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Optimal Charging Infrastructure Planning for Electric Taxi Fleet

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Summary

Replacing the taxis fleet with battery electric vehicles (BEVs) has the potential to reduce greenhouse gas emissions and other harmful pollutants in highly populated areas. Consequently, several electric taxi pilot projects have been deployed around the world, such as in New York City, USA, Tokyo, Japan, and Shenzhen, China. One of major barriers that impede wide-scale adoption of BEVs in the taxi fleet is the inadequate charging infrastructure. As taxis are usually driven heavily, the daily travel distances are likely to exceed the typical BEV range of 80 to 120 miles. Therefore, it is desirable for electric taxi drivers to charge the battery in a convenient and timely fashion, preferably during the time when they take a break or wait for customers. This paper presents a data driven approach to determine optimal allocation of chargers that maximizes the acceptance of BEVs in the taxi fleet.

In particular, GPS tracked vehicle trajectories of conventional gasoline taxis are used to estimate the potential charging demand. At popular locations, multiple taxis might dwell and charge during the same time period. Therefore, an M/G/s/s queueing model is adopted to describe charging congestion effect and estimate the number of lost customers (i.e. the fraction of customers who find the charging station full and are turned away). The optimal charger allocation problem is formulated as an integer program—given the driving and dwell activities of the taxi fleet, determine the number of chargers to be installed at each popular dwell location so as to minimize the rejection probabilities at the charging stations. Genetic algorithm is used to search for the near optimal solution for systematically planning the public charging system. In addition to the taxi fleet, the proposed approach can also be adapted for charging infrastructure planning of other fleet vehicles and private vehicles.

Key words: Electric taxi, Charging infrastructure planning, Queueing model, Integer Programing, Genetic Algorithm

1. Introduction

Replacing conventional gasoline vehicles (CGVs) with alternative fuel vehicles, such as battery electric vehicles (BEVs), offers an appealing chance to reduce greenhouse gas (GHG) emissions and other harmful

pollutants in highly populated urban areas. Electric taxi fleets, which are usually driven heavily in urban areas, have been introduced in several major cities around the world, such as New York City, USA, Tokyo, Japan, Amsterdam, Netherlands, Jeju, South Korean, Shenzhen, China and so on [1, 2]. Deploying BEV taxis is one way to reduce GHG emissions and air pollution, and also helps to promote the acceptance of electric vehicles among the citizens. However, inadequate charging infrastructure becomes one of the major barriers that impede wide-scale adoption of BEVs. The lack of charging infrastructures and the long recharging time reduce the operating time of taxis, resulting in low acceptance of BEV taxis [3].

Unlike the private BEVs, which usually have a fixed charging location such as at their home, school, or workplace, BEV taxis cruise around the city and are in favor of public charging stations equipped with fast chargers. The utilization of each charging station depends on the spatial and temporal distribution of BEVs [4]. To better allocate charging infrastructure, it is essential to understand the stochastic charging demand at different charging stations. Using the GPS trajectories data, it is possible to examine taxis' habitual driving and dwelling behavior, from which we can discover the popular dwell places (i.e. candidate sites for siting public charging stations) and gain insight on charging congestion phenomenon, and design a charger network that can best serve BEV customers.

The objective of this study is to develop a data-driven approach to determine optimal allocation of chargers that best serves the charging demand. Based on GPS trajectory data collected from CGV taxis in Changsha, China, we optimize the allocation of the electric vehicle chargers. In particular, the popular destinations where taxi drivers dwell are selected as locations to site public charging stations. Assuming the selected locations are available for charging, the arrival and departure patterns of BEVs are extracted from the taxi GPS trajectory data. Since the arrival rates of taxis vary over time, the peak period for charging service is identified for each site and used in the analysis. The peak periods differ from station to station, for example, some drivers prefer to head to urban fringe areas in order to avoid traffic jam during evening rush hours, while some drivers get together for lunch around noon in places which are convenient to park. Thus, an M/G/s/s queueing model is adopted to describe charging congestion effect and estimate the fraction of customers who are turned away because all chargers are occupied. Accordingly, the optimal charger allocation problem is formulated as an integer program—determine the number of chargers to be installed at each popular dwell location so as to minimize the rejection rate for the entire taxi fleet.

The remainder of this paper is organized as follows. In Section 2, a review of charging congestion effect and charging station planning models is presented, followed by the data description of GPS trajectories collected from Changsha in Section 3. After that, the M/G/s/s queueing model with no waiting space and the integer program formulation are presented in Section 4. Results and conclusions are summarized in Section 5 and 6, respectively.

2. Literature review

Various mathematical models have been proposed to optimize hydrogen refueling, electric vehicle charging, and battery swapping station siting, including flow-capture [5], p-median [6, 7], set covering [8, 9], and agent-based [10] approaches. In particular, the optimal planning of charging infrastructure for electric taxi fleet has different optimization objectives. Shahraki et al. [11] and Cai et al. [12] select locations of public charging stations by maximizing taxis' travel distance that can be electrified, while the optimization method proposed by Sellmair et al. [13] is to maximize the economic benefits of electric taxis per year. Recharging the battery takes a much longer time, from 30 min to several hours, depending on the charger power, battery size and its state of charge. Therefore, the waiting times may be significant if all the chargers are occupied during the peak hours, yet the above-mentioned research does not consider charging congestion and queueing as a significant impact factor. One reason is that charging queueing may be rare at an immature market with a small number of electric vehicles (Dong et al. [14]). However, charging congestion will become ineluctable with the expanding of BEV fleet in the foreseeable future. Pioneering work involving charging queueing is found in the research

by Jung et al. [15], which proposed a bi-level planning method called SDIRQ to optimized the infrastructure of electric taxis, and Ahn et al. [16], which optimized the density of charging station networks.

Most research with respect to charging congestion effect concerns the prediction of electric vehicles' charging demand and its impacts on power grid. The most widely-adopted queueing model is M/M/s, assuming that both BEV arrival rate λ and charging service rate μ follow the Poisson distribution, and a vehicle will join the queue for an available charging space no matter how long the queue is [17-21]. However, charging characteristics of electric vehicles may vary spatially and temporally. Therefore, Munoz and Ruspini [22] modeled BEV arrival and charging service as time-varying Poisson processes with fuzzy parameters. Fan et al. [23] applied an M/G/s/k queueing model which assumes a general service time distribution and a charging queueing system with at most k BEVs can wait or be served at a station. In this paper, we adopt an M/G/s/s queue, which assumes a Poisson arrival and a general distribution of service time with s chargers and no waiting space. This is a reasonable assumption for electric taxi charging.

Despite the recognized importance of developing spatial and temporal BEV charging demand, to the best our knowledge none of the studies have examined the realistic charging demand at a public charging station. Few research has been done to study the scale of charging infrastructure from perspective of charging congestion to minimize the probability that an arriving BEV is rejected. This paper is intended to fill the gap.

3. Data description

3.1 GPS trajectory data

By the end of 2014, there were about 7,957 taxis operating in Changsha, China. It is required by the local government that GPS devices need to be installed on all taxis by for monitoring purpose. A GPS signal is captured roughly every 10 seconds for each taxi. The data include time-stamped location (i.e., longitude and latitude), spot speed, azimuth, and operational status (i.e., empty or occupied). This paper uses a dataset collected from 0:00 on October 8, 2015 00:00 to 23:59 pm on October 14, 2015 (local time) to estimate potential charging demand of BEV taxis. Statistical analysis shows that a CGV taxi travels over 250 miles daily on average, indicating electric taxis, even with a range of 200 miles, need to charge at least once a day.

3.2 Potential fast charging stations

To maximize charger utilization and driver convenience, charging stations are expected to site at locations where taxis often dwell. Specifically, a dwell trip is defined as a trip during which an unoccupied vehicle is parked at a certain location for at least 20 minutes. 185,404 dwell trips during the week are identified from the taxi GPS dataset. In order to determine the popular destinations where the dwell trips occurred, the study area (27~29 N°, 111~115 E°) is divided into 320,000 cells. Each cell covers an area of approximately 0.5×0.5 km². For each cell, the number of parked vehicles is counted. There are 2,460 valid cells have the records of vehicles parked. 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 dwell vehicles that parked in the cells. Each category covers 20% of the dwell trips, about 37,081 times per week. Category C1 has 10 cells with the most popular parking places, and Category C2 has 34 valid cells. These 44 cells are determined as candidate locations to install public charging stations. We assume that fast chargers are installed in Category C1 and C2, which include top 1.8% of the valid cells and cover 40% of the total dwell trips. As shown in Fig. 1, the most popular cell covers 10,777 dwell trips weekly, with an average frequency of nearly 64 times per hour. A charging queue and congestion problem might be observed if the taxi fleet is replaced by BEVs.

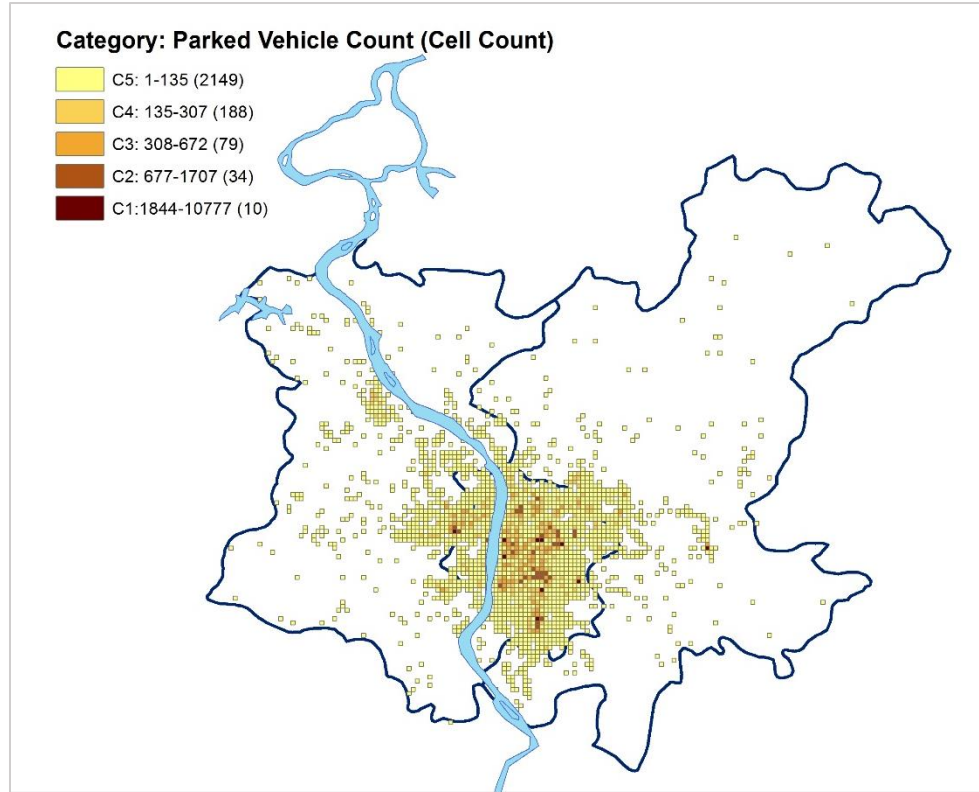


Figure 1: Distribution map of dwell locations of taxis in Changsha

3.3 Peak periods of dwell trips

The peak periods of dwell trips vary by cells. In order to find the peak hours of each stations, we divide the 24-hour period into six time segments based on taxis' activity pattern—S1: 2:00~6:00 (after midnight), S2: 6:00~10:30 (morning), S3: 10:30 ~13:30 (midday), S4:13:30 ~16:30 (afternoon), S5: 16:30 ~20:00 (nightfall), and S6: 20:00~2:00 (late evening and midnight). For each station, the numbers of taxi arrivals are counted for each time segment. The segment with the highest arrival rate is considered as the peak period for that station. As shown in Table 1, the peak hours occur after midnight for 14 stations. Cell 10 is a representative location where taxis prefer to park after midnight (see Fig. 2 (a)). In particular, 50.4% of the dwell trips occur during 2-6 AM on October 9, 2015. Since there are few customers after midnight, taxi drivers are inclined to park the vehicle in places where demand for taxi service is expected, rather than cruising around the city to search for customers. The time segment S3 is the period when taxi drivers take a short break for lunch. Cell 26 is a typical location for drivers gathering for lunch (see Fig. 2 (b)). The lunch places usually provide packed meals and have sufficient parking space. The time segment S5 is the peak period for only 2 cells, one of which is near the airport (see Fig. 2 (c)) and the other is at a suburb refueling station. Drivers heading to these two cells during the evening rush hours intend to avoid the congested downtown areas and use the time to refuel or take more profitable long-distance trips. There are 15 cells have the peak period from 20:00 to 2:00. These cells are mainly located near hospitals, restaurants, hotels, and leisure places. Fig. 2 (d) shows the arrival distribution of Cell 6. There are two obvious peak periods—one during midday and accounting for 27.9% of arrivals, and the other during night (S6), accounting for 54.1% of arrivals. According to the weekly observation, S6 is considered as the peak period for Cell 6. None of the cells adopt S2 and S4 as their peak period, because the operating profit is much better during the morning period compared with other time, and it is natural for drivers go back to work after lunch.

Table 1: Results of peak period identification

Time segments	S1	S2	S3	S4	S5	S6
	2:00~6:00	6:00~10:30	10:30~13:30	13:30~16:30	16:30~20:00	20:00~2:00
Cell counts	14	0	13	0	2	15

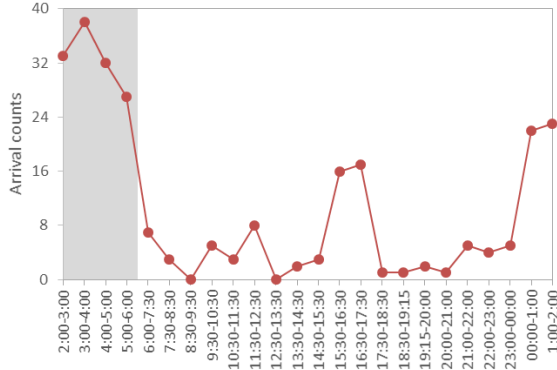
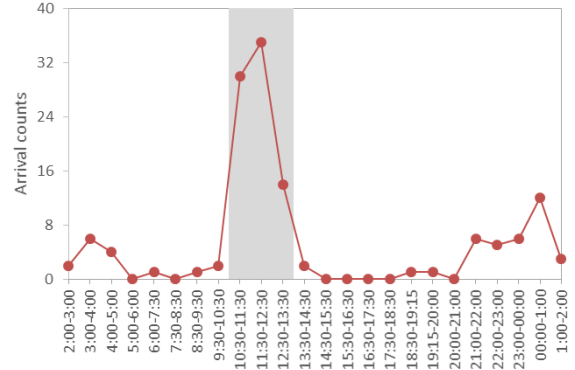
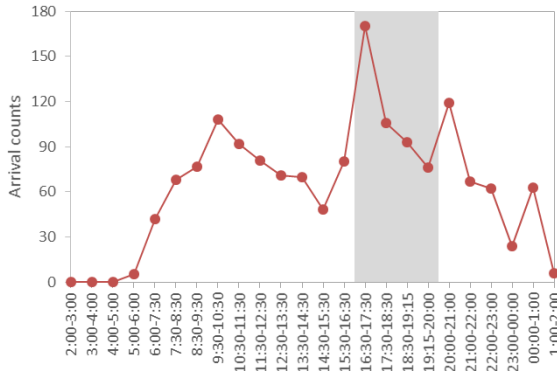
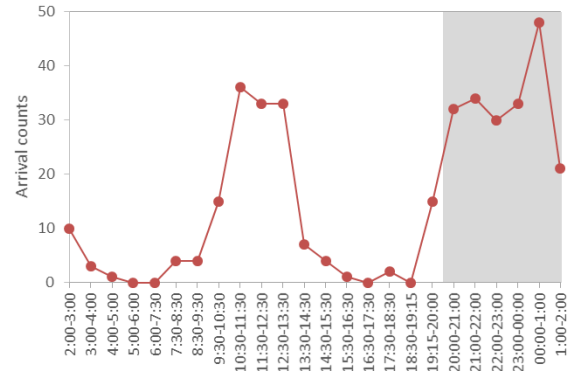
(a) Cell ID: 10, Location: Gaoling St.,
Peak period: S1(b) Cell ID: 26, Location: Xiaoyuan Rd.,
Peak period: S3(c) Cell ID: 1, Location: Huanghua Airport,
Peak period: S5(d) Cell ID: 6, Location: Chaoyang Rd.,
Peak period: S6

Figure 2: Temporal distributions of taxi arriving at the charging stations (Date: October 9, 2015)

4. Methodology

4.1 Arrival rate and service rate

Charging congestion is most likely to occur during peak periods of dwell trips. The hourly arrival counts of taxis during the peak period are considered as the arrival rate of the charging station. Fig.3 presents time gaps between successive vehicle arrivals of the four representative cells during peak periods of the entire week. Because the selected cells are the most popular dwell spots, taxis arrive frequently and most of the arrival headways are within the range of 0~15minutes. Vehicles with a time gap larger than 1 hour are removed from the dataset as they have little impact on charging congestion. The time between successive vehicles arrivals is assumed to follow an exponential distribution with an average time of $1/\lambda$, where λ is the arrival rate. Namely, the arrivals can be described by a Poisson process with a mean arrival rate of λ .

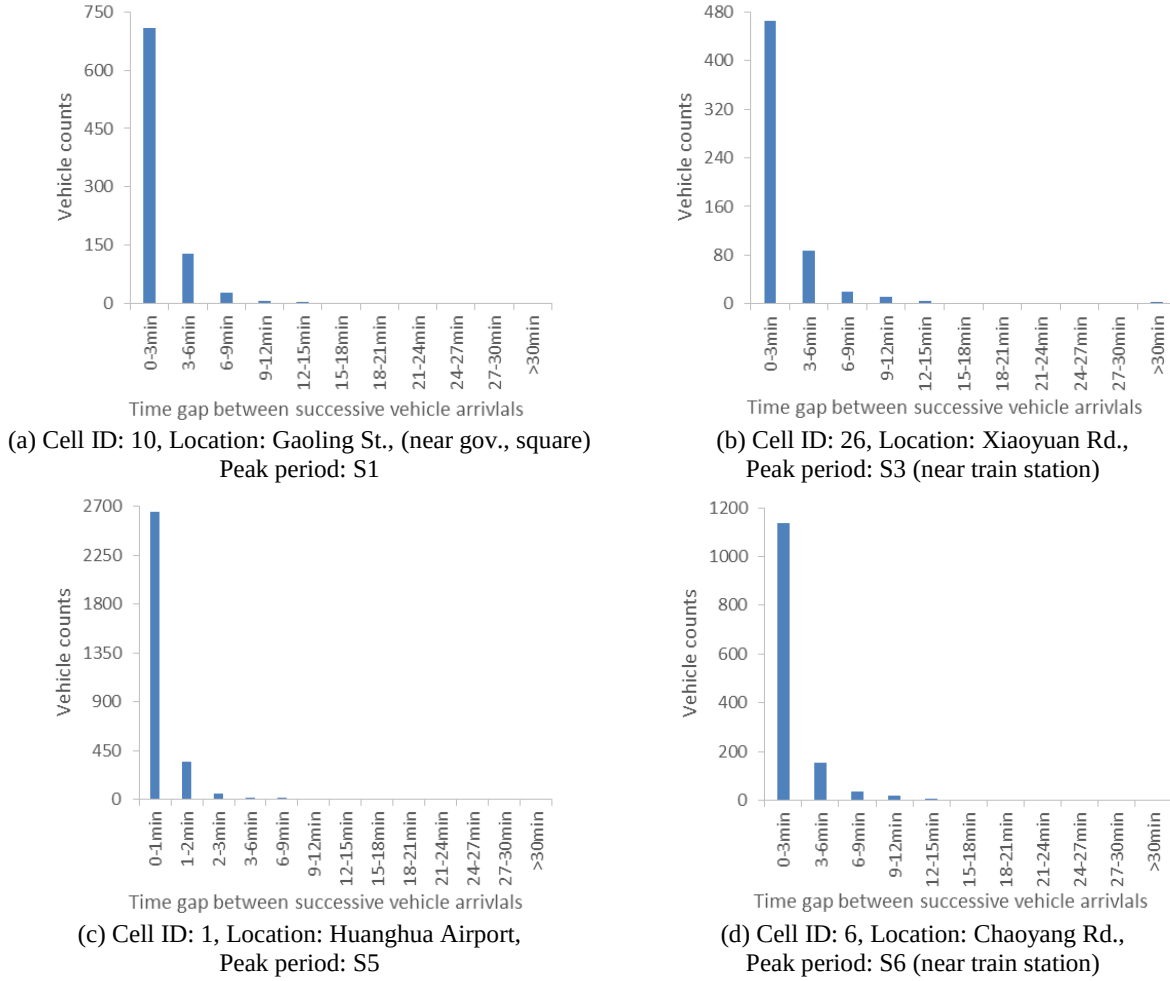


Figure 3: Distribution of time gap between successive vehicle arrivals

A taxi's dwell time span is assumed as its service time. That is to say, drivers will not move their vehicles when the charging is completed. Rather, they will move the vehicle when they depart. Thus, the service rate μ during peak time can be calculated accordingly. Table 2 presents the summary statistics of service times of four representative cells. Cell 10 has the largest average service time (i.e. dwell time) during the peak period since the dwell trips occur after midnight.

Table 2: Statistics of service time for representative cells

Peak period		Cell ID	Vehicle counts	Arrival rate (veh/h)	Service rate (veh/h)	Service time (min)				
						Mean	St.d	Min	Median	Max
S1	2:00~6:00	10	881	7.58	0.32	186	136	20	169	1157
S3	10:30~13:30	26	594	4.00	1.84	33	16	20	28	167
S5	16:30~20:00	1	3067	67.78	0.85	70	30	20	70	427
S6	20:00~2:00	6	1358	8.70	1.49	40	74	20	28	1373

4.2 M/G/s/s queueing model

Based on the analysis of the previous section, we assume that, at each charging station, the arrival rates, λ , follows a Poisson distribution and the service rate, μ , is generally distributed. Since BEV drivers are unable to predict the waiting time, it is reasonable to assume that a BEV taxi driver will either charge the battery immediately upon arrival, or is turned away if all chargers are occupied. Accordingly, we adopt an M/G/s/s queueing model where the number of chargers equals to the maximum number of vehicles the system can hold, namely, there is no waiting queue.

The probability of all chargers are occupied is calculated as [24]

$$P = \frac{(\lambda / \mu)^k / k!}{\sum_{j=0}^k (\lambda / \mu)^j / j!} \quad (1)$$

This is the probability that an incoming electric taxi is turned away, or a customer is lost. An ideal scenario is that every station has sufficient chargers installed so that the rejection rate is minimal. However, due to the budget constraint, a limited number of chargers can be allocated to each station. In order to minimize the total number of lost customers the allocation of the chargers among different charging stations needs to be optimized.

4.3 Optimization model

The problem of optimal charging infrastructure planning is to decide the number of chargers s_i to be installed at each charging station i . First, an individual-based allocation approach is conducted, in which each station has to satisfy a certain criteria of rejection rate. For example, when the rejection rate is set as 20%, it means the rejection probability of each station cannot exceed 20%. Thus, the minimum number of chargers can be calculated based on Eq. (1). The total number of chargers S for 44 stations can be obtained. Clearly, the allocation plan based on individual requirement does not represent a system optimum. A system-optimized allocation approach is proposed to reallocate the S chargers to minimize overall rejection rate. The objective function, Eq. (2), minimizes the total number of lost customers at all charging stations. Due to the limited budget, the total number of chargers needs to be less than or equal to S (Eq. (3)). Arrival rate λ_i and service rate μ_i at charging station i are estimated from the GPS dataset. The capacity of station i depends on the number of chargers installed, s_i . The probability of a BEV being turned away at station i , P_i , is determined by Eq. (4). An additional constraint is set that the stations' rejection rate can exceed 50% (Eq. (5)). The values of decision variables are positive integers (Constraint (6)). Generic algorithm is applied to solve this integer program.

$$\min \sum_{i \in I} \lambda_i P_i \quad (2)$$

Subject to

$$\sum_{i \in I} s_i \leq S \quad (3)$$

$$P_i = \frac{(\lambda_i / \mu_i)^{s_i} / s_i!}{\sum_{j=0}^{s_i} (\lambda_i / \mu_i)^j / j!} \quad \forall i \in I \quad (4)$$

$$P_i \leq 0.5 \quad \forall i \in I \quad (5)$$

$$s_i \in N \quad \forall i \in I \quad (6)$$

5. Results and discussions

5.1 Individual-based allocation

The minimum numbers of chargers at each station are calculated to meet the rejection rate requirement. The maximum rejection rate is set as 20%, 15%, 10% and 5%, respectively. Fig. 4 shows the total numbers of chargers required by all the stations. Clearly, more chargers are needed if a lower rejection rate is set. When less than 5% of BEVs can be turned away at any station, at least 406 fast chargers need to be allocated among the selected 44 stations.

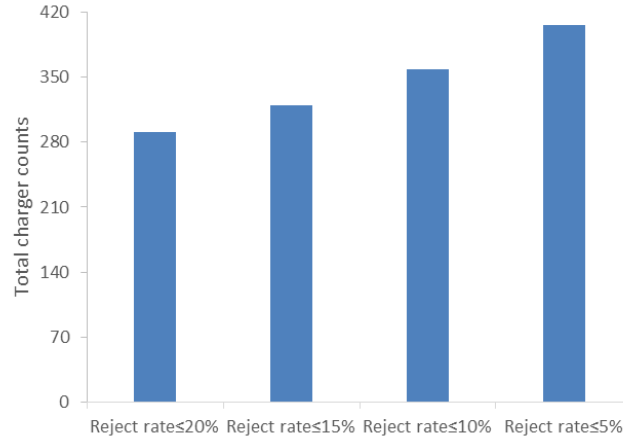


Figure 4: Required charger counts with the restrictions of rejection rate

The ratio of λ and μ is denoted by ρ , representing the utilization ratio. With a higher value of ρ , more chargers are in demand. As for the busiest station with the cell ID of 1, 85 chargers have to be equipped to guarantee the probability of BEVs being rejected do not exceed 5%. When there are 5 chargers allocated at the ID 26 cell, both the rejection requirements of 10% and 5% can be satisfied.

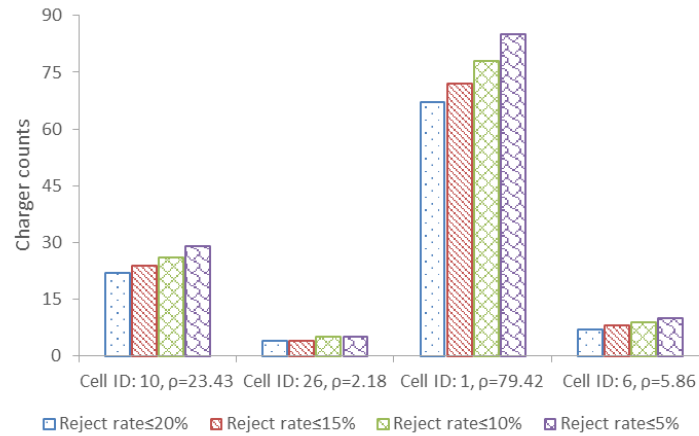


Figure 5: Required charger counts for representative cells with the restrictions of rejection rate

5.2 System-optimized allocation

System-optimized allocation method generates optimal allocation results based on the total number of chargers determined by individual-based allocation. As shown in Fig. 4, 291, 320, 358 and 406 chargers are supposed to be re-allocated among the stations. Changes of rejection rate after re-allocation are witnessed from Fig. 6. Some stations with higher arrival rates are assigned with more chargers so as to reduce their rejection rates, while some stations have less chargers after re-assignment resulting in higher rejection rates. It is possible for a certain station having a rejection rates exceed the corresponding requirement of individual-based allocation plan.

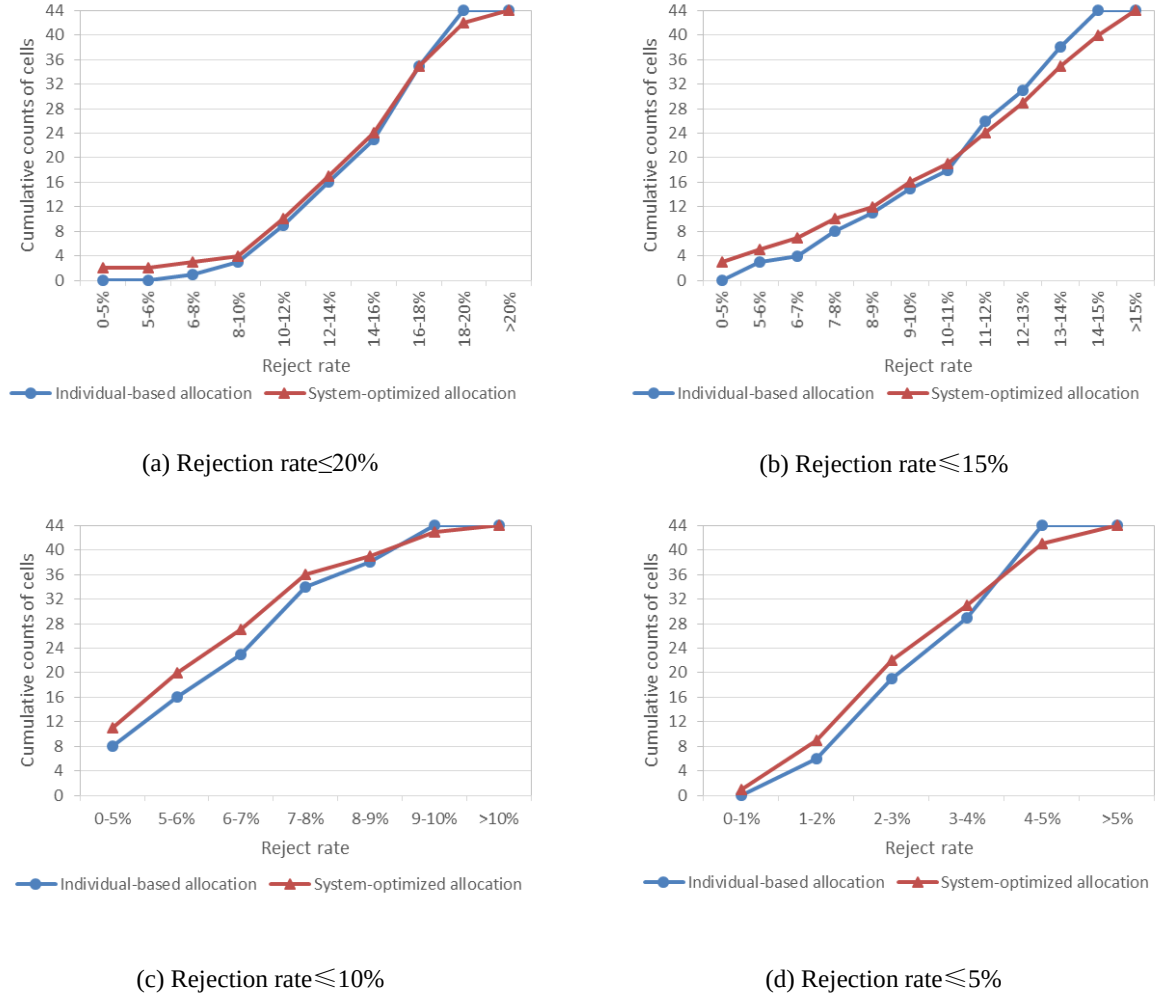
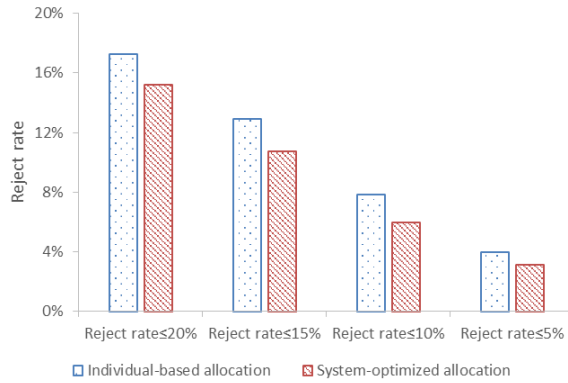
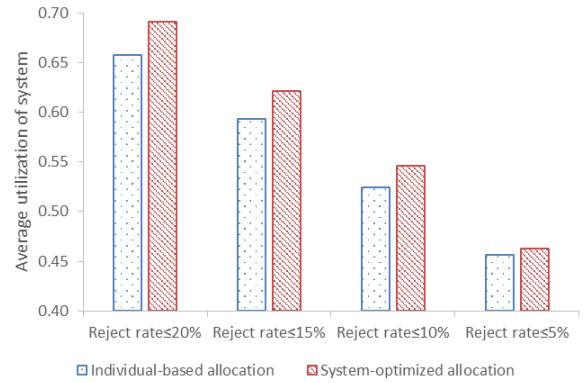


Figure 6: Rejection rate distribution

After a global optimization of charger allocation, system rejection rates are reduced, indicating fewer vehicles will be turned away, while the total number of chargers remains the same. Accordingly, the average utilization of queueing system increases regardless of rejection restricts. It can be concluded that charging infrastructure are utilized more efficiently following a system-optimized allocation.



Comparison of rejection rate



Comparison of average utilization of system

Figure 7: Comparison of rejection rate and average system utilization

6. Conclusions

Using the taxi GPS trajectory data from Changsha, China, this paper analyzes taxi arrival patterns at the charging stations in order to optimize charger allocation for better deploying BEV taxis. The key findings from the results include (1) the gathering places of taxis' dwell trips can be observed from GPS trajectory data, providing spatial distribution of BEV charging demand; (2) vehicle arrival patterns are different for different public charging stations, which result in different charging peak periods; (3) the operating characteristics of queueing system can be estimated based on the assumption of M/G/s/s model; (4) the system rejection rate can be reduced and the utilization can be improved by adopting the proposed integer program for charging infrastructure planning.

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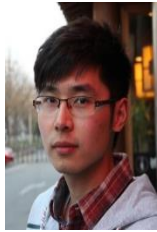
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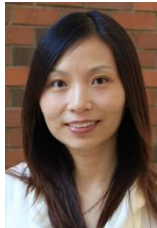
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