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To cite this article: Keying Zhang and Suyang Zhou 2019 *IOP Conf. Ser.: Earth Environ. Sci.* **223** 012034

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# Data-Driven Analysis of Electric Vehicle Charging Behavior and Its Potential for Demand Side Management

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**Abstract.** This paper presents a comprehensive analysis of the Electric Vehicles (EVs) charging behaviour based on the data collected from the UK flagship demonstration project – Low Carbon London. Data of seventy residential charging facilities over one year are processed and analysed. The charging behaviour of the cluster of charging facilities and selected charging facilities are analyzed respectively. Based on the in-depth analysis, the potential of the EV charging facilities for joining the demand side management program are further investigated. To evaluate the performance of using charging facilities to join Demand Side Management (DSM) program, numerical analysis based on different DSM programs are presented.

## 1. Introduction

Electric vehicles are playing an increasingly important role in transportation sector. The EV new sales market share has hit 1% in 2017, and is expected to increase to more than 20% in 2025 in U.S. [1]. The increasingly penetration of EV will bring significant benefits for reducing the carbon emission because transportation takes large share of energy consumption all around the world [2]. However, large amount of EVs will bring serious burden to the distribution network due to the convergence of charging behavior, and could make the evening peaks even worse, especially during winter and summer seasons[3].

Aiming to evaluate the impacts of EVs on distribution network, a number of research have been performed on EV charging modeling, EV charging behavior analysis and EV charging scheduling [4-8]. [4] evaluated the impact of EV charging in the single wholesale electricity market in Ireland under the assumption of 10% vehicles are powered by electricity, and found that off-peak charging is more beneficial than peak charging. [5] investigated the impacts of EV recharging on Western Australia network. It highlighted that the annual peak demand will not be significantly influenced by EV charging if the share of EV is less than 10%, but the electricity transmission and distribution network operators can achieve reasonable benefits if the EV charging can be regulated. [6] modeled the EV charging behavior using the long-term electric energy data of an electric vehicle charging station, and verified the model accuracy with the field-measurement data. The proposed model has sounding accuracy and can assist the distribution network analysis. [7] performed the impact analysis of EV charging on Malaysia distribution network. It made similar conclusion given in [5] that 10% EV penetration level is safe to the distribution network. It also highlighted that a newly built residential



LV network can accommodate up to 60% EV penetration if the charging of EV can be regulated. [8] modeled the EV charging profile based on a population of electric vehicles with GPS travel data that collected during an electric vehicle demonstration trial.

Most of the aforementioned researches model the EV charging profile using simulated data or the petrol powered vehicles data. The change of EV charging behavior over time is less considered, and the inertia of the charging activities is not investigated. However, how often the EV owners charge their vehicles in the real-world and whether they charge their vehicles in a regular way are important factors for evaluating their impacts to distribution network and their potential for participating the DSM schemes. [9] observed that the average distance for each drive of EV(Nissan Leaf) owners are 6.9 miles, and the daily average driving mileages is around 30 miles based on the 8,300 U.S EV driving data. [10] analyzed the EV charging profile with considerations of actual state-of-charge of the battery, parking duration and parking type. The proposed methodology showed good performance for predicting the plug-in EV load for the region that the EV usage data are not available.

Aiming to further analyze the EV charging behavior and explore the operation characteristics of residential EV charging facilities, especially the inertia of EV charging activities and their charging connection time, this paper performed a comprehensive analysis on the EV charging data of 70 residential users collected from UK flagship demonstration project. The charging behavior of the cluster of charging facilities and selected charging facilities are analyzed respectively. Based on the in-depth analysis, the potential of the EV charging facilities for joining the demand side management program are later investigated. To evaluate the profitability of using charging facilities to join Demand Side Management (DSM) program, numerical analysis based on different DSM programs are presented.

The remainder of this paper is organized as follow: Section II presents the analysis of 70 EV charging facilities. Section III presents the remarkable DSM schemes and the evaluation methodologies for EVs that participate the DSM schemes. The numerical results of the potential of residential EV charging facilities for participating the DSM schemes are presented in section IV, and a brief conclusion is given in section V.

## **2. ANALYSIS OF RESIDENTIAL CHARGING FACILITIES**

The EV charging data used for analysis in this paper are collected from the UK flagship demonstration project – Low Carbon London. The EV charging load profiles consists residential EV charging information from 70 different users (saved in CSV format) over one year from January 2013 to April 2014. 5 of the 70 EV charging CSV files are empty and 27 of the 70 CSV files include null values with percentage larger than 50%, thus 38 EV charging load profiles are analyzed in this sector aiming to evaluate the charging behavior of EV owners.

### *2.1 General Charging Behavior Analysis of All Charging Systems*

This section analyses the EV charging behaviour from the perspectives of charging power, charging connection time and the charging durations points of view. The analysis aims to explore the in-depth EV charging characteristics that can be coupled with DSM schemes.

The average EV charging power by time is presented in Figure 1. The charging power of 38 EV charging profiles are aggregated by time over one year time period. It is obvious that the charging peak time of residential users is between 8PM and 9PM. The minimum charging power is at 4AM, which means most of EV charging activities are finished by early morning. According to the normal departure time, the residential vehicle users usually leave home at around 7AM [11]. This means most of the flexible charging time for EVs are larger than 3 hours.

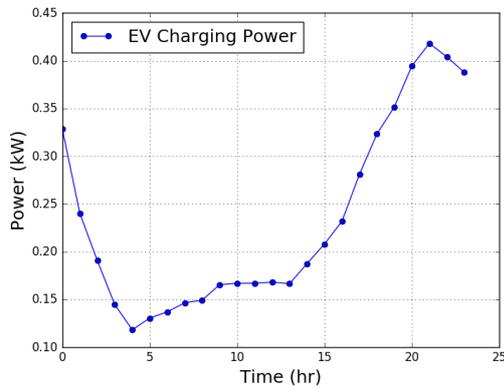


Figure 1. Mean EV Charging Power

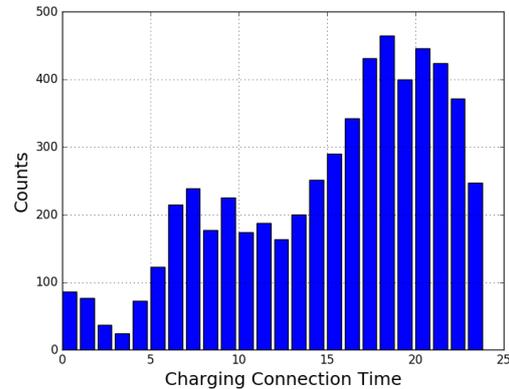


Figure 2. Distribution of EV Charging Connection Time

In order to further investigate the EV charging behaviour, the charging connection time of the EVs are analysed. The connection time of EVs are calculated based on the logic that if the power of charger is larger than 0.5kW (means the time period of EV connected with the charger with 3.2kW rating power is longer than 10 minutes) and the previous charging power in the previous two times slots are smaller than 0.1kW (aim to mitigate the influence of standby current on EV charger), the connection time of EV is determined and recorded. The EV charging connection time is shown in figure 2. It can be found that most of EVs are connected to the charger between 4PM and 10PM, which can support the conclusion of EV charging peak usually occurs between 8PM and 9PM.

The charging duration of single charging activity is another factor that will influence the flexibility of EVs. The charging duration calculation is performed based on the logic that once the connection of EV is detected, the charging duration starts calculating until the charging finishing time (charging power is smaller than 0.1kW) is detected. The charging duration of 38 EVs over one year is presented in Figure 3. It can be found that the charging duration between 1hour and 2 hours are the most frequent among all the durations. According to the survey of the EV residential users of Low Carbon London trials, most of them declared that their daily travel distance using EV is less than 30 miles. The charging duration can be calculated using the equation below.

$$T_c = D * \frac{E}{P} * \eta \tag{1}$$

Where  $T_c$  represents the charging duration of EV,  $D$  represents the distance the EV travelled,  $E$  represents the energy that EV consumes per mile,  $P$  represents the rating power of EV charger and  $\eta$  represents the charging efficiency of EV charger.

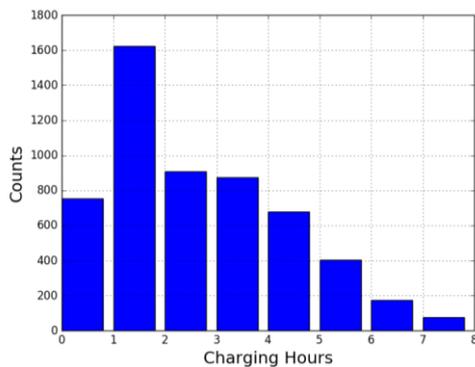


Figure 3. EV Charging Durations

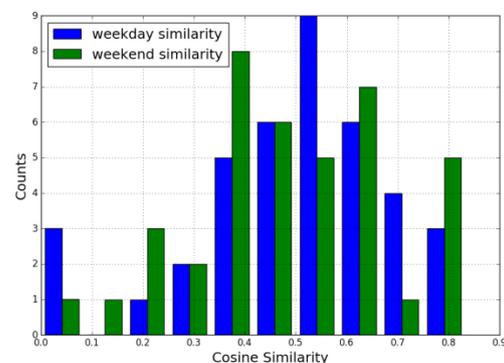


Figure 4. Cosine Similarities of EV Chargers

According to the parameters of the EV and chargers used during the trial, the charging duration is equal to 1.92 hours if the daily mileages are 20 miles (with assumptions that the charging efficiency  $\eta = 0.95$ ,  $E = 0.2\text{kWh/km}$ ,  $P = 3.2\text{kW}$ ), which is similar to the average charging duration 2.27 hours obtained from demonstration projects.

## 2.2 Charging Behaviour of Selected Charging System

In this section, the inertia of EV charging activities are analysed and selected charging profile are evaluated. The inertia of individual EV charging profile refers to the strength of users that follow their charging behaviour. If users' charging activities have larger inertia, it means the users are more likely to charge their EV at same frequency and same connection time, which are valuable controllable resources for DSM schemes.

The inertia can be represented by similarities in mathematics such as Euclidean distance, Manhattan distance and cosine similarity. Cosine similarity is used as a metric for measuring distance when the magnitude of the vectors does not matter. Since the EV chargers have the same charging rating power during the trial, the magnitude of the vector will be generally same when the EV are being charged, and the connection time and disconnection time are the two most important factors for measuring the charging behaviour similarity. Therefore, the cosine similarity is selected to measure the EV charging inertia.

The calculation of EV charging inertia using cosine similarity follows the equations below.

$$C_{sim} = \frac{A \cdot B}{\|A\| \cdot \|B\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}} \quad (2)$$

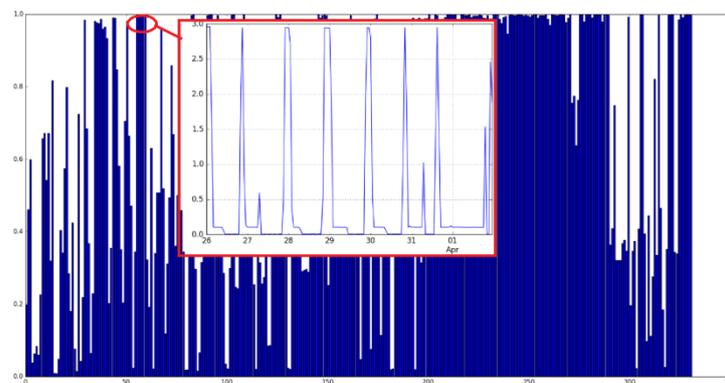
$$A = [P_t, P_{t+1}, P_{t+2}, \dots, P_{t+23}] \quad (3)$$

$$B = [P_{t+24}, P_{t+25}, P_{t+26}, \dots, P_{t+47}] \quad (4)$$

Where **A** and **B** are the 24-dimension vectors that represents the 24-hr power of EV charger.

The day-by-day similarities of EV chargers in weekdays and weekends are shown in figure 4. It can be found that 72.5% EV chargers have the cosine similarities equal to or more than 0.4 during weekends, and 74.2% EV chargers have the cosine similarities equal to or more than 0.4 during weekdays, which conclude that the EV charging behavior has reasonable inertia.

To further evaluate the inertia of EV charging behaviour with regarding to the cosine similarity. An EV charger with cosine similarity equal to 0.65 is taken as an example. The similarity distribution of the EV charger over one year is given in figure 5. It is observed that the day-by-day similarities is ranged between 0 and 1, and more than 30% of the similarities are more than 0.9. A seven-day charging profiles of the EV with cosine similarities larger than 0.9 is presented in the sub-figure in figure 5. It can be observed that the EV is connected to the charger at similar time and with similar charging duration during the seven days. Such characteristics indicates that the EV users would maintain their charging behaviours in certain periods, and their daily vehicle usage are similar in the same period.



**Figure 5.** Cosine Similarities Distribution of one EV Charger with Mean Similarity=0.65

### 2.3 Charging Behaviour of Selected Charging System

According to the analysis presented in part A and part B, a number of findings can be concluded as below.

- 1) Residential users in the London trial start charging their charging connecting time most frequently between 6pm – 8 pm.
- 2) The charging peak of residential EV users usually happens between 8PM – 9PM.
- 3) The average daily traveling distance of the residential EV owners is less than 30 miles, which can be charged in full in 2 hours.
- 4) The charging behaviour of EV users has high similarities in both weekday and weekend.
- 5) There are obvious inertia observed from the charging profiles that users have similarity larger than 0.5.

## 3. ANALYSIS OF RESIDENTIAL CHARGING FACILITIES

This section introduces the DSM schemes that would be available for the electric vehicles. The limitations and challenges of using EV to participate the DSM schemes are also presented.

### 3.1 Time of Use (TOU) Tariff

The TOU tariff allows energy companies charge energy consumers at different rates in different time period. The mainstream TOU tariffs available in the market are Economy 7, Economy 10 and Critical Peak Pricing (CPP). Economy 7 tariff usually allows energy consumers get a lower price between 0:00AM – 7:00Am, and Economy 10 tariff allows consumers get a lower price between 8PM – 8AM. CPP tariff usually notices the energy consumers higher energy rates for selected hours/days if utility companies anticipate a price rise in energy wholesale market.

For using TOU tariff to shift the EV charging load from DSM point of view, the pricing mechanism is the key factor that influencing the load shifting performance. It is difficult for utility companies to balance their savings in shifting the load to off-peak time and the cost of encouraging EV users to change their energy using behaviour.

### 3.2 Direct Load Control (DLC)

DLC is one kind of DSM schemes that allows utility companies to manage consumers' appliance/devices (i.e water boiler, electric heater, and air conditioner) when the increase in peak demand or price rise in wholesale market is anticipated. The incentives for DLC participants could be invoke payment, annual reservation payment, electricity discounts or free hardware. The DLC events would be limited under certain frequency during the time period and the total number of invoking DLC events would also be regulated under different contracts.

EV can also participate the DLC scheme as an interruptible load [12]. There are a number of demonstration projects across the world that use EV for DLC scheme [13],[14] reported that only about 13% customers might accept the DLC program based on a total of 1,499 householders from one state in Australia. Thus, for encouraging EV owners to accept the DLC scheme, the scheme needs to be designed carefully and enough freedom should be allocated to the participants.

### 3.3 Vehicle to Grid (V2G) Technology

The V2G technology gives the capabilities of bi-directional charging to EVs, so that the EVs can communicate with the power grid to sell demand response service by taking electricity from grid and selling their stored electricity to grid to balance the electricity demand and supply.

The V2G technology is still a relatively new technology and most of V2G infrastructures are still in Research and Development (R&D) stages [15]. [16] highlighted that the V2G technology would have great potential for the electric power grid balancing, but at current stage it is still difficult to promote unless the cost of battery degradation can decrease to a reasonable level.

#### 4. NUMERICAL ANALYSIS

According to the analysis performed in section III, the TOU and DLC scheme would be two reasonable choices for encouraging EVs to participate into the DSM program. The V2G technology could be the DSM choice for EVs only if the cost of battery degradation can be covered by the DSM financial incentives, which is still difficult to achieve at the moment. Therefore, the potential of using EVs to participate into TOU scheme and the DLC scheme are analysed in this section.

##### 4.1 EV potential for DSM under TOU scheme

To evaluate the EV potentials for DSM in TOU scheme, the pricing mechanism and the willing of EV owners to shift their EV charging time should be taken into account. A CPP tariff pricing problem is presented in the following part and the numerical analysis of using such pricing mechanism to manage the EV charging is shown behind.

The pricing of CPP can be formulated as a mathematical optimization problem as below.

$$\min [\sum_{m=0}^M (P_{t+m}^C - P_{t+m}^W) \times \Delta Q_{t+m} + \sum_{n=M}^{M+N} P_{t+n}^W \times \Delta Q_{t+n}] \quad (6)$$

$$\text{Subject to} \quad \Delta Q_{t+m} = Q_{t+m}^{EV} \times \frac{P_{t+m}^C}{\partial_{t+m}} \quad (7)$$

$$\sum_{m=0}^M \Delta Q_{t+m} = \sum_{n=M}^{M+N} \Delta Q_{t+n} \quad (8)$$

$$\frac{\Delta Q_{t+n}}{\sum_{m=0}^M \Delta Q_{t+m}} \leq \theta \quad (9)$$

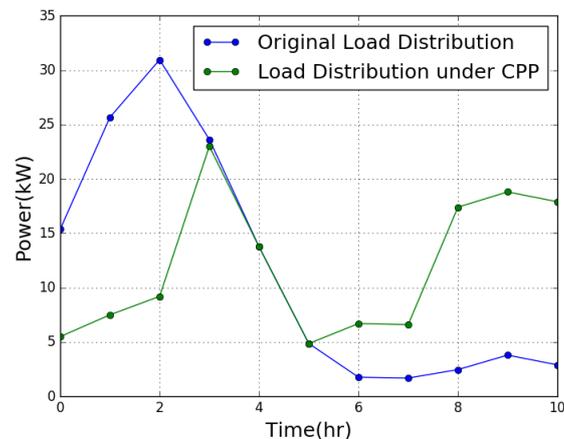
$$P_{t+m}^C \geq 0 \quad (10)$$

$$\partial_{t+m} \geq P_{t+m}^C \quad (11)$$

Equation (8) is the objective function for the CPP pricing problem.  $P_{t+m}^C$  represents the critical time price at time t+m (M refers to the length of critical pricing period),  $P_{t+m}^W$  and  $P_{t+n}^W$  represents the wholesale electricity price at time t+m and t+n,  $\Delta Q_{t+m}$  represents the energy of EV that would like to be shifted,  $\Delta Q_{t+n}$  represents the energy of EV that will be shifted to the time slot t+n. Equation (7) – (11) illustrate the constraints of the pricing problem. Equation (7) describes the relationship between the willing of EV owners to participate into the CPP scheme and the price of CPP. It shows that the willing will increase along with the increase of the CPP price. Equation (8) ensures the balance of the shifted energy. The pricing problem is a Quadratic Programming (QP) problem and all the constraints are linear, which can be solved by Gurobi, CPLEX and other commercial solvers.

The numerical analysis of evaluating the EV potential under CPP scheme using the above mathematical model is given in the following part. The wholesale market price used in the analysis is obtained from the EPEX wholesale market, the energy of EV which is available for load shifting during CPP period is calculated based on the EV connection time and charging duration distributions in the Low Carbon London trial. The CPP event period is assumed as 3 hours between 8:00PM – 11:00PM. It is also assumed that the shiftable EV loads can be shifted to post CPP event time periods of 8 hours (7AM).

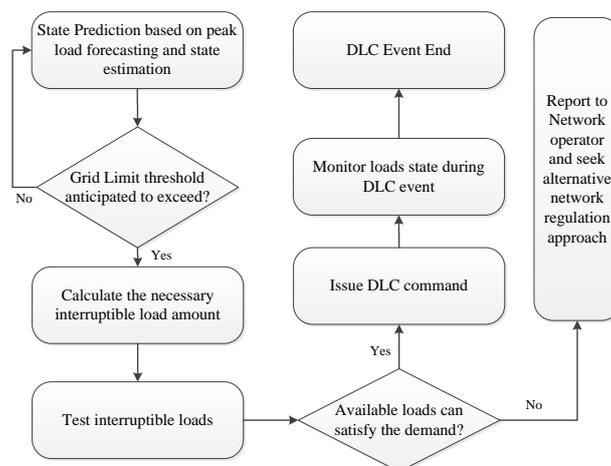
Figure 6 presents the shifting of EV charging loads under CPP scheme. The price of CPP scheme during the CPP event is optimized to 0.415€/kWh (66% higher than the original electricity price), and a total of 49.78kWh EV loads between 8:00PM – 11:00PM are shifted to the later time till 7:00AM. It can be found that the peak load during the 10 hours has been reduced from 30.95kW at 10:00PM to 23.62kW at 11:00PM, which is a 23.7% peak load reduction. The EV charging loads are shifted to the time period between 00:00AM and 7:00AM, and most of the charging loads are moved to the time periods with lower wholesale electricity price (3:00AM – 6AM). The shifted load to a single slot is limited to 30% of all shiftable load using the constraint of equation (9), which ensures the shifted load will not generate another evening peak. It can be concluded that the EVs have good performance under CPP scheme if the CPP price is set appropriately, and the load shifting will not generate other evening peaks if constraints of load shifting are configured.



**Figure 6.** EV Charging Load under CPP scheme

#### 4.2 EV potential for DSM under DLC scheme

The control logic of DLC will influence the performance of using interruptible loads in DLC scheme [17]. A number of DLC control methodologies have been proposed in previous research [18-20]. Since the paper aims to analyze the potential of EV for DSM under DLC scheme, the control logic of DLC is not the most important factor. A simplified DLC control logic is proposed in figure 7 to evaluate the EV charging shifting potential based on the DLC control logic proposed in [21].



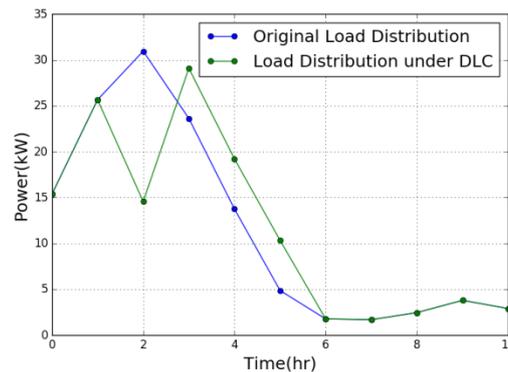
**Figure 7.** DLC Flowchart from Network Operator Point of View

Based on the proposed DLC control logic, when a DLC event needs to be invoked, the network operator will firstly search the interruptible loads that are available during the DLC event. In the numerical analysis performed in this section, following assumptions are made to simplify the analysis of EV potential for DSM under DLC scheme:

- 100% EVs that connected to the grid during DLC event are available for DLC control.
- EVs connected to the grid in the previous hour of DLC event and the expected charging durations are longer than 1 hour are available for DLC control (The percentages of EV that have charging duration longer than 1 hour can be obtained from the charging hours duration distribution in Figure 3).
- EVs that connected to the grid two hours earlier than DLC event and their expected charging durations are longer than 2 hours are available for DLC control.
- The EVs that are invoked during DLC event can be reconnected to the network evenly during the post 3 hours after DLC event.
- The EVs that are connected to the grid three hours earlier than DLC events are considered as un-

interruptible loads.

According to the assumptions given above, and the DLC event is assumed to occur at 10:00PM for one hour, the EV charging profile under DLC scheme is shown in Figure 8. The peak load at 10:00PM is reduced from 30.95kW to 14.56kW, which is a 53.6% load production during DLC event. However, it can be found that another peak load equal to 29.01kW occurs at 11:00PM, and it is because 5.47kW EV charging load is shifted to 11:00PM. The loads between 00:00AM to 2:00AM are increased as well with the shifted EV loads. It can be concluded that EV achieve good performance on reducing peak load during DLC event. However, other evening peaks (as seen in Figure 8) could be generated as the EV load could be reconnected to the grid after the DLC event.



**Figure 8.** EV Charging Load under DLC scheme

## 5. Conclusion

This paper has given a comprehensive analysis of EV charging behaviour based on the data from Low Carbon London project. From the analysis performed in section II, it is found that most of EV charging durations of residential users are shorter than 3 hours, and obvious inertia of charging behaviour are detected. Such inertia could assist the forecast of EV charging load and the design of DSM program. In section III, the mainstream DSM program including TOU, DLC and V2G are discussed. Two DSM program, CPP (one kind of TOU) and DLC, are selected to evaluate the potential of EV for participating the DSM program in section IV. It is found that EVs achieve good performance of shaving the loads under CPP and DLC scheme. However, other evening peaks could be generated under DLC scheme, which is caused by the reconnection of EV after DLC event. Thus, it is important to schedule EV reconnection time after DLC event when designing the DLC control logic.

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