2020

Assess the Performance of Electric Autonomous Taxi System Using a Data-Driven Simulation Model

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Citation: Yang, J., & Dong, J. (2020). *Assess the Performance of Electric Autonomous Taxi System Using a Data-Driven Simulation Model* (No. 2020-01-5148). SAE Technical Paper.

Assess the Performance of Electric Autonomous Taxi System Using A Data-driven Simulation Model

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Abstract

This paper presents a data-driven simulation model to estimate the potential of replacing conventional taxis with electric autonomous vehicles (EAVs). Vehicle trajectory data collected by onboard global positioning system (GPS) units in Shanghai, China, are used to study taxi travel patterns, in terms of the distribution of taxi travel demand, idle time between two consecutive occupied trips, and the places where vehicle stock imbalances may occur. The operational performances and fleet size are quantified using a data-driven simulation model that stimulates EAV taxis' charging, idling and relocating activities. It is found that EAV taxis can serve the same amount of travel demand using 69.4% of the current fleet size; while because of vehicle stock imbalances, relocating idling vehicles is inevitable. Simulation results also demonstrate that the deployment of EAVs can improve taxi operation efficiency in terms of increasing the proportion of occupied travel distance.

Introduction

Ongoing developments of fully autonomous vehicles (AVs) will likely result in commercial autonomous taxi services [1][2]. In December 2018, Waymo launched self-driving taxi service in Phoenix, USA [3]. In China, Didi Chuxing has introduced an on-demand autonomous taxi service in a Shanghai suburb since 2020, and Baidu's robotaxi service now covers around 700 kilometers across China, making it the largest network in the country. It is predicted that by 2030, fully self-driving vehicles will likely offer major benefits to taxi-type services, as they are able to autonomously reposition themselves efficiently and effectively to meet a wider array of customers and their needs [4]. Autonomous taxis can refuel or charge themselves or travel autonomously for cleaning and maintenance [5]. Without the labor cost of drivers, they are likely to be cheaper than traditional taxis or even ride-hailing services such as Uber and Lyft [6], costing about $0.60-1.00 per mile [7]. Besides, since taxi drivers usually need at least one break during the day for changing shift or resting, autonomous taxis are able to extend operating hours, resulting in a smaller fleet size.

AV technology is compatible with electric vehicles. Since AVs can drive to charging stations autonomously and coordinate charging activities with other AVs, the biggest disadvantage of electric vehicles – their limited range – is less of a concern [8]. The taxi fleet has some desirable features for deploying electric vehicles as well. With high annual mileages, the adoption of electric autonomous vehicles (EAVs) serving as taxis will lower tailpipe emissions compared with conventional gasoline vehicles (CGVs). Deploying a fleet of EAV taxis to serve as a more convenient form of public transit will help reduce pollutants and noise in the densely populated downtown areas. For the US, it means a decrease of greenhouse gas emissions per mile by up to 94% [9]. Completely replacing CGV taxis with EAVs becomes an attractive option for cities around the globe in the following decades.

Replacing private vehicles with shared AVs leads to a reduction in vehicle ownership and parking demand while accelerate vehicle annual travel distance. A simulation conducted by Rigole [10] indicate that, one shared AV without ride sharing can replace more than 12 private vehicles in Stockholm, Sweden, whereas the total mileage is expected to increase by 24.4%. The situation is different in the context of replacing CGV taxis with AVs. The taxi fleet size cannot be reduced as significantly as that of private vehicles. Using a nearly optimal method that amenable to real-time implementation, Vazifeh et al. find that with a 30% fleet reduction, more than 90% of the taxi trip requests in New York, USA, can be successfully served if autonomous taxis are adopted [11]. Comparatively, a reduction of 60-90% of the private car fleet is possible if individual travel demand is served by AVs [13]-[17]. Another difference is that due to the better obedience of AVs, VKTs (Vehicle Kilometers Traveled) driven without customers are likely to be reduced under the control of an intelligent coordinator. To our best knowledge, no publicly available works exist to quantify the operational performances of EAV taxis.

The trip-based mobility data is often used in the simulation of shared AVs' operation. Vazifeh et al. have developed a computationally efficient method to find the minimum fleet size of autonomous taxis if the daily travel demand of the entire taxi fleet is known [11]. The drawback of this method is that the solution is often specific for a certain day, and of low adaptability and robustness. Besides, autonomous taxis are often assumed to park where the last trip ended until they receive a dispatch message for next trip. Imbalances between vehicle supply and demand for a certain location occur inevitably.

Vehicle imbalance can be avoided or eliminated by dynamically relocating vehicles from oversupplied to undersupplied regions [12]. Relocating vehicles, which is not an issue for taxis operated by human drivers, is a concern for the operation of autonomous taxis.

Considering the spatially and temporally varying taxi travel demand in large cities, this paper presents a distribution-based simulation model to estimate the fleet size of EAV taxis and quantify their operational performances. GPS-tracked vehicle trajectory data collected from CGV taxis in Shanghai, in April of 2015 are used to extract the origin and destination (OD) distributions of taxi travel demand, the distribution of time interval between two consecutive customer requests at a limited service area, and places where vehicle stock imbalances may occur. Using a data-driven simulation model, this study simulates EAV taxis' travel, charging, and relocating behaviors, and evaluates the fleet size and vehicle utilization in comparison with CGV taxis.

The main contributions of this paper include: (1) offering a computationally efficient yet robust method to estimate the fleet size and operational capacity of EAV taxis in large cities. (2) The behavior of EAV taxis, in terms of parking, relocating, charging, and transporting customers, are simulated based on the OD distribution of customer demand and vehicle supply conditions. (3) The relocation mechanism is embedded in the simulation model to relocate vehicles which end their trips at the place with an oversupply of taxis or with little chance to find a new customer.

Literature review

Several pioneering works involving simulating travel behaviors of shared AVs and autonomous taxis are found in recent years. One of the applications of the simulation models is to evaluate fleet size requirements. Fagnant and Kockelman proposed a simulation method to study travel and environmental implications of shared AVs. Their results indicated that each shared AV could replace around 11 private vehicles, but add up to 10% more travel distance [13]. Based on transportation data of Singapore, a study suggested that a shared AVs mobility solution could meet the personal mobility needs of the entire population with a fleet whose size was approximately 1/3 of the total number of passenger vehicles currently in operation [14]. The simulation conducted by Burghout et al. in Stockholm, Sweden indicated that using 5% of the current private cars and parking places, the shared AVs personal transport system would provide an on-demand door-to-door transport with a high level of service [15]. Took Zurich, Switzerland as the area of the study, the simulation study showed a reduction of up to 90% of the private car fleet if transported by AVs [16]. Another simulation study conducted in Berlin, Germany indicated that one autonomous taxi could replace10 private vehicles [17].

Once electric vehicles are adopted as shared vehicles, multiple charges during a day are probably needed as they are likely to be operated continuously day and night. The charging demand results in more out-of-service time thereby might require more vehicles to serve the same amount of travel requests. Chen et al. explored the operation of shared EAVs under various battery range and charging infrastructure scenarios using a regional discrete-time, agent-based model. The results showed that, one 200-mile range shared EAV could replace 5.5 and 6.8 private vehicles, respectively, under Level II (240-volt AC) and Level III (480-volt DC) charging infrastructure [18]. Nguyen et al. [19] pointed out that, under the control of an intelligent coordinator, most battery charging could be done using slow chargers during out-of-service intervals (i.e., when vehicles were parked and waiting for customers) for a fleet of shared AVs in the city of Jeju, Republic of Korea.

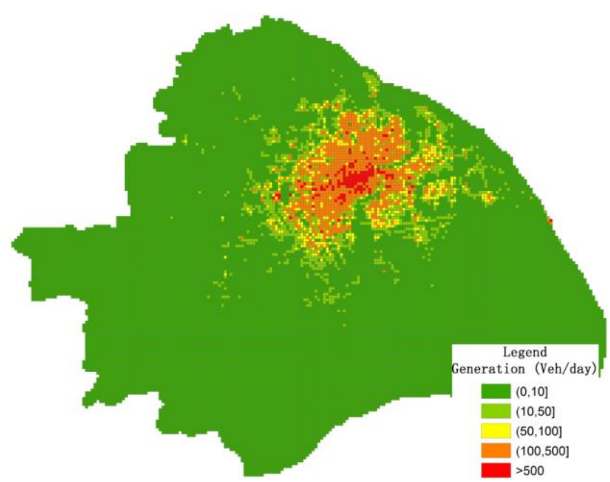
Studies conducted by Jager et al. [20] and Vazifeh et al. [11] took the dynamic interactions between customer requests, dispatching strategy, and a shared AV fleet into consideration, which provided a high-resolution solution to the minimum fleet problem. Neither of their studies addressed the issue of vehicle relocation. In the study of Jager et al. [20], the customer demand was derived from individual motorized private travel in Munich, Germany. The simulation started with a small fleet and iteratively added vehicles until all customer requests were fulfilled. Vazifeh et al. [11] translated the minimum fleet problem into a minimum path cover problem on directed graphs, by which the exact solution could be find. The method was applied on a dataset of 150 million taxi trips taken in the city of New York. However, except for the reduction in fleet size, the improvements on taxis' operational performance were not illustrated in this work.

Overall, little research has been done to study the operational performance of EAV taxis based on the spatial and temporal distributions of taxi travel requests. In this paper, we propose a distribution-based simulation model that simulates EAV taxis' operational behaviors based on passengers' arrival and departure patterns in a given area. In the proposed model, we do not assume ride sharing, and the relocation of vehicle is considered as a part of the dispatch strategy.

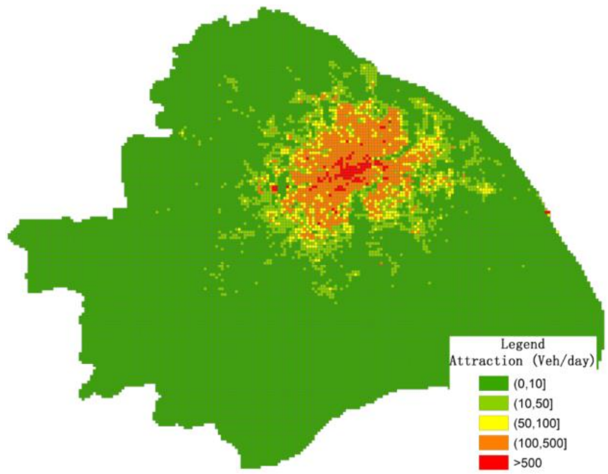
Data Description

Taxi Trajectories

This research uses GPS trajectories of conventional taxis in Shanghai, China, collected from 0:00 on April 1, 2015 to 23:59 pm on April 30, 2015 (local time). The data is provided by Shanghai open data Apps (SODA). By the end of 2015, there were about 58,000 taxis operating in Shanghai. The dataset includes the trajectories records of 13,761 taxis from Qiangsheng Taxi Company, accounting for 23.7% of the entire taxi fleet in Shanghai. A GPS signal is captured roughly every 10 seconds for each taxi. The data include time-stamped location (i.e., longitude and latitude), spot speed, azimuth, and operational status (i.e., empty, occupied, operating, and non-operating). Invalid points caused by data recording or transmission errors were removed.



(a) Trip Origin



(b) Trip Destination

Figure 1. Distribution map of trip origin and destination locations.

11,725,580 occupied trips are recorded in April 2015. To examine the OD distribution, the study area is partitioned into equal sized cells. Each cell has a quadrate edge of 0.005° latitude and longitude, approximately equivalent to 0.5 km×0.5 km. The study area (i.e. 30°~33° N, 120°~122.7° E) is divided into 324,000 non-overlapping square cells. During the one-month period, 12,998 valid cells have the records of customer pick-ups, and 17,008 valid cells have the records of customer drop-offs. Figure 1 shows the spatial distribution of valid cells with daily demand generation and attraction. The popular taxi pick-up and drop-off cells are located in the densely populated area of the inner city and transportation hubs, such as Hongqiao airport and inter-city railway hub (with 5016 pick-ups and 8053 drop-offs per day) and Pudong airport (with 2197 pick-ups and 2894 drop-offs per day).

Imbalances between Vehicle Supply and Demand

Since population density is critical to the utilization of EAV taxis, only the cells with at least 50 customer arrivals and 50 departures per day are selected as the places where EAV taxis offer service to customers. In addition, since transport hubs occupy large areas, the cells around Hongqiao hub, Shanghai railway station, South Shanghai railway station and Pudong airport are merged as one cell, respectively. Thus, a network with 1,450 nodes (i.e., 1,450 valid cells) and 1,015,017 OD pairs with non-zero trip counts are formed. The simplified network covers 76.62 % of the total taxi travel demand, that is, 8,984,010 occupied trips. The average trip length between each pair of origin and destination is 7.5 km (st.d. =7.1 km). The longest trip occurs from Huaqiao (which is located at the boundary of Shanghai and Suzhou city) to Pudong airport and lasts about 81.4 km.

Almost all taxi travel demand are one-way trips, resulting in imbalances in vehicle stocks at some destinations. Let α denote the ratio of the generated trips and the attracted trips ("G/A ratio" for short). Figure 2 shows the spatial distribution of G/A ratio among the selected cells. 43% of the cells have the ratio larger than 1, which means taxis are under supply. The other cells are with a value of α less than 1. In that case, it is necessary to relocate idle taxis to nearby over-loaded cells once vehicles have been parked for a long time.

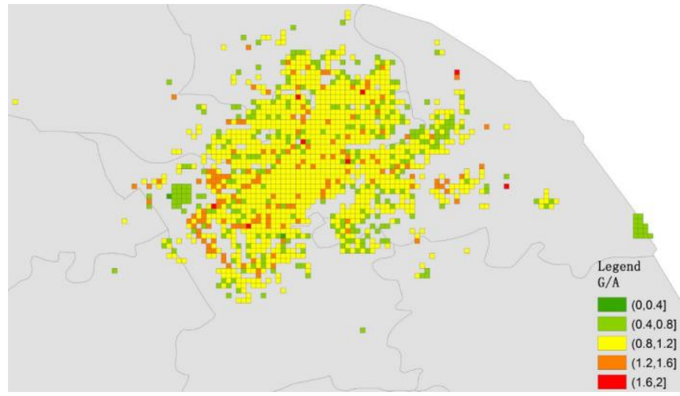


Figure 2. Spatial distribution of trip origin and destination ratio.

Methodology

Definition of Events and Parameters

A data-driven simulation model is proposed to evaluate the performance of EAV taxis. In the simulation model, three types of events, i.e., the service event E_{od}, the relocate event E_{rl}, and the idle event E_{idle}, are assumed to follow certain distributions. All customer requests are sent to the dispatch center using taxi-hailing application. The service event E_{od} is determined by the OD distribution of passenger demand, containing the information of travel distance d_O (in km) for each occupied trip. The relocate event E_{rl} describes the process of vehicle relocating decisions. The distance of each relocate trip d_D (in km) is embedded in E_{rl}. The current average travel speed of the occupied trip is 28.1km/h. Since the traffic condition is expected to be improved if AVs are adopted, an average travel speed v of 45 km/h is assumed to estimate travel time of occupied trips t_O (in hour) and travel time of relocate trips t_D (in hour). The idle time after each occupied trip t_{idle} (in hour) is generated from the idle event E_{idle}. Once the idle time exceeds an hour, taxis will be relocated.

The travel pattern T of one EAV taxi can be expressed as a function of the basic random events:

$$T(D_O, D_E, T_{idle}, N_S, N_R, N_C) = f(E_{od}, E_{rl}, E_{idle}, R) \quad (1)$$

where D_O is the occupied distance traveled during the day (in km), D_E is the empty distance traveled (in km), T_{idle} is the amount of idle time (in hour), N_S is the total number of daily occupied trips, N_R is the number of EAVs being relocated to the other cells, N_C is the number of charges during the day, and R is the electric range of EAVs (in km).

Input Distributions

Distribution of E_{od}

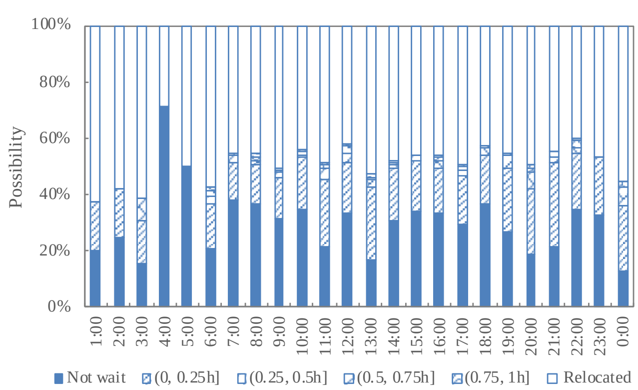
Define T_{ij} as the number of occupied trips from origin cell i to destination cell j. An origin-destination matrix can be extracted from the trajectory data. Denote P_{ij} as the probability of cell j being the destination of the trip which starts from cell i. The Pseudo-random number sampling method is adopted as the random number generators to determine the occupied trip destination [21]. The cumulative distribution of P_{ij} defines several ranges on the interval [0, 1]. Pseudo-random numbers, a sequence of numbers on the range [0, 1] which can be generated by a computer algorithm, are then compared to these ranges to see within which range they fall. This identifies the cell where passengers are dropped off. The average distance of trips from origin cell i to destination cell j is used to estimate trip travel time.

Distribution of E_{idle}

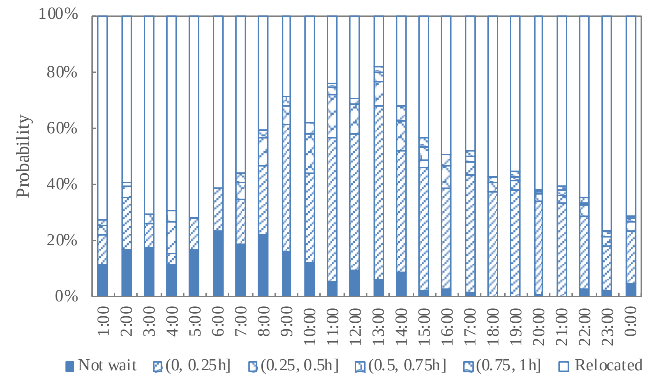
Vehicle utilization can be improved greatly if taxis pick up passengers at the same cell where they drop off last customers. However, because of the imbalances in vehicle stocks, sometimes drop-offs and pick-ups are not likely to match each other. For each cell, the occurrences of pick-ups and drop-offs are extracted from the GPS trajectory data. A match mechanism is designed to pair customer requests (i.e. pick-ups) with the arriving taxis (i.e. drop-offs). Accordingly, the distribution of vehicle idle time is generated.

Conventional taxi dispatch strategies usually adopt the rule of FCFS (first come, first served), namely, the taxi which has been waiting the longest in line will be dispatched to serve the next customer first. For EAV taxis, however, to provide enough time for charging, it is better to have a long idle period. Hence, the priority rule of FCLS (first come, last served) is adopted as the queuing rule to construct vehicle idle time distribution. When the supply is sufficient to meet the demand, the incoming taxi will be stocked until all taxis followed its arrival have been dispatched. Once an idle taxi has parked more than one hour, it will be relocated to a nearby cell. Customers are assumed to be served following the FCFS rule. If a customer has been waiting for 15 minutes and no taxi is stocked in the cell, the customer will be served by the taxi dispatched from the nearby cell. Except for the vehicles relocated to the other cells and the customers served by vehicles from the other cells, the pick-ups and drop-offs are paired based on the rules of FCLS and FCFS.

The idle time is assumed as zero if a taxi arrives and customers are waiting. Otherwise, the idle time is calculated as the time gap between the matched pick-ups and drop-offs. For simplicity, t_{idle} has five values in the simulation, that is, 0, 0.25, 0.5, 0.75, and 1 hour. Figure 3 plots the idle time distributions of two cells. The G/A ratio of Cell 389 is 1.69, indicating an over-loaded system. Accordingly, the probability that EAVs leave the system as soon as they drop off passengers without idle time is relatively large, accounting for more than one third of the cases during peak hours (i.e., from 7:00 to 8:00, and from 17:00 to 18:00). Cell 1334, on the other hand, is a surplus system. More than 95% of the arrival vehicles must wait for 15 minutes or more, and the probability that EAVs need to be relocated to the other places is greater than 40%.



(a) Cell ID: 389, α=1.69



(b) Cell ID: 1334, α=0.59

Figure 3. Idle time distributions of two sample cells.

Distribution of E_{rl}

Taxis are assumed to be relocated under two scenarios. One scenario is that taxis are relocated to one of the five nearest cells once the idle time is longer than an hour (referred as Type 1). Denote p^{60} as the possibilities that the arriving taxis will not be relocated in an hour. Taxis are relatively undersupplied in the cell with a higher p^{60}. For example, Cell 389 is with a relative higher average p^{60} than Cell 1334 (0.52 vs. 0.47). The one among the five nearby cells which has the highest p^{60} is selected as the destination of the relocate event. The other scenario is that an occupied trip ends at the cell where the G/A ratio α is below 0.8, indicating the chance of picking up a new passenger in a short time is relatively low. If the probability of having a new customer in 15 minutes (denoted as p^{15}) is less than 0.5, taxis will be relocated as well (referred as Type 2). The destination of Type 2 relocate events must meet two conditions: (1) one of the nearest five neighboring cells of which the G/A ratio α is larger than 1.2, and (2) with the least possibility that Type 1 relocate event occurs in an hour.

Data-driven Simulation Model

Figure 4 illustrates the procedure of the simulation. For each trial, EAV taxis start operating with a fully charged battery. The initial location is selected randomly from 1,450 cells, that is, generating a random integer number from a uniform distribution in the range [1, 1450].

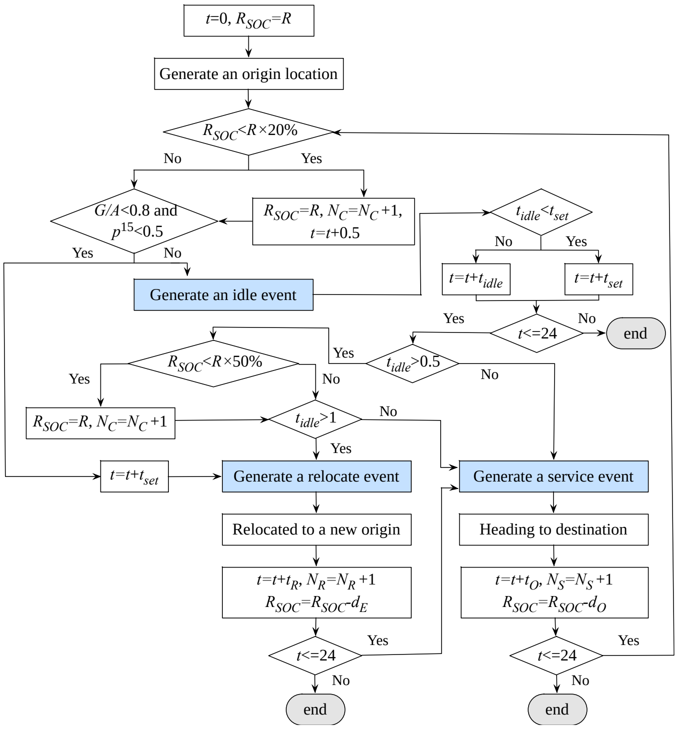


Figure 4. Flowchart of data-driven simulation.

All the selected cells are assumed to have fast chargers, and charging congestion is ignored. The remaining SOC, denoted as R_{SOC} (in km), is checked before generating an idle event. If R_{SOC} is less than 20% of battery range R, taxis will be fully charged before operating. Assuming DC fast charging at a maximum of 200 kW, it takes about 21 minutes for BEV with the battery capacity of 70kWh (i.e. R=350km) to get a full charge. The charging time is assumed as 30 minutes considering the time of traveling to charging facilities within the selected cell and plugging in. The trigger of Type 2 relocate events is also checked. Once the conditions are satisfied, after a setup time (t_{set}) of 5 minutes, taxis will head to the nearby cell and serve customers immediately as they arrive.

During an idle event, EAV taxis likely encounter four scenarios: (1) start next service after a setup time t_{set} of 5 minutes; (2) dwell for 15 or 30 minutes till an open request generates; (3) park more than half an hour and vehicles are fully charged if their SOC is lower than 50%; or (4) stock for more than one hour and relocate (i.e. Type 1 relocate event). Once a Type 1 relocate event occurs, potential destinations of vehicles to be relocated are selected from nearby valid cells, according to the imbalance of demand generation and attraction. The simulation of one taxi stops when the sum of operating time and idle time reaches 24 hours.

Results

Fleet Size

The simulation is performed to generate a fleet consisting of 10,000 EAVs with a range of 350km. Figure 5 plots the probability distributions of occupied trip length. 333,462 occupied trips are generated, with an average trip distance of 7.3km (st.d. =6.8km). Since the service event is generated according to the OD distributions of CGV taxis, the occupied trip length distributions of CGVs and EAVs are similar. Figure 6 shows the daily number of occupied trips served by CGV and EAV taxis. On average one CGV taxi serves 25.4 occupied trips every day (st.d.= 10.8), whereas EAV taxis can complete 33.3 occupied trips per day (st.d.= 3.4). Consequently, one EAV completes, on average, 244.9km occupied distance per day; while CGV taxi travels an average of 214.9km occupied distance.

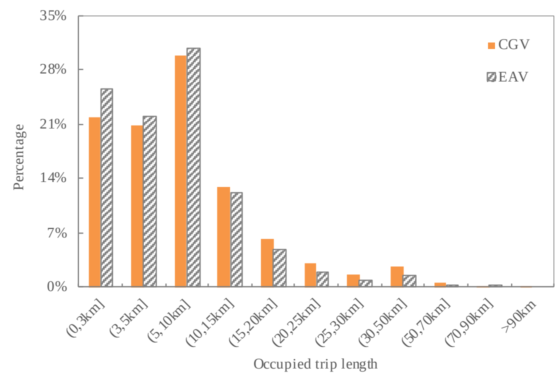


Figure 5. Occupied trip length.

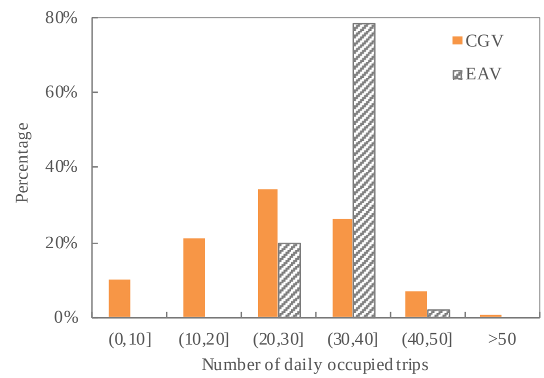


Figure 6. Number of daily occupied trips.

There are 13,621 CGV taxis in the selected dataset. The overall daily occupied distance is 1,934,388 km. The minimum fleet problem is to find the minimum number of EAV taxis to serve the same occupied distance. The fleet size is estimated in two ways. First, divide the overall daily occupied distance of the selected network by the average daily occupied distance of each taxi. A fleet size of 7,899 EAVs will be sufficient for serving the current travel demand in the selected network. To serve the same demand, a fleet size of at least 9,002 CGVs are required. Notably, the average daily occupied distance of CGV taxis is calculated after removing the samples with incomplete daily trajectories records. That is, if CGV taxis take a day or half a day off, their records are not considered in the estimation of the average daily occupied distance of the fleet.

To consider the impacts of taxis without 24-hours operating records, the relationship between the fleet size and the overall daily occupied distance is used in the second way to estimate the minimum fleet size. Figure 7 shows the daily number of operating vehicles to serve the entire taxi demand. The colors of the dots correspond to different weekdays. The number of operating taxis of weekends and public holidays is less than that of working days, resulting in less overall daily occupied distance. There is a linear relationship between the number of operating taxis and the overall daily occupied distance, with an overall R^2 value of 0.7204. Using the regression model presented in

Figure 7, a fleet with 11,379 CGV taxis are needed to serve the demand of the selected network.

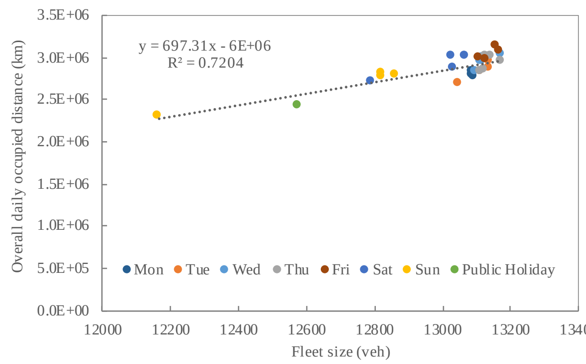


Figure 7. The correlation between the overall daily occupied distance and the fleet size of CGV taxis.

To capture the relationship between the overall daily occupied distance and the number of required EAV taxis, we select vehicles randomly from the simulated EAV set to form fleets with 7,500 to 8,500 vehicles, in the increment of 100. For each fleet size, 10 replications are generated. The daily occupied distances of the selected vehicles and the number of EAV taxis are plotted in Figure 8. The R^2 value of the regression model is 0.9976. Accordingly, a fleet with 7,898 EAV taxis are supposed to be capable of serving the occupied distance of 1,934,388 km per day. The minimum fleet size of EAVs almost equals to that in the first method, implying a small variance of daily occupied distances of EAV taxis (i.e. st.d.=41.6km).

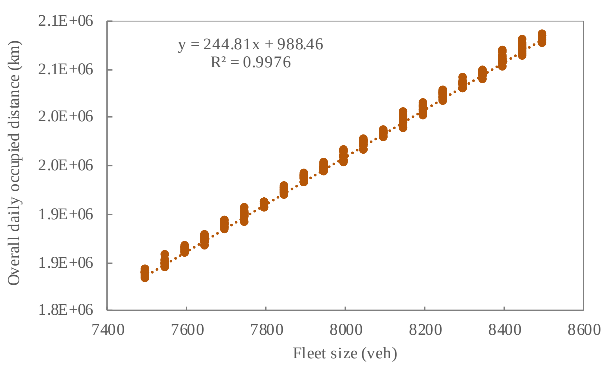


Figure 8. The correlation between the overall daily occupied distance and the fleet size of EAV taxis.

According to the results of the second way, if replaced by EAV taxis, the fleet size of CGV taxis can be reduced by 30.6%. The result is consistent with the finding of [11]. However, compared to the reduction rate of private vehicle fleet if they are replaced by shared AVs [13][15][16], the reduction of taxi fleet is not as significant. This is because that the average daily utilization of conventional private vehicle is remarkably lower than taxis. For example, the average time spent driving a private vehicle in the US is 55.6 minutes per day [22], and in Berlin, Germany, it takes about 40 minutes [17]. Relatively most of the conventional taxis are running 24 hours per day. The utilization of conventional taxis can be improved slightly, but not significantly.

Vehicle Relocation

The probability distributions of the number of daily relocate events are illustrated in Figure 9. Averagely, one EAV taxi is relocated 12.0 times per day, including 8.5 times Type 1 relocate and 3.5 times Type 2 relocate. Since Type 1 relocate occurs after one-hour idle time, the more occurrences a taxi has to be relocated, the less time it can be used to serve passengers' requests.

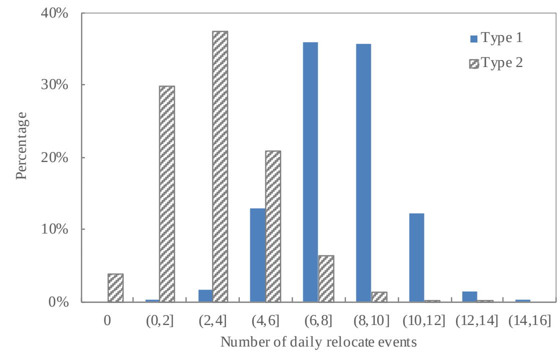


Figure 9. Number of daily relocate events.

CGV taxis operated in China tend to cruise around to find customers. We extract daily unoccupied distance and unoccupied time from 5,438 CGV taxis with 24-hours operating records in 30 days. For a full-day operated CGV taxi, its daily unoccupied distance is 115.6 km on average. The adoption of EAV taxis helps to reduce the daily unoccupied distance significantly. Figure 10 presents the distribution of the daily travel distance for relocating. The average distance of EAV taxis driving without passengers is 26.9 km per day. The reduction in daily unoccupied distance leads to shorter daily VKT for EAVs—on average, 272.2km per day. The average share of total mileage driven with passengers on board is 90.1%, compared to a 66.9% for CGV taxis.

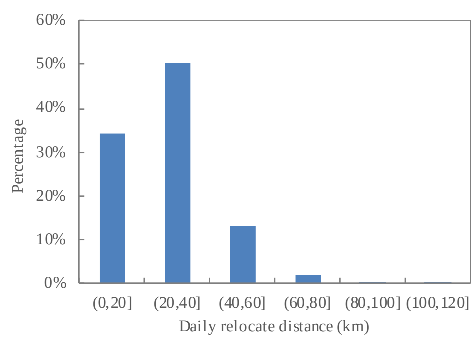


Figure 10. Daily travel distance for relocating.

Idle Events

There are 298,103 idle events for the simulated EAV taxi fleet. As mentioned above, the idle time in the simulation is assumed as 0, 15, 30, 45, or 60 minutes for simplicity. Figure 11 illustrates the distribution of idle times. After dropping off passengers, 24.3% of taxis pick up passengers immediately in the same cell after a 5-minute setup time, and 39.9% of them find a customer in 15 minutes. The rest wait at least half an hour, during which vehicle battery can be charged. 94.8% EAV taxis charge the battery once a day. For taxis idling for one hour or longer, 96.1% of them are relocated to the nearby cells.

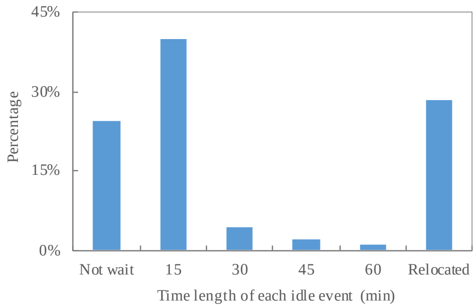


Figure 11. Time length of idle events.

The daily unoccupied time of EAV taxis is compared with that of CGV taxis (see Figure 12). Although EAVs travel less unoccupied distance, the percentage of idle time is larger. On average the amount of unoccupied time for one EAV taxi is about 15.1 hours during the day, which results in low utilization of vehicles. If we shorten the time threshold of vehicle relocation, the vehicle utilization might be improved. However, the occurrences of daily relocate events will increase, as well as the distance traveled without passenger. The tradeoff between improving vehicle utilization and frequently relocating vehicles is unclear and needs further studies. Another reason for the low vehicle utilization is the time-varying travel demand. Since a fixed fleet size is assumed, some EAVs will be idling when the demand is low.

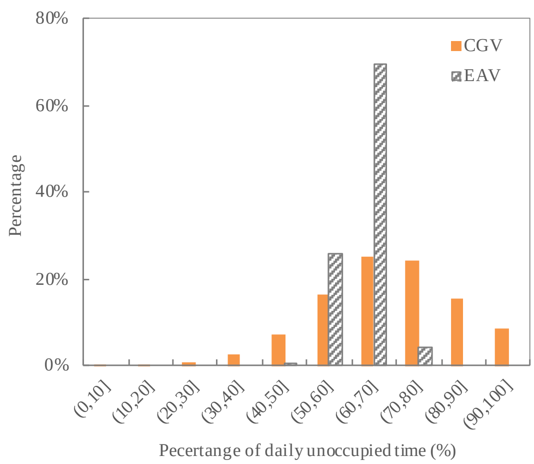


Figure 12. Daily unoccupied time.

Conclusions

Using the GPS trajectory data collected from CGV taxis in Shanghai, China, this paper simulates travel patterns of EAV taxis and quantifies taxis' operational performance using a data-driven simulation model. The key findings include (1) because of the vehicle stock imbalances, EAV taxis must be relocated 8.5 times per day on average in case of idling for more than one hour; (2) the deployment of EAVs helps to improve taxis' full-load ratio and reduce their daily empty VKTs by 76.7%; (3) the fleet size can be reduced by 30.6% if replace CGV taxis with EAVs. The methodology presented in this paper provides a tool for simulating and assessing the performance of EAV taxi system based on the actual customer demand for the cities with large-scale deployment of taxis. The findings have the potential to assist policy makers in allocating public resources efficiently in aiding the deployment of EAV taxis in the future, for example, determining how many EAV taxis need to be assigned and where charging stations should be located. The proposed approach could be further improved if the customer acceptance of EAV taxi service is considered.

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