  
 8 pattern, while empty rebalancing vehicles are assigned onto the traffic network in a way that  
 9 minimizes the rebalancing impact on the passenger vehicles.

#### 10 *i. Passenger Vehicles Assignment*

11 The objective function is to assign passenger vehicles in the network onto the shortest paths.

$$12 \quad \min_{n_{ij}} \sum_{ij \in E} t_{ij}(x_{ij}) \cdot x_{ij} \quad (16)$$

13 *s.t.*

$$14 \quad \sum_k f_k^{ij} = \lambda_{ij}^{OD} \quad (\forall i, j) \quad (17)$$

$$15 \quad \sum_k f_k^{ij} > 0 \quad (\forall k, i, j) \quad (18)$$

$$16 \quad x_{ij} = \sum_{k,i,j} f_k^{ij} \sigma_{a,k}^{ij} \quad (19)$$

1 *ii. Rebalancing Vehicles Assignment*

2 The following objective function minimizes the rebalancing impact on passenger vehicles.

3 
$$\min_{x_{ij}} \sum_{ij \in E} t_{ij}(x_{ij} + n_{ij}) \cdot x_{ij} \quad (20)$$

4 *s.t.*

5 
$$\sum_k f_k^{ij} = \lambda_{ij}^{OD} + \lambda_{ij}^R (\forall i, j) \quad (21)$$

6 
$$\sum_k f_k^{ij} > 0 (\forall k, i, j) \quad (22)$$

7 
$$x_{ij} + n_{ij} = \sum_{k,i,j} f_k^{ij} \sigma_{a,k}^{ij} \quad (23)$$

8 To provide an outline of fleet size estimation procedure with passenger prior traffic assignment  
 9 strategy, we divide the algorithm into five steps as shown below:

Step	Input	Algorithm to compute the lower bound of fleet size	Output
(1)	trip requests: $\lambda_{ij}^{OD}$	SO traffic assignment for loaded vehicles.	loaded vehicle travel paths $P_1$ ; SO link flow.
(2)	Initialization: $M_0 = \sum_{i \in V} \lambda_{ij}^{OD}(t_0)$	Feedback + proportional predictive rebalancing.	rebalancing trip OD data: $\lambda_{ij}^R$
(3)	$\lambda_{ij}^{OD}$ and $\lambda_{ij}^R$	SO traffic assignment for rebalancing vehicles.	rebalancing vehicles travel paths $P_2$
(4)	$P_1, P_2$ , and network information	Perform simulations.	loaded vehicles travel time: $T_{ij}^{OD}$ rebalancing vehicles travel time: $T_{ij}^R$
(5)	$\Delta m$	while $\sum_{i,j} \lambda_{ij}^{OD} T_{ij}^{OD} + \sum_{i,j} \lambda_{ij}^R T_{ij}^R > M$ : $M = M_0 + \Delta m$ ; redo (2); redo (3); redo (4); return $M$ ;	estimated fleet size: $M$ (lower bound)

1

*Table 2 Fleet Size Estimation Framework: Passenger Prior Approach*

2 For each time step  $\Delta T$ , we first solve (16) – (19) to obtain the shortest travel time as well as the  
3 system optimal link flow pattern; Secondly, we perform linear programming (4) – (6) with initial  
4 fleet size  $m_0 = \sum_{i \in V} \lambda_i$  to decide the rebalance OD trip table; Thirdly, we assign the rebalancing  
5 trip OD table onto the network in a way that minimizes total rebalancing impacts on loaded  
6 vehicles by solving (20) – (23); Step four, perform simulations which keep tracking positions of  
7 all vehicles in the fleet to get the loaded vehicles travel time  $T_{ij}^{OD}$  and the rebalancing vehicles  
8 travel time  $T_{ij}^R$ ; Step five, compute total service units then plug the result into the system  
9 stability equation (2), if the total service units is greater than current fleet size  $m$ , increase  $m$  by  
10  $\Delta m$  then redo step(2) – step(4).

## Chapter 4 Case Study in Manhattan Area

Concretely, this study provides planning guideline of fleet size estimation of an AMoD system by taking traffic congestions, traffic assignment, vehicles routing and automated vehicles rebalancing into consideration. To apply our analytical model to estimate fleet size for a real-world scenario, we consider midtown Manhattan area as a case study.

### 1. Data Sources and Network

We use the recorded Yellow Taxi trip data from NYC Taxi and Limousine Commission. The data chronicles the movement and activities of all operating yellow taxis by recording each pick-up location, pick-up time, drop-off location and drop-off time of all the 13,500 current operating vehicles.

The analytical zone is the Mid-Town Manhattan area (from 23<sup>rd</sup> street to 59<sup>th</sup> street, from 1<sup>st</sup> avenue to 11<sup>th</sup> avenue) which covers 360 blocks, 407 intersections and 766 links. One-way traffic control is also considered in our traffic network.

To simplify the passenger pick-up and drop-off location problem, we use hub model where we partition the analytical area into a 10 by 10 grid marked as regions  $R_0 \dots R_{99}$ . Each region is a 270-meter by 250-meter block, so that a demand is on average less than 3-minute walk. Origin and destination points are assigned to the nearest hub, thus defining pick-up and drop-off bins. By and large, there are 100 hubs in network covering all the analytical area.

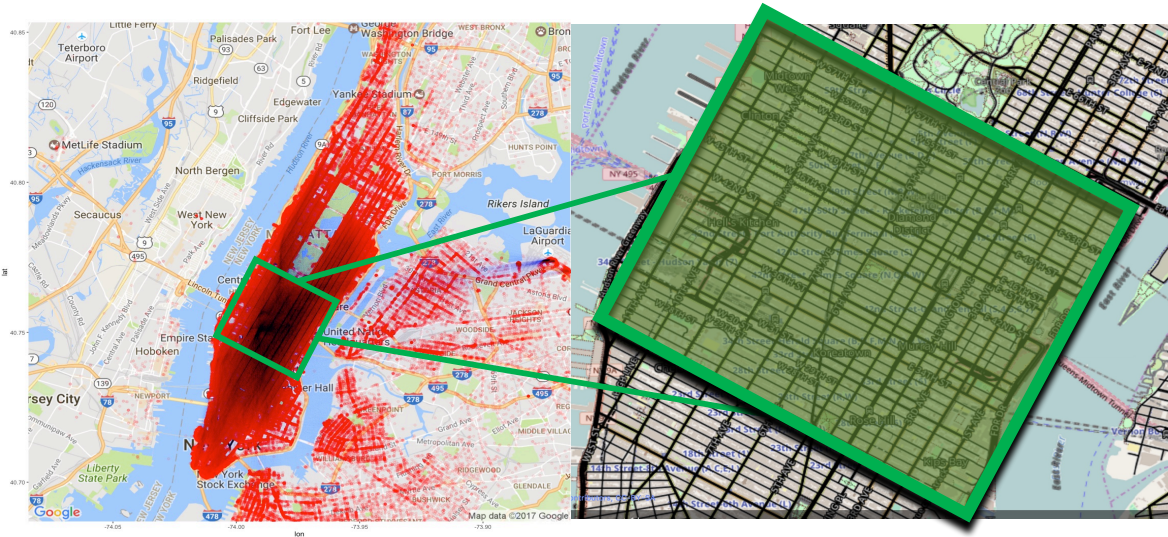


Figure 3 Define the Analytical Area

## 1 2. Model Calibration

### 2 Passenger Travel Demands $\lambda_{ij}^{OD}(t)$

3 Since the experiment field is the midtown Manhattan area, we first select trips which take place  
 4 within midtown Manhattan using recorded trip GPS data and ignore trips that start or end outside  
 5 Manhattan area. Let  $\lambda_{ij}^{OD}(t)$  be the passenger travel demands from origin  $i$  to destination  $j$  at time  
 6  $t$ .

7 In 2016, over 13,000 yellow taxi in New York City made over 380,000 trips a day, with 17% of  
 8 trips started and ended in our analytical area. This study use taxi trip data collected in June 2016  
 9 by New York City Taxi & Limousine Commission. After averaging, the travel demand per day is  
 10 approximately 377,000 among which the peak hour demand is about 9,000. In this case study,  
 11 we choose the work day, Jun.17 2016, morning peak hour from 8:00 to 9:00 as the simulation  
 12 period. According to Uber, the customer impatient waiting time is six minutes, which means that  
 13 a customer cancel the trip request if he or she spend more than six minutes waiting for a pick up.

1 We divide one hour into ten six-minutes time intervals. For the time being, we assume an  
2 omniscient fleet operator with perfect knowledge of  $\lambda_{ij}(t)$ .

### 3 **Rebalancing a Fleet**

4 Since rebalancing aims to address supply and demand imbalance by preemptively moving excess  
5 vehicles, the rebalancing frequency should meet the changing of travel demand and the looking  
6 ahead window should give empty vehicles enough time to be dispatched to their desired node.  
7 Therefore, we set rebalancing frequency to 6 minutes and set the looking ahead window to the  
8 network average travel time. The rebalancing trip is computed using the aforementioned  
9 objective function that minimize the amount of work (Also see [5] for detail).

## 10 **3. Simulation Results**

11 In this study, a hub-based spatial queueing model is deployed to obtain a tighter lower bound of  
12 the fleet size of a hypothetical AMoD system.

13 To primarily summarize the study results: (i) in midtown Manhattan during weekday morning  
14 peak hours, an AMoD fleet whose size is 1700, 63% of that currently in operation, can satisfy all  
15 travel demands with the passenger waiting time less than 6 minutes; (ii) an AMoD fleet with  
16 rebalancing strategy allows transportation service providers to significantly reduce the fleet size  
17 while providing higher quality services.

18 The number of vehicles needed in an AMoD system is determined by temporal trip demand  
19 rates, number of rebalancing trips and traffic network travel time. Adding up all yellow taxis that

1 pick up and drop off passengers within midtown Manhattan area, there are 2,712 vehicles in the  
 2 fleet that serves travel demand during morning peak hours in midtown Manhattan. By replacing  
 3 current fleet with self-driving vehicle fleet which is centralized controlled so that all passenger  
 4 vehicles are ensured to be assigned on the fastest path traveling from origins to destinations  
 5 while the empty rebalancing vehicles are assigned throughout the network to achieve system  
 6 optimal, the current peak hour demand can be satisfied with a fleet size of 1,700 which is 63% of  
 7 the current fleet size. Promisingly, with fewer vehicles, an AMoD fleet meets all travel demand  
 8 with passenger waiting time less than 6 minutes.

9 Figure 4 indicates simulation results of total travel time, passenger vehicles travel time, and  
 10 rebalancing vehicles travel time of a fleet with 1700 vehicles. As figure 4 shows, at the lower  
 11 bound of fleet size, system optimal traffic assignment always guarantees minimized total travel  
 12 time and favorable rebalancing time. Passenger prior traffic assignment reduces passenger travel  
 13 time at the cost of letting empty vehicles detour to longer routes.

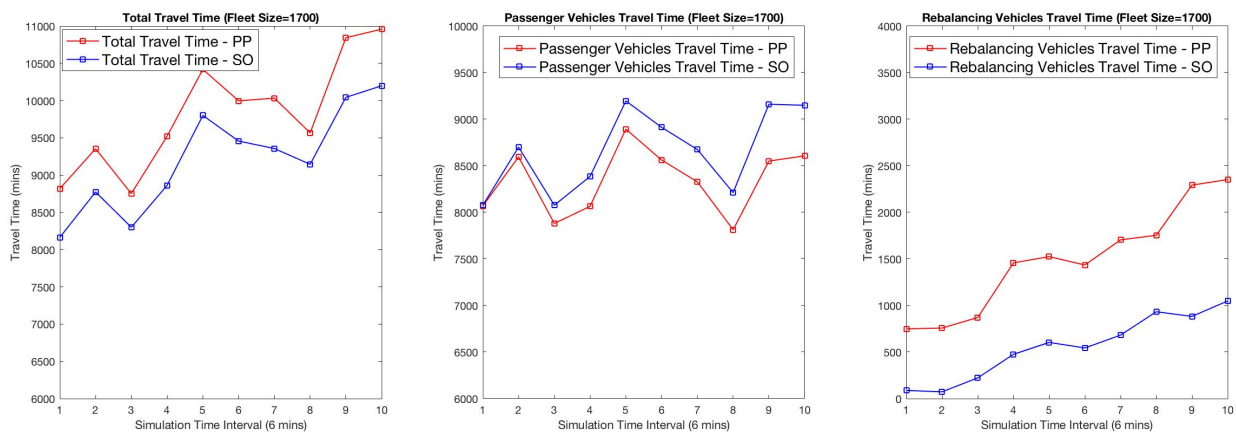


Figure 4 Vehicles Travel Time (Fleet Size=1700)



1 Starting from the lower bound of fleet size, we attempt to see differences between system  
 2 optimal and passenger prior traffic assignment strategies with larger fleet size. Increasing fleet  
 3 size to 2300, we can find in Figure 5 that the total travel time of passenger prior strategy  
 4 approximates to that of system optimal strategy, and that passengers still can get, even though  
 5 get less, benefits from passenger prior strategy. This result indicates that with a larger fleet size,  
 6 passenger prior strategy is feasible and favorable compared with system optimal strategy.  
 7

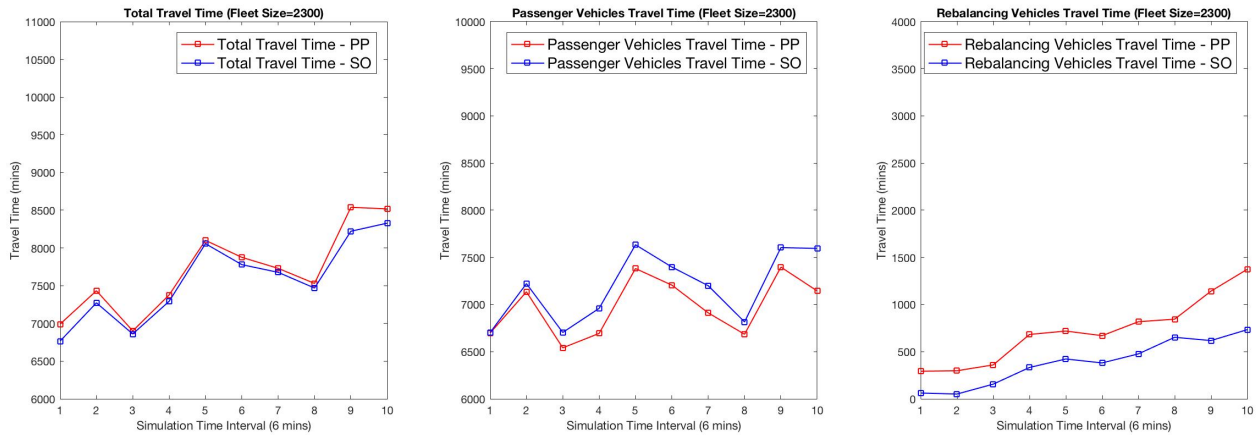


Figure 5 Vehicles Travel Time (Fleet Size=2300)

8 Figure 6 depicts an overall picture of fleet size – travel time relationship for both system optimal  
 9 and passenger prior strategies. As Figure 6 shows, all three kinds of travel time decrease with the  
 10 fleet scale getting larger from its lower bound. However, in practice, the increase of fleet size  
 11 comes with a trade-off. Excess vehicles parking or idling on the street inevitably take space of  
 12 traffic lanes. As a result, immoderately expanding fleet scale not only leads to inefficient  
 13 operation but traffic network congestions.

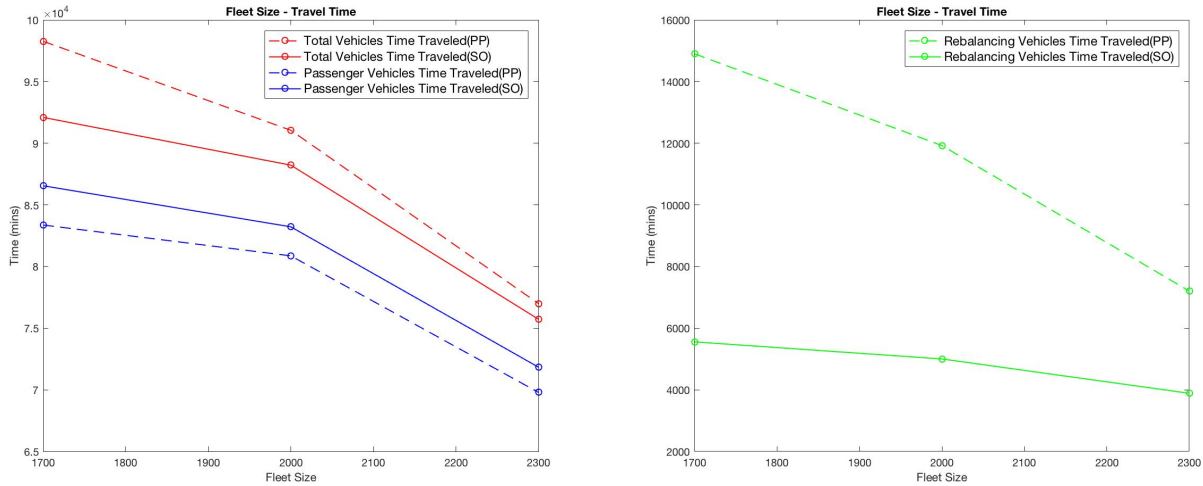


Figure 6 Vehicles Travel Time of the AMoD System

1 In addition to travel time, the next two metrics of interest, empty vehicle miles traveled (VMT)  
 2 and average travel speed, indicate how intensely the fleet is redistributed and how is the traffic  
 3 condition correspondingly. Figure 7 describes that for passenger prior strategy, vehicles move  
 4 through longer empty distance at a higher average speed. For system optimal strategy, the empty  
 5 VMT is less than half of that of passenger prior strategy coming together with the trade-off that  
 6 vehicles moves, on average, at a lower speed. The reason behind is that under passenger prior  
 7 strategy, rebalancing vehicles are dispatched to the least used routes which are likely to generate  
 8 extra miles.

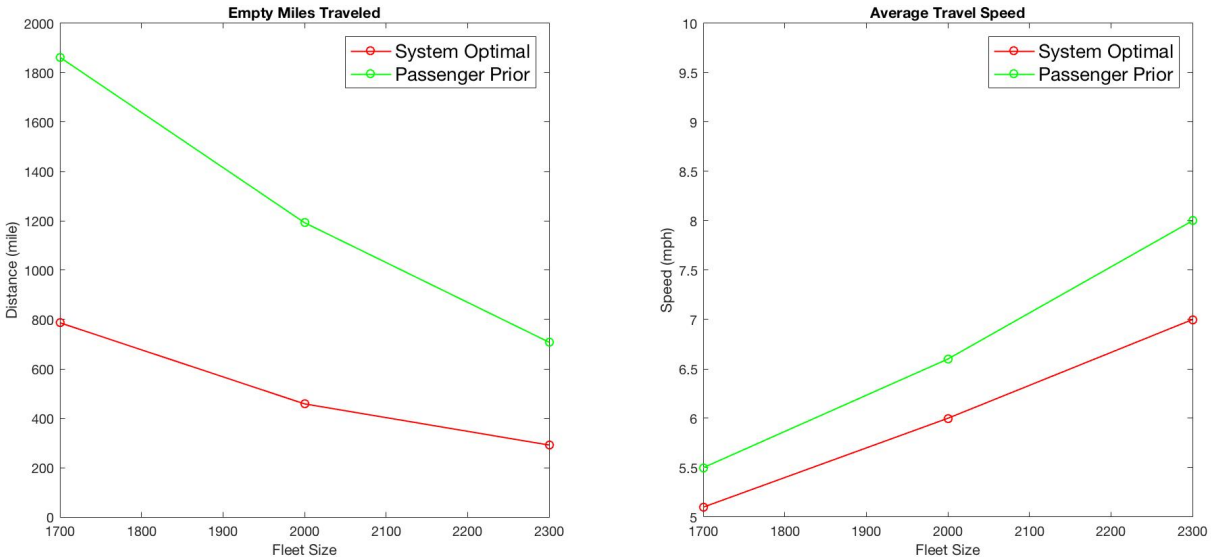
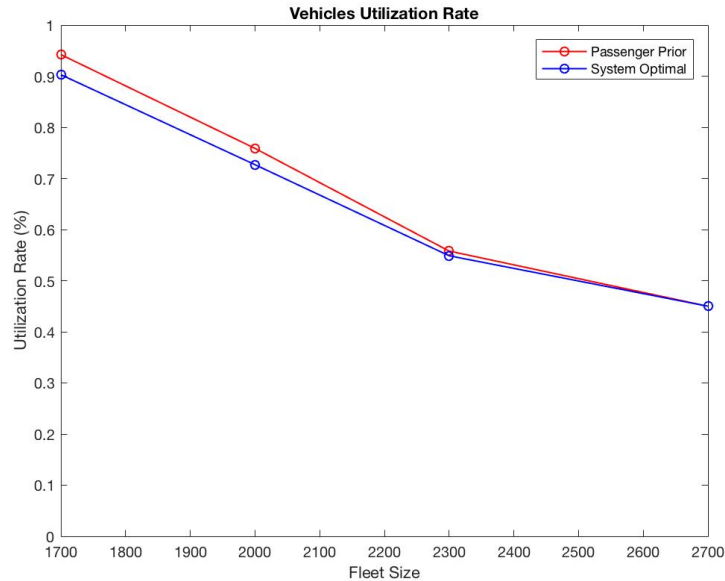


Figure 7 Empty Vehicle Miles Traveled and Average Speed

1 Utilization rate, refers to the fraction of time that vehicles are operating to fulfill missions which  
 2 can either be transporting customers or rebalancing over the course one hour. Due to the low  
 3 matching efficiency caused by the imbalance between supply and demand distribution, vehicles  
 4 in current MoD system spend 55% of operational time idling around or parking on the street,  
 5 which is relatively inefficient in term of vehicle utilization. As Figure 8 illustrates, by  
 6 implementing vehicles rebalancing and different routing strategies in our analytical area, at the  
 7 lower bound of fleet size, vehicle utilization rate increases to over 90%. As we expand the fleet  
 8 scale in mid-town Manhattan, vehicles utilization rate descents gradually. Recall that since the  
 9 empty VMT is inversely proportion to fleet size, there is a trade-off between Vehicles utilization  
 10 rate and the empty VMT.



*Figure 8 Fleet Size - Utilization Rate*

1 Regarding to traffic demand and supply, Figure 9 shows the spatio-temporal distributions of  
 2 demand and excess supply of all 100 hubs at 8:00am and 8:30am. Figure 10 describes the  
 3 rebalancing trips needed between each pair of OD. From Figure 9, we find that the fluctuation of  
 4 solid blue line which represents the number of excess vehicles become intense. Continuing, this  
 5 means without vehicle rebalancing continuous spatial-imbalanced demands lead to severe  
 6 shortage of supply at high demand hubs and meanwhile excess vehicles are stocked at hot drop-  
 7 off hubs. Rebalancing trips occurs to mitigate this imbalance as well as to improve service  
 8 efficiency. Rebalancing trips most likely generate along the diagonal as seen in Figure 10. This is  
 9 because the rebalancing task aims to minimize the cost, total travel time in our setting. And most  
 10 of the adjacent hubs located along the diagonal of the plane in Figure 10.

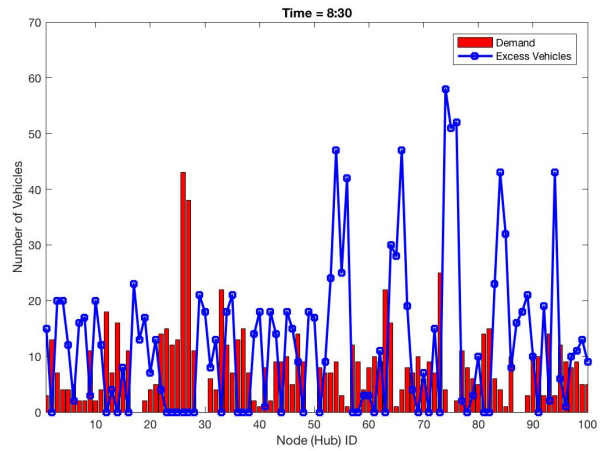
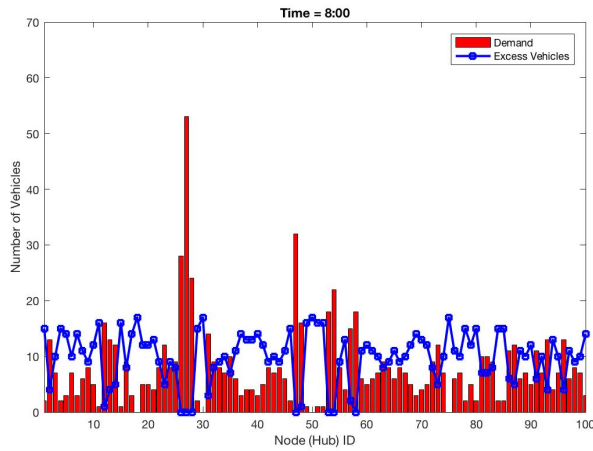


Figure 9 Spatio-temporal Distributions of Demand and Excess Vehicles

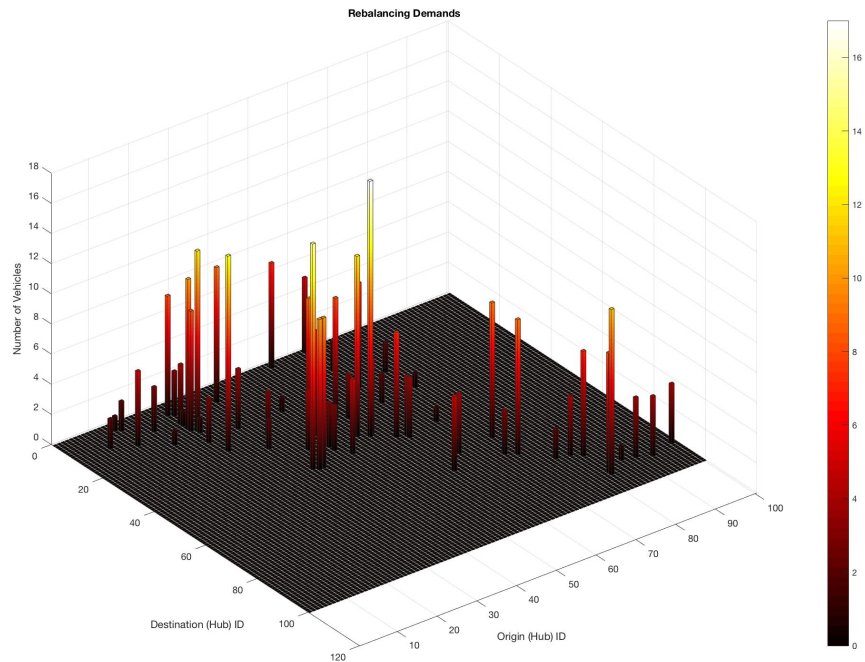


Figure 10 Spatial Distribution of Rebalancing Trips

- 1 In the future, with the rapid development of autonomous vehicle technology and machine
- 2 learning applications in predicting travel demands, the AMoD based service will dispatch

- 1 available vehicles preemptively to passenger pick-up location so that passenger waiting time will
- 2 be minimized.

## Chapter 5 Conclusions

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This study proposed a practical framework for the fleet size estimation of AMoD systems. The model integrates: (i) various traffic assignment strategies, (ii) network congestion effects, and (iii) automated vehicles rebalancing. Simulation results show that current demands of the mobility market can be satisfied with AMoD fleet which is 63% of the current fleet size in midtown Manhattan New York. In addition, simulation results of various traffic assignment schemes revealed how the number of the travel time, the utilization rate, and the number of empty vehicle miles varies as a function of fleet size.

During morning peak hours, intercity stations and stations that have transportation modes connecting with suburban areas are most likely to be high demand areas. Therefore, AMoD systems have the potential to integrate with rail, metro, and city path. Taking advantages of door-to-door service capabilities, AMoD systems are ideal to serve as a last-mile solution within a multi-modal transportation system.

However, this study has its limitations. This study approximates a dynamic model using a series of static approaches. Nor does it account the high occupancy vehicle which is a promising and innovative modal that not only improves fleet operation efficiency but also further reduces fleet size.

In near future, with the synergy of autonomous vehicle technology and machine learning applications in travel demand prediction, intelligent carpooling and AMoD-Transit mode

- 1 integration, AMoD systems will be a promising approach to mitigate transportation problems
- 2 cities are obsessed today.
- 3 Finally, this study suggests a few new directions for future research.



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