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# Analyzing battery electric vehicle feasibility from taxi travel patterns: The case study of New York City, USA☆

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ABSTRACT

Electric taxis have the potential to improve urban air quality and save driver's energy expenditure. Although battery electric vehicles (BEVs) have drawbacks such as the limited range and charging inconvenience, technological progress has been presenting promising potential for electric taxis. Many cities around the world including New York City, USA are taking initiatives to replace gasoline taxis with plug-in electric vehicles. This paper extracts ten variables from the trip data of the New York City yellow taxis to represent their spatial-temporal travel patterns in terms of driver-shift, travel demand and dwell, and examines the implications of these driving patterns on the BEV taxi feasibility. The BEV feasibility of a taxi is quantified as the percentage of occupied trips that can be completed by BEVs of a given driving range during a year. It is found that the currently deployed 280 public charging stations in New York City are far from sufficient to support a large BEV taxi fleet. However, adding merely 372 new charging stations at various locations where taxis frequently dwell can potentially make BEVs with 200- and 300-mile ranges feasible for more than half of the taxi fleet. The results also show that taxis with certain characteristics are more suitable for switching to BEV-200 or BEV-300, such as fewer daily shifts, fewer drivers assigned to the taxi, shorter daily driving distance, fewer daily dwells but longer dwelling time, and higher likelihood to dwell at the borough of Manhattan.

## 1. Introduction

Vehicle electrification has been widely considered as a way to reduce the dependency of transportation sector on petroleum and reduce emissions of greenhouse gases and harmful air pollutants. In particular, since taxis usually drive in highly-populated areas, substituting the battery electric vehicles (BEVs) for conventional gasoline vehicles (CGV) in the taxi fleet has the potential to improve urban air quality. BEVs are also attractive to taxi drivers, because of the lower electricity cost compared to gasoline and the less maintenance expenditure (Sathaye, 2014). As a result, cities around the world such as New York City (NYC), USA (NYC TLC, 2013), Berlin, Germany (Bischoff et al., 2015), Shenzhen, China (Tu et al., 2016) and Bogota, Colombia (Urban Foresight Limited, 2014) have been promoting electric taxis. In particular, New York City has a vision to replace one-third of taxi fleet with BEVs by 2020 (NYC

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TLC, 2013).

Nevertheless, BEV taxi deployment is impeded by several obstacles. Since taxis are usually continually operated by multiple shifts day and night, overnight charging at home might not be an option. Instead, within-day charging at public charging stations during taxi operation hours becomes necessary. However, in most cities the coverage of charging stations is still sparse. The profit-driven taxis would not want to wait for a long time to charge the batteries at the expense of losing customers. Frequent charging and depleting batteries may shorten the life of batteries (Barré et al., 2013), which is another concern over adopting BEVs in the taxi fleet. With the advances in battery technology, longer battery life, higher energy density and faster charging will relieve the range anxiety and reduce charging inconvenience. Ride-hailing services, coupled with self-driving cars, are expected to achieve a more efficient dispatch system and may help promote large-scale BEV taxi deployment (Golson, 2017; Hawkins, 2017).

This paper analyzes the electric taxi feasibility based on the travel activities of current CGV taxis. BEV feasibility research typically extracts travel patterns from the travel data collected from vehicles for a period of time. Daily vehicle miles traveled (DVMT) is often used as one indicator to infer a vehicle's suitability for BEVs, as seen in Atlanta, USA (Pearre et al., 2011), Seattle, USA (Khan and Kockelman, 2012), Sydney, Australia (Greaves et al., 2014). For example, the driving data collected from 484 private CGVs over a year in Atlanta revealed that the daily driving needs of 9% of the sampled vehicles could be fulfilled by BEVs with a 100-mile range because their daily driving distance never exceeded 100 miles during the data collection period (Pearre et al., 2011). Other than DVMT, BEV feasibility is also quantified as the probability that the ratio of travel distance between two charges to the battery range remains within a certain level in Dong and Lin (2014). This research concluded that about 10% of the sampled private car drivers in Seattle needed to make adjustment to less than 0.5% of travel days if they were comfortable with using up the range of 76 miles (i.e. representative of a Nissan Leaf 2012 model).

The above-mentioned studies focused on the BEV feasibility of private vehicles. Taxis, on the other hand, have their own distinct characteristics in terms of shared use, long operational time, and dwell patterns. In New York City, a typical yellow taxi is assigned 3 drivers and travels 70,000 miles annually, and the average shift lasts for 9.5 h (NYC TLC, 2014; NYC TLC, 2016). The data collected from taxis in Shanghai (Luo et al., 2017), Beijing (Li et al., 2016), and Shenzhen (Nie, 2017), China revealed long daily driving distances that are likely to exceed BEV range. In terms of dwell patterns, it is found that approximately 80% of the studied taxis in Beijing had average parking time of at least 5 h per day (Cai et al., 2014), and taxis in Berlin, Germany were in favor of waiting for customers at airports for several hours (Bischoff et al., 2015). BEV feasibility of taxis has been examined from different perspectives, including benefit-to-cost ratio (Baek et al., 2016), environmental benefits (Yang et al., 2016), energy consumption (Zou et al., 2016), daily driving distance (Chrysostomou et al., 2016), and electrification rate of vehicle miles traveled (Li et al., 2017). Different from previous studies, this paper examines electric taxi feasibility based on taxis' spatial-temporal travel patterns in terms of driver-shift, travel demand and dwelling, as well as the impact of charging infrastructure coverage. The feasibility is quantified as the percentage of occupied trips that can be completed by BEVs during a year. The findings from the study can help taxi drivers make informed decisions to adopt BEVs and assist policy makers in allocating public resources in support of electric taxi deployment.

## 2. Data

### 2.1. Data description

New York City owns a large number of taxis, among which 13,587 were yellow taxis driven by 38,139 active drivers in 2015 (NYC TLC, 2016). Yellow taxis provide street hails and e-hails in the five NYC boroughs (i.e. Bronx, Brooklyn, Manhattan, Queens, and Staten Island) and the two airports (i.e. LaGuardia airport and John F. Kennedy international airport), as shown by Fig. 1. Onboard GPS devices are implemented on the yellow taxis to track and record the timestamped trajectories during operation. NYC Taxi and Limousine Commission (TLC), the agency responsible for managing the city's taxicabs, published the taxi trip data since 2009.

The data used in this paper span the whole year of 2013 and was pre-processed by Donovan and Work (2016, 2017), who rendered the vehicle ID and driver ID pseudo anonymous. The high resolution timestamped vehicle trajectories are not available. Instead, only records of occupied trips are available, which include when and where customers were picked up and then dropped off, travel distance, and travel time. Table 1 lists the data fields used in the study.

### 2.2. Data filtering

There are a considerable number of errors in the data, for example, trip length of 1000 miles, zero travel time, and out-of-boundary GPS coordinates. Validity of the research results could suffer from these erroneous values, so the trip records that do not satisfy all the following three criteria are discarded.

(a) Travel time is a positive value and does not exceed 3 h.
(b) Trip length is a positive value and does not exceed 100 miles.
(c) The pick-up and drop-off GPS coordinates are within the range of 73.5–74.25°W longitude, and 40.4°N and 41.1°N latitude.

As long distance trips have a significant impact on BEV feasibility, criterion (a) and (b) allow to keep long trips provided that the travel time and trip length are reasonable. The study area defined by criterion (c) is wider than the city boundary and covers three main airports—John F. Kennedy International (JFK), LaGuardia (LGA) and Newark Liberty International (EWR) that lie in the NYC suburb areas.


**Fig. 1.** Location of NYC boroughs and airports (NYC TLC, 2014).

**Table 1**
Data fields used of the NYC yellow taxi trip data.

| Data field | Description |
|---|---|
| Medallion | The anonymous identification of each taxi |
| Hack license | The anonymous identification of each driver |
| Pickup datetime | The date and time when customers are picked up. The precision is up to seconds |
| Dropoff datetime | The date and time when customers are dropped off. The precision is up to seconds |
| Trip time in secs | The travel time measured by taximeter (second) |
| Trip distance | The trip distance measured by taximeter (mile) |
| Pickup longitude | The longitude of the location where customers are picked up |
| Pickup latitude | The latitude of the location where customers are picked up |
| Dropoff longitude | The longitude of the location where customers are dropped off |
| Dropoff latitude | The latitude of the location where customers are dropped off |

The whole-day data of a taxi is then removed if there is one or more erroneous trips, for these errors break up trip continuity and make DVMT estimation inaccurate. Trips that occurred on November 3rd, 2013 when the daylight saving time ended are also discarded because on that day clocks were tuned backward 1 h to the standard time, making some trips chronologically disordered.

### *2.3. Unoccupied trip estimation*

Although not captured in the data, unoccupied trips can be approximately reconstructed on the basis of two adjacent occupied trips, that is, an unoccupied trip starts from the drop-off location of the last occupied trip and ends at the pick-up location of the next occupied trip. With the GPS coordinates of the last drop-off and the next pick-up location, the empty trip's straight-line distance $L$ is calculated as the Euclidean distance. Yang and Gonzales (2016) used Euclidean distance to represent real travel distance of unoccupied trips, which tends to result in underestimation. Zhan et al. (2016) estimated real distance by taking advantage of the road network of NYC, but this method is computationally heavy. In this paper, the actual distance $D$ of unoccupied trips is estimated by equation (1), that is the least-squares fitting result from the actual and straight-line travel distance of occupied trips. Here we assume that occupied and unoccupied trips share the same spatial relationship. With the help of taxi dispatch and e-hailing system drivers might know the location of the next customers and will drive along the shortest path.

$$D = 1.4413L + 0.1383 \quad (R^2 = 0.9485) \tag{1}$$

where $D$ is the actual travel distance (mile), and $L$ is the straight-line distance (mile).

Between two occupied trips, taxi drivers might cruise around, have a meal, take a short break, alter shifts, go back home, etc. Dwell time during an unoccupied trip is defined as the time intervals between the two consecutive occupied trips minus the travel time of the unoccupied trip. The travel speed of the unoccupied trip is calculated as the average of the speeds of the previous and the next occupied trips. The travel distance is estimated using Eq. (1) and the straight-line distance between the drop off location of the previous trip and the pickup location of the next trip. The travel time of the unoccupied trip is calculated as the travel distance

**Table 2**
Summary of the travel patterns of the sampled taxi fleet.

| | Minimum | Mean | Maximum | Standard deviation |
|---|---|---|---|---|
| Occupied trip length (mile) | 0.01 | 2.91 | 100 | 3.36 |
| Occupied trip time (minute) | 1 | 12.5 | 180 | 9.3 |
| Unoccupied trip length (mile) | 0 | 1.72 | 55 | 2.82 |
| Number of occupied trips per day | 1 | 36 | 122 | 14.5 |
| DVMT (mile) | 0.09 | 168 | 858 | 59 |
| Number of dwells (> 30 min) per day | 0 | 3.4 | 13 | 1.6 |

divided by the travel speed. Dwell location is assumed to be the drop-off location of the last occupied trip. As shown in Table 2, the estimated average unoccupied trip length in NYC is 1.72 miles, which is 41% lower than average occupied trip length. This number is similar to taxis in Nanjing, China, where both occupied and unoccupied trip information is available. In Yang et al. (2016), the average unoccupied trip length is 42% lower than the average occupied trip length. Note that taxis in both NYC and Nanjing are mainly street-hailed in current operations.

### 2.4. Summary statistics of the dataset

During the year of 2013, the entire dataset includes 14,144 yellow taxis, which were driven by 43,191 drivers, completed 173 million occupied trips with a total distance of 501 million miles. On average each taxi operated for 331 days in one year. After data filtering, there are 13,336 taxis with at least 70 days and an average of 306 days of trip data remaining. The sampled fleet completed 149 million occupied trips with a total distance of 432 million miles, which represents 86% of the total occupied trips in 2013. Table 2 lists the summary statistics of the 13,336 taxis' travel patterns.

## 3. Methodology

### 3.1. Quantification of electric taxi feasibility

This study quantifies a taxi's BEV feasibility as the percentage of occupied trips that can be completed by BEVs among all occupied trips during the year. Different from personal vehicles, taxis are usually driven day and night by multiple shifts. Thus, assuming that batteries can be fully charged overnight at home (Dong et al., 2014) is not practical for taxis. Instead, the proposed approach allows taxis to continuously operate for a one-year period and charge batteries during long dwell events. If taxis run out of electricity and have to resort to emergency charging, several subsequent occupied trips are probably missed.

Consider a fleet of electric taxis $I = \{1, 2, \ldots, n\}$. Assume the batteries are fully charged at the beginning of the first occupied trip in 2013. For each taxi, travel distances of both occupied and unoccupied trips can be estimated from the trip data. Accordingly, distance variables are defined as follows.

$od_{i(k)}$ Travel distance of taxi $i$'s $k$-th occupied trip (mile).
$ud_{i(k)}$ Travel distance of taxi $i$'s $k$-th unoccupied trip (mile), that is, the trip immediately after the $k$-th occupied trip.

BEV-associated parameters include electric range and electricity consumption rate. Tesla Model S (maximum 351-mile range) is among the candidates for NYC electric taxis in spite of its high price tag (NYC TLC, 2013). BEVs with shorter range, such as Tesla Model 3 (215-mile range) and Chevrolet Bolt (238-mile range), are more affordable—the price is about $35,000 and $30,000 after incentives, respectively (Chevrolet, 2017; Tesla, 2017). With technology advancement, it is predicted that BEVs will feature longer range at lower price in the near future (Ajanovic, 2015). Thus, this study considers the feasibility of using BEVs with ranges of 200 miles and 300 miles (i.e. $R_i = 200, 300, \forall\ i$) as taxis. Electricity consumption rate varies greatly due to different driving habits, traffic conditions and environmental factors. In this study a fixed consumption rate is assumed as 0.3 kW h/mile (i.e. $r_i = 0.3, \forall\ i$) (Plugin America, 2016).

$R_i$ Electric range of taxi $i$ (mile).
$r_i$ Electricity consumption rate of taxi $i$ (kW h/mile).

The charging decision depends on the dwell time, remaining electric range, distance to the nearest charging station, and so on. In this study, two types of charging are considered—dwell charging and emergency charging. For *dwell charging*, a taxi will charge if three conditions are satisfied. First, the dwell time is longer than 30 min. Currently almost all charging stations in NYC are installed with 20-kW AC Level 2 chargers. With such chargers, the BEV's remaining range can increase by about 33 miles in half an hour. Taxi drivers might be reluctant to charge if dwell time is short. The 30-min assumption was also used in other studies to define potential charging opportunities (e.g. Yi and Bauer (2016), Li et al., 2017). Second, remaining electric range is below 50%. By studying the distribution of battery SOC before charging, Zou et al. (2016) found that around three quarters of BEV taxi drivers will not charge their cars until SOC drops below 50%. Thus, this paper assumes taxi driver will consider charging if the SOC is below 50%. Third, the nearest charging station is within 0.5 mile. In the literature, the service radius of a charging station is assumed as 1 mile in (Cai et al., 2014) and 1.25 miles in (Li et al., 2017). This study assumes a smaller service radius of 0.5 miles considering taxi drivers' unwillingness to detour for charging and the heavy traffic in Manhattan. The related variables are defined below.

$dt_{i(k)}$ Dwell time between taxi $i$'s $k$-th and $(k+1)$-th occupied trip (minute).
$ct_{i(k)}$ Charging time between taxi $i$'s $k$-th and $(k+1)$-th occupied trip (minute).
$st_i$ Setup time for charging of taxi $i$ (minute). Assume to be 2 min, $\forall$ $i$.
$R_{SOC,i(k)}$ Remaining electric range at the drop-off location of the $k$-th occupied trip (mile).
$cd_{i(k)}$ Straight-line distance from the drop-off location of taxi $i$'s $k$-th occupied trip to the nearest charging station (mile).

Therefore, the charging time is the dwell time minus a setup time for charging. The detour time is ignored for dwell charging since the charging station is within 0.5-mile radius.

$$ct_{i(k)} = \begin{cases} dt_{i(k)} - st_i & \text{If } dt_{i(k)} > 30 \text{ min}, R_{SOC,i(k)} < 0.5R_i, \text{ and } cd_{i(k)} \leqslant 0.5 \text{ mile;} \\ 0 & \text{Otherwise} \end{cases} \tag{2}$$

Multiple charging levels might be available at a charging station. This paper considers 2-kW AC Level 1 chargers, 20-kW AC Level 2 chargers, and 50-kW DC fast chargers for the analysis, according to the SAE J1772 standard (SAE, 2016). Since taxi drivers generally prefer faster chargers, when multiple levels of chargers are available at a charging station the fastest charger will be chosen.

$P_{i(k)}$ The highest charging power at the nearest charging station from the drop-off location of taxi $i$'s $k$-th occupied trip (kW).
$R_{add,i(k)}$ Electric range increase by recharging at the $k$-th unoccupied trip (mile), which is determined by charging time and power, but will not exceed the battery capacity. Therefore,

$$R_{add,i(k)} = \min\left\{R_i - R_{SOC,i(k)}, \ \frac{P_{i(k)} \times ct_{i(k)}}{r_i}\right\} \tag{3}$$

$R_{SOC,i(k)}$ is calculated based on the remaining range at the end of the previous trip, possible charging, and travel distance.

$$R_{SOC,i(k)} = R_{SOC,i(k-1)} + R_{add,i(k-1)} - ud_{i(k-1)} - od_{i(k)} \tag{4}$$

When $R_{SOC,i(k)}$ drops below 10% of range, taxi $i$ needs *emergency charging* from the drop-off location of the $k$-th occupied trip, because it is very likely stranded in the next trip. If $R_{SOC,i(k)}$ becomes negative, taxi $i$ has to resort to emergency charging from the drop-off of the $(k-1)$-th occupied trip. That is, the taxi will not have accepted the $k$-th customer due to the insufficient range. During emergency charging, the taxi drives to the nearest charging station at the average speed calculated from the dataset—13 mph, and gets batteries fully charged (100% SOC). The detour distance ($dd_{i(k)}$ in miles) is estimated by equation (1). After charging is finished, the taxi will continue from the occupied trip that starts after the charging completion time. Since over 90% of taxi pick-ups and drop-offs occur in Manhattan (NYC TLC, 2014) that is only a small part of the studied area (see Fig. 1), the trips from emergency charging stations to the next customer are short compared to BEV range (200 or 300 miles) and thus are ignored. As a consequence, several occupied trips probably are missed due to emergency charging, and the percentage of occupied trips during the year that can be electrified by public charging is used as the indicator of taxi $i$'s BEV feasibility ($F_i$). A taxi is regarded as BEV feasible if at least 99% of its occupied trips can be completed by BEVs; otherwise the taxi is BEV infeasible. On average, a taxi works 306 days in the year and completes 36 occupied trips per working day. Therefore, a BEV-feasible taxi will miss only 2 $\left(\frac{306 \times 7 \times 36 \times 1\%}{365} = 2\right)$ occupied trips per week.

The model of quantifying electric taxi BEV feasibility is illustrated in Fig. 2.

### 3.2. Taxi travel patterns

Travel patterns represent how NYC yellow taxis are operated, and hence have some important implications on whether the CGV taxi can switch to a limited range BEV. For each taxi, we extract 10 variables from its travel activity data, to characterize its driving behavior in 3 aspects—driver-shift, travel demand, and dwelling. Table 3 describes these variables.

The first four variables are driver-shift related, explaining the features of shifts and drivers assigned to a taxi. Taxis are driven by one or more shifts during a day. Intuitively, more daily shifts are likely associated with longer hours of operation and longer travel distance, which might make it less suitable to switch to a BEV. In addition, a taxi might be assigned to different drivers over a year, denoted by $X_3$. Some taxis have one or two fixed drivers during the entire year, while others change drivers frequently. The other driver-shift related variable ($X_4$) is calculated based on Eq. (5), which indicates, for a certain taxi, the average number of shifts that a driver is assigned to the taxi in a year. $X_3$ and $X_4$ reveal whether a taxi has stable driver assignment.

$$X_4 = \text{Number of working days} \times X_1 \times X_3^{-1} \tag{5}$$

In terms of travel demand, the variables of interest include the average length of occupied trips ($X_5$) for each taxi and the daily vehicle miles traveled ($X_6$). A taxi that often drives a lot might not be suitable for BEVs. To account for limited coverage of public charging network in the city, the travel distance between two consecutive charging opportunities ($X_7$) is calculated based on the charging station locations. When a taxi dwells for more than 30 min and the nearest charging station is within 0.5 miles, the taxi has an opportunity to charge.

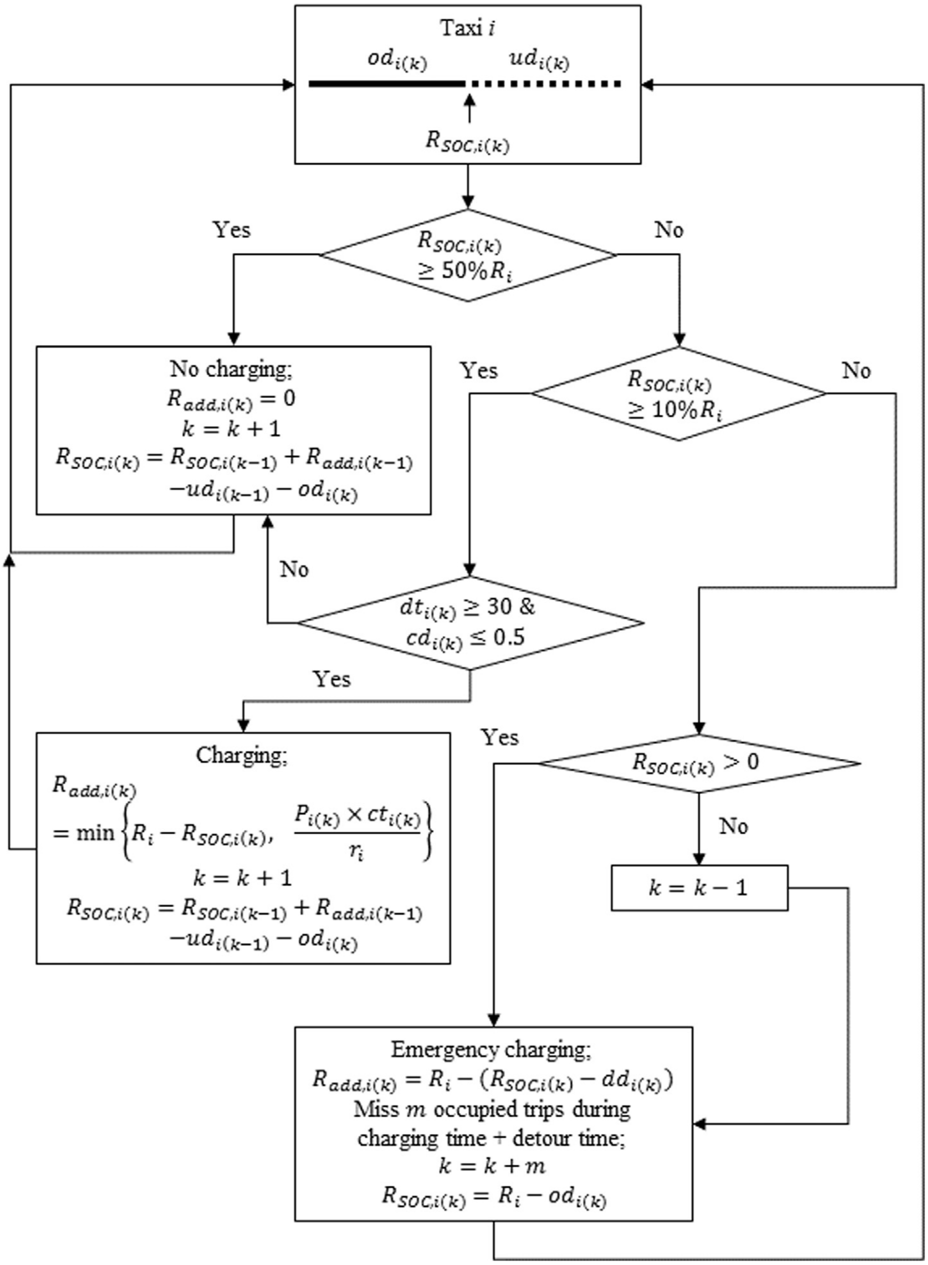



**Fig. 2.** Flow diagram of the model of quantifying electric taxi BEV feasibility.

Furthermore, dwell patterns are important for electric taxis, because taking advantage of parking time to charge batteries causes minimal inconvenience. The temporal characteristics of dwell events are captured by the average number of daily dwells ($X_8$) and the average dwell length ($X_9$), which collectively determine the possible charging time during a day. The spatial characteristics of dwell events are represented by the percentage of dwells occurred in Manhattan ($X_{10}$), as this borough has better charging infrastructure coverage and taxis are more likely to find a charger.

### 3.3. Expansion of charging infrastructure

As of December 22, 2016, there were 280 public charging stations in use in New York City, among which 223 (80%) are located in Manhattan, 2 in JFK airport and 4 in LGA airport (US DOE, 2016). Detailed information associated with these stations such as address, number of chargers, levels of chargers is available through (US DOE, 2016). Almost all the charging stations are installed with Level 2 chargers. Fig. 3 illustrates the station locations, with the corresponding service area covered (i.e. a buffer of 0.5-mile radius). It is seen that Manhattan has extensive charging station coverage, while very few chargers are located at other boroughs.

**Table 3**
Ten taxi travel pattern variables extracted from data.

| Type | Variable | Description |
|---|---|---|
| Driver-shift related | $X_1$ | Mean of the number of daily shifts |
| | $X_2$ | Mode of the number of daily shifts |
| | $X_3$ | Number of drivers assigned to the taxi in a year |
| | $X_4$ | Mean of the number of shifts per driver in a year |
| Travel demand related | $X_5$ | Mean of occupied trip length (mile) |
| | $X_6$ | Mean of DVMT (mile) |
| | $X_7$ | Mean of travel distance between two charging opportunities (mile) |
| Dwelling related | $X_8$ | Mean of the number of daily dwells |
| | $X_9$ | Mean of dwell length (minute) |
| | $X_{10}$ | Percentage of dwells occurred in Manhattan (%) |

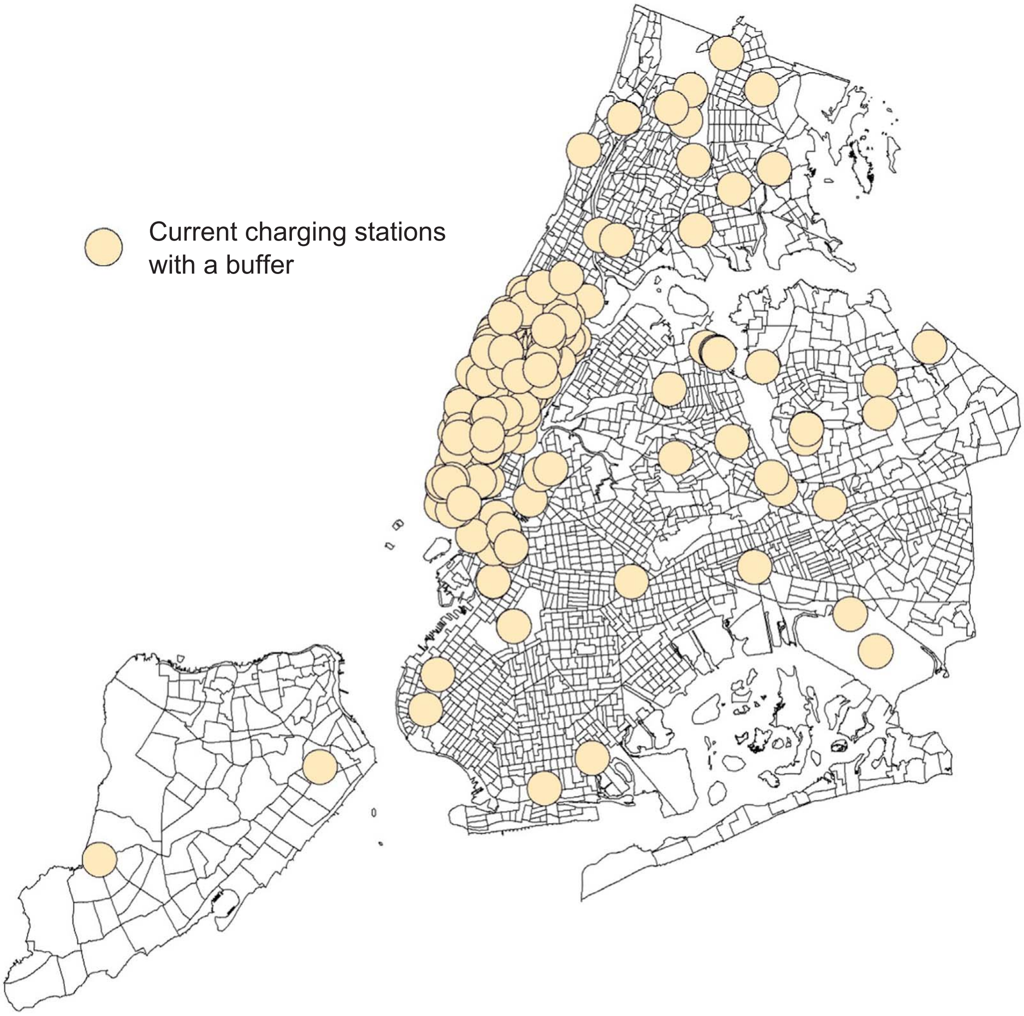



**Fig. 3.** Current public charging network in NYC, with a buffer of 0.5-mile radius.

Insufficient charging infrastructure is one of the hindrances to electric vehicle adoption. New York City plans to expand the charger network to boost BEV taxis because the current charging stations are nearly impossible to meet the charging demand of a large-scale fleet of BEV taxis (NYC TLC, 2013). Thus, in this paper, a scenario of expanded charger network is considered for BEV taxi feasibility analysis. Various approaches have been proposed in the literature to site charging facilities (e.g. He et al. 2015, Yang et al., 2017, Shahraki et al., 2015). This paper considers the centers of the census tracts as potential charging station locations. For each census tract of NYC, a spatial joining is conducted to count the number of dwell locations where taxis cannot reach a charger within

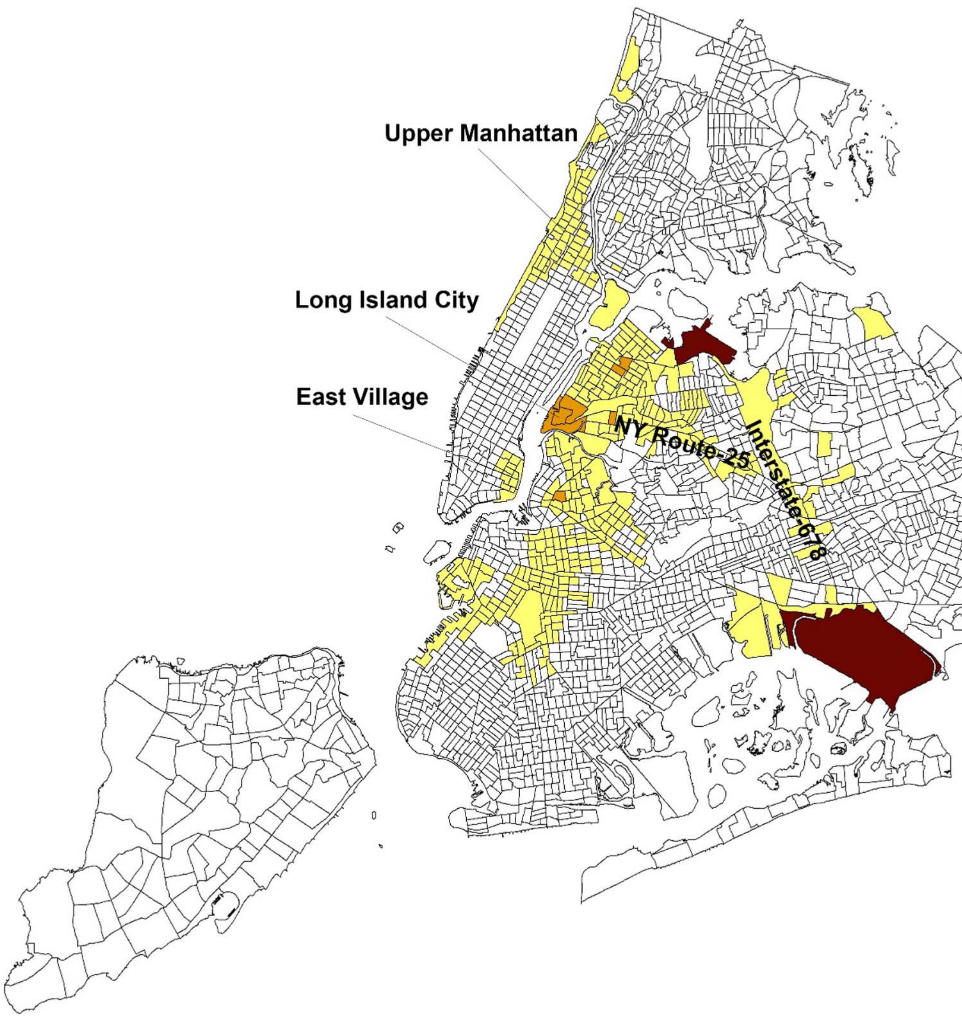



**Fig. 4.** Distributions of daily dwells without charging opportunities.

0.5 mile based on the existing charger network. New charging stations are added in the census tracts where taxis frequently dwell. Since taxis prefer waiting for customers at airports, new charging stations are placed at several parking lots within the JFK and LGA airport census tracts to cover as many dwell locations as possible.

## 4. Results

### 4.1. Expanded charging network

New charging stations are sited at the census tracts where taxis frequently dwell. Fig. 4 shows the distributions of daily dwell events without a nearby charging station. JKF and LGA airport have averagely 773 and 122 dwells without charger per day, respectively, constituting the top 2 places where taxis have large unmet charging needs. Although the trips to EWR airport are considered in this study, no additional charging station is added, as EWR is in the state of New Jersey. Another area with relatively large unmet charging demand (i.e. 50–100 dwells per day) is Long Island City, which is the westernmost neighborhood of Queens and adjacent to midtown Manhattan. This is likely where drivers change shifts (Grynbaum, 2011). The other census tracts with considerable unmet charging demand (i.e. 5–50 dwell per day) are mainly distributed at Upper Manhattan, East Village of Manhattan, Northwest Queens adjacent to Manhattan, Middle North Brooklyn, along Interstate-678 connecting the two airports, along New York Route-25 connecting Manhattan and Interstate-678, and the areas near JFK airport.

A new charging station is placed at the geometric center of a non-airport census tract polygon that has more than 5 dwells without charging opportunities per day. 364 census tracts, colored with yellow and orange in Fig. 4, satisfy the condition and accommodate 73% of charging demands in non-airport census tracts. Fig. 5 plots the number of new charging stations and the percentage of satisfied charging demands with different selection thresholds, from > 20 to > 0 dwells. With lower threshold and more charging stations, more charging demands can be covered, however, the marginal benefit decreases after > 5 dwells.

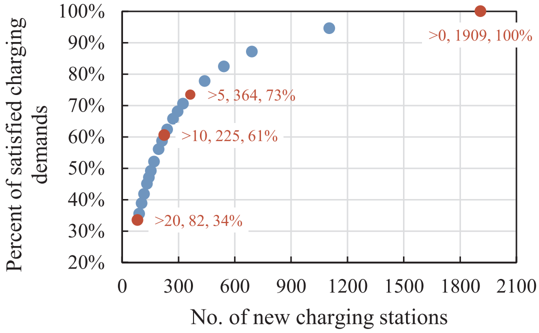



**Fig. 5.** Relationship between number of new charging stations and percent of satisfied charging demands.

The airports, however, cover a larger area and have more available parking spaces for building charging stations. Thus, we select 2 parking lots at LGA airport and 6 parking lots at JFK airport to add charging stations, in order to cover as many dwell locations as possible. In total, 372 new stations are added in the expanded charging network. With the additional charging stations, the entire public charging infrastructure in NYC is displayed in Fig. 6.

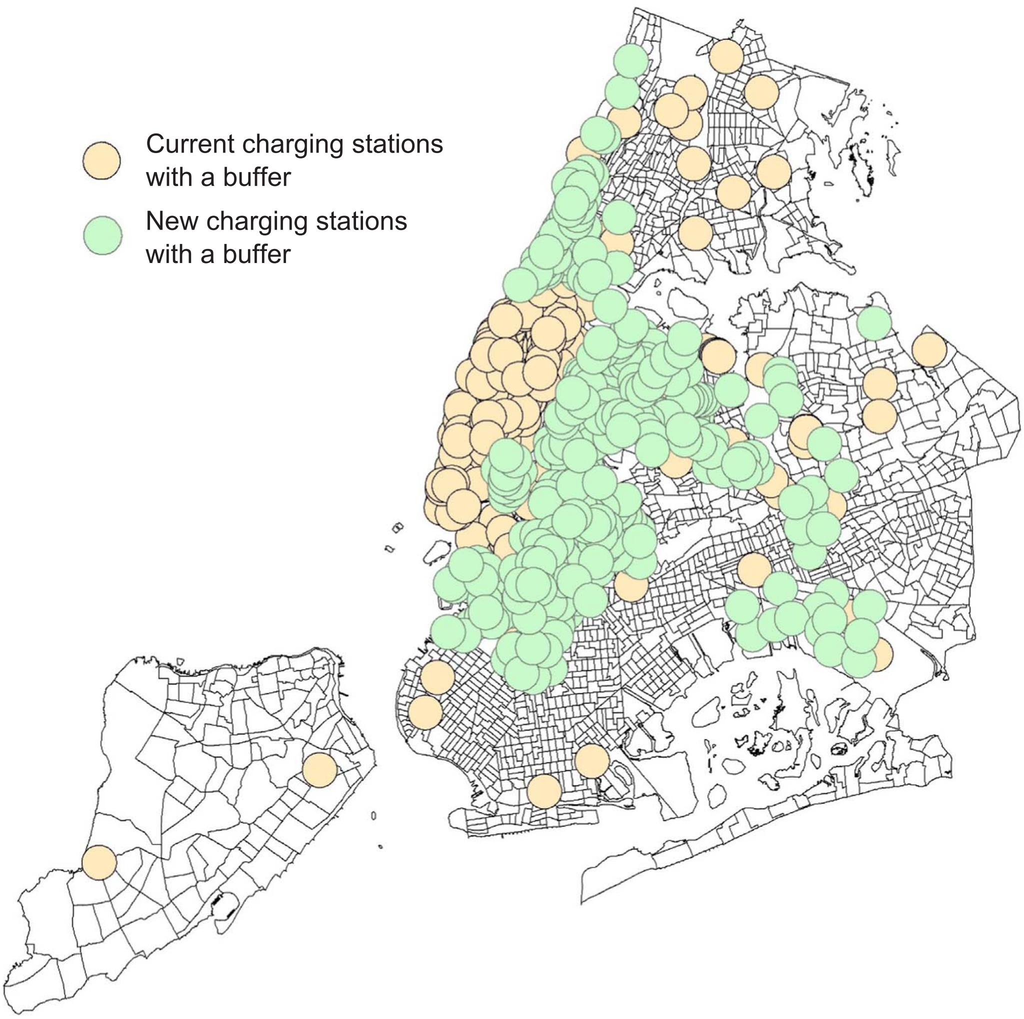



**Fig. 6.** Expanded public charging network in NYC, with a buffer of 0.5-mile radius.

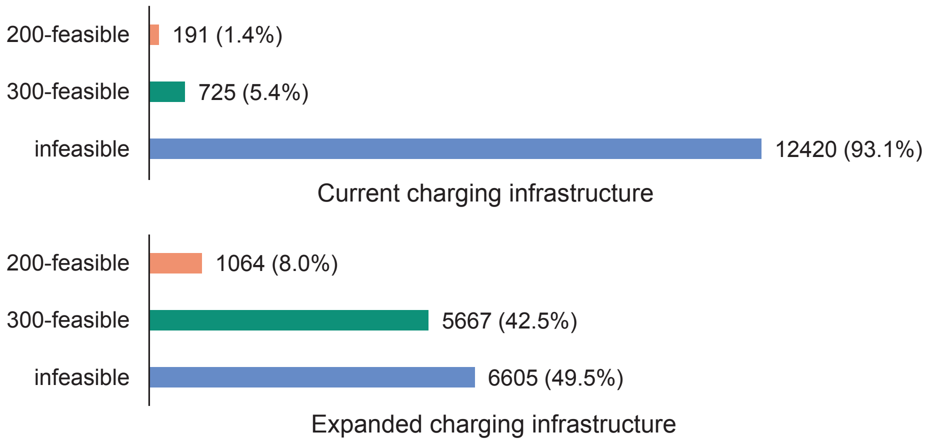



**Fig. 7.** Electric taxi feasibility by group for current and future charging infrastructure.

### 4.2. BEV taxi feasibility

The feasibility of replacing CGV taxis in New York City with BEVs with a range of 200 miles and 300 miles is examined. If a taxi can complete at least 99% of the occupied trips using a BEV, it is considered BEV feasible. Some taxis might achieve the feasibility with 200-mile range BEVs; while others might require a battery range of 300 miles. If 300-mile range still cannot complete a majority of occupied trips for some taxis, they are considered as BEV infeasible. Therefore, all taxis are categorized into 3 groups—BEV 200-feasible, BEV 300-feasible, and BEV infeasible.

Fig. 7 compares the electric taxi feasibility by group for current and expanded charging infrastructure in New York City. The existing 280 public charging stations are far from adequate to serve electric taxis. Only 1.4% of taxis are BEV 200-feasible and 5.4% of taxis are BEV 300-feasible, while 93.1% of the fleet cannot complete 99% of occupied trips using a BEV-300. However, when the number of charging stations is expanded to 652, taxis have more charging opportunities and thus fewer occupied trips will be missed. About half of the infeasible taxis become BEV feasible. In particular, BEV 300-feasible group increases dramatically to 5667 taxis (or 42.5% of the fleet), and the share of BEV 200-feasible taxis increases to 8.0%.

### 4.3. Impacts of travel patterns on BEV taxi feasibility

Considering the expanded charging infrastructure, the travel patterns of the three groups exhibit distinct characteristics. Fig. 8 shows the boxplots by group of the 4 driver-shift related variables after removing outliers. The group means are marked by the square points. Fig. 8(a) and Fig. 8(b) show that fewer daily shifts are associated with higher BEV feasibility, probably because these taxis are driven fewer hours and are more likely to have long dwell time between shifts for charging. Specifically, we have found that (1) BEV 200-feasible taxis have the lowest average number of daily shifts, with the mean of 1.8 shifts per day; while BEV infeasible taxis, as expected, are driven intensively, with the mean of 2.5 shifts per day; (2) BEV 200-feasible group also has the largest variation in daily shifts, as the taxis with 1 shift per day generally fall in this category; (3) the distributions of the mode of the number of daily shifts confirm that BEV 200-feasible taxis have fewer shifts, and most BEV 200-feasible taxis operate 1–2 shifts per day; and (4) most BEV 300-feasible and BEV infeasible taxis have 3 shifts per day. Other than shifts, we also examine the number of drivers assigned to a taxi and the yearly shifts a driver conducts to explore the relationship between drivers and taxis. As shown in Fig. 8(c), BEV feasible taxis tend to have fewer drivers, that is, more stable driver assignment over a year. By contrast, BEV infeasible taxis could have as many as 329 different drivers during the year. The distributions of the average number of shifts per driver, as shown in Fig. 8(d), also reveal that BEV feasible taxis tend to have more stable driver assignment. The median of the yearly number of shifts per driver for the BEV infeasible group is 54, much lower than the BEV feasible groups (i.e. 195 for BEV 200-feasible and 141 for BEV 300-feasible). In short, the driver-shift patterns imply that fewer shifts and less frequently change of drivers are favorable to BEV use.

Fig. 9 compare the distributions of the travel demand related variables for different BEV feasibility groups. We concern about whether the CGV taxi travel needs can be met by a BEV-200 or BEV-300. First, in terms of the average occupied trip length (Fig. 9(a)), there is no significant difference between groups. One possible reason is that over 90% of occupied trips occurred in Manhattan (NYC TLC, 2014) and these trips tend to have similar length. The average of DVMT, however, have a direct impact on BEV feasibility as shown in Fig. 9(b). Taxis with shorter DVMT are most suitable for BEVs. The group means are 111 miles, 157 miles and 184 miles for BEV 200-feasible, BEV 300-feasible and BEV infeasible group, respectively. Since DVMT indicate demand for BEV range, taxis that travel fewer miles a day are more likely to adopt BEVs. A few taxis with average DVMT of over 200 miles are BEV 200-feasible, which is possibly because they have proper within-day charging opportunities. On the other hand, the average DVMT of the majority of BEV infeasible taxis are less than 200 miles. Neither BEVs-200 nor BEVs-300 can complete 99% of the occupied trips of these taxis. This is due to the day-to-day variations in DVMTs and the lack of charging opportunities. Mean travel distances between two charging opportunities also show significant differences among groups (seen in Fig. 9(c)). On average, a BEV 200-feasible taxi will dwell near a

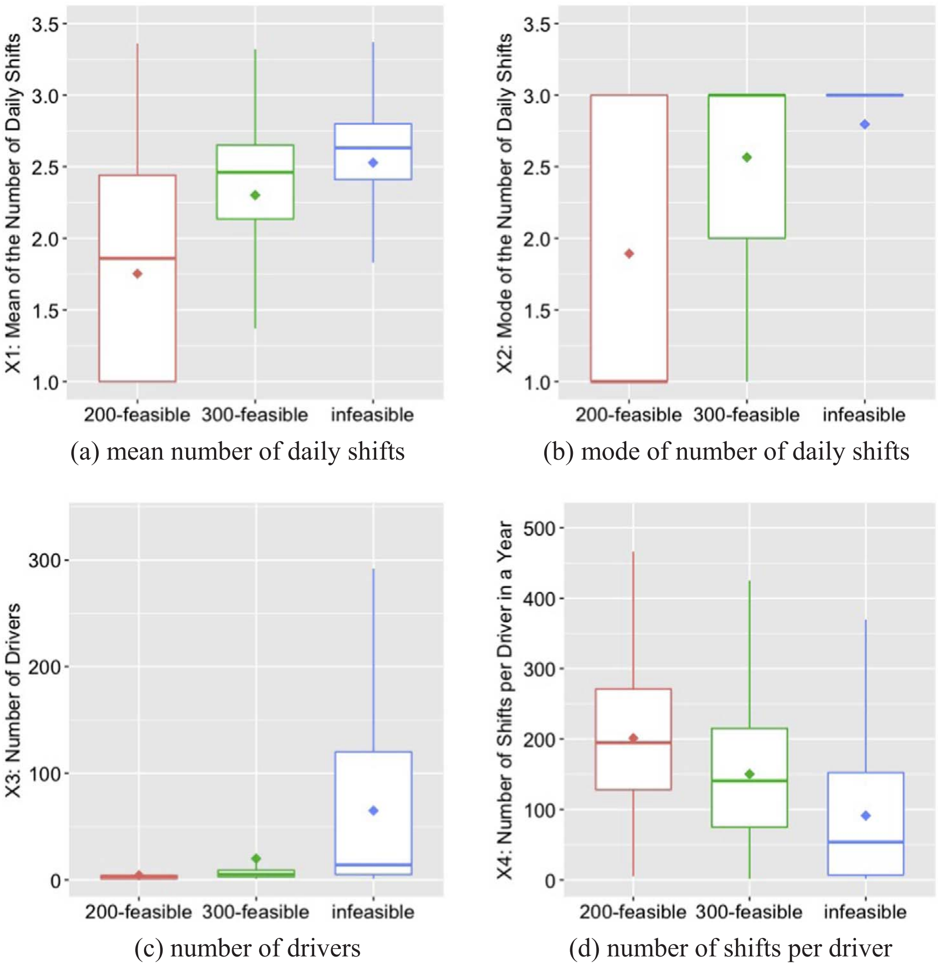



**Fig. 8.** Boxplots by group of driver-shift related variables.

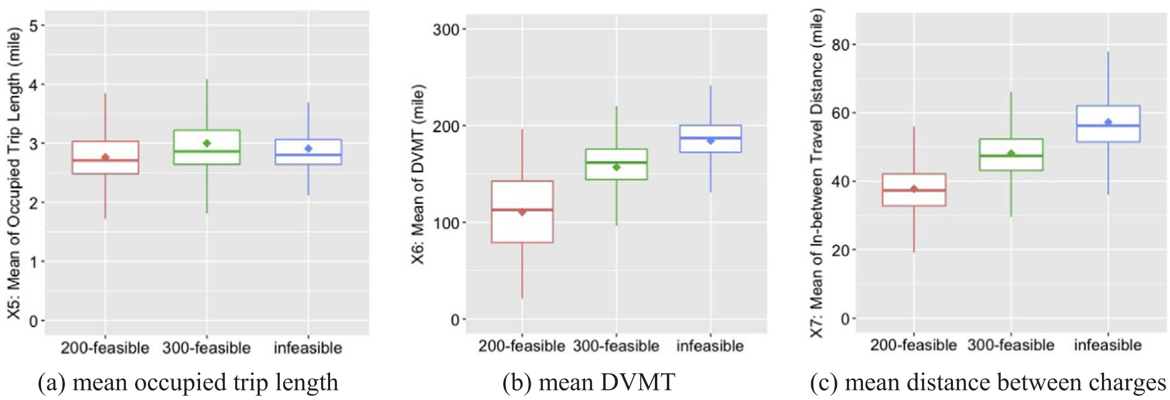
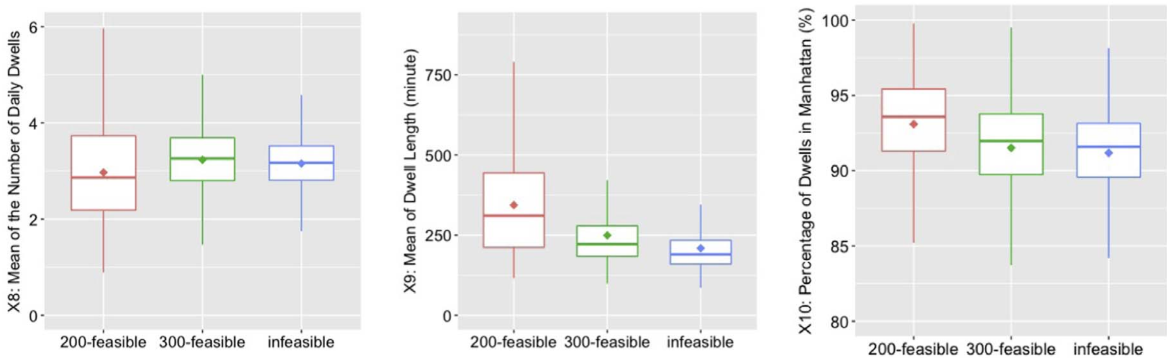



**Fig. 9.** Boxplots by group of travel demand related variables.

charging station after traveling 38 miles. BEV 300-feasible and BEV infeasible taxis, on average, need to drive 48 miles and 58 miles, respectively, to find a charging opportunity. The likelihood of coming across charging opportunities depends on where and how often the driver dwells for more than 30 min. If a taxi usually dwells outside the charging station coverage areas, its chance of switching to a BEV would become lower.

The spatial-temporal dwell patterns are associated with where and when taxis can potentially charge battery. From the boxplots of the mean of daily number of dwells in Fig. 10(a), it is found that BEV 300-feasible and BEV infeasible taxis share similar mean values, that is, around 3.2 dwells per day, but a slightly larger variance is observed in the BEV 300-feasible group. BEV 200-feasible taxis




(a) mean of daily dwells (b) mean of dwell length (c) percent of dwells in Manhattan

**Fig. 10.** Boxplots by group of dwelling related variables.

have even larger variance, peaking at 6 times of dwelling per day, with slightly lower mean and median than the other two groups. The distributions of dwell lengths are shown in Fig. 10(b). BEV 200-feasible taxis have significantly longer dwell durations, with the group mean of 356 min. BEV infeasible taxis dwell for the shortest time period (209 min on average), indicating the time can be used for charging is limited. The spatial dwell feature is represented by the percentage of dwells that occurred in Manhattan, as this borough has wider charger coverage. The results in Fig. 10(c) show that BEV 200-feasible taxis are more likely to dwell in Manhattan (92.7% on average), and correspondingly these taxis have more access to charging facilities.

In summary, from the above analysis, it can be concluded that a taxi with such travel patterns are more suitable to switch to a BEV—fewer daily shifts, fewer different drivers, more shifts per driver conducts in a year, shorter daily driving distance, shorter travel distance between charges, less number of daily dwells but longer dwelling time, and a higher possibility of dwelling in Manhattan.

### *4.4. Factors influencing the change of BEV feasibility*

With the current 280 charging stations, 12,420 taxis are labeled as BEV infeasible. If the additional 372 charging stations are built, 44% of the currently BEV infeasible taxis will become BEV 300-feasible and 3% will become BEV 200-feasible, while the remaining 53% will still be BEV infeasible. To examine how travel patterns influence the change from currently BEV infeasible to BEV feasible (either BEV 200-feaible or BEV 300-feasible) after the expansion of charging network, classification models that use the 10 travel pattern variables as input are developed. Five classification models, including logistics regression, linear discriminant analysis, quadratic discriminant analysis, K-nearest neighbors, Bayes classification and support vector machine, are trained by 70% of the dataset and tested by the rest 30% of the dataset. The training and testing accuracies are shown in Table 4.

Since logistic regression has the highest training accuracy (82.01%) and testing accuracy (81.87%), it is selected to classify BEV feasible taxis and BEV infeasible taxis after the expansion of the charging network. The model form is as follows:

$$\log\left(\frac{p}{1-p}\right) = b_0 + b_1X_1 + b_2X_2 + \ldots + b_{10}X_{10} \tag{6}$$

where $p$ is the probability that a currently BEV infeasible taxi will become BEV feasible when charging network is expanded, and $b$'s are model coefficients. The estimated model parameters are given in Table 5. The Cox & Snell R-square and the Nagelkerke R-square of the model is 0.443 and 0.591, respectively, suggesting a moderate fit. The Wald chi-square test is applied to each estimated coefficient. The significance (smaller than 0.5) associated with the Wald statistics shows that all the coefficients are significantly different from zero, indicating all the 10 variables representing taxi travel patterns have a significant contribution to discriminating BEV feasible and infeasible taxis. Therefore, the logistic regression model can predict whether a currently BEV infeasible taxi will become feasible when charging infrastructure is expanded.

The odds-ratios in Table 5 are exponents of the model coefficients and indicate the impacts of one unit change in the taxi travel

**Table 4**
Training and testing accuracy of classification models.

| Classification model | Training accuracy (%) | Testing accuracy (%) |
|---|---|---|
| Logistic regression | 82.01 | 81.87 |
| Linear discriminant analysis | 81.72 | 81.65 |
| Quadratic discriminant analysis | 79.51 | 79.23 |
| K-nearest neighbors | 77.66 | 77.09 |
| Bayes classification | 76.20 | 76.12 |
| Support vector machine (linear kernel) | 71.98 | 72.05 |

**Table 5**
Estimated parameters of the logistic regression model.

| Variable | Coefficient | Standard deviation | Wald chi-square test statistics | Significance | Odds-ratio |
|---|---|---|---|---|---|
| $X_1$: Mean of the number of daily shifts | 1.388 | 0.176 | 61.963 | 0.000 | 4.009 |
| $X_2$: Mode of the number of daily shifts | −0.076 | 0.092 | 0.675 | 0.411 | 0.927 |
| $X_3$: Number of drivers | −0.007 | 0.001 | 102.783 | 0.000 | 0.993 |
| $X_4$: Number of shifts per driver in a year | 0.003 | 0.000 | 64.656 | 0.000 | 1.003 |
| $X_5$: Mean of occupied trip length | 0.141 | 0.057 | 6.101 | 0.014 | 1.152 |
| $X_6$: Mean of DVMT | −0.055 | 0.004 | 242.337 | 0.000 | 0.947 |
| $X_7$: Mean of travel distance between charges | −0.145 | 0.010 | 215.517 | 0.000 | 0.865 |
| $X_8$: Mean of the number of daily dwells | 0.427 | 0.167 | 6.520 | 0.011 | 1.532 |
| $X_9$: Mean of dwell length | 0.003 | 0.001 | 12.021 | 0.001 | 1.003 |
| $X_{10}$: Percentage of dwells occurred in Manhattan | 0.079 | 0.012 | 42.795 | 0.000 | 1.082 |
| Constant | 3.815 | 1.509 | – | – | 45.365 |

pattern variables on the odds of becoming BEV feasible $\left(\frac{p}{1-p}\right)$. The odds-ratio of $X_7$ is smaller than that of $X_6$, indicating that the BEV feasibility odds are more sensitive to the average travel distance between charges than to the average DVMT. Therefore, improving charger network coverage and reducing the travel distance between charges might be more effective in increasing BEV feasibility than adopting longer range BEVs. In terms of dwell patterns, the currently BEV infeasible taxis are 1.532 times and 1.082 times more likely to become BEV feasible by increasing the average number of daily dwells by 1 (i.e. $X_8$) and increasing the percentage of dwells in Manhattan by 1% (i.e. $X_{10}$), respectively.

## 5. Conclusions and discussions

This paper examines the feasibility of substituting the gasoline-powered yellow taxis in New York City with BEVs from the perspective of the taxi travel patterns. Ten variables are extracted from a whole year taxi trip dataset to characterize the taxi spatial-temporal driving patterns in terms of driver-shift, travel demand and dwelling. An activity-based approach is proposed to quantify the BEV taxi feasibility as the percentage of occupied trips that can be electrified. It is found that the existing charging network in New York City is far from sufficient to satisfy the charging demand of a large-scale electric taxi fleet—only 8% of yellow taxis can complete 99% or more of the occupied trips if switching to BEVs with a range of 200 miles or 300 miles. 372 new charging stations are sited at census tracts of New York City where taxis frequently dwell without available chargers. With the expanded charging network, about half of the currently BEV infeasible taxis may become suitable for a BEV-200 or a BEV-300. In particular, taxis with certain travel patterns are more suitable for BEVs, including fewer daily shifts, fewer assigned drivers, shorter DVMT, shorter travel distance between charging opportunities, less number of dwells but longer dwelling time, and a higher possibility of dwelling in Manhattan.

There are four main caveats in this paper. First, the travel distance, travel time and speed of unoccupied trips are estimated based on adjacent occupied trips, as the actual unoccupied trip information is not available. With street-hailing operations, unoccupied trips may have more detours than occupied trips. However, considering a future scenario when taxis are replaced by BEVs and assisted by the increasingly popular taxi dispatch and e-hailing systems. Taxi drivers will know the location of next customers and drive along the shortest path. As a result, the unnecessary detours of unoccupied trips will be significantly reduced. Second, during emergency charging, the taxi might not have enough electricity to drive to the nearest charging station. After charging is completed, the travel distance from emergency charging station to the next customer is also ignored in the simulation. Since over 90% of taxi pick-ups and drop-offs occur in Manhattan (NYC TLC, 2014), these detour trips are short and have negligible impacts on the BEV taxi feasibility analysis. Third, the study assumes that BEV taxis will serve the same occupied trips as the CGV taxis, except for missing trips due to insufficient range. In practice, the BEV taxi fleet can satisfy the same customer demand without following their original routes. Since the results show how taxis' spatial-temporal travel patterns, in terms of driver-shift, travel demand and dwelling etc., affect electric taxi feasibility, BEV taxis could follow trajectories different from CGV taxis to achieve the same electrification target, as long as the collective travel patterns remain the same. In addition, optimizing the dispatch of taxis to customers can reduce the empty miles and may further improve the BEV feasibility. The taxi dispatching problem is, however, beyond the scope of the present paper. Fourth, charging congestion is not considered. Given the limited public charging resources in New York City, BEV taxis might have to wait for charging at the expense of missing more occupied trips if the charging station is fully occupied. In addition, since usage rates of charging facilities vary over time, charger congestion could be worse during peak hours. Therefore, charging congestion might decrease taxis' BEV feasibility. On the other hand, installing fast chargers at popular locations might alleviate charging congestion. By ignoring the charging congestion issue, we implicitly assume the market efficiency of charging location owners in adding charger capacity or implementing smart grid technologies in response to charging demand.

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