Impact of core charging station's cease operation in the entire charging station system: a case study in Shenzhen

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***Abstract*— As the rapid development of Electric Vehicles (EV), how to strategically deploy charging stations becomes an emerging and challenging question to EV communities. However, the cease operation of charging stations and the consequent impacts have been discussed little. In this paper, by analyzing a large scale electric taxi GPS data, we make the first attempt to investigate this problem. A case in Shenzhen is analyzed in this paper, where a core charging station ceases operation due to the security consideration, offering us a real situation. We develop a regression model to predict load increments of charging stations based on the analysis of EV taxi drivers' recharging behavior patterns. Based on the model, an allocation strategy of charging resources is proposed to minimize the average waiting time at charging stations, and maximize the charging resources utilization at the same time. To evaluate the performance of our proposed strategy, we conduct experiments on half-year real EV taxi GPS data. The evaluation results demonstrate that our suggested strategy can achieve a 32%-88% reduction rate on average waiting time at charging stations, over baseline methods. Moreover, our strategy can perform better in charging resources utilization.**

I. Introduction

Electric Vehicles (EV) are more and more popular, due to the strengthen public willingness of contributing to environment protection. Compared with Internal Combustion Engine Vehicles (ICEV), EVs have less air pollution.

However, as charging infrastructure putting into market for EVs, charging stations (CS) will probably cease operation due to some reasons. For example, a CS needs maintenance after a long time operation, or it will be pulled down considering power line aging and security issues. All these will lead to the cease operation of CSs, and it can be commonly observed in cities where EV mode is adopted.

Cease operation of CSs means EVs can't be charged at these CSs. In that case, EV drivers will rush to those normal CSs for recharging, leading to a load increment in normal CSs, thus making EV drivers queue a long time for waiting to be charged. This phenomenon will directly affects satisfaction of EV drivers, moreover, it will hinder the further development of EVs. Therefore, the cease operation problem of CSs deserves to be studied.

Measures should be taken to address the issue. More EV recharging events will be finished in those normal CSs via dispatching mobile charging vehicles or building more charging points to tackle with the load increment. Due to the cease operation of a CS, other different CSs will suffer from different load increment. Therefore, given a certain number of charging resources and with a objective of reducing waiting time at normal CSs, how to allocate charging resources to those normal CSs will be discussed in this paper.

Obtaining the value of load increment of a CS is the basis for the above discussed allocation. The more load increment a CS suffers, the more charging resources will be allocated to it. However, the value of load increment is not easy to predict. Which factors will impact the load increment of a normal CS? How to predict the value of the load increment by modeling? Such questions challenge us when faced with charging resource allocation problem.

To solve this, we use real taxi GPS records data from a fleet with about 800 EV taxis operating in Shenzhen, China since there exists a CS suffering maintenance due to security consideration. The load increment of other normal CSs is based on a real situation. The main contributions of this paper include:

- Recharging behavior patterns of EV taxi drivers have been classified and analyzed according to their past visit frequency to the maintaining CS. Those drivers having high visit frequency incline to choose CSs sitting around the maintaining one as a substitution, while those drivers with low visit frequency change little compared with their former recharging behaviors.
- The load increment of a normal CS has direct relationship with its distance away from the maintaining CS and the number of charging points it possesses. Besides, a new concept named *Relevancy* has been proposed to illustrate the relevance degree between two different CSs. Relevancy also has a significant impact in the load increment of a normal CS.
- A regression model has been proposed to predict the load increment of a normal CS by utilizing the features selected from recharging behavior pattern analysis. Besides, the model has been evaluated based on the real recharging event data generated in Shenzhen. Simulation results show that depending on our prediction, the allocation will perform better to minimize the waiting time of EV taxi drivers at those normal CSs compared with some baseline methods.

This rest of the paper is organized as follows. In Section II,

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the related works are discussed. Then in Section III, we describe the data sets and the case study analyzed in this paper. Section IV depicts the features related with CSs' load increments and model the increments by utilizing a regression model. In Section V, we evaluate the experiments results. And finally, we conclude the paper in Section VI.

II. Related Work

In recent years, the promotion of EV and deployment of EV infrastructure have led to massive researches, which can be divided into EV charging location problem and EV charging schedule problem. Two models are used in EV charging location problem: flow-based model and activity-based model. For example, Kuby et al. [1] proposes a Flow Refueling Location Model (FRLM) for EVs and Capar et al. [2], Hong et al. [3] extend the raw FRLM by adding new features to solve the siting problem of charging stations by utilizing graph theory. Jung et al. [4] use activity-based model to analyze queue delay of charge stations and offer decision support for choosing locations of undeployed charge stations aiming for minimizing EV taxi drivers' queue time for charging. Besides, Gharbaoui et al. [5] use activity-based model finding that in urban areas public charge stations can be underutilized and location selecting of charge stations should be considered to reduce EV owners' range anxiety.

Compared to EV charging location problem, more factors should be considered into EV charging schedule problem. For example, Gan et al. [6] use different decentralized charging control for reducing charging cost by avoiding charging during the electricity-used peak hours; Lu et al. [7] propose dispatching strategies for reducing EV charging waiting time so that EV taxi drivers can have more operation time. Sun et al. [8] explores how battery electric vehicle users choose where to fast-charge their vehicles from a set of charging stations, as well as the distance by which they are generally willing to detour for fast-charging.

III. Studing Case

A. Overview of Charging Station Deployment in Shenzhen

Charging Station Distribution The studying case used to address allocation problem is in Shenzhen, China. By August,2016, there were in total 31 CSs deployed in Shenzhen city. Figure 1 indicates the spatial distribution of those CSs, with marker size indicating the number of charging points deployed in the stations. The CS with more than 100 charging points is the large station marked with a large red circle symbol, where two CSs with about 50 charging points are medium stations marked with medium blue circle symbols while other stations equipped with 6∼8 charging points are marked as small stations.

Load Increment Measurement The large station is defined as the core station in this paper. Reasons for that mainly lie in the following two aspects: on one hand, the number of charging points deployed in the large station is much more than other stations, on the other hand, the large station is located in the downtown area of Shenzhen. However, this core CS ceases to operate since March 10th,2016 due to the considerations of security and maintenance, thus leading to the load increments of other normal CSs.

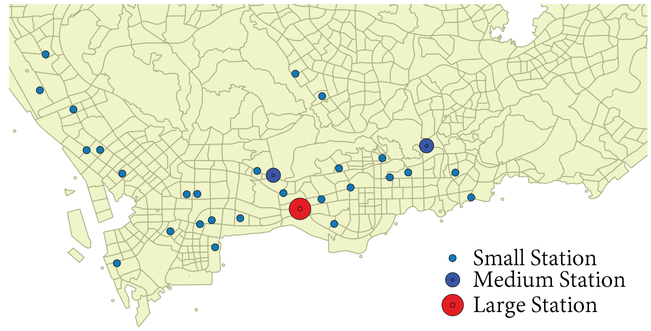

Fig. 1. Distribution of charge stations in Shenzhen

Due to the maintenance of the core station, many EV taxis will rush to other normal CSs for recharging, resulting in the load increments of those CSs. The load increment of a normal CS is decided by the number of increased recharging events in that CS during the period of the core station maintenance, thus recharging event detection is critical for load increment measurement. Relative data and detective method will be discussed in the following part.

B. Dataset Description

The major dataset is taxi GPS records. The dataset consists of over 13,800 taxis, including around 800 EV taxis and around 13,000 ICEV taxis. Each taxi updates a GPS record per 30 seconds in average, together there are around 4 GB data per day and over 28 GB per week. We use the dataset from January 1st, 2016 to June 1st,2016, lasting for half a year. Detailed description of dataset and related data preprocessing can be observed in our previous study [9].

IV. modeling

To allocate the limited charging resources in an optimal way, estimations for load increments of normal CSs should be performed well. We firstlys extract and analyze some features related with the load increment by utilizing recharging event data, and then we use a regression model to predict the load increment of a normal CS based on those selected features.

A. Feature Selection

Charging Station Dependency It's obviously observed that EV taxi drivers that used to recharge at the core station will suffer a big influence during the maintenance period, thus it's necessary to analyze their recharging behavior patterns. Before that, we should distinguish those drivers with high frequency recharging at the core station in the past from the other drivers. A new concept of dependency degree is proposed here to address the issue. As for an EV taxi v, its recharging event data of two months before the maintenance has been collected. The sum number of v's recharging events during these two months is notated as N, while the number of v's recharging events occurring at the core station is denoted

Fig. 2. Distribution of CS Choices among Drivers with large DD

as n, then v's dependency degree (DD) of the core station can be computed as

$$DD_v = \frac{n}{N} \tag{1}$$

Charging station choices of EV taxi drivers with high value of DD can be observed in Figure 2. The maintaining core station is marked by a red box with a text note, while the blue columns indicate the load increments of other normal CSs caused by those drivers. Obviously, those drivers prefer to choose CSs surrounding the core station as substitutions, indicating that the distance away from the core station is a factor impacting the load increment. Besides, two medium CSs also hold a big load increment, thus the number of charging points deployed in a CS should be also taken into consideration.

Charging Station Relevancy For other drivers, a concept of charging station relevancy borrowed from the traditional relevancy theory is proposed here to analyze their choices. Given a time period (e.g. two months), assume that N EV taxis have visited charging station cs_1 during the period, while there are n EV taxis reaching charging station cs_2 for recharging among N, then the charging station relevancy of cs_1 and cs_2 can be computed as

$$Rev(cs_1, cs_2) = \frac{n}{N} \times \frac{n}{M} \tag{2}$$

While M refers to the number of the EV taxi fleet.

Large value of $Rev(cs_1, cs_2)$ means the number of EV taxis having visited cs_1 and cs_2 is big, thus when cs_1 is in the state of maintenance, cs_2 will become these drivers' first choices for recharging, reflecting their recharging preferences to a certain degree.

B. Modeling Process

This study adopts a traditional linear regression formulation to model load increments of normal CSs. Specifically, for a CS i, its load increment LI_i can be modeled as

$$LI_i = w_0 + w_1 Dis_i + w_2 Num_i + w_3 Rev_i \tag{3}$$

Notice that the load increments of other normal CSs are resulted from the maintenance of the core station, thus the parameters in Equation 3 are proposed in terms of the core station. Assuming the core station is symbolled by c, then Rev_i is actually the abbreviation of $Rev(i,c)$ while Dis_i refers to i's spatial distance from c. As for Num_i, it refers to the number of charging points deployed in i, which is independent of c.

TABLE I

ESTIMATION RESULT OF FOLD ONE

CS	Real Load Increment	Estimated Load Increment	Relative Error (RE)
$test_1$	37	42	13.5%
$test_2$	5	4	20%
$test_3$	184	174	5.4%
$test_4$	52	58	11.5%
$test_5$	22	24	9.1%
$test_6$	7	6	14.3%

As for the CS i, we use Avg_i^b to express the average number of charging events occurred in i during two months before the date of maintenance, while Avg_i^a corresponds to the average number in two months after the maintenance, thus i's real load increment $\hat{LI}_i$ can be computed as

$$\hat{LI}_i = Avg_i^a - Avg_i^b \tag{4}$$

We use a vector $\vec{W}$ to express the regression coefficients in Equation 3, i.e., $\vec{W} = (w_0, w_1, w_2, w_3)$, then the modeling process is to find a proper $\vec{W}^*$ to satisfy the Equation 5.

$$\vec{W}^* = \arg\min_{\vec{W}} \sum_i^N (LI_i - \hat{LI}_i)^2 \tag{5}$$

While N refers to the number of normal CSs in Shenzhen. The value of $\vec{W}^*$ can be calculated by the gradient descent method.

V. EXPERIMENTS AND RESULTS

A. Evaluations on Regression Model

To evaluate our regression model, we firstly collect recharging event data occurred in normal CSs to obtain their real load increment values. Each normal CS holds a load increment value, thus the size of the data used in model evaluation corresponds to the number of normal CSs. Due to the small size of the data set, 5-fold cross validation method is adopted for model evaluation. Specifically, for each fold, 24 CSs are used for training and 6 CSs for testing, then we use root mean squared error (RMSE) as a metric to evaluate the trained model. The results of fold one are shown in Table I.

For fold one, its RMSE value can be computed as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{6} RE_i^2}{6}} \tag{6}$$

Based on 5-fold cross validation method, the model with minimal RMSE value can be selected for the initial charging resources allocation problem.

B. Baseline Allocation Strategies

The core station is equipped with about 100 charging points, thus we assume the number of charging resources (e.g., mobile charging points or vehicles) awaiting to be allocated is also 100. Different allocation strategies will lead to different results. The allocation strategies to be compared

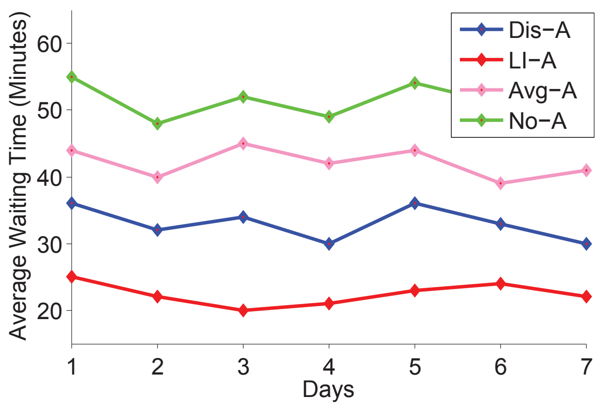

Fig. 3. Waiting Time Comparison in Different Allocation Strategies

in this study include the results with LI-Allocation, Distance-Allocation (Dis-A for short), Average-Allocation (Avg-A for short) and No-Allocation (No-A for short). LI-Allocation means the charging resources will be allocated to those normal CSs based on their load increments estimated by our regression model, while the baseline allocation strategies include Dis-A, Avg-A and No-A. Dis-A strategy means CSs near the maintained core station will obtain more charging resources, i.e., based on their spatial distances from the core station. And then, Avg-A strategy means the charging resources will be allocated in a average way, that is, normal CSs will obtain the same number of charging resources. And finally, No-A means no charging resources are allocated to CSs, reflecting the current situation in Shenzhen. Those four strategies will be compared in two aspects: waiting time at CSs and utilization of charging resources allocated to CSs.

C. Evaluations on Waiting Time

To evaluate the above different allocation strategies, we firstly collect the recharging events of every EV taxi from July 1st,2016 to July 7th,2016. During this week, the time periods ranging from 2:00 A.M.-6:00 A.M. are selected for our experiments, which covers the morning recharging peak period. When all the charging points at a CS are occupied for recharging, EV taxis reaching later will have to wait until an EV taxi finishes its recharging, leading to the long waiting time at CSs. Waiting time can be calculated in a direct way by combining the information of charging points deployed in CSs with recharging events occurred at those CSs, shown as our previous work [10]. The results of waiting time under different allocation strategies are shown in Figure 3.

We obtain the average waiting time of the EV taxi fleet for a week and then make a everyday comparison. Figure 3 indicates the average waiting time is about 52 minutes in No-A while other three strategies can reduce the waiting time in different degrees. Obviously, our LI-A strategy outperforms Dis-A and Avg-A, reducing the waiting time by more than half. Besides, Dis-A performs better than Avg-A since the distance away from the core station is taken into consideration in Dis-A, while no factors related with load increment is included in Avg-A.

Figure 4 indicates the waiting time distribution at every CS in different allocation strategies. Every circle refers to a CS. The deeper a circle's color is, the more waiting time the CS corresponding to the circle holds. Figure 4 (a) shows the waiting time distribution at every CS in No-A strategy, indicating the maintenance of the core station has a big impact in EV taxi drivers. The position of the core station is marked by a black arrow. Figure 4 (b) displays the waiting time distribution in Avg-A strategy, reducing waiting time a little for every CS. Figure 4 (c) presents the waiting time distribution in Dis-A strategy and CSs are classified into four zones based on their distances and directions from the core station. It's obviously observed that the waiting time of CSs located in Zone A has reduced a lot compared with No-A, due to the fact that those CSs are near the core station and then will be allocated more charging resources. However, the waiting time of CSs in Zone B, C and D has improved a little since their long distance from the core station. Especially, the waiting time of a medium CS located in Zone D has changed little, leading to the complaints of local EV taxi drivers. And finally, Figure 4 (d) indicates the waiting time distribution in our LI-A strategy, reducing the waiting time of every CS a lot. Therefore, our LI-A strategy outperforms Avg-A and Dis-A strategies in reducing the waiting time of the entire charging system.

D. Evaluations on Utilization of Charging Resources

Besides waiting time, the utilization of charging resources can also reflect the performance of different allocation strategies. When the amount of recharging requests is constant, smaller number of occupied charging points means larger number of EV taxis waiting at CSs. Thus a proper allocation strategy for EV taxis should make more charging resources occupied, improving the level of charging resources utilization. We use the ratio of the number of occupied charging resources over the number of total charging resources to define the utilization rate. The utilization ratio is evaluated with the periods ranging from 2:00 A.M.-6:00 A.M, as the same with the setting of waiting time experiments. We choose 30 minutes as the size of the interval because recharging events always take up to hours. The average charging resources utilization across all normal CSs in different allocation strategies is presented in Figure 5.

When calculating the ratio, we assume the original charging points deployed in CSs will be the prior options for EV taxis, that means the allocated charging resources will be used until the original ones are all occupied for recharging. As shown in Figure 5, the utilization achieved by our LI-A allocation strategy outperforms Dis-A and Avg-A almost in all periods. Meanwhile, the changing trends of curves marked by Dis-A and LI-A can respond to time distribution of EV taxi drivers' recharging requests, that is, the morning recharging peak period occurs during everyday's 3:30 A.M.-4:30 A.M. While the utilization in Avg-A strategy is less than

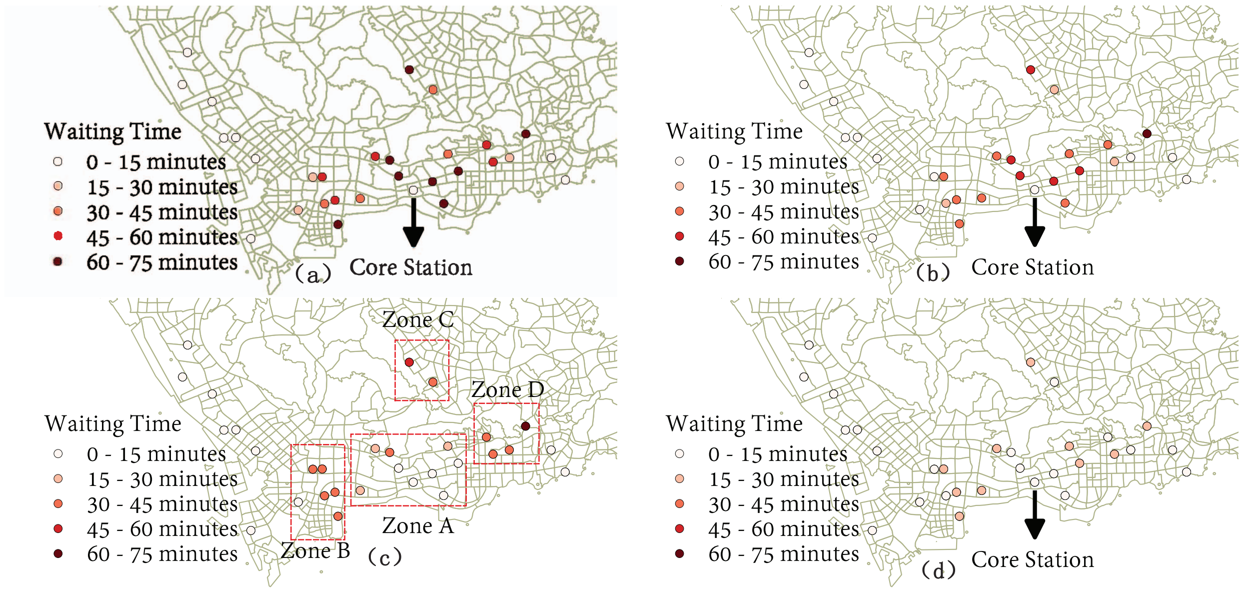

Fig. 4. (a) Waiting Time Distribution in No-A (b) Waiting Time Distribution in Avg-A (c) Waiting Time Distribution in Dis-A (d) Waiting Time Distribution in LI-A

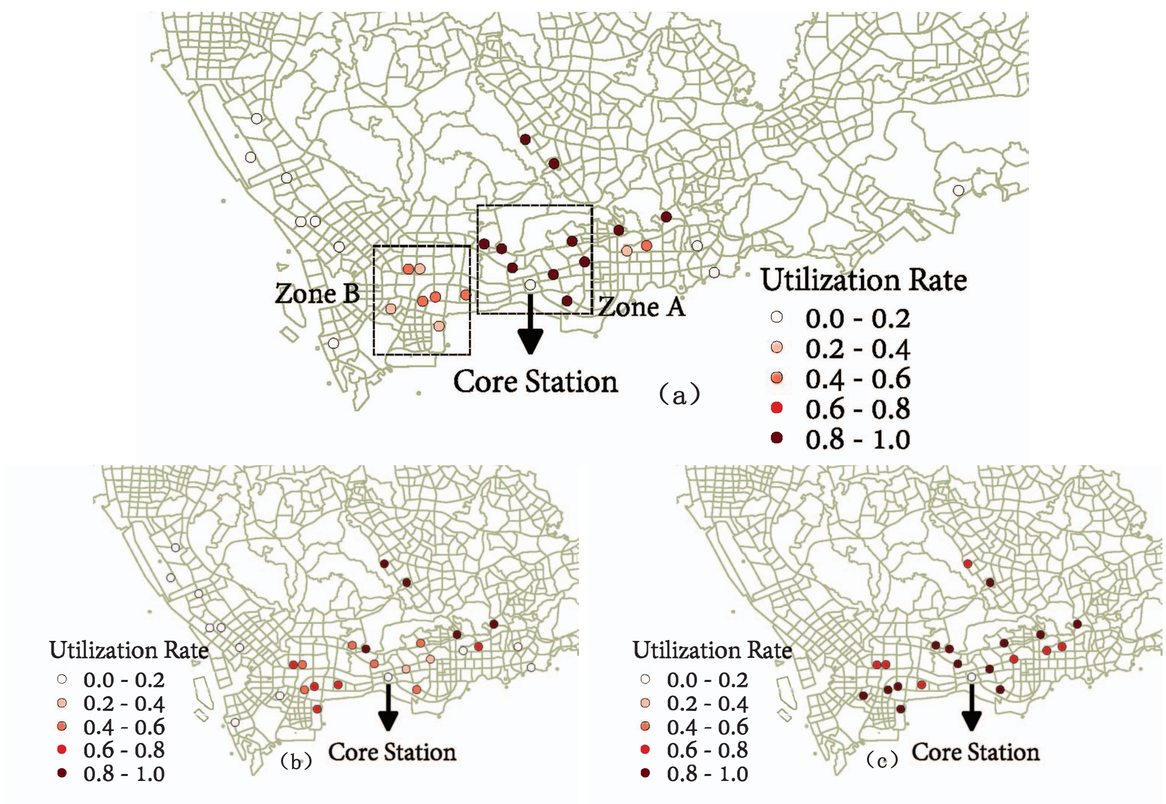

Fig. 6. (a) Utilization Rate Distribution in Avg-A (b) Utilization Rate Distribution in Dis-A (c) Utilization Rate Distribution in LI-A

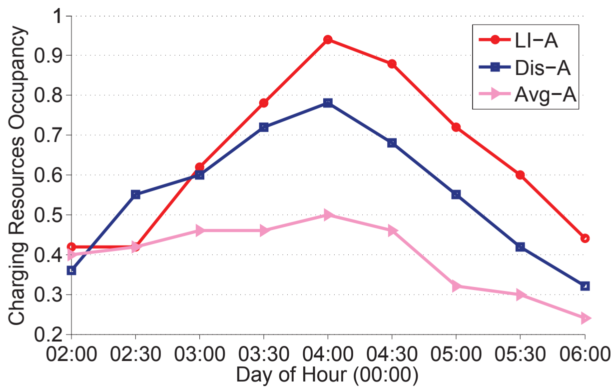

Fig. 5. Utilization of Charging Resources in Different Allocation Strategies

50% even in the morning recharging peak period, indicating its unreasonableness of charging resources allocation.

Figure 6 presents charging resources' utilization rate distribution at every CS in different allocation strategies. It's evaluated still at the morning recharging peak time (i.e., 4:00 A.M.). Every circle refers to a CS. The deeper a circle's color is, the larger utilization rate the CS corresponding to the circle holds. Figure 6 (a) shows the utilization rate distribution at every CS in Avg-A strategy. Avg-A strategy means each CS will obtain 3 charging points. Despite the CSs in Zone A hold larger values of utilization rate, the waiting time at those CSs is still not reduced much. Reasons for that lie in the fact that the number of EV taxis reaching those CSs exceeds the offered charging resources, thus EV taxis drivers still have to wait despite of the high charging resources' utilization rate. On the other hand, the offered charging resources are sufficient for those CSs in Zone B since the utilization rate at those CSs ranges from 0.2 to 0.6. It's obviously observed that many other CSs hold 0 utilization rate, meaning the original charging points deployed in those CSs are enough to meet recharging needs, thus charging resources allocated to those CSs will be wasted.

Figure 6 (b) displays the utilization rate distribution in Dis-A strategy, meaning CSs near the core station will obtain more charging resources. However, utilization rate of those near CSs is overall small, indicating that charging resources allocated to those CSs are excessive. While some CSs far from the core station still suffer from the long waiting time problem since the number of charging resources allocated to them is small due to their remote distance. There also exists charging resources waste in Dis-A strategy, but it's less than Avg-A strategy. Figure 6 (c) indicates the waiting time distribution in our LI-A strategy. Since charging resources are allocated based on load increment of CSs, those CSs with zero load increment will not be allocated charging resources, and then they are removed from the figure. It's obviously observed that every CS in LI-A strategy holds a large value of utilization rate, therefore, it can reduce the overall waiting time and improve the overall utilization rate, performing better than Dis-A and Avg-A strategies.

VI. Conclusion

In this paper, by utilizing GPS records of EV taxis and information of charging stations deployed in Shenzhen, we study the impact of core charging station maintenance in the entire charging system. We firstly extract and analyze some features related with the load increment, and then we use a regression model to predict the load increment of a normal CS based on those selected features. And finally, a strategy based on our regression model is proposed for charging resources allocation. Our experiments on the real data set shows that our proposed allocation strategy can reduce the waiting time at CSs by more than half, and improving charging resources occupancy at the same time.

In the future, we would like to analyze the impact of charging station maintenance in a more fine-grained way. We should consider the chain reactions under such maintenance, e.g., which EV taxis lead to the load increment of a normal CS, and how the EV taxis that used to recharge at the CS will react to the load increment.

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