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Dynamic ride sharing using traditional taxis and shared autonomous taxis: A case study of NYC

Mustafa Lokhandwala[a], Hua Cai[a,b,*]

[a] School of Industrial Engineering, Purdue University, West Lafayette, IN, United States
[b] Environmental and Ecological Engineering, Purdue University, West Lafayette, IN, United States

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ABSTRACT

This study analyzes the potential benefits and drawbacks of taxi sharing using agent-based modeling. New York City (NYC) taxis are examined as a case study to evaluate the advantages and disadvantages of ride sharing using both traditional taxis (with shifts) and shared autonomous taxis. Compared to existing studies analyzing ride sharing using NYC taxi data, our contributions are that (1) we proposed a model that incorporates individual heterogeneous preferences; (2) we compared traditional taxis to autonomous taxis; and (3) we examined the spatial change of service coverage due to ride sharing. Our results show that switching from traditional taxis to shared autonomous taxis can potentially reduce the fleet size by 59% while maintaining the service level and without significant increase in wait time for the riders. The benefit of ride sharing is significant with increased occupancy rate (from 1.2 to 3), decreased total travel distance (up to 55%), and reduced carbon emissions (up to 866 metric tonnes per day). Dynamic ride sharing, wich allows shared trips to be formed among many groups of riders, up to the taxi capacity, increases system flexibility. Constraining the sharing to be only between two groups limits the sharing participation to be at the 50–75% level. However, the reduced fleet from ride sharing and autonomous driving may cause taxis to focus on areas of higher demands and lower the service levels in the suburban regions of the city.

1. Introduction

Urban roadways, despite being one of the most important infrastructures in the modern world, often bear high levels of congestion and pollution. In 2014, the transportation sector accounts for 26% of all greenhouse gas (GHG) emissions in the United States, which was just behind the electric power sector (U.S. DoE, 2016). There are different ways of reducing the environmental impacts from the transportation sector. Current solutions mainly focus on solving the problem at the vehicle level, such as (1) improving the vehicle fuel economy by making the engine more efficient or reducing the vehicle weight (Farrington and Rugh, 2000; Greene and Plotkin, 2011) and (2) switching the transportation fuel to less carbon intensive sources such as biofuel and electricity (Fontaras et al., 2008) by adopting flex-fuel and electric vehicles in cities with appropriate power generation mix (Cai and Xu, 2013; Hawkins et al., 2013). However, solutions at the system level are less explored. One of the factors contributing to the significant environmental impacts of the transportation sector is its inefficiency. According to the recent national household travel survey (NHTS) data, the average occupancy of personal vehicles is 1.6 (FHWA, 2011), showing that most cars do not run at their full capacity.

* Corresponding author at: 315 N. Grant Street, West Lafayette, IN 47907, United States.
E-mail address: huacai@purdue.edu (H. Cai).

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In recent years, with the growth and acceptance of the sharing economy and autonomous vehicles (Teubner et al., 2014; Krueger et al., 2016; Wadud et al., 2016; Gurumurthy and Kockelman, 2018), ride sharing has emerged as a potential avenue to reduce the transportation sector's energy use and emissions. We define ride sharing as sharing a vehicle with other groups of riders[1] along a fully or partially overlapped route, serving the travel demands of multiple groups of riders in the shared vehicle (for example, a shared taxi). This is different from car sharing, for which a car owner or a fleet owner allows others to use their car when it is not in use (for example, ZipCar, car2go, UberX). Ride sharing using personal vehicles has been tested and implemented in various platforms, such as UberPool and Lyft Line. Uber claims that about 20% of its rides globally are shared rides using UberPool (Fortune, 2016). While the social and environmental impacts of these ride service apps are still in debate (e.g., increasing the total vehicle miles traveled and the total number of cars on the road, competing with taxi drivers for jobs and public transit for riders) (NYC DOT, 2016b), increasing vehicle occupancy rate in private and public vehicles (e.g., taxis) through ride sharing still offers great opportunities in improving the transportation sector's efficiency.

Many earlier studies (Barth and Todd, 1999; Galland et al., 2014) have focused on the traditional ride sharing (i.e., car pooling), for which the ride sharing is pre-arranged (e.g., with friends, family members, and colleagues) and often has the same trip origins and/or destinations. For example, Caulfield (2009) analyzed one day's commute trip data (reported as part of a Census survey) in Dublin, Ireland and found that 4% of the respondents ride-share to work. They estimated that this ride sharing reduced 12,674 t of CO_2 emissions annually. Hong et al. (2017) proposed a clustering algorithm on GPS trace data to match trips and select routes for carpooling. Most recently, Dong et al. (2018) analyzed data from China‘s ride sharing service DiDi and concluded that it is a viable mode of transportation to complement taxis in serving increasing demand.

In recent years, enabled by the development of information and communication technologies, dynamic ride sharing has received increasing attentions. Dynamic ride sharing allows shared rides to form in short notice and among strangers who do not know each other's trip itinerary. The higher flexibility of dynamic ride sharing offers additional opportunity to maximize sharing benefits and improve system efficiency. Fig. 1 presents an example of dynamic ride sharing where three rides are being combined into one single shared ride.

In a dynamic ride sharing system, it is critical to match the appropriate riders to form the shared ride. Therefore, many researchers focus on developing algorithms for ride matching. In particular, Kleiner et al. (2011) proposed an auction mechanism to match rides between two parties and tested its performance using the map of Freiburg, Germany with simulated rides randomly sampled from a uniform distribution. Agatz et al. (2011) compared the optimization-based approach with a simple rule-based greedy matching algorithm using travel data from Atlanta, Georgia and concluded that optimization methods have better system performance in matching rides and reducing total system vehicle-miles-traveled (VMT). However, to simplify the analysis, these studies limited the number of rides that can be shared at a time to be two (i.e., maximally, two passengers can share a vehicle). More recent research has proposed more flexible models to optimize passenger-vehicle matching and vehicle routing, considering the vehicle capacity and the number of passengers traveling together (Lin et al., 2012; Santos and Xavier, 2015). Levin (2017) designed an algorithm to optimize route choice for autonomous vehicles, considering congestions due to other vehicles in the network, using linear optimization models. Other recent research, Li et al. (2016) has focused on finding an optimal route choice model for last mile parcel delivery using shared autonomous vehicles. While these studies have focused on providing efficient solutions to the dynamic ride sharing problem with given requests and vehicle instances, we cannot draw conclusions on the city-scale impacts of implementing these systems.

Qian et al. (2017) proposed a "group ride" system, in which different groups of riders gather at a predefined location and are picked up together. They tested the system using taxi trip data from 30-min periods during peak and off-peak hours in three cities and concluded that this types of ride sharing can reduce vehicle VMT by over 47%. However, being different from the door-to-door service provided by traditional taxis, group ride requires the riders to walk to and from the taxi pick-up and drop-off locations, reducing the convenience of taking taxis. Santi et al. (2014) introduced the concept of share-ability networks and proposed a mathematical model to quantify the benefits of ride sharing. They analyzed the taxi trip data in New York City and concluded that ride sharing can reduce cumulative trip length by 40% or more. However, their model also constrained the sharing to be between two riders, ignoring the potential benefits from a more flexible system. Additionally, they assumed that the tolerance level for trip delay is identical for all riders, ignoring the individual heterogeneous tolerance and needs in the real world.

Agent-based models have been used in the field of transportation for many purposes, including travel time estimation (Chen and Rakha, 2016), disaster relief logistics (Wang et al., 2016), and choice models (Zou et al., 2016) to incorporate individual preferences with regards to transportation modes. In the field of ride sharing, to account for the individual heterogeneity, researchers developed efficient agent-based models to simulate dynamic ride sharing (Nourinejad and Roorda, 2016; Fagnant and Kockelman, 2014; Chen et al., 2016). However, these models are mostly based on simplified system setups, not considering the real-world road infrastructure and the actual travel demands. Some studies (Brownell and Kornhauser, 2014; Ma et al., 2015; Fagnant and Kockelman, 2016) focused on the economics of ride sharing and showed significant potential monetary savings in New Jersey, Beijing, and Austin. Ma et al. (2015) also showed that using ride sharing, 2.2 million kg of carbon dioxide can be saved every year in Beijing, while Fagnant and Kockelman (2016) showed that each shared autonomous vehicle has the potential to replace eleven private cars. Martinez et al. (2015, 2014) studied shared taxis in Lisbon and Porto, respectively, to infer system level benefits. Both papers (Martinez et al., 2015; d'Orey and Ferreira, 2014) showed that taxi sharing can help passengers reduce travel costs with an increase in total transit time. Alonso-Mora et al. (2017) showed that the percent of riders served by the system is improved with the increased amount of fixed delay in travel time that is accepted by the riders using small and large capacity autonomous vehicles. However, most existing work

[1] We consider a group of riders to be made up of one or more persons riding from and to the same origin and destination using a single request.

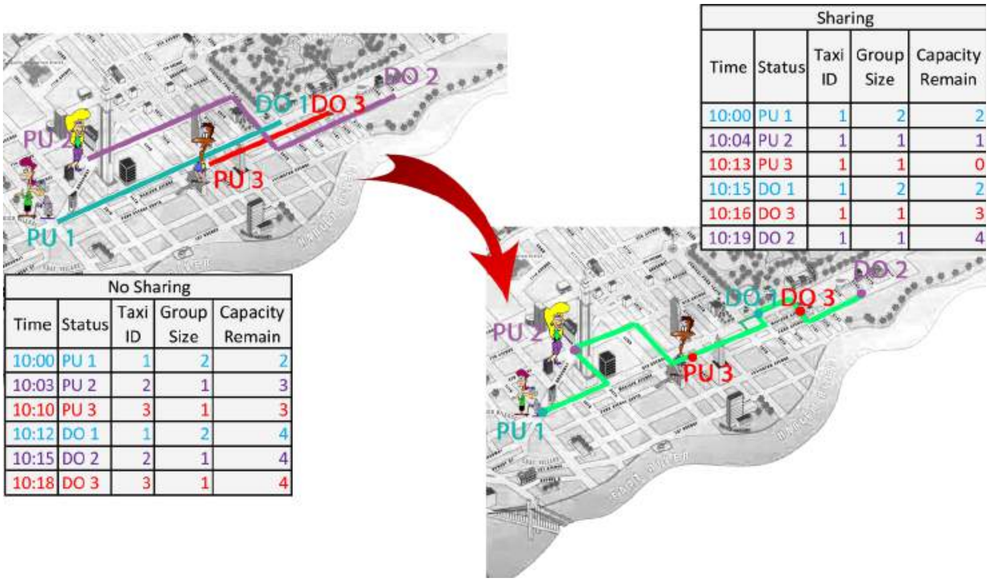

Fig. 1. Dynamic point-to-point ride sharing - the three rides shown can be combined to a single ride by a car with a capacity of 4 with a small amount of delay in arrival for each rider. (PU- Pick Up, DO - Drop Off).

does not consider the fact that taxis and riders could have individual preferences on the thresholds for the inconvenience (e.g., longer ride time) caused by sharing. For example, Ma et al. (2015) restricts feasible shares based on the same threshold of the ratio of monetary gain to time delay for all the riders; Alonso-Mora et al. (2017) uses a fixed allowable time delay for all riders, while other work (Brownell and Kornhauser, 2014; Fagnant and Kockelman, 2016) match taxi rides appearing within a certain fixed grid area, with nearby origins and destinations, and within a time window. Only a few studies (d'Orey and Ferreira, 2014) consider individual sharing preferences to reflect the individual heterogeneity.

Additionally, with the fast development of autonomous vehicles, ride sharing provided by shared autonomous vehicles has also received more and more attention. Unlike taxis whose drivers need to change shifts and take breaks, autonomous vehicles can be available 24 × 7. So shared autonomous taxis can offer additional benefits compared to the traditional ride sharing. However, the differences and synergies between the two systems have not been fully evaluated. Existing studies either ignored the driver shifts since their analysis was on a short time frame (often limited to an hour), focused exclusively on the peak demand periods (Brownell and Kornhauser, 2014; Ma et al., 2015; Fagnant and Kockelman, 2016), or studied dynamic ride sharing using either exclusively autonomous vehicles (Ma et al., 2015; Martinez et al., 2015; d'Orey and Ferreira, 2014; Alonso-Mora et al., 2017) or exclusively traditional vehicles (with shifts) (d'Orey and Ferreira, 2014). It is essential to compare both types of vehicles in the same system in order evaluate their impacts on a fair ground.

To address the above mentioned limitations of existing models, this research aims to use agent-based modeling to quantify the environmental and energy benefits of dynamic ride sharing using traditional and autonomous taxis by taking into account (1) the individual heterogeneous preference in whether or not to participate in ride sharing and what level of trip delay is considered as acceptable, (2) real-world travel demands and road infrastructures, (3) the flexibility to allow multiple groups of riders to share the ride when vehicle capacity permits, and (4) the different availability of autonomous and traditional taxis (traditional taxis are unavailable during the time between two shifts while autonomous taxis are always available).

We apply our agent-based model on a case study of New York City (NYC) taxis. The rationale for studying NYC is provided in Section 2.2. Compared to existing studies analyzing ride sharing using NYC taxi data, our contributions are that (1) we proposed a model that incorporates individual heterogeneous preferences; (2) we compared traditional taxis with shifts to autonomous taxis; and (3) we examined the spatial change of service coverage due to ride sharing.

2. Method and data

2.1. Agent-Based Model (ABM)

We used agent-based modeling to study ride sharing because of its capability to incorporate individual agent's different needs and preferences. Additionally, we can also collect statistics of each rider entering the system and follow every taxi as it moves through the city, which enables us in analyzing the data at an individual level. In this study, we have two types of agents: taxis and rider groups. A rider group refers to one or more passengers that are traveling together as a group (organized before the ride sharing, e.g., a family). Each taxi and every rider group has their own parameters in this model as discussed below.

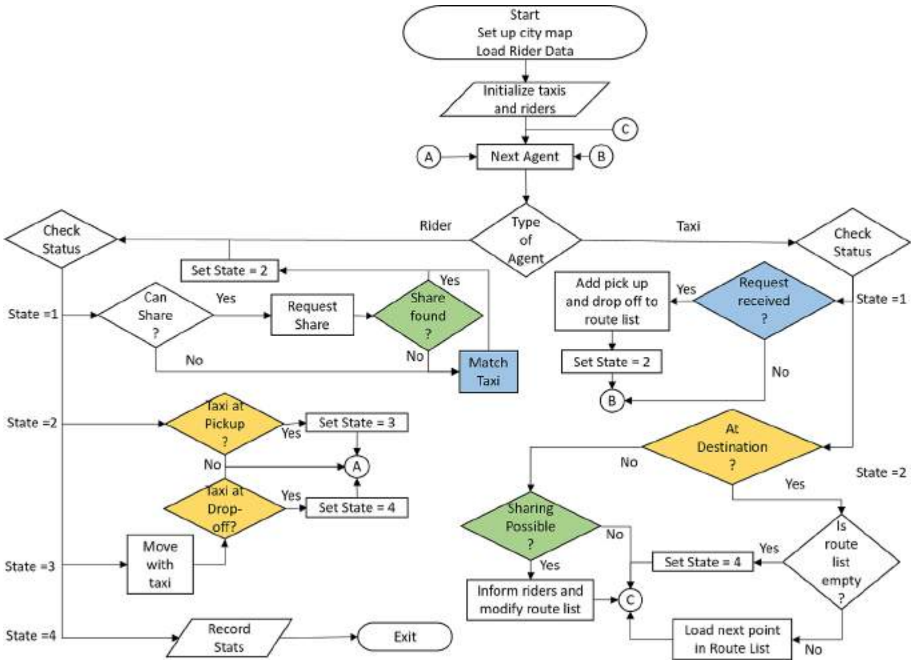

Fig. 2. Model Overview. Matching colors in the flowchart represent an event/decision taking place simultaneously by the rider and the taxi. The circular blocks labeled A, B, C are used as "connectors" to imply a transfer of flow to their corresponding connector.

The system-level parameters in the model are the number of taxis (fleet size) and the percent of riders who are willing to share their ride with others (Percent Sharing). The taxis have a parameter for taxi capacity (set to 4 passengers in this study). The parameters of the rider groups include the pick up and drop off location and time, the number of passengers in the group, and the fraction of distance that a rider group considers as an acceptable deviation (deviationTolerance[2]). In order to represent the heterogeneity of riders, we have set the deviation tolerance to be distributed as a triangular distribution between 0 and 1 with the mode set to be 0.5. A triangle distribution has been chosen because there is a lack of information to estimate the actual deviationTolerance. The triangular distribution gives us the flexibility to adjust its mode according to what we believe to be the most common acceptable route deviation. These deviation tolerances are assigned randomly to all the riders in the network. A detailed list of all parameters in the model are provided in the Supplementary Information (Section SIA). This model is built using the AnyLogic simulation software.

Fig. 2 shows an overview of the model. The system is initialized by loading the map[3] of the city-of-interest. The rider data (from historical trip data) is also loaded into the memory. All the taxis enter the model at the beginning and the riders enter the model one by one as per the pick up time in the historical trip data. The initial setup allows 30% of the taxis (randomly chosen) to be available and assigns the remaining 70% taxis a random destination (sampled from historical trip data). The initial number of busy taxis does not impact the model results because the demand between midnight and the morning peak is very low (more in Section SIB in the Supplementary Information). So the system has time to "self-balance" the available taxis. All the taxis will follow actions as described in Algorithm 2, while all the riders will follow actions as described in Algorithm 1.

Algorithm 3 serves the purpose of linking the taxi algorithm (Algorithm 2) and the rider group algorithm (Algorithm 1). It does so by providing a method for the rider groups and taxis to be matched with each other. A rider group first seeks a shared ride before seeking an unoccupied ride. While seeking an unoccupied ride, the rider group is matched with the closest unoccupied taxi. In the shared mode, the taxi first filters all potential sharing requests using the *preCheck* algorithm (SIA.4.2.2 *preCheck*), which is a two-step process. We use two rectangular bounding boxes to indicate the "direction" of the trips. Step 1: the first biggest bounding box is formed using all the pick up and drop off points that are yet to be visited by the taxi (the current trip chain) and the current location of the taxi (shown as the yellow colored cells in Fig. S1 in Section SIA.4.2.2). This bounding box covers the entire original trip chain. The drop off point of the candidate share is then evaluated relative to this bounding box. If the drop off point of the candidate share is within the bounding box, then this candidate share passes the *preCheck* and will be further evaluated by the *bestRoute* algorithm (Fig.

[2] The deviationTolerance is calculated as $deviationTolerance = \frac{\text{Acceptable maximum trip distance after sharing} - \text{Original Trip Distance}}{\text{Original Trip Distance}}$. We have defined the distance that a rider group allows for deviating from their original path to be proportional to the unshared trip distance, because it is unreasonable to expect a rider group whose trip is short (e.g., 0.5 miles) to accept a large change in route (e.g., 2 miles).

[3] The map has information about the locations of the load links and the speed on these roads. All movement by the agents in the model is done on the road links on the map that is loaded in at the start of the simulation. Specific routes are chosen by using the routing service provided by Anylogic, which uses Dijkstra's algorithm to calculate routes.

S1 a). Step 2: If the drop off point of the candidate share is outside of this bounding box, a second bounding box will be formed using the drop off point of the candidate share and the current location of the taxi (shown as the gray shaded boxes in Fig. S1 c and d). If the second bounding box fully covers the first bounding box (Fig. S1 c), then this candidate share also passes the *preCheck* and will be further evaluated by the *bestRoute* algorithm (SIA.4.2.3*bestRoute*). Basically, the second bounding box makes sure that we don't reject candidate trips that travel further than the existing trip chain. Because the pick up location of the candidate will be close to the current location of the taxi (sharing requests are only broadcast to nearby taxis), only the drop off location need to be evaluated.

The *bestRoute* algorithm evaluates all the share requests by selecting the best possible permutation of points within a given share that minimizes inconvenience caused to all the rider groups involved in the share request (more details in Section SIA.4.2.3 of the Supplementary Information).

Algorithm 1. Rider Group Algorithm

```
for All r in RiderGroups do
    if State = 1 // Searching (SIA.3.2 Step 5)
    then
        if r is willing to share and searching time is less than shareLimit
        time then
            Broadcast sharing request;
            // (SIA.3.2 Step 18)
        else
            Broadcast request to idle taxi. Request includes maximum
            allowable deviation ;
            // (SIA.3.2 Step 9) Rider searches for a shared taxi
                for shareLimit time before searching for a
                regular taxi
        end
        if match is found // Algorithm 3 has assigned rider group
            to a taxi (Section SIA.3.2 Step 23)
        then
            set State = 2;
        end
    end
    if State = 2 // Wait for Pick up (SIA.3.2 Step 31)
    then
        if taxi is at pick up then
            set state = 3
        end
    end
    if State = 3 // Ride to drop-off (SIA.3.2 Step 35)
    then
        if taxi is not at the drop-off location then
            Move with taxi // Algorithm 3 updates the deviation
                tolerance if a share is found
        else
            Record stats and exit the system
        end
    end
end
```

Algorithm 2. Taxi Algorithm

```
for All x in Taxis do
    if State = 1 // Searching (SIA.4.2.1 Step 7 - 25)
    then
        receive requests from nearby non-sharing riders and add request
            to requestList // (SIA.4.2.1 Step 9)
        Call Algorithm 3 // to match the taxi to the nearest
            available rider groups that requested rides
        if a match is found then
            add pick-up and drop-off point to route list
            Proceed to first point on the route list
            Set State = 2
        end
    end
    if State = 2 // in service (SIA.4.2.1 Step 34)
    then
        if destination reached then
            Load / Unload rider group as per type of destination (pick up
            / drop off)
            // (SIA.4.2.1 Step 49)
            if there are more points to visit in route list then
                Move to next point in route list
            else
                Set Status = 1 // (SIA.4.2.1 Step 53)
            end
        else
            search for share requests and add request to requestList
            Call Algorithm 3 // to evaluate the feasibility of
                sharing and identify the optimum rerouting
        end
    end
end
```

Algorithm 3. Matching Algorithm

```
Data: x_c ← Taxi that calls Algorithm 3 ;
requestList ← All rider groups that have requested taxi x_c
remove all req ∈ reqList where req.State ≠ 1 // Each rider group
    sends requests to multiple taxis and could have been
    matched before x_c evaluating their request
Set bestMatch ← NULL;
for All req in requestList do
    if x_c.State = 2 // Evaluating a sharing request
    then
        Use preCheck to eliminate infeasible shares // for more
            details refer to (SIA.4.2.2)
        if If req passes preCheck then
            run bestRoute algorithm to insert req in the route list of x_c in
                the most optimum way while validating deviation
                tolerances for all riders involved in the share
                // (SIA.4.2.3)
            if bestRoute algorithm does not return a valid route then
                match is not found
            else
                match is found;
                if req is better than bestMatch // A better match is
                    defined as a one that has a lower score based
                    on (Equation S1)
                then
                    Set bestMatch ← req
                end
            end
        end
    else
        // Evaluating a non-sharing request
        if rider req is the closest rider to taxi x_c in requestList // Taxi
            prefers the closest rider group (SIA.4.2.1 Step 24)
        then
            Add req pick-up and drop-off point to routeList;
            Add req to list of possible rides;
        end
    end
end
if match has been found then
    Modify route for taxi x_c;
    Communicate change to all riders currently in taxi x_c;
    All riders in x_c adjust their deviationTolerance
end
```

For the purpose of model verification and validation, we tested all the model parameters (as discussed in Section SIA of the Supplementary Information). We also tested various scenarios ran by other similar studies using NYC taxi data, and obtained similar results. Additionally, we compared our base model, which has 13,500 traditional taxis without sharing, to the current NYC taxis, and they have similar shift schedules.

The outputs of the model include:

- The number of rider groups leaving the system without being served. A group of rider is left unserved if the total time in system for

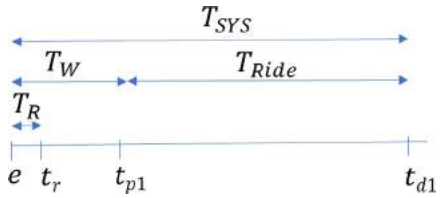

Fig. 3. Time stamps recorded for each rider group in the system. e is the time that the rider group enters in the system; t_r is the time that the taxi responds to the rider group to commit a pickup; t_{p1} is the time that the rider group is picked up; and t_{d1} is the time that the rider group is dropped off at its destination.

the rider group exceeds their acceptable waiting time.

- Time stamps for each rider at every status change, the information of which we can use to calculate the following: (Fig. 3)
  - Time taken for a taxi to respond to each rider group's request and commit a pickup, T_R
  - Time that a taxi took to reach a rider group, T_W
  - Riding time for each trip, T_{Ride}
  - Time between the arrival of the rider in the system and its departure from the system after reaching its destination, T_{SYS}
- The number of rider groups and total passengers in a taxi at any time
- The distance traveled by each taxi with and without passengers

Using the information from these outputs, we can infer:

- The number of vehicles that can be reduced in the system under different scenarios
- The degradation in quality of service for the riders in terms of the additional distance traveled, additional time taken to reach destinations, as well as the increase in waiting time for the riders.
- The reduction of distance traveled by the taxis due to ride sharing and consequently the reduction of greenhouse gas emissions from the taxis. We use 4.17×10^{-4} metric tons CO_2-eq/VMT estimated by EPA (2017) to convert the changes in VMT under different scenarios to emission reductions.

2.2. Data and exploratory analysis

We applied our model to NYC taxis as a case study to quantify the impacts of ride sharing at the city-scale. Although our analysis is based on one city, it is notable that the model and framework is applicable to any city if similar data is available. We choose NYC as our case study due to the following reasons:

- Data availability: NYC DOT (2016b) has published an extensive and highly detailed database which allows us to validate the agent-based model at a micro level.
- Potential impacts: The great demands of taxi rides in NYC indicate potential significant saving opportunities. The average number of daily trips by taxis in NYC is 485,000 (NYC DOT, 2014). During the evening peak hour, on average, there are over 8000 pickups within every 15 min (Fig. 4a).
- Spatial sharability: Trips in NYC are highly concentrated (e.g., over 90% of the taxi pickups are in the Manhattan region)(Fig. 4b). The high number of taxi rides along with the high spatial and temporal concentration of rides make ride sharing a great transportation alternatives.
- High ratio of single-rider trips: Over 65% of all trips in NYC are single-person trips (Fig. 4c), which leaves a large amount of unused capacity in the vehicles. This unused capacity can be filled by shared trips.

A sample of the data used in this study is shown in Table 1. The data we used are the green and yellow taxi trip data from the year 2014 (NYC DOT, 2016b). We chose data from 2014 because, at that time, ride sharing applications such as Uber and Lyft had not been widely adopted to impact taxi ride demands (NYC DOT, 2016a). Hence the trip data from 2014 is more representative of the total demands in the city than the most recent data. The NYC-TLC records each pick up and drop off for all yellow and green taxis registered in the city. The green taxis are not allowed to pick up passengers below West 110th Street and East 96th Street, or at the two NYC airports (NYC DOT, 2014), while the yellow taxis do not have such restrictions. The reason for having this distinction between the Green and Yellow taxis was to have more taxis available in the suburban region of the city (NYC DOT, 2014). The data recorded by the NYC-TLC is the trip pick up time and location (in longitude and latitude), drop off time and location (in longitude and latitude), and group size (number of people traveling together).

We have divided the travel demands in NYC into four phases as shown in Fig. 4a based on pick up time. While we have data for all phases and the models are ran for the entire day for multiple days, we focus our discussions on the two peak demand periods (the morning peak from 7:00 am to 3:00 pm and the evening peak from 5:01 pm to midnight), because peak demand periods can benefit more from system efficiency gain through ride sharing.

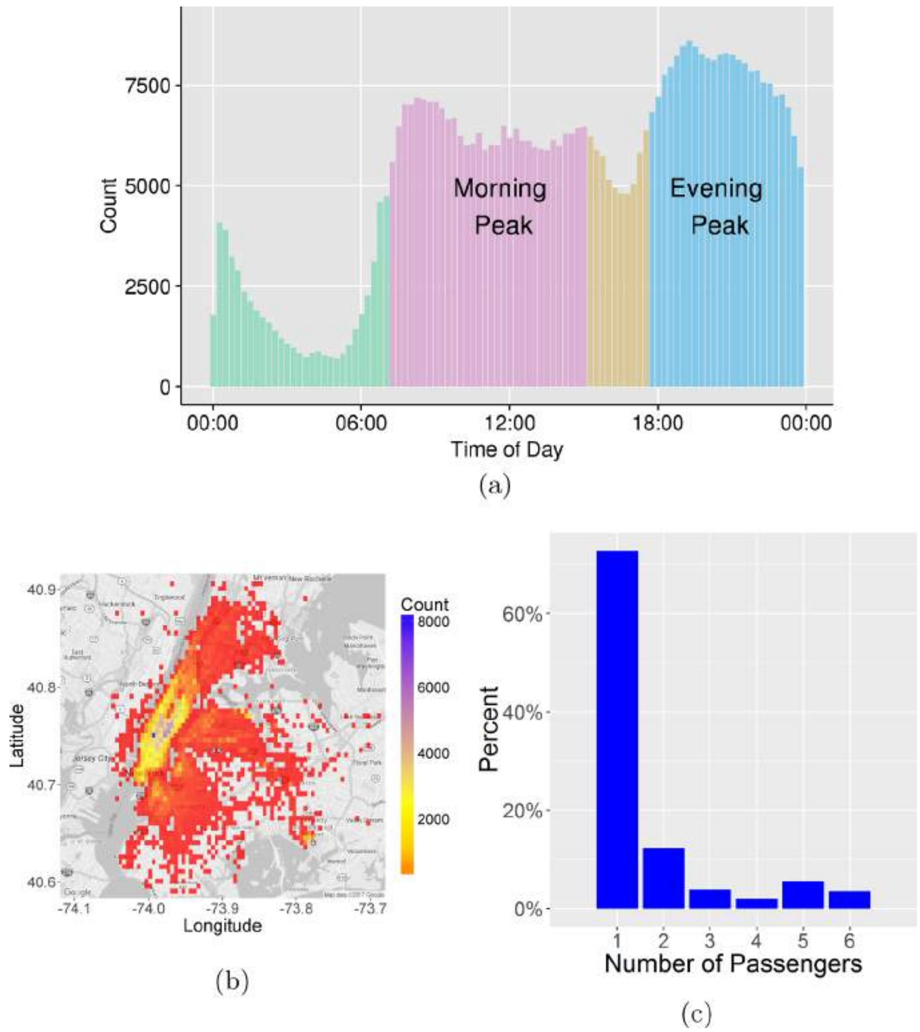

Fig. 4. NYC Taxi demand represented as pickups. (a) is a temporal histogram for the pick ups every 15 min, (b) shows the spatial density of taxi pick ups in NYC. (Grid resolution is 0.005° × 0.005°, roughly equivalent to 0.5 km × 0.5 km). (c) Histogram for the number of passengers in a rider group. (a) and (b) plots use the data from the date 8/24/2014. (c) uses data from the year of 2014.

Table 1
Sample Data from NYC-TLC with pick up (PU) and drop off (DO) time and locations in latitudes (Lat) and longitudes (Long), and the number of passengers traveled together (Group Size).

PU Time	DO Time	PU Lat	PU Lat	DO Long	DO Lat	Group Size
06/12/2014 0:00:00	06/12/2014 0:13:24	−73.937	40.797	−73.964	40.760	1
06/12/2014 0:00:00	06/12/2014 0:05:00	−73.993	40.719	−74.001	40.717	3
06/12/2014 0:00:00	06/12/2014 0:04:00	−73.983	40.771	−73.984	40.765	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮

2.3. Model assumptions

We have summarized the key assumptions in the model here: (1) all rider groups that are willing to share will first try to find a shared ride before searching for an idle taxi; (2) a rider group who is not willing to share will search for a ride for 5 min. If no match is found, the ride group will exit the system unserved. Correspondingly, the rider groups who are willing to share will search for a shared taxi for a time that is equal to $deviationTolerance \times 5$ minutes. If no sharing match is found within this time, the rider group will send requests to idle taxis. (3) The capacity of all taxis is limited to 4; (4) A rider is only eligible to share a ride if they allow a distance overage of at-least 100 m. Similarly, the maximum a rider can deviate has been capped to 10,000 m. These numbers were tested for sensitivity and we found that the model output parameters did not change significantly by allowing less than 100 m or more than 10,000 m of sharing; and (5) We consider the time required for refueling to be negligible.

2.4. Modeling taxi shifts (for traditional taxi scenarios only)

Unlike the current taxis that are temporarily unavailable during the off-shift periods, autonomous vehicles can operate 24 × 7. Fig. 5 shows the service valleys of NYC taxis. These valleys can be eliminated by autonomous taxis. In order to compare the impact of ride sharing using autonomous and traditional taxis, we modeled the change of shifts for the traditional taxis to have shift schedules that are similar to the existing NYC taxi operation schedules (Fig. 5).

To model the shift changes, at the initialization of the model, we determine the number of taxis that are in-shift (n_s) based on the availability ratio at the model start time (normally midnight) and day (weekday or weekend), according to Fig. 5. From all taxis, n_s of them are then randomly selected to be in-shift while the rest to be out-shift. Then, the Algorithm 4 is run every 15 min to make shift changes. Only taxis that are in-shift are allowed to participate in serving rider groups. Further details are provided in the Supplementary Information SIA.5.2.

Algorithm 4. Shift Change

```
Randomly select n_i out of shift and rested taxis to begin shifts ;
for All x_c in Taxis that are in-shift do
    if x_c is in-shift then
        if time of in-shift > 8 hours then
            if State = 2 //still delivering riders then
                Stop accepting new shares;
                Set to be out of shift after the last drop off;
            else
                Set to be out-shift;
            end
        end
    end
end
```

2.5. Simulation scenarios

We ran several scenarios to analyze the impacts of adopting ride sharing and autonomous driving. We used the demand from May 7th, 2014 from the yellow and green NYC-TLC dataset (NYC DOT, 2016b). We varied the percent of rider groups who were willing to ride share with others (ride sharing participation) among the values {0%, 25%, 50%, 75%, 100%}, and the fleet size among the values {3000, 4000, 5000, 5500, 6000, 7000, 8000} for each of the autonomous vehicle case and the traditional vehicles (shifted) scenario. To compare our results against the existing NYC taxi system, we also ran a base scenario with 13,500 traditional taxis running in shifts (13,500 is approximately the number of yellow taxis currently in operation (NYC DOT, 2014)). We focused on yellow taxis in this study because the areas they serve (e.g., Manhattan) have higher trip density and can potentially benefit from ride sharing more.

3. Results

We have evaluated the scenarios mentioned in Section 2.5 to infer city level statistics such as service levels[4], fleet reduction, waiting time, resource utilization, distance traveled by the taxis and the riders, and spatial service level change. We focus on these statistics because ride sharing can potentially reduce the required fleet size and increase resource utilization. However, ride sharing may increase riders' waiting time and requires longer trips due to deviations. So we quantify both the potential benefits and negative impacts of ride sharing.

3.1. Fleet reduction

By better utilizing the available space in each vehicle, ride sharing can help reduce the fleet size needed to serve the same demand. We consider a reduced fleet with ride sharing as having the same service level as the existing system, if it can serve the same

[4] We define the service level as the number of rider groups that were served by the system. (Rider groups may leave the system unserved if they could not be matched with a taxi within five minutes. This represents the situations that people give up and seek alternative transportation options after waiting for too long.)

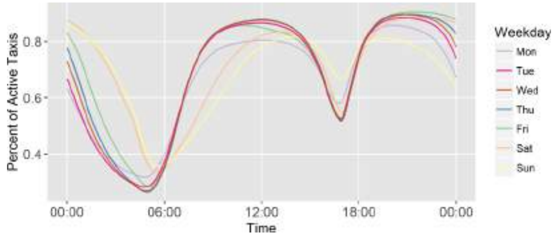

Fig. 5. Average number of taxis in operation (on shift) every minute (NYC DOT, 2014).

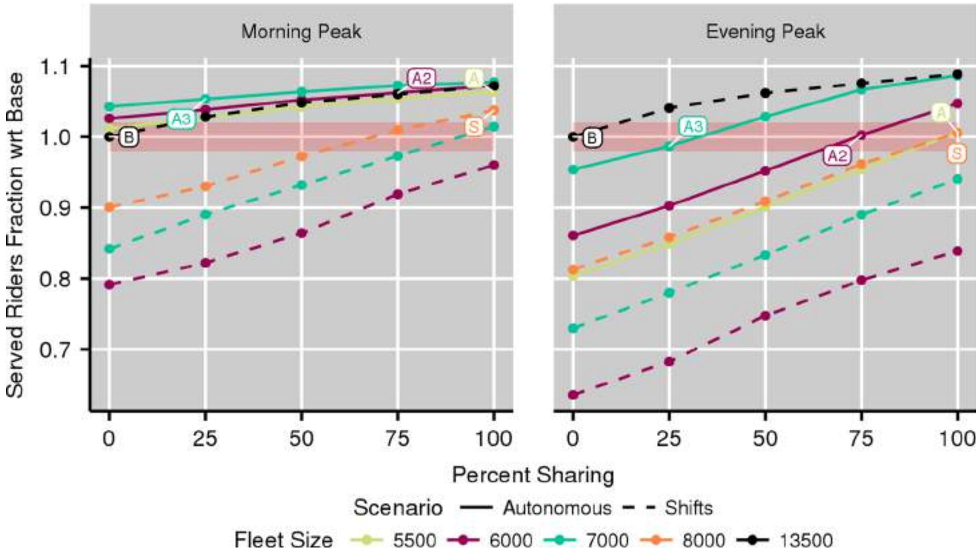

Fig. 6. The average fraction of served rider groups (the ratio of rider groups served by the taxis to the total ride groups) in the morning (7:01 am-3:00 pm) and evening (5:01 pm-12:00 am) peak periods with different sharing and vehicle type scenarios. The light-red band indicates a service level within 2% of the base scenario.

Table 2
Scenarios and their parameter sets that can provide service within 2% of the base scenario, during the evening peak. We will from here on refer to these scenarios by the label.

Scenario Label	Parameter Set
B	Base Scenario 13,500 traditional taxis and 0% sharing participation
A	5500 autonomous taxis and 100% sharing participation
A2	6000 autonomous taxis and 75% sharing participation
A3	7000 autonomous taxis and 25% sharing participation
S	8000 traditional taxis and 100% sharing participation

number of rider groups as the base scenario (percent of rider groups transported from their pick up points to the drop off points as compared to the scenario with 13,500 taxis without sharing). Fig. 6 shows that a fleet of 5500 autonomous vehicles is sufficient to serve the demands during the morning peak period without sharing. However, to satisfy the demand of the evening peak period at the same level as the base scenario (labeled as “B” in Fig. 6), 5,5000 autonomous vehicles with 100% ride sharing participation (labeled as scenario “A” in Fig. 6) is needed. This service level can also be achieved by scenarios with other parameter sets as described in Table 2.

It is notable that, with the same ride sharing participation, a fleet of 5500 autonomous vehicles has similar service level as a fleet of 8000 traditional taxis, indicating that autonomous driving is roughly equivalent to adding 2500 traditional taxis to the system. We can also see that shared autonomous taxis (Scenario A) has better service level than all the other equivalent scenarios in the morning peak. The main reason for this is that, for the B and S scenarios, the number of taxis available during the morning peak is less than the number of taxis in the evening peak (Fig. 5).

A potential concern with ride sharing and a reduced fleet is the increased waiting time and ride time for riders. However, our results (Fig. 7a) show that, with a fleet of 5500 autonomous taxis (Scenario A), the average waiting time for the served passengers (T_W) only increases by less than two minutes compared to the base scenario. The other sharing scenarios also have similar waiting time increase. One reason for the increased wait time is that the rider groups are spending additional time searching for a shared ride

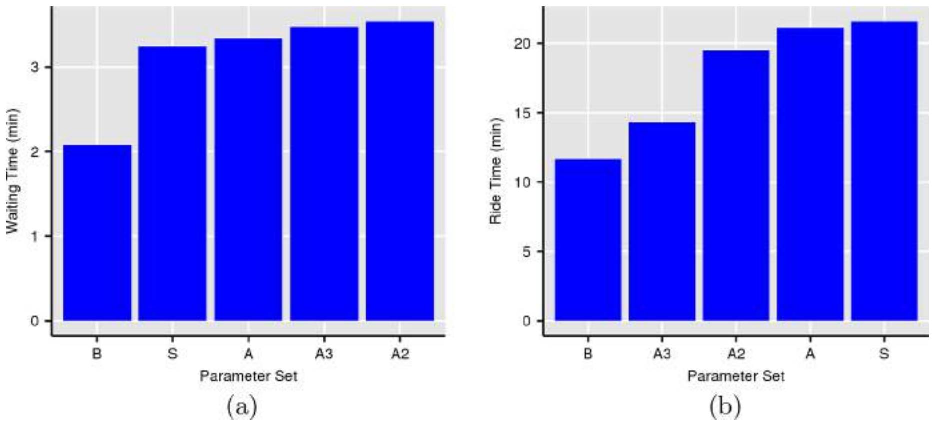

Fig. 7. Change in (a) Waiting time (T_W) and (b) ride time (T_{Ride}) under different ride sharing participation and fleet size scenarios.

when an unoccupied taxi may be more readily available. The average ride time, on the other hand, increases with more ride sharing participation. In Fig. 7b, we can see that scenarios with higher sharing participation (A, S, A2) have a higher ride time, approximately 10 min longer on average.

Fig. 8a shows that the extra distance traveled by shared riders increases only with the percent sharing and does not change significantly with the fleet size. This is due to the fact that higher sharing participation increases the number of rider groups that

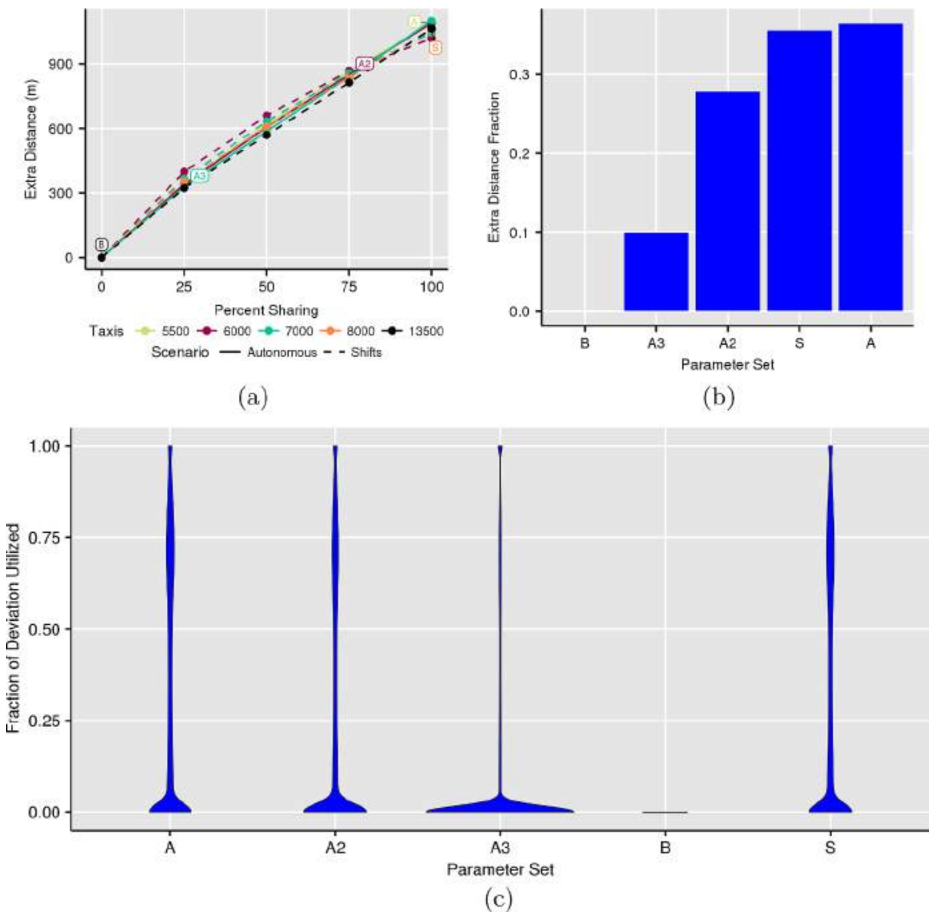

Fig. 8. (a) Average increase in trip distance for the riders. (b) Average fractional increase in distance for the riders. (c) The average fraction of individual utilized trip deviation relative to the individual acceptable level, presented as a violin plot. (A violin plot is two vertical density plots attached together at their bases. The vertical bar shows the range of the values while the horizontal width shows the density of the points at that value).

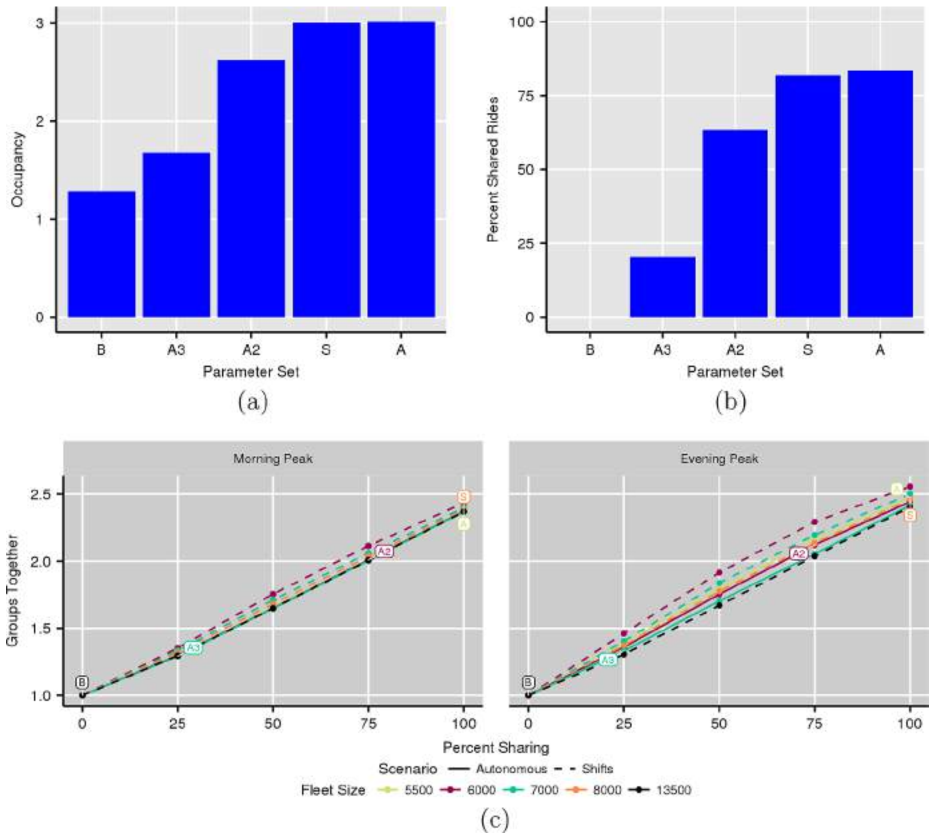

Fig. 9. Sharing performance: (a) Change in occupancy in different scenarios with similar service levels; (b) The actual percentage of rider groups that participated in sharing; (c) Number of rider groups shared a ride together varied with service levels.

shared the ride together (Fig. 9c). Having more rider groups sharing a ride increases the required deviations and the extra distance. However, this increase is, on average, less than 33% of the original trip distance (Fig. 8b). Compared to the individual trip deviation tolerance, Fig. 8c shows that very few people utilizes the full tolerance level in the sharing. About 40% of the riders in scenarios S, A, and A2 only used less than 25% of the tolerable trip deviation. In scenario A3, where the sharing participation is lower (25%), the utilized tolerance is even less (over 70% of the riders only used less than 10% of their trip deviation tolerance).

3.2. Increased resource utilization

The vehicle occupancy (calculated as the average number of passengers in a taxi) is a measure of the utilization efficiency of the taxis in the system. Higher occupancy indicates better system efficiency. Fig. 12 indicates that, on average, the vehicle occupancy increases with higher participation of ride sharing. With the 4-seat vehicle capacity modeled in this study, the occupancy can increase from 1.2 (Scenario B) to 3 (Scenarios S and A). The average number of groups in a vehicle indicates the average number of shares taking place. This value is 1 without sharing (Scenario B) and increases to 2.5 per vehicle (Scenarios S and A) as a result of sharing (Fig. 9c). This results show that studies which constrain the sharing to be only between two rider groups (Kleiner et al., 2011; Agatz et al., 2011). are limiting the sharing participation to be at the 50–75% level. The results show that the actual percentage of sharing participation is lower than the percentage of rider groups that are willing to share. In scenarios that all riders are willing to share, the actual percentage of rides that are shared is only about 80% (Fig. 9b).

3.3. Environmental benefits

Our simulations have shown that the total distance traveled by the taxis reduces as the ride sharing participation increases. Also, when compared to the base scenario, we see a reduction of approximately 2.8×10^6 km in total per day (which is 55% of the distance traveled by the taxis) in scenario A, with 5500 autonomous taxis and 100% ride sharing participation (Fig. 10a). This reduction in total travel distance translates to approximately lowering CO_2 emissions by 725 metric tonnes per day. Compared the 40% trip reduction in NYC from ride sharing estimated by Santi et al. (2014), our value is higher because we did not constrain sharing to be only formed between two groups. We note though, that this emission reduction is computed purely on the basis of total distance traveled. However, as estimated by Wadud et al. (2016), autonomous vehicles may help achieve, on an average, a net of 10–15%

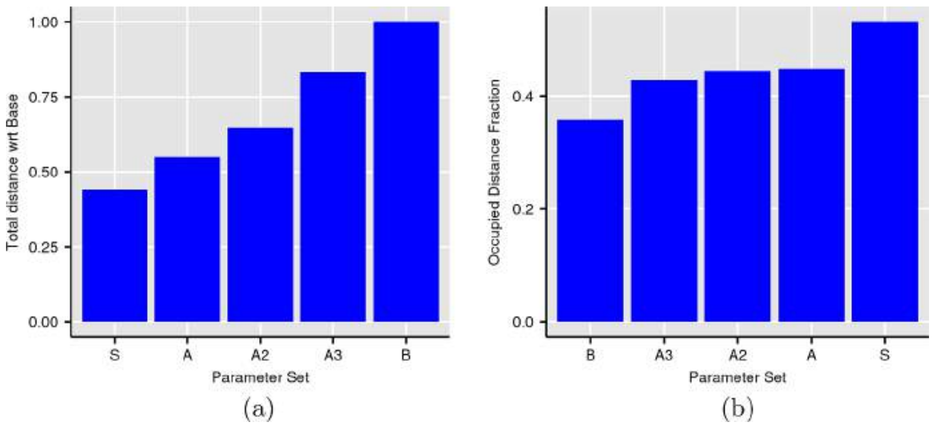

Fig. 10. (a) Total distance traveled with respect to the base scenario (Scenario B) for different scenarios. The total distance traveled in the base scenario is approximately 6.2×10^6 km (b) The fraction of occupied distance (distance traveled to deliver passengers) for all scenarios.

energy consumption saving due to potential changes in driving patterns such as platooning, smoother driving, crash avoidance mechanisms. Another paper, Gawron et al. (2018), has used life cycle assessment to estimate that introducing connected automotive vehicles could reduce energy consumption by 9% due to these driving pattern changes. If we consider this additional 9% reduction, for scenario A, the overall reduction in CO_2 emissions will be 802 metric tonnes per day. On the other hand, for ride sharing with traditional taxis, even though the number of vehicles in Scenario S is higher, the total travel distance is lower than Scenario A (approximately 45% of the base scenario B). This results in a reduction of 3.42×10^6 km or a reduction of approximately 866 metric tones per day of CO_2 emissions.

The percentage of distance for which the taxi is occupied can be studied to gauge the efficiency of the system from an environmental perspective. Fig. 10b shows that the percent of occupied distance traveled by the traditional taxis (with shifts) increases with higher sharing participation (from scenario B and S). For the autonomous taxis, the fraction of distance for which the taxi remains occupied stays relative stable regardless of the level of sharing participation. This tells us that, even though the taxi is sering more customers, it will be traveling less to do so.

3.4. Spatial coverage change

In order to evaluate the impact of ride sharing on the spatial distribution of service levels, we compared scenarios that have nearly equivalent service levels (within 5% difference in served riders) and analyzed the fractional change in service level in different regions. Fig. 11a shows the fractional difference between the base scenario (Scenario B) and Scenario A with 5500 autonomous vehicles and 100% sharing. We can see that using conventional taxi cabs without sharing as opposed to the SAVs has a positive effect in the suburban region (shown as the purple and blue cells in Fig. 11a), but has a negative effect (shown as the red cells in Fig. 11a) in the regions where the demand is the most dense (Manhattan and, more significantly, Times Square). To identify whether this service coverage change is due to autonomous driving or sharing, we further compared scenarios B and A3 to evaluate the impact of autonomous driving with no/low sharing and scenarios B and S (Fig. 11c) to evaluate the impact of sharing with traditional taxis. In both cases, we observed similar spatial service coverage change. On the other hand, when we compare scenarios A and S (Fig. 11e) or scenarios A and A3 (Fig. 11c), the spatial service coverage is quite similar.These results show that both ride sharing and autonomous vehicles will cause taxis to focus more on areas with higher demands. While better serving the demands in the regions with more demand, the reduced fleet decreases the service level in the suburban regions. We justify this in Section SIC by studying the radius of gyration of the taxis (Cai et al., 2016; Gonzalez et al., 2008). To remedy this disproportionate change in service, appropriate policies would be needed to insure service in the suburban regions. Such policies could include providing price incentives or restricting a portion of the fleet to the suburban regions (similar to the way NYC currently distinguishes between Green and Yellow taxi cabs as mentioned in NYC DOT (2014)).

3.5. Changes in efficiency of matching

The response time (T_R) represents the efficiency of matching. Our results show that T_R is lower in the scenarios where the riders are homogeneous (all sharing or all non-sharing) but higher in scenarios with a mix of sharing and non-sharing riders (Fig. 12). The reason for this is that our model assumes that all riders who are willing to share will first search for a shared ride. So in scenarios with mixed rider types (some rider groups are willing to share and some are not), it is possible that a sharing taxi is close to a rider group that is not willing to share or an occupied non-sharing taxi is close to a rider group that is willing to share. In these situations, the matching cannot be formed. As a result, the time required to find a match increases in the scenarios with mixed rider types, indicating a lower efficiency of matching. However, the delay is less than one minute.

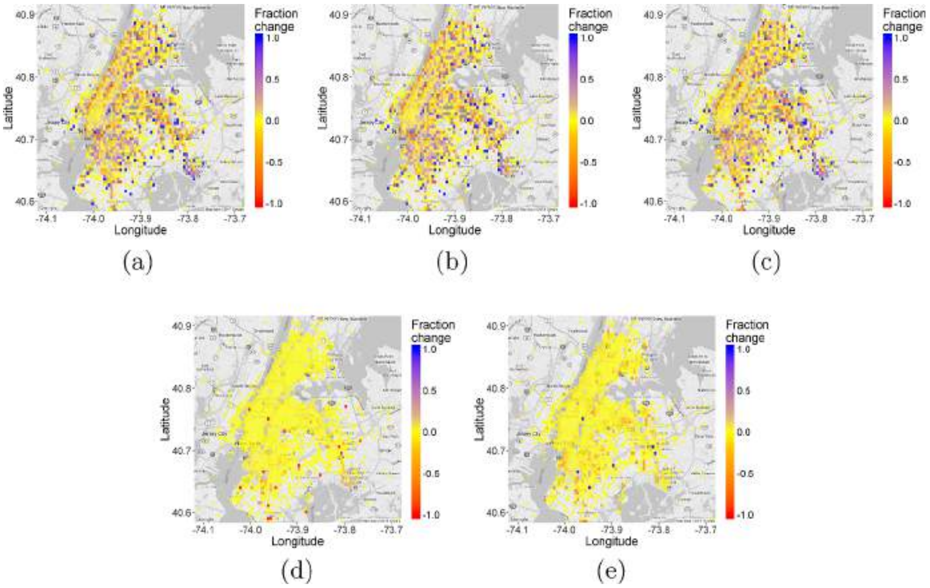

Fig. 11. Spatial distribution change in terms of service level. (a) The fraction change in service level in Scenario A compared to Scenario B, calculated as $\frac{Service_B - Service_A}{Service_B}$. (b) The fraction change in service level in Scenario B compared to Scenario A3, calculated as $\frac{Service_B - Service_{A3}}{Service_B}$ (c) The fraction change in service level in Scenario B compared to Scenario S, calculated as $\frac{Service_B - Service_S}{Service_B}$ (d) The fraction change in service level in Scenario A compared to Scenario A3, calculated as $\frac{Service_A - Service_{A3}}{Service_A}$. (e) The fraction change in service level in Scenario A compared to Scenario S, calculated as $\frac{Service_A - Service_S}{Service_A}$. Blue color indicates Scenario B or S has better service level than Scenario A, while red color indicates Scenario A provides better service. Grid resolution is $0.005° \times 0.005°$, roughly equivalent to $0.5\ \text{km} \times 0.5\ \text{km}$.

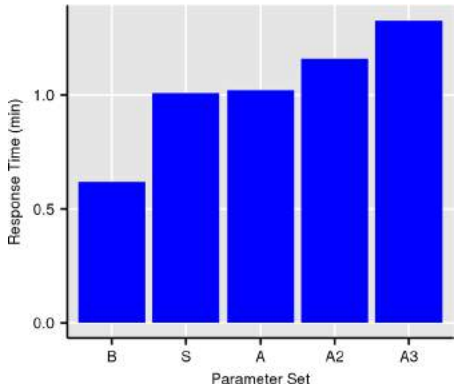

Fig. 12. Change in Response time (T_R) under different ride sharing participation and fleet size scenarios.

4. Conclusion

We have proposed an agent-based simulation model to study the impacts of dynamic ride sharing using both traditional taxis and autonomous taxis. Our model incorporates the individual heterogeneity in acceptable trip deviation due to sharing, considers the numbers of passengers traveling together in a group and the available vehicle capacity, and allows shared rides to be formed among several groups and in the middle of a delivery. We tested our model using New York City taxis as a case study and ran the model based on real world road infrastructure and historical trip data. The insights we have learned from this study are: (1) while maintaining the same service level, ride sharing combining autonomous driving with autonomous vehicles can potentially decrease the fleet size by up to 59% without significant waiting time increase or additional travel distance; (2) the benefit of ride sharing is significant with increased occupancy rate (from 1.2 to 3), decreased total travel distance (up to 55%), and reduced carbon emissions (725 metric tonnes per day); (3) constraining the sharing to be only between two groups limits the sharing participation to be at the 50–75% level and underestimates the potential benefits; and (4) ride sharing may reduce the service level in the suburban areas, which will require complementary policies or incentives to help balance service in different regions.

It is notable that this study does not account for a pricing structure (e.g., discounts) of ride sharing and the potential rebound effects of having increased demand due to the reduced costs. Additionally, the effect of mode choice change due to ride sharing has not been considered in this study. Including the pricing, rebound effects, and induced demands due to mode choice change can help further improve the model and provide additional insights. Additionally, while our model accounts for the heterogeneous preference of riders in the form of the allowable distance deviation and the sharing participation level, the model can be improved by incorporating better sharing decision making process (e.g., considering the time value of money for different riders) when relevant data and research on the sharing preference is available.

Appendix A. Supplementary information

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.trc.2018.10.007.

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