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Predicting market potential and environmental benefits of deploying electric taxis in Nanjing, China

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Keywords

Battery electric vehicles, Taxi service, Charging infrastructure, Taxi apps, GPS trajectory data, Tailpipe emissions

Disciplines

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Comments

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Predicting market potential and environmental benefits of deploying electric taxis in Nanjing, China

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Abstract

This paper investigates the market potential and environmental benefits of replacing internal combustion engine (ICE) vehicles with battery electric vehicles (BEVs) in the taxi fleet in Nanjing, China. Vehicle trajectory data collected by onboard global positioning system (GPS) units are used to study the travel patterns of taxis. The impacts of charger power, charging infrastructure coverage, and taxi apps on the feasibility of electric taxis are quantified, considering taxi drivers' recharging behavior and operating activities. It is found that (1) depending on the charger power and coverage, 19% (with AC Level 2 chargers and 20% charger network coverage) to 56% (with DC chargers and 100% charger network coverage) of the ICE vehicles can be replaced by electric taxis without driving pattern changes; (2) by using taxi apps to find nearby passengers and charging stations, drivers could utilize the empty cruising time to charge the battery, which may increase the acceptance of BEVs by up to 82.6% compared to the scenario without taxi apps; and (3) tailpipe emissions in urban areas could be significantly reduced with taxi electrification: a mixed taxi fleet with 46% compressed-natural-gas-powered (CNG) and 54% electricity-powered vehicles can reduce the tailpipe emissions by 48% in comparison with the fleet of 100% CNG taxis.

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1 Introduction

Battery electric vehicles (BEVs) generate zero tailpipe emissions. Replacing the internal combustion engine (ICE) vehicle fleet with BEVs has the potential to reduce greenhouse gas emissions and other harmful pollutants. The taxi fleet has some desirable features for deploying BEVs. Fuel cost savings are significant, as taxis are driven heavily, and thus the payback period tends to be shorter. In addition, taxis are usually driven in areas with high population density. Deploying BEV taxi fleets can significantly reduce pollutants and noise that are harmful for public health in these highly populated downtown areas (Buekers et al., 2014). In recent years, several electric taxi pilot projects have been deployed around the world, such as in New York City, USA (NYC, 2010), Tokyo, Japan (Kim, 2012), and Shenzhen, China (EVN, 2010). In 2015, the Ministry of Transport in China unveiled its BEV promotional program, which plans to deploy 300,000 BEVs on the road by 2020, including buses, taxis, and urban logistics distribution vehicles (MOT, 2015). Take the city of Nanjing for example, one of the most populated and popular tourist cities in the Yangtze River delta of China, where more than 600 BYD E6 vehicles (a BEV with a range of 200 km in practice (DOE, 2015) and manufactured by the BYD Auto Company Ltd) have been used as taxis since July 2014. Currently, there are 13 BEV charging stations with 286 chargers distributed throughout the city (Qiu, 2014).

Limited driving ranges and long charging times hinder market acceptance of BEVs and may be greater challenges for taxi use. Whereas most passenger electric car drivers can rely on recharging the battery at home during the night, taxi drivers usually need to be out of service for a significant period of time during the day to charge the battery. For example, based on the operational data of taxis in Nanjing, the average daily travel distance of taxis is nearly 350 km in 2014 (NPB, 2015 (a)), which is beyond the range of typical BEVs. Thus, multiple charges during a day are probably needed for most BEV taxis and almost certainly for BEV taxis that are operated continuously day and night by multiple drivers. An analysis conducted by Lee et al. (2014) pointed out that, under the control of an intelligent coordinator, most battery charging can be done using slow chargers during out-of-service intervals (i.e., when vehicles are parked and waiting for customers) for a fleet of taxis in the city of Jeju, Republic of Korea. However, this finding may not be transferrable to cities in China, where taxi drivers tend to cruise around to find customers, instead of waiting to receive reservations from a taxi operator (Zong, 2014). Therefore, out-of-service intervals are scarce and short. With the growing popularity of taxi-hailing apps, taxi drivers in China have started to find customers through such apps, which reduces the empty cruising distance. A taxi's GPS traces offer a good way to analyze the taxi's operational characteristics (Castro et al., 2013), as well as to better plan charging infrastructure to match real world charging needs (Cai et al., 2014).

The deployment of electric taxis is determined by several factors. Government support policies play an important role (Zheng et al., 2012). The local government of Nanjing provides financial support for electric car buyers and in 2015 heavily invested in deploying charging stations around the city. A purchaser of a new BYD E6, whether a taxi company or a personal car buyer, can get a stimulus of $6,000 from the government. Installation of a DC fast charger qualifies for a subsidy of $200 for every kW of charging power (NPB, 2015 (b)). Adequate coverage of charging infrastructure is critical to promote market acceptance of BEVs, which is probably why the government is investing so heavily in installing chargers (Peterson and Michalek, 2013; Pieltain et al., 2011; Xi et al., 2013). Although installation of charging stations has been moving forward in many cities, little research has been done to study how to maximize the market potential given drivers' operating behavior, especially for taxi drivers who may be the major consumer groups of public charging, at least in some Chinese cities in the near term. Additionally, people have come to realize that mobile apps for locating electric vehicle charging stations and providing real-time information help to relieve drivers' range anxiety (Miao et al., 2014). In the foreseeable future, communication technologies will likely offer taxi drivers more charging opportunities if combining the function of taxi-hailing apps and vehicle-charging apps. Charging infrastructure siting strategies will also be affected by the development of mobile communication technologies.

Because BEVs store power in large lithium-ion batteries, which are particularly material- and energy-intensive to produce, their global warming emissions at this early stage usually exceed those of conventional ICE vehicles. The adoption of electric taxis is under debate from the aspect of well-to-wheel energy efficiency. Additionally, it is noted that conventional gasoline vehicle (CGV) taxis have gradually been replaced by compressed natural gas (CNG) taxis in Nanjing since 2012. The percentage of Nanjing's taxi fleet consisting of CNG fueled bi-fuel taxis reached 96% in 2014. Similar shifts to CNG taxis have taken place in other Chinese cities as well, which are promoted as a climate change mitigation strategy because CNG has lower carbon per unit energy than coal or oil. But methane (CH_4), the prime constituent of natural gas, is itself a more potent greenhouse gas (GHG) than carbon dioxide (CO_2), which can offset benefits from fuel-switching (Alvarez et al., 2012). In addition, increases in HC and NOx emissions were observed for CNG taxis compared with gasoline vehicles (Yao et al., 2014). So far, no detailed research has been done to assess the environmental effects caused by the shift from CNG taxis to BEV taxis.

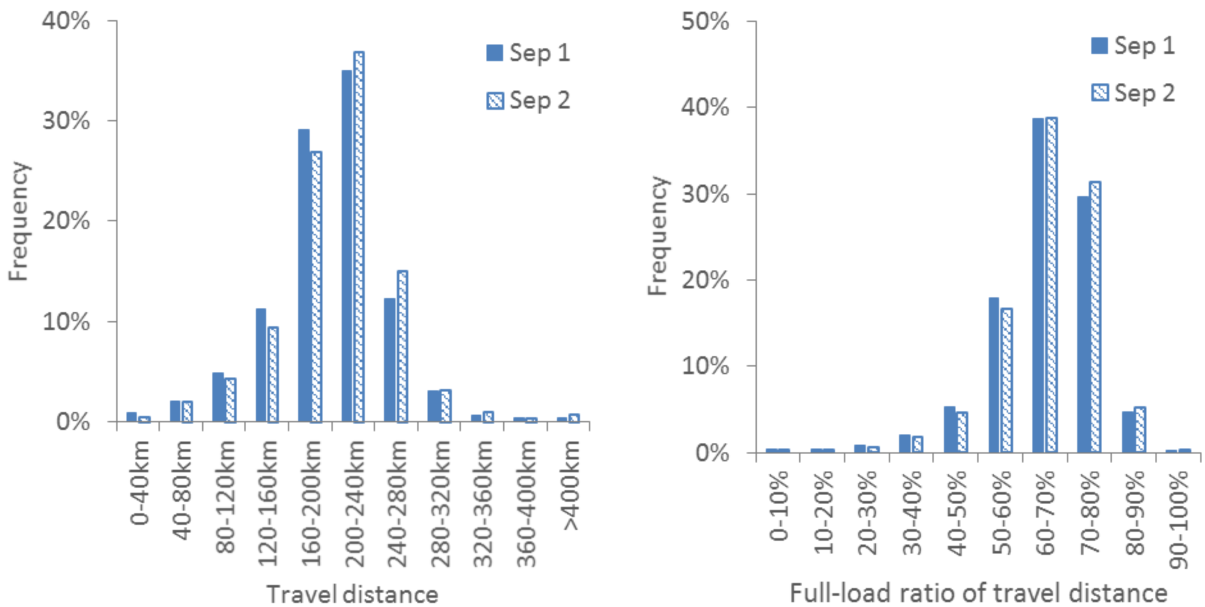
The objective of this paper is to predict the market potential of electric taxis in urban areas of Nanjing, China, and quantify the associated health and environmental benefits. GPS-tracked vehicle trajectory data collected from CGV taxis in Nanjing, China, in 2010 are used to examine the feasibility of replacing CGV or CNG vehicles with BEVs—that is, whether limited-range BEVs can accomplish the driving activities of conventional taxis or not, with opportunities to charge during idle time. This study simulates BEV taxi drivers' driving and charging behaviors and evaluates the impact of charger power, charging station coverage, and taxi apps on electric taxi feasibility. The findings from the study have the potential to assist policy makers in allocating public resources efficiently in aiding the deployment of electric taxis.

2 Data Description

In Nanjing, like most cities in China, taxis play an important role in intra-urban transportation. According to the 2011 Nanjing Transport Annual Report, by the end of 2010 there were 10,145 taxis in the city, and more than 252 million person-trips were carried by taxis in that year. The total annual operational travel distance of taxis reached 1.2 billion kilometers. All commercial taxis in Nanjing are required to install GPS devices for the purpose of fleet monitoring by the government. A GPS signal is captured roughly every 10 seconds for each taxi. The data include each taxi's time-stamped location (i.e., longitude and latitude), spot speed, azimuth, and operational status (i.e., empty or occupied).

This research uses a dataset collected on Wednesday Sep. 1 and Thursday Sep. 2 in 2010[1]. Due to unknown reasons, the two-day data are discontinuous. Data are available from only 12:00 AM to 10:30 PM on Sep. 1 and 7:40 AM to 11:59 PM on Sep. 2. Delays or missing data may occur depending on the GPS signal. All trajectories were cleaned by removing invalid points caused by data recording or transmission errors. Combining the two days' data, there are a total of 697,475 trips extracted from 11,914 taxis (5,928 samples from the dataset of Sep. 1 and 5,986 samples from the dataset of Sep. 2).

Although the combined dataset is not around-the-clock, the busy time of day is covered. Fig. 1 compares the frequency distributions of the total travel distance and full-load ratio per vehicle during the period 8:00 AM to 10:00 PM on the two days. The full-load ratio of travel distances is calculated as the occupied distance divided by the total travel distance. The distributions show no significant difference between the two days' records. The performance measures of these two days share a similar proportion at various levels, which helps capture the characteristic features of taxi travel patterns. Since the taxi service is not mainly used for commuting, there is no strong evidence to show the difference in travel patterns between weekdays and weekends (NYC Taxi and Limousine Commission, 2014). Thus, we assume the dataset is representative of taxi operations on a typical day.



(a) (b)

Fig. 1. Operational characteristics of the two-day dataset from 8:00 AM to 10:00 PM: (a) distributions of travel distances and (b) distributions of full-load ratios by travel distance.

Fig. 2. plots the distribution of the taxi fleet's daily travel distances. As determined from the recorded data, taxis on average traveled about 265 km per day (because of the missing data, the actual daily vehicle kilometers traveled (VKT) should be larger than this value). When the 12 AM–7:39 AM data on Sep. 1 are pooled with the 7:40 AM–11:59 PM data on Sep. 2, the average

[1] Data source: http://www.datatang.com/data/44074. Access date: June 12, 2015

daily travel distance is 313 km, with a standard deviation of 80.61 km. Since the BYD E6 is the current electric taxi model used in Nanjing, the technical parameters of the E6 are adopted in this study. Although BYD Auto Company claims the range of the E6 to be around 300 km (186 miles) (BYD, 2014), the Environmental Protection Agency's (EPA's) test data show the current E6's range in practice is about 200 km (DOE, 2015). Therefore, in this study we assume 200 km as the electric taxis' range. Only 18.33% of total vehicles traveled less than 200 km (i.e., the BEV range). If replaced by BEVs with a 200 km driving range, these taxis would not run out of battery range even if there is no charging opportunity during the operating period. The rest of the taxis need to recharge during the operating period in order to complete all activities. The conclusion may be less optimistic if the uncertainty of the real-world BEV driving range, due to weather, terrain, driving style, load, and other factors, is taken into account (Rodgers et al., 2014; Yuksel and Michalek, 2015).

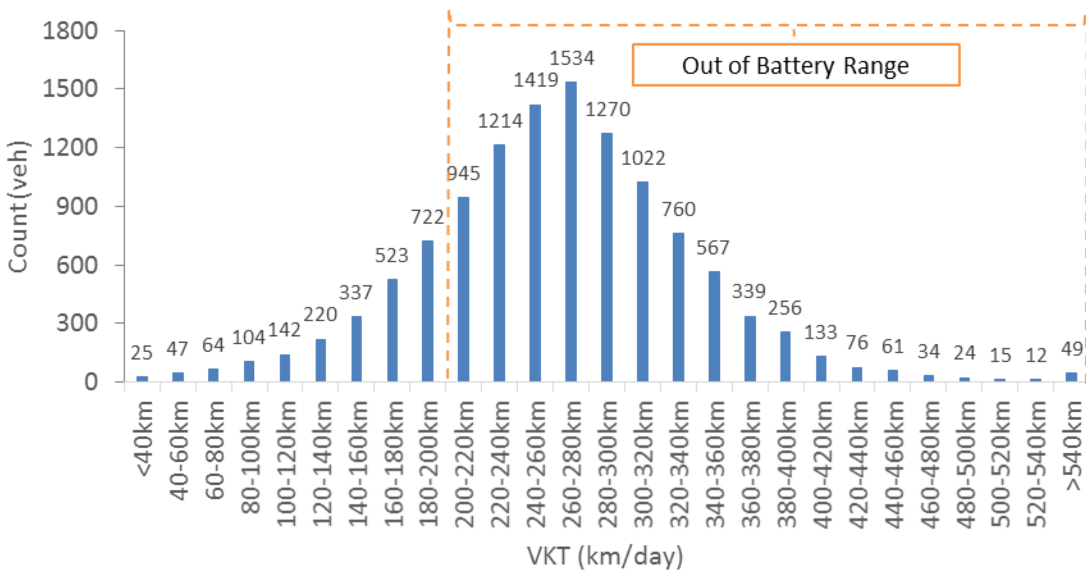


Fig. 2. Distribution of taxi fleet's distance traveled per day.

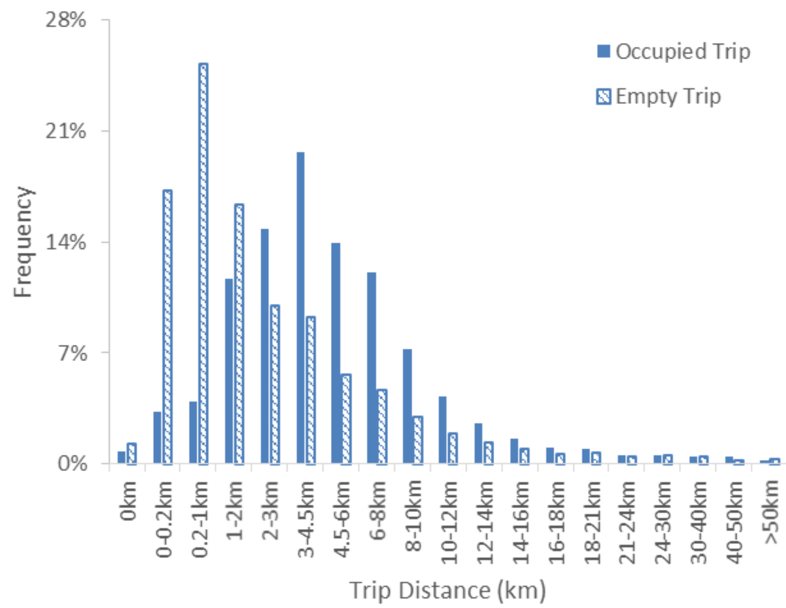


Fig. 3. Distribution of trip distance.

The dataset included 346,784 occupied trips with an average trip length of 5.71 km (st.d.=6.72 km) and 350,691 empty trips with an average trip length of 3.29 km (st.d.=6.69 km). Fig. 3 presents the trip length distributions of occupied and empty trips. The long-tailed distributions result in high standard deviations. In particular, there are 21 occupied trips and 26 empty trips exceeding the BEV range (i.e., 200 km), with a maximum trip length of 402.5 km. The long empty trips likely occurred when taxis provided daily chartered services, in which case taxi drivers usually negotiated a fixed price with the passengers instead of charging by distance (i.e. the trip is labeled as “empty” in the database). Although such long-distance trips are not suitable for BEVs given current charger network coverage, these records are kept in the dataset for BEV feasibility analysis to represent the realistic operational characteristics of taxis.

The empty trips were divided into two categories, namely, the dwell event and the cruising trip. A dwell event is when the vehicle is parked at a certain location for more than 20 minutes while unoccupied. The dwell events mainly occurred from 12:00 PM to 1:30 PM (i.e., lunch time for the drivers) and from 5:30 PM to7:30 PM (dinner time and shift change between two drivers). It seems counterintuitive that taxis dwell during the evening rush hours which are presumably one of the busiest time of day for taxi service. But heavy traffic and low travel speed reduce the operational efficiency and increase fuel consumption. Taxi drivers are reluctant to operate during this period and would rather head to suburban fueling stations during the rush hours. A cruising trip is defined as the time and distance traveled between the ending of one occupied trip and the beginning of the next occupied trip without parking. Since the empty taxis are usually cruising around to search for customers, assisted with the taxi apps and electric vehicle charging apps, an empty taxi could easily find the nearby passenger and the nearest charging station. Fig. 4 plots the distribution of time length during the cruising period and the dwell periods. Among all the cruising trips, 12.7% of the trips lasted more than 20 minutes, which could potentially be used for BEVs’ charging.

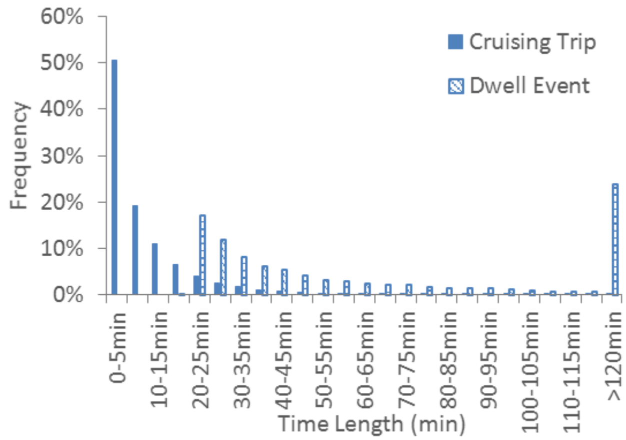


Fig. 4. Distribution of trip time during the cruising period and the dwell period.

3 Method

In the context of personal vehicles, GPS tracked vehicle trajectory data, collected from conventional gasoline vehicles and representing real world travel activities, have been used for assessing market potential and estimating energy consumption of plug-in electric vehicles. For example, travel activities collected from GPS-instrumented vehicles in the St. Louis metropolitan area (Gonder et al., 2007) and Austin, Texas (Dong and Lin, 2012), have been used for analyzing plug-in hybrid electric vehicle energy efficiency. Multiday GPS vehicle data have also been used to analyze BEV range requirements in selected areas, including Winnipeg, Canada (Smith et al., 2011), the Atlanta, Georgia greater metropolitan area (Pearre et al., 2011), and the greater Seattle, Washington metropolitan area (Dong et al., 2014). GPS-based taxi trajectory data have been used to site public electric vehicle charging stations in Beijing, China (Cai et al., 2014), and Seoul, Korea (Jung et al., 2014). In this study, we use the GPS trajectory data collected from conventional gasoline taxis and examine the feasibility of partially replacing the ICE vehicles with BEVs in the taxi fleet.

3.1 Scenarios

3.1.1 Charging power

Charging equipment for BEVs is classified by the rate at which the batteries are charged. The SAE J1772 standard defines two levels of AC chargers. AC Level 1 chargers, using a standard 120 voltage, 12 to 16 ampere branch circuit, are suitable for overnight home charging and possibly workplace charging. AC Level 2 equipment offers charging through 240 voltage electrical service, requiring a dedicated circuit of 20 to 100 ampere, depending on the electric vehicle supply equipment (EVSE) requirements. The SAE J1772 committee has also proposed a DC connector based on the SAE J1772-2009 AC connector shape with additional DC and ground pins to support charging at 200–450 voltage DC and 80 ampere (36 kW) for DC Level 1 and up to 200 ampere (90 kW) for DC Level 2. The SAE DC Level 3 charging levels have not been determined, but the standard as it exists as of 2009 has the potential to charge at 200–600 voltage DC at a maximum of 400 ampere (240 kW) (SAE, 2011).

It is noted that not all the charging power can be directly transferred to battery energy, and a portion of the power is lost during the charging process. Let α denote the charging efficiency. In this paper, we set α as 1.3 (Nie and Ghamami, 2013). For example, if the input charging power is 78 kW, the effective charging power is 60 kW. Five levels of effective charging power are considered, 60 kW, 45 kW, 20 kW, 7 kW, and 3.3 kW, respectively (Table 1). Theoretically, depending on the masses of the electrode materials, the acceptable charging current is determined by initial state of charge (SOC) and internal resistance of the EV battery. The higher the SOC remains, the lower the acceptable power is (Meissner and Richter, 2003). However, in the range of SOC from 15% to 90%, the power outlet is fairly stable, which is not true at an extra-low or extra-high SOC. In order to extend the battery life, BEV taxi drivers are encouraged to charge the battery before the SOC drops below 20%. Moreover, taxi drivers usually do not want to wait a long time for the battery to be fully charged and are more likely to charge up to 90%. Therefore, we assume the input power remains constant during the charging process in the subsequent analysis.

Table 1
Electric vehicle charger specification.

Charger type	DC60	DCL2-45	ACL2-20	ACL2-7.0	ACL2-3.3
Effective charging power (kW)	60	45	20	7.0	3.3

3.1.2 Potential charger location

The place where a taxi is parked more than 20 minutes while unoccupied (namely, where the taxi dwells) represents a charging opportunity for the taxi without requiring behavior change from the driver. Therefore, locations where many taxis choose to park are considered as potential charging station locations. In order to find the popular destinations where taxis are parked, the study area is discretized into cells. The region is limited to 31.23° – 32.63° *N*, 118.35° – 119.24° *E* to remove outliers and limit the parking spots within the city boundary. Each cell is with the quadrate edge of 0.005° latitude and longitude, approximately equivalent to 0.5×0.5 km^2. For each cell, the number of parked vehicles (i.e. dwell events) is counted, and 1,868 valid cells have the records of dwell events amounting to 38,303 times. Based on the frequency distribution, the valid cells are classified into five categories, defined as C*p* (*p=1*, *2*, …, *5*). Categories are ranked by the number of vehicles that parked in the cells.

Each category covers 20% of the dwell events, approximately 7,661 events on average. Table 2 lists the numbers of the valid cells and dwell events for each category. Category C1 includes 16 cells where a total of 7,677 taxis parked during the two-day period. In particular, 1,448 taxis parked at the most popular cell, where a charging congestion problem might be observed if charging infrastructure is built. The GPS coordinates reveal that such popular parking spots are mainly located at the airport or railway stations of Nanjing. Category C5 accounts for 79% of the total valid cells and has the largest average dwell time. These locations are least favorable for placing fast chargers. Fig. 5 shows the spatial distribution of valid cells. The cells in Categories C1, C2, and C3 are mostly located in the densely populated area of the inner city. The cells in Category C5 are scattered in the outlying areas of downtown. Three of the thirteen existing charging stations are located in the cells of Categories C4, seven are located in the cells of Categories C5, and the rest are located in the place where no taxis dwell in during the two days.

We speculate that due to the land restrictions, the newly-built, large stations have to be sited outside the downtown area.

Table 2

The summary of category characteristics for potential charger location.

Category		C1	C2	C3	C4	C5
No. of valid cells		16	57	105	210	1480
No. of dwell events		7677	7674	7631	7673	7648
No. of dwell events per cell	Max	1448	220	96	54	24
	Min	221	97	55	25	1
Dwell time (min)	Mean	59.35	89.34	102.92	120.05	134.82
	St.d.	66.28	114.75	125.44	139.37	148.04

Varying levels of charger network coverage are considered to examine their impacts on the electric taxis' market potential. We adopt a symbol C(1:*P*), which means the cells in the aggregated categories of C*p* ($1 \leq p \leq P$), namely, C(1:*P*)={C1, C2, …, C*P*}. In particular, case C(1:1) assumes that chargers are installed at the cells in Category C1, which include the top 1% of the valid cells and cover 20% parked vehicles. Case C(1:2) assumes that chargers are installed at the celled in Category C1 and C2, which include top 4% of the valid cells and cover 40% parked vehicles. Case C(1:3) includes the top 10% of the valid cells, covering 60% of parked vehicles. Case C(1:4) includes the top 21% of the valid cells and covers 80% parked vehicles. Case C(1:5) assumes that chargers are installed at all of the valid cells where vehicles are parked during the study period.

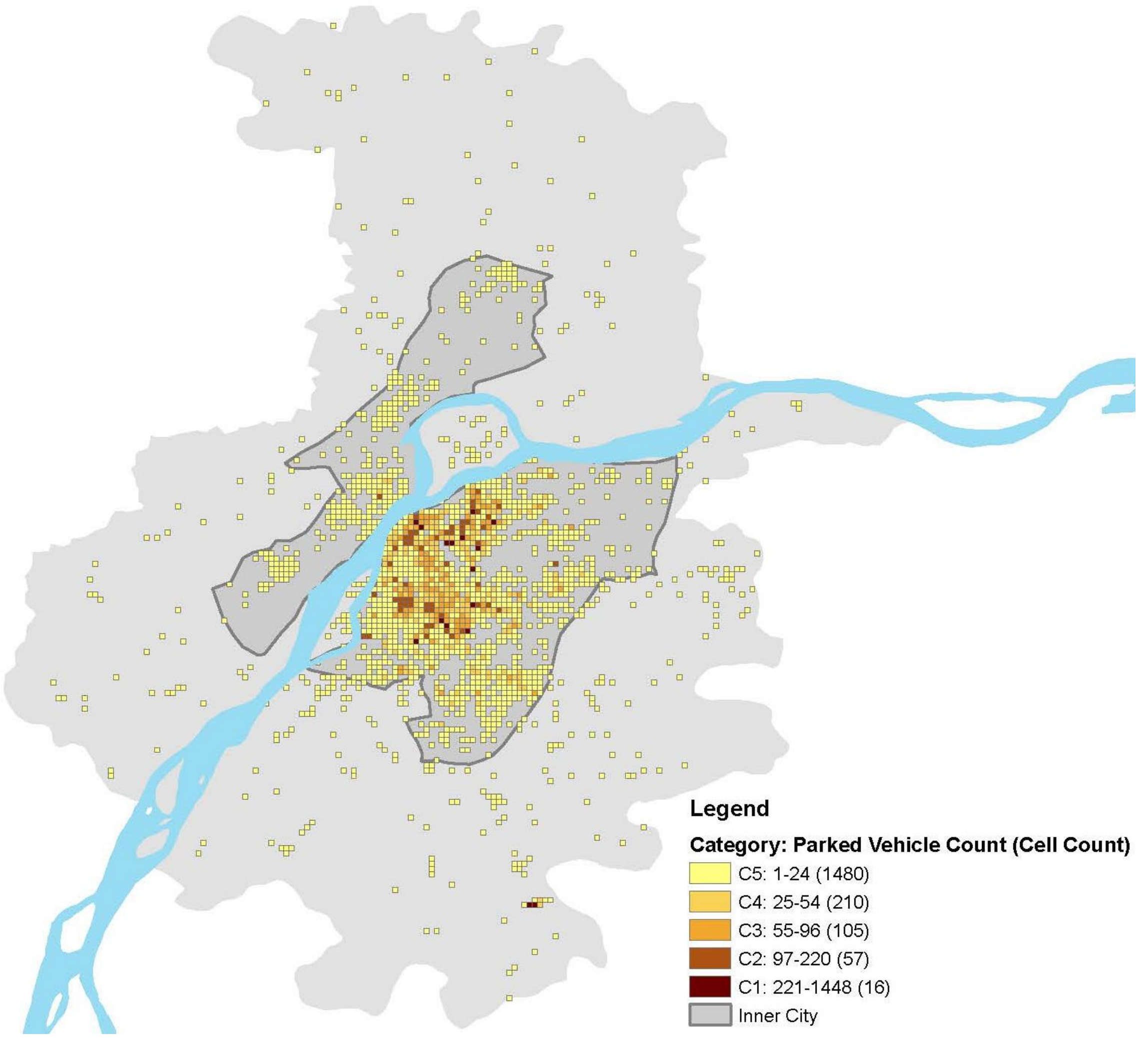


Fig. 5. Distribution map of potential charger location.

3.1.3 Taxi Apps

With the rapid development of mobile commerce, taxi apps are experiencing rapid growth and changing the way traditional taxi services do business. Current prevalent mobile apps on taxi dispatching help drivers and passengers find each other, and it is foreseeable and operable to help drivers find charging stations and schedule their itineraries as well. The taxi-hailing apps, coupled with EV charging apps, have the potential to increase the charging opportunity for an empty EV taxi by reducing cruising trips. We assume the battery can be charged only during the dwell time if a taxi app is not available. While with the help of taxi apps, drivers are assumed to know the pick-up location and time of the next passenger and the nearby charging stations. Thus, the long empty cruising trips can potentially be used to charge the BEVs.

Two types of charging scenarios are illustrated in Fig. 6. In the scenario of dwell charging, drivers charge the battery when the vehicle is parked more than 20 minutes during a dwell event. The scenario of cruising charging assumes drivers know the next pick-up time and location via taxi apps. If there is enough time for charging and there is a charger nearby, the driver may choose to charge the battery while waiting, instead of cruising around. Specifically, apart from the detour time, if the remaining time for charging exceeds 20 minutes, the empty cruising trip offers a detour charging opportunity. To reduce the detour distance, the driver will charge only when the closest charging station is within a range defined by the drop-off spot and the subsequent pick-up spot, that is, the rectangle determined by Q1 and Q2 as illustrated in Fig. 6. Given the coordinates of Q_1 and Q_2, that is, (x_{Q_1}, y_{Q_1}) and (x_{Q_2}, y_{Q_2}), respectively, any charging station with an x-coordinate within (x_{Q_1}, x_{Q_2}) and a y-coordinate within (y_{Q_1}, y_{Q_2}) is considered as a potential location to charge. If multiple charging stations are within this range, taxi drivers are assumed to choose the one with the shortest detour distance.

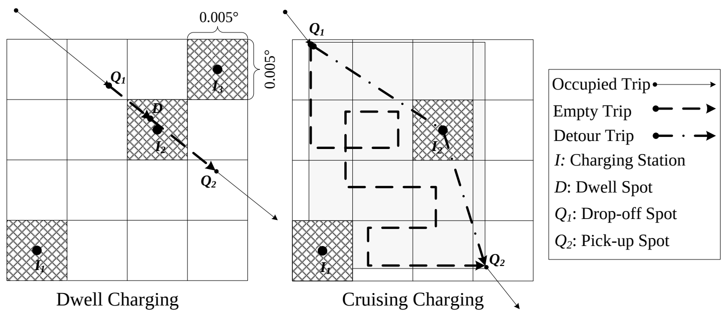


Fig. 6. Dwell charging and cruising charging.

3.2 Simulation

Consider a set of candidate cells *I*={1, 2,…, *m*} for installing charging stations and a set of electric taxis *J*={1, 2,…, *n*}. An electric taxi is considered feasible for taxi *j* if all the trips that are conducted by a conventional gasoline vehicle can be completed when switching to a BEV. 11,914 taxis (i.e., *n*=11,914) with the intraday consecutive trip records are used for simulation. Vehicles' trajectories, including trip distance and the idle time between two consecutive occupied trips, and BEV characteristics, including the battery range and electricity consumption rate, are known. These input variables are defined as follows:

$D_{j(k)}$ Travel distance of taxi *j*'s *k*-th trip (km).

$T_{j(k)}$ Time duration of taxi *j*'s *k*-th trip (min).

R_j Electric range of BEV *j* (km).

r_j Electric consumption rate of BEV *j* (kWh/km).

A set of additional parameters is defined and used in the model. By changing the value of these parameters, hypothetical scenarios can be generated to study the impact of various factors on BEV market potential and the associated environmental benefits.

$O_{j(k)}$ Charging opportunity during taxi *j*'s *k*-th trip (=0, if no charger installed within the coordinates' range of the drop-off spot and the subsequent pick-up spot; =1, if charging opportunity is available).

$T^d_{j(k)}$ Detour time when taxi *j* goes to the nearby station for charging during the *k*-th cruising (min).

$D^d_{j(k)}$ Detour distance when taxi *j* goes to the nearby station for charging during the *k*-th cruising (km).

$V^d_{j(k)}$ Detour velocity when taxi *j* goes to the nearby station for charging during the *k*-th cruising (km/h).

$T^{c}_{j(k)}$ Charging time during taxi *j*'s *k*-th trip (min).

$T^{s}_{j(k)}$ Setup time for charging during taxi *j*'s *k*-th trip, including parking, paying and plugging in the vehicle (min).

P_i Effective charger power at candidate cell $i \in I$ where chargers are installed (kW).

$E_{j(k)}$ Energy obtained from the charging place of taxi *j*'s *k*-th trip (kWh).

$R^{c}_{j(k)}$ Range increase from the recharge at the charging place of taxi *j*'s *k*-th trip (km).

$R^{r}_{j(k)}$ Remaining range when taxi *j* arriving at the charging place of the *k*-th trip (km).

The entire fleet is assumed to be BYD E6 with a 200 km range (i.e., R_j=200, $\forall j$). The average electricity consumption rate is 0.2 kWh/km (i.e., r_j=0.2, $\forall j$) (EVN, 2010). For each charging opportunity, charging time $T^{c}_{j(k)}$ should be at least 20 minutes, including a 2-minute setup time (i.e., $T^{s}_{j(k)}$=2, $\forall j, k$). The charging time, $T^{c}_{j(k)}$, can be expressed as below

$$T^{c}_{j(k)} = \begin{cases} 0, \text{ when taxi } j\text{'s } k-\text{th trip is an occupied trip} \\ T_{j(k)}, \text{ when taxi } j \text{ dwells during the } k-\text{th trip} \\ T_{j(k)} - T^{d}_{j(k)}, \text{ when taxi } j\text{'s } k-\text{th trip is a cruising trip} \end{cases} \quad \text{Eq. (1)}$$

In Eq. (1), the detour time $T^{d}_{j(k)}$ is determined by the detour distance $D^{d}_{j(k)}$ and the detour velocity $V^{d}_{j(k)}$. In most cases, the detour distance is less than the empty cruising distance, since the taxi has to wander around to find the next passenger. As shown in Fig. 6, $D^{d}_{j(k)}$ is simplified as the summation of the Euclidean distance from Q_1 to I_2, and from I_2 to Q_2. I_2 is assumed to be at the center of the cell. $V^{d}_{j(k)}$ is set as 25 km/h.

The initial range of each BEV is set as R_j .When the daily VKT exceeds the BEVs' range, that is, $\sum_k D_{j(k)} > R_j$, taxi drivers need to recharge the battery at some charging stations so as to complete the remaining trips. The drivers are assumed to consider recharging after the SOC has dropped below 50% (Zou et al., 2016). Therefore, under the circumstance that (1) $R^{r}_{j(k)} \leq R_j$ ×50%, (2) $T^{c}_{j(k)}$ ≥20 min, and (3) $O_{j(k)}$=1, the vehicle is charged and the energy obtained from the charger is expressed as below:

$$E_{j(k)} = P_i \times (T^{c}_{j(k)} - T^{s}_{j(k)}) \quad \text{Eq. (2)}$$

The energy increase in the battery, measured in distance, can be calculated based on the battery's state of charge, charging power, and charging time.

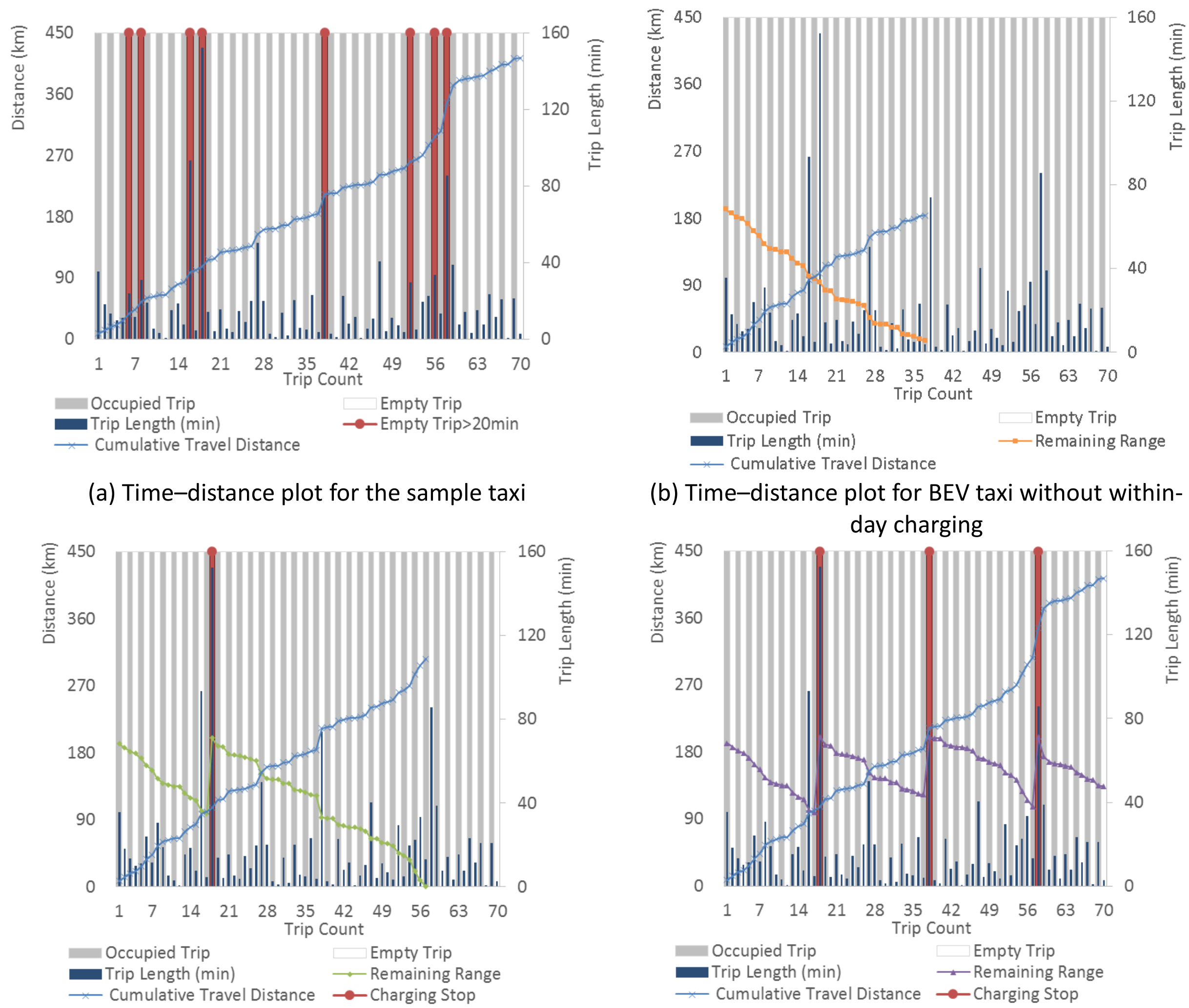
$$R^{c}_{j(k)} = \min\{R_j - R^{r}_{j(k)}, E_{j(k)}/r_j\} \quad \text{Eq. (3)}$$

The pre-charging SOC of the BEV at the charging place of the *k*-th trip ($R^{r}_{j(k)}$) can be calculated on the basis of battery SOC at the previous stop, possible recharge, and trip distance:

$$R^{r}_{j(k)} = R^{r}_{j(k-1)} + R^{c}_{j(k)} - D_{j(k)} \quad \text{Eq. (4)}$$

A negative pre-charging SOC ($R^{r}_{j(k)}$) indicates that the range of the electric taxi is insufficient to complete the daily travel. Thus, the *k*-th trip and all subsequent trips on the travel day are considered as missed trips.

Fig. 7 illustrates the travel and charging activities derived from the GPS trajectory data of one taxi. Assume the battery is fully charged at the beginning of the day. There are eight potential charging stops selected from empty trips with the time length more than 20 minutes (Fig. 7 (a)). If the vehicle is not recharged during the day, as shown in Fig. 7 (b), the electric taxi would run out of the battery during the 37th trip. If the taxi can be fully recharged at the dwell stop, as illustrated in Fig. 7 (c), the range can be extended to the 57th trip. Under the assumption that the taxi could be charged during some of the empty cruising times, the charging time of which exceed 20 minutes apart from detour time, as shown in Fig. 7 (d), all the trips can be completed.



(a) Time–distance plot for the sample taxi

(b) Time–distance plot for BEV taxi without within-day charging

(c) Time–distance plot for BEV taxi with dwell charging

(d) Time–distance plot for BEV taxi with dwell charging and cruising charging

Fig. 7. Time–distance plot for travel and charging activities of an example taxi.

Since the charging station capacity constraint is not considered in the proposed simulation process, potential charging congestion, that is, a vehicle arrives at a charging station when all chargers are occupied, is ignored. At an early market with a small number of BEVs on the road, charging congestion may be rare. With more BEVs on the road, it is likely that smart grid technologies will be used to coordinate queuing and charging for multiple vehicles. Consideration of queuing and charger capacity will significantly increase the complexity of the simulation model and is an important issue to be addressed in future research.

4 Results and discussion

4.1 Charging power and network coverage impact

Table 3 shows the simulation results under different charging power and charging infrastructure coverage scenarios. It is not surprising that the percentage of BEV feasible taxis increases with increased charging power and network coverage. At the network coverage of C(1:1), when 16 cells are equipped with DC60 chargers potentially serving 20% parked vehicles, it is feasible to replace 22.49% of the taxis with BEVs without driving pattern changes. In fact, since 18.33% of the samples traveled less than 200 km in a day, it is feasible to replace only 4.16% of the taxis with BEVs as a result of installing these public chargers. However, if drivers can also use the cruising time to charge, enabled by taxi apps, the BEV feasibility is improved to 37.02% with the same charger coverage.

At the early stage of the electric taxi deployment with a limited budget for installing chargers, it is a trade-off between expanding the charger network coverage using lower power chargers and installing high power chargers at fewer locations. From Table 3 it can be found that, to make 30% of the taxis BEV feasible, one can either allocate ACL2-20 chargers at the coverage of C(1:3) (i.e., in 178 cells) or ACL2-7.0 chargers at the coverage of C(1:5) (i.e., in 1,868 cells). The simulation results suggest installing high power chargers if ACL2-3.3 and ACL2-7.0 chargers dominate the current market. But when the chargers with power more than 20 kW are deployed, it is preferred to improve the infrastructure coverage with the same type of chargers. For example, under the scenario of dwell charging, if current charger coverage is C(1:2) with charging power of ACL2-7.0, by upgrading to a higher charging power of ACL2-20, 3.35% improvement can be achieved, while by increasing the coverage to C(1:3), only 2.26% improvement can be achieved. But if the current charger is ACL2-20 with the coverage of C(1:2), upgrading to a higher charger gains 2.73% improvement, which is less than the improvement of 5.15% by increasing the network coverage to C(1:3). This result is different from the strategy of public charging infrastructure investment for private electric vehicles (Dong et al., 2014). In the context of private electric vehicles, installing more low-cost and low power chargers (e.g., ACL2-3.3 and ACL2-7.0) is encouraged instead of installing fewer expensive and high power chargers. The fast chargers are prerequisite since taxi drivers do not want to waste precious operating time on battery charging. When the charging time is less than 2 hours (correspond to a charging power more than 20 kW), the impacts of charging power on the electrification rates become less sensitive.

Table 3

Percentage of feasible taxis under the scenarios of dwell and cruising charging.

Network Coverage \ Charging Type / Charger Power	Dwell Charging					Cruising Charging					Legend
	DC60	DCL2-45	ACL2-20	ACL2-7.0	ACL2-3.3	DC60	DCL2-45	ACL2-20	ACL2-7.0	ACL2-3.3	80% 70%
C(1:5)	56.14%	54.13%	44.34%	30.43%	23.96%	78.69%	76.93%	65.30%	39.40%	27.48%	60%
C(1:4)	45.38%	43.61%	36.06%	26.21%	21.92%	70.28%	68.10%	56.39%	33.78%	25.03%	50%
C(1:3)	35.74%	34.44%	29.28%	23.04%	20.43%	61.52%	59.13%	48.00%	29.32%	23.06%	40%
C(1:2)	27.40%	26.86%	24.13%	20.78%	19.42%	50.04%	48.03%	38.33%	25.40%	21.40%	30%
C(1:1)	22.49%	22.34%	21.26%	19.55%	18.74%	37.02%	35.67%	29.25%	22.03%	19.73%	20%

The charger installation cost is determined by several factors such as the charger type, number of chargers at the station, station location, grid capacity, labor cost, and permit fee. The costs vary greatly depending on the types of chargers and charging stations. Single-port chargers with AC Level 2 capabilities can cost $1,000-2,000 excluding installation and potential electrical upgrades in order to provide the appropriate outlet near the EV parking spot, while the cost of

DC fast chargers can be as high as $10,000-$40,000 depending on the features and brands (Delucchi et al., 2013, Schroeder and Traber, 2012, Agenbroad and Holland, 2014). Since charging congestion is not considered in the simulation, the number of chargers for each valid cell cannot be estimated in this study. Additionally, charger installation costs are highly variable depending on the location of the site. Curbside and surface lot stations tend to be much more expensive than parking garage installations (Agenbroad and Holland, 2014). If detailed cost data are available, the cost-effectiveness assessment can be conducted, and the tradeoff between extending the coverage and upgrading to faster chargers can be concluded. However, it needs to be further studied and is beyond the scope of this article.

4.2 The improvement with taxi apps

With the help of taxi apps, the number of feasible vehicles increases significantly. The rates of increase, in terms of improvement of BEV feasibility due to taxi apps, are listed in Table 4. In particular, when 4% of valid cells (i.e., C(1:2)) are installed with the most powerful chargers, if assisted by taxi apps, the feasibility rises from 27.40% to 50.04%, occurring with a most efficient improvement of 82.60%. It is worth noting that taxi apps have a more prominent effect when the charging power increases, yet the improvements have a non-monotonic relationship with increasing charger network coverage. The fast chargers markedly reduce charging time and offer cruising taxis more charging opportunities. However, the detour distance and detour time are not dramatically shortened by increasing the coverage of chargers. That is because even when all the valid cells have chargers installed, the total coverage area is about 467 km^2 (the area of each cell is about 0.25 km^2, and there are 1,868 valid cells in all). The study area includes nine urban and suburban districts of Nanjing—Xuanwu, Gulou, Qinghuai, Jianye, Yuhua, Qixia, Pukou, Luhe, and Jiangning Districts—with a land size of 4,733 km^2. Therefore, taxis drivers might not be able to find a nearby charger when less than 10% of the city area is covered by charging stations.

Table 4

Rate of increase for feasible vehicle by using taxi apps.

Charger Power / Network Coverage	DC60	DCL2-45	ACL2-20	ACL2-7.0	ACL2-3.3	Average
C(1:5)	40.16%	42.12%	47.26%	29.49%	14.72%	34.75%
C(1:4)	54.88%	56.16%	56.38%	28.85%	14.17%	42.09%
C(1:3)	72.15%	71.70%	63.96%	27.25%	12.86%	49.58%
C(1:2)	82.60%	78.81%	58.85%	22.21%	10.20%	50.54%
C(1:1)	64.55%	59.71%	37.58%	12.71%	5.28%	35.97%
Average	62.87%	61.70%	52.81%	24.10%	11.44%	42.58%

Sensitivity analyses are conducted to evaluate the impacts of the key assumptions including battery range (R_j), electric consumption rate (r_j), setup time ($T^s_{j(k)}$) and detour velocity ($V^d_{j(k)}$). The results are calculated under the scenario that the average charging power is 45kW and the network coverage is 60% (Table 5). With the increase of battery range, the BEV feasibility is improved significantly, especially for the scenario when vehicles can be charged only during the dwell time. Compared with the scenario of cruising charging, vehicles under the scenario of dwell charging have less chance to charge during operating periods, which makes long-range BEVs more favorable. Negative correlation is observed between BEV feasibilities and electric consumption rates. With the development of technical innovation, electric consumption rate is expected to decrease which will result in a higher acceptance of BEV taxis. If wireless charging and automatic payment are available, the setup time would be decreased. However, the feasibility changes slightly with the setup time. Detour velocity only has the impact on cruising charging. Lower detour velocity is detrimental to the BEV feasibility since charging time will be insufficient if too much time is spent on detouring.

Table 5
Parametric sensitivity analysis.

Range (Baseline: R_j=200 km)					
R_j Increment		-25%	+25%	+50%	+75%
Feasibility Increment	Dwell Charging	-37.1%	+54.5%	+123.8%	+165.1%
	Cruising Charging	-23.6%	+23.9%	+46.7%	+60.3%
Electric Consumption Rate (Baseline: r_j=0.2 kWh/km)					
r_j Increment		-50%	-25%	+25%	+50%
Feasibility Increment	Dwell Charging	+6.1%	+3.8%	-3.8%	-7.2%
	Cruising Charging	+6.1%	+4.0%	-4.0%	-7.9%
Setup Time (Baseline: $T^s_{j(k)}$=2 min)					
$T^s_{j(k)}$ Increment		-50%	+100%	+200%	+300%
Feasibility Increment	Dwell Charging	0.5%	-1.4%	-2.9%	-4.2%
	Cruising Charging	0.8%	-1.3%	-3.2%	-4.9%
Detour velocity (Baseline: $V^d_{j(k)}$=25 km/h)					
$V^d_{j(k)}$ Increment		-50%	-25%	+25%	+50%
Feasibility Increment	Cruising Charging	-13.9%	-6.0%	+4.8%	+8.3%

4.3 Environmental impact

A life cycle analysis of BEVs' emissions conducted by the union of concerned scientists (UCS, 2015) found that battery electric cars generate half of the emissions of the average comparable gasoline cars, even when pollution from battery manufacturing is accounted for. The vast bulk of auto-related carbon emissions come from operations, not from manufacturing. The higher manufacturing emissions of a BEV are quickly offset by emissions savings from driving the vehicle. The offset occurs as fast as six months or at most within three years. Therefore, only the tailpipe emissions from the operation of the taxis are considered in this research. The emissions are calculated under the scenario that the average charging power is 45kW and vehicles can be charged only during the dwell time.

We estimate the reduction of tailpipe emissions based on the following assumptions: the feasible CGV taxis will be replaced by BEVs, and the infeasible taxis will be CNG powered vehicles. The emissions of six air pollutants (CO, NO_x, SO_x, VOCs, PM_{10} and $PM_{2.5}$) and three traditional greenhouse gases (CO_2, CH_4 and N_2O) are calculated and compared. The emission factors of gasoline E10 in GREET (ANL, 2015) are adopted because E10 shares the most characteristics in ingredients and standards with gasoline 92# refilled for Nanjing CGV taxis. Since the GREET model has not examined the emission factors of NO_x, N_2O, PM_{10} and $PM_{2.5}$ for the CNG fueled bi-fuel vehicles, we adopt these emission factors from other studies (Borsari and de Assunção (2012), Hesterberg et al. (2008), Yao et al. (2014)) (Table 6).

Table 6
Tailpipe Emissions factors (g/km) from transport by conventional gasoline, compressed natural gas and electricity.

	CO	NO_x	SO_x	VOCs	PM_{10}	$PM_{2.5}$	CO_2	CH_4	N_2O
CGV	1.946	0.129	0.003	0.141	0.003	0.003	225.016	0.009	0.005
CNG	1.751	1.880[1]	0.001	0.127	0.006[2]	0.006[2]	191.100	0.095	0.033[3]
BEV	0	0	0	0	0	0	0	0	0

[1] from Yao et al. (2014); [2] from Hesterberg et al. (2008); [3] from Borsari and de Assunção. (2012).

Table 7
Comparison of tailpipe emissions under varying charging network coverages.

Network Coverage	Vehicle Percentage (%)				Emission Type								
	CGV	CNG	BEV		CO	NO_x	SO_x	VOCs	PM_{10}	$PM_{2.5}$	CO_2	CH_4	N_2O
	100	0	0	Amount (g/veh/day)	605	40	1.1	44	1.1	0.9	69936	3	1.5
	0	100	0	Amount (g/veh/day)	544	584	0.3	40	1.7	1.7	59395	29	10.3
				Reduction (%)	10	-1360	75	10	-61	-82	15	-900	-595
C(1:1)	0	77.66	22.34	Amount (g/veh/day)	463	497	0.2	34	1.5	1.5	50512	25	8.7
				Reduction (%)	23	-1142	78	23	-37	-55	28	-750	-491
C(1:2)	0	73.14	26.86	Amount (g/veh/day)	439	471	0.2	32	1.4	1.4	47868	24	8.3
				Reduction (%)	27	-1077	79	27	-30	-47	32	-706	-460
C(1:3)	0	65.56	34.44	Amount (g/veh/day)	397	426	0.2	29	1.2	1.2	43331	21	7.5
				Reduction (%)	34	-965	81	34	-18	-33	38	-630	-407
C(1:4)	0	56.39	43.61	Amount (g/veh/day)	346	371	0.2	25	1.1	1.1	37737	19	6.5
				Reduction (%)	43	-828	84	43	-3	-16	46	-535	-342
C(1:5)	0	45.87	54.13	Amount (g/veh/day)	286	307	0.1	21	0.9	0.9	31170	15	5.4
				Reduction (%)	53	-666	87	53	15	4	55	-425	-265

In addition to emission factors, the tailpipe emissions are determined by daily VKT of each taxi. As mentioned earlier, from the recorded data, taxis on average traveled about 265 km per day, while if the data from both days are pooled to create a 24-hr coverage data set, the average daily VKT is estimated as 313 km. We adopt a unitless parameter β to adjust the travel distance for each recorded taxis, where β=313/265=1.18. Namely, if one taxi's daily travel distance derived from GPS data is d, the adjusted daily VKT $d' = d \times \beta$. Table 7 compares the average daily emissions per vehicle of a mixed fleet of CNGs and BEVs with the base case of 100% CGVs. Compared with the gasoline-powered vehicle, CNG taxis have lower CO, VOCs, SO_x, and CO_2 emissions but discharge more NO_x and GHGs. With the increase of charger network coverage, more taxis are BEV feasible, which contributes to improving air quality in urban areas. Fig. 8 plots the reduction rate of tailpipe emissions when part of the CNG taxis are replaced by BEVs. A mixed taxi fleet with 45.87% CNG-powered and 54.13% electricity-powered vehicles can reduce the tailpipe emissions by 47.52% in comparison with the fleet of 100% CNG taxis.

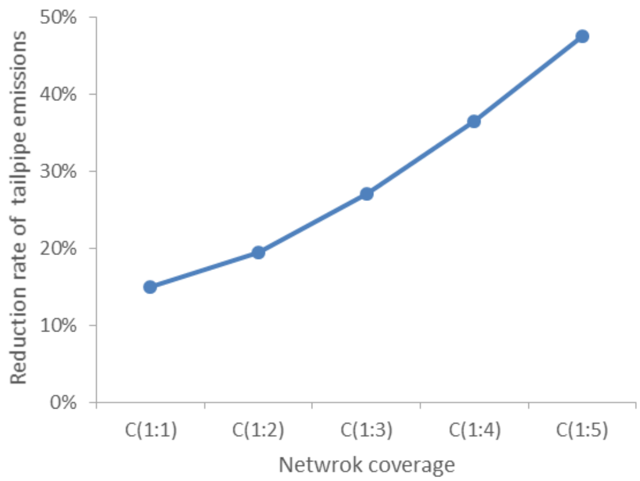


Fig. 8. Reduction rate of tailpipe emissions in comparison with the fleet of 100% CNG taxis.

Note that only tailpipe emissions are considered in this study. Emissions associated with electricity generation are not taken into account. In fact, coal currently dominates the electricity mix in China. More than 95% of electricity is generated by fossil fuel-fired power plants in Jiangsu province, where the city of Nanjing is located. 32-34% of CO_2, 28-50% of SO_2, and 32-33% of NO_x in China were contributed by power plants during 2005 and 2010 (Zhang et al., 2009, 2012; Zhao et al., 2013). Huo et al. (2015) pointed out that if electric vehicles are charged with 80% renewable electricity in China, they could reduce GHG emissions by more than 85%, reduce SO_2 and NO_x emissions by more than 75%, and reduce PM emissions by more than 40%. China plans to rely more on nuclear, biomass, hydro and wind for electricity generation in the future (EIA, 2015, Shen et al., 2012). A cleaner power supply in the foreseeable future will make electric taxis an attractive option for reducing emissions.

5 Conclusions

Using the taxi GPS trajectory data from Nanjing, China, this paper analyzes market potential and the environmental benefits of deploying electric taxis. The key findings from the results include (1) installing fast chargers is essential for electric taxi drivers to conduct within day recharge during the operating period; (2) charger infrastructure coverage becomes an important enabler for electric taxi acceptance when the charging power of public chargers reaches 20 kW or higher; (3) equipped with taxi apps, taxis drivers can not only charge the battery during the dwell time but also take advantage of some empty cruising times for charging, which helps further increase the acceptance of BEVs; and (4) tailpipe emissions will be reduced if CGV or CNG taxis are replaced by electric taxis.

The methodology presented in this paper can be applied to study the opportunities of increasing market share for BEV taxis based on taxis' travel pattern in other areas. Some caveats regarding the present paper are as follows: First, the GPS data cover 2 (incomplete) days. A multiday, preferably over a year, dataset is desired to account for day-to-day variations, which can also help identify the popular taxi dwell spots more precisely. Second, the examination of the impact of taxi apps on electric taxi feasibility can be improved by comparing the behavior of taxi drivers using apps vs. traditional drivers. Third, charging congestion is not accounted for in the model. Electric taxis are not the only vehicles that might use the charging facilities; personal car drivers might also use them. Thus, it is possible that a BEV taxi driver would find all chargers occupied when arriving at a charging station.

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