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An Investigation of Battery Electric Vehicle Driving and Charging Behaviors Using Vehicle Usage Data Collected in Shanghai, China


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Abstract

This paper investigates the driving and charging behaviors of battery electric vehicle (BEV) drivers observed in Shanghai, China. The summary statistics are compared with the observations from the U.S. EV Project. A machine-learning approach, namely self-organizing feature map (SOM), is adopted as a classifier to analyze BEV drivers' habitual behaviors. The inter-driver heterogeneities are examined in terms of: the distributions of distance traveled per day, the start time of charging, the number of charges per day, distance traveled between consecutive charges, battery state of charge (SOC) before and after charging, and time-of-day electricity demand. It is found that (a) BEV drivers demonstrate conservative charging behaviors, leading to short distances between consecutive charging events; (b) a significant number of BEV drivers in Shanghai charge during daytime; (c) the distributions depicting the driving and charging patterns vary greatly due to the diversity in travel activities among different drivers.

Keywords

Battery electric vehicles, Driving and charging behaviors, Heterogeneity, Self-organizing feature map

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ABSTRACT

This paper investigates the driving and charging behaviors observed from battery electric vehicle (BEV) drivers in Shanghai, China. The summary statistics are compared with the observations from the U.S. Department of Energy's EV Project. A machine-learning approach, namely self-organizing feature map (SOM), is adopted as a classifier to analyze BEV drivers' habitual behaviors. The inter-driver heterogeneities are examined in terms of the distributions of distance traveled per day, the start time of charging, the number of charges per day, distance traveled between consecutive charges, battery state of charge (SOC) before and after charging, and time-of-day electricity demand. It is found that (1) BEV drivers demonstrate conservative charging behaviors, leading to short distance between consecutive charging events; (2) a significant number of BEV drivers in Shanghai charge during daytime; (3) the distributions depicting the driving and charging patterns vary greatly due to the diversity in travel activities among different drivers.

Keywords: Battery electric vehicles, Driving and charging behaviors, Heterogeneity, Self-organizing feature map

1 INTRODUCTION

The depletion of fossil fuels, as well as its adverse impact on the environment and human well-being, have raised serious concerns over the sales and usage of fossil-based vehicles. Consequently, to overcome these challenges, many countries have declared plans to ban the sale of gas and diesel cars in the coming years while the trend and focus of the automotive industry are shifting towards green vehicles. These initiatives have led to the development and popularity of battery electric vehicles (BEVs) that produce zero tailpipe emissions. Thus, replacing the vehicle fleet with BEVs has the potential to reduce greenhouse gas emissions and other harmful pollutants. In many metropolitan cities of China, where the high concentration of vehicles has caused severe air pollution, there is an increasing interest in large-scale deployment of BEVs in the near future. The Chinese government has set pure electric driving as the primary strategic direction of new energy vehicles (NEVs) development and the auto industry transition (1). Correspondingly, a series of financial incentive policies have been implemented to promote the deployment of BEVs (2).

To better quantify the societal benefits of BEVs, forecast their market acceptance, design charging infrastructure, and reduce vehicles energy consumption, it is essential to characterize the driving and charging behaviors of BEV users. The EV Project in the U.S., initiated and managed by ECOtality North America, has collected and analyzed vehicle usage data from approximately 8,300 Nissan Leaf BEVs and Chevrolet Volts extended-range electric vehicles (EREVs) since 2010. A number of similar projects have been developed to analyze the behavioral and mobility patterns of electric vehicles, including the SwitchEV project (3), the CABLED project (4), the FREVUE project (5), the ZeEUS project (6) and so forth. These realistic and systemic data help researchers better understand users' real-world driving and charging patterns (7-11). Likewise, cities in China, such as Beijing, Shanghai, and Shenzhen, have launched various programs to develop NEVs monitoring and service platforms. Several pioneering works, focused on commercial vehicles (i.e. BEV taxis), have been carried out based on the dataset collected from these platforms (12, 13). In this paper, we use the data collected by Shanghai Electric Vehicles Data Center (SHEVDC) that is developed to remotely monitor electric vehicles driven across the city. 50 BEVs, used as personal vehicles, with the same model of Roewe E50 are extracted from the SHEVDC database.

Empirical observations show that the variations exist in BEV owners travel activities. With respect to such variations, many existing studies are focused on modeling the diversity in trip length (13, 14), daily vehicle kilometers traveled (VKT) (15-18), dwell time (14), travel distance between charges (14, 17) and so on. The travel pattern of one BEV owner is relatively constant, yet the uncertainties make the travel demand vary from day to day (i.e. intra-driver heterogeneity). To better understand the diversity of travel activities for different drivers (i.e. inter-driver heterogeneity), this paper not only presents the summary metrics of the real-world BEV owners' driving and charging behaviors, but also investigates the inter-driver heterogeneity by classifying vehicles according to their daily traveled distance and start charging time, which helps to eliminate the interference of the intra-driver heterogeneity.

The main contributions of this paper can be summarized as follows: (1) compare the driving and charging behaviors of BEV owners in Shanghai with the observations from the EV Project; (2) use a machine-learning approach, namely self-organizing feature maps (SOM), to cluster the collected vehicle samples; (3) examine the inter-driver heterogeneity from the perspective of the distributions of distance traveled per day, start time of charging, daily number of charging events, distance traveled between consecutive charges, battery state of charge (SOC) before and after charging, and time-of-day electricity demand.

The next section describes the observed driving and charging behaviors of Roewe E50 owners in Shanghai, China, followed by vehicle grouping using the SOM method in Section 3. After that, results and discussions are presented in Section 4. Conclusions and caveats of the study are discussed in Section 5.

2 DATA DESCRIPTION

2.1 Data Collection

This study makes use of a rich database collected from 50 BEVs (i.e. Roewe E50) over a period of 4-12 months (covering a time period from June 2015 to June 2016). The longest recording time lasted for 357 days (i.e. VID 14), while the shortest recording time is 94 days (i.e. VID 43). The average recording time for each vehicle is about 225 days. Developed by SAIC Motor, Roewe E50 is a pure electric passenger car with a 22.4kWh battery pack and a claimed range of 170km (19).

Vehicle terminals, such as global positioning system data loggers and instruments to measure voltage and current are installed on BEVs, to record in-use data and vehicles' driving information at a rate of about 2 samples per minute. In-use data includes turn on time, turn off time, total mileage, SOC, voltage, current, etc. Vehicles' driving information includes time-stamped location (i.e., longitude and latitude), spot speed, azimuth, etc. After data cleansing and consistency checking procedure to remove invalid and erroneous data from the records, BEV owners' driving and charging information, such as the average distances traveled per day, the average number of charging events per day, distances traveled between charging events, start time for charging, SOC before and after charging, etc., are extracted.

2.2 Observed Driving Behavior

Table 1 presents summary metrics describing driving behaviors of the 50 BEVs considered in this study. The mean values of the daily VKT and the distance traveled between charges are compared with the observations from the US EV Project, which collected in-use electronic data from 3499 Nissan Leafs (20). The Nissan Leaf is a BEV with a 24 kWh battery pack, and the manufacturer's expected range is 100 to 220 km on a single full charge depending on driving conditions (21).

Place TABLE 1 here.

The average daily VKT is adopted to characterize the diversity of different drivers as it indicates drivers' travel intensity (22-24). Overall, E50 owners have higher average daily VKT than Leaf owners. The maximum average daily VKT is 95.3km observed from VID 8. The average daily VKT of VID 17 is the lowest, indicating a low vehicle utilization. All the average daily travel distance is far below the E50 range. Drivers might have limited their daily driving due to concerns about BEV range.

Examining distance traveled between consecutive charging events helps to better understand the driver behavior with respect to BEV range. Similarly, for both Shanghai and US BEV drivers, the average distance traveled between charging is lower than the average daily VKT. The results reveal that most drivers would charge their vehicles when provided with convenient opportunities, regardless of the remaining range. This conservative behavior helps to avoid the risk of fully depleting their battery before next charging opportunity. Nevertheless, some drivers prefer to use a large portion of the vehicle's range before charging. For example, the longest average distance traveled between charges is observed from VID 11, while its average daily VKT is 20.9 km, only about one-fifth of the traveled distance between two charges. It could be speculated that the remaining range might play a more important role in deciding whether or not to charge for

BEV owners with short daily VKTs. Section 4.1 presents more detailed analysis regarding these findings.

2.3 Observed Charging Behavior

Table 2 shows summary metrics of charging events. Because of the missing records, VID 7 only has the information of the number of charging events and the start time for each charging and thus is not included in the calculation of other metrics. The mean values are compared with the observations from the US EV Project (20).

Place TABLE 2 here.

Table 2 shows that Shanghai E50 drivers exhibit the same charging frequency as their US counterparts, charging 1.1 times per day on average. This is consistent with the observation described in the preceding section, where distance driven between charging events is slightly less than distance driven per day. The average charging frequency varies from vehicle to vehicle, from 0.2 charges to 1.6 charges per day. Drivers with short daily VKTs choose not to charge more often than is necessary.

The charging power is calculated based on the charging time and the increase in SOC. It can be inferred that almost all the charging events are performed using AC Level 2 Electric Vehicle Supply Equipment (EVSE) at home or workplaces (25). The starting SOC indicates how much of the battery pack's capacity has been depleted prior to charging. There is a wide variation in the starting SOC from vehicle to vehicle. The high starting SOC, e.g., VID 38 with an averaged value of 61.6%, indicates drivers are likely to charge their vehicles whenever they have charging opportunities. Battery SOC at the end of charging represents how full the battery pack is after charging. The data shows that the majority of charging events result in a fully charged or nearly fully charged battery pack, which is consistent with the findings from the EV project (20). Thus, it can be speculated that the variation in charging time of E50 is mainly determined by the starting SOC.

The starting time of charging represents when charging units are connected to BEVs. Based on charging power and charging demand, we can assess the impact of charging BEVs on the electric grid. Similar to the daily VKT, a particular BEV owner has a relatively fixed time for charging on different days. The mean and median values of starting time are around 14:00, and 33.9% of the participants plug in their vehicles in the afternoon (from 12:00 to 18:00). Some drivers prefer charging the battery in the morning, e.g., VID 36 is often plugged in at 9:00; while some prefer to connect their vehicles to their residential EVSE in the late evening, e.g., VID 1 is often plugged in after 21:00. The impact of charging demand on the electric grid is discussed in Section 4.6.

3 METHODOLOGY

3.1 Self-Organizing Feature Map

To gain better insights into inter-driver heterogeneous behaviors, we apply the Self-Organizing Feature Map (SOM), an unsupervised machine-learning approach, to group the 50 BEVs.

The SOM consists of neurons arranged systematically on a two-dimensional surface (known as a "map"). Each neuron has a prototype weight vector that represents the characteristic features in the input space. Such structure is capable of mapping patterns in the high dimensional input space into a two-dimensional map. According to the unsupervised learning rule, vectors that are similar to each other in the multidimensional space will be clustered in the same neighborhood in the SOM's two-dimensional space, which makes it possible to be adopted as a tool for data

classification. Because of its unique structure, users of the SOM do not need to specify the function between the input features and its output variable. No equation needs to be pre-defined and no parameter calibration is necessary. Therefore, the SOM is considered as a non-parametric approach to measure similarities and dissimilarities among different BEV drivers.

A SOM is a two-dimensional grid, as shown in [FIGURE 1](#). The map is usually square, but can be of any rectangular or hexagonal shape. Each point on the grid, denoted by its coordinates (x,y) , has a neuron and an associated weight vector W_{xy} . The N -dimensional weight vector, $W_{xy} = (w_{xy_1}, w_{xy_2}, \dots, w_{xy_n}, \dots, w_{xy_N})$ represents the centroid of a data cluster of similar input vectors. The weight vectors are collectively known as the SOM's memory.

Place [FIGURE 1](#) here.

When an input vector $A = (a_1, a_2, \dots, a_n)$ is presented to the SOM, the “distance” between A and each of the weight vectors in the entire SOM is computed. The neuron whose weight vector is “closest” to A will be declared as the “winner” and has its output set to 1, while others are set to 0. Mathematically, the output b_{xy} of a neuron located at (x,y) is:

$$b_{xy} = \begin{cases} 1 & \text{if } \|A - W_{xy}\| = \min_{i,j} \{\|A - W_{ij}\|\} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where the operator $\| \ \|$ represents the Euclidean distance, and i, j are indices of the grid positions in the SOM. The input vectors that are categorized into the same cluster, i.e., the same winning neuron, have the similar driving and charging patterns.

The training of a SOM is to code all the W_{xy} so that each of them represents the center of a cluster of similar training vectors. Once trained, W_{xy} is known as a prototype vector of the cluster it represents. The SOM training is based on a competitive learning strategy. More details on the SOM training can be found in [\(26\)](#).

3.2 Mapping Framework

The SOM is used to classify the vehicles embedded in the input vectors. The average distance traveled per day when the vehicle was driven (denoted as d_{VKT}) and the starting time of charging (denoted as T_{start}) are selected to form the input vectors. That is, $A = (d_{VKT}, T_{start})$. These two components are selected because different drivers may have different magnitudes of d_{VKT} and T_{start} due to their preferences. The distribution of d_{VKT} is commonly used to investigate whether the range of a certain type BEV can satisfy the daily VKT of most drivers [\(16, 18\)](#). The general insights into T_{start} can help assess the impact of BEV charging on the electric grid.

Before the SOM training, each component of the input vector is linearly scaled to $[0, 1]$ between its minimum and maximum values in the dataset, i.e., $a_n \in [0, 1], n = 1, 2$. The training of the SOM is performed with the MATLAB R2015b Neural Network Toolbox [\(29\)](#) running on a personal workstation with 3.50 GHz CPU and 16GB of RAM. After training, the matrix of W_{xy} is formulated representing the characteristic of each group. Once the winning neuron has been identified, the distributions of driving and charging patterns associated with each neuron in the SOM can be plotted and analyzed. The parameters of the patterns of the winning neuron are used to study the inter-driver heterogeneity.

The size of the SOM is selected considering the following two factors. First, the grid has to be large enough so that there are sufficient neurons to distinguish the varied patterns among the prototype weight vectors. Since the SOM has two input components and the value of each component may be viewed at two or three levels (e.g., d_{VKT} may be described as long, medium,

and short; T_{start} may be described as daytime and nighttime), there will be 6 possible combinations of input levels. Second, the number of neurons must be small enough such that most, if not all neurons have sufficient winning frequencies (sample sizes) to observe the distribution of the pattern characteristics. After some trials involving SOMs with different numbers of neurons and with different arrangements (square grid, rectangular grid and linear) on the map, the SOM is determined to have 4 neurons arranged in a 2x2 square grid. Accordingly, we name these four groups as Cluster A, Cluster B, Cluster C, and Cluster D.

3.3 Group Characteristics

After training and clustering, each neuron in the SOM has a winning frequency of 34, 2, 5, and 9, respectively. The trained weight matrix W_{xy} is as follows:

$$W_{xy} = \begin{matrix} & & w_{xy_1} & w_{xy_2} \\ \text{Cluster A} & & 0.5391 & 0.3762 \\ \text{Cluster B} & & 0.9684 & 0.6296 \\ \text{Cluster C} & & 0.1697 & 0.7687 \\ \text{Cluster D} & & 0.0649 & 0.3128 \end{matrix}. \quad (2)$$

From the trained weight matrix W_{xy} , Cluster A represents vehicles with a modest daily VKT and generally charging during the daytime. Vehicles in Cluster B are associated with long daily VKTs, and often charging in the late afternoon. Cluster C and D capture the vehicles with relatively short daily VKTs. Vehicles in Cluster C are usually connected to the chargers at night while vehicles of Cluster D are usually plugged in during the daytime.

Table 3 presents the statistics of the two input components for different groups. There are 34 vehicles grouped into Cluster A. Although some initial trials have been carried out in an attempt to further divide this group, e.g., taking the number of daily charging events, or the variance of d_{VKT} and T_{start} as additional input components, no obvious differences are found among these vehicles. The numbers of travel days in Cluster A and B are less than the numbers of charging events, indicating the charging frequency is more than once per day. For Cluster C and D, the numbers of charging events are less than the days when the vehicle was driven. This matches the observations mentioned previously that BEVs with short daily VKTs are usually not charged every day.

Place TABLE 3 here.

4 RESULTS AND DISCUSSIONS

4.1 Distribution of Distance Traveled Per Day

FIGURE 2 plots distributions of daily VKTs in different groups. It can be seen that daily VKT distributions are significantly different among four clusters. In the case of Clusters, A, C, and D, the distribution interval with the largest probability is 0-20km, and the share declines with the increase in the distance. As compared to Cluster C and D, the decline of Cluster A is much slower, which share the similar pattern as the observation from (7). Because the average daily VKT of Cluster C and D are 31.7 km and 23.3 km respectively, more than 70% of daily VKTs occur in the interval of 0-40km. In the literature, a gamma distribution is often used to characterize daily VMT variations (17, 30, 31). We find that the distribution of Cluster B satisfies a gamma distribution with the shape of 3.44 and the rate of 0.04.

Place FIGURE 2 here.

4.2 Distribution of Start Time of Charging Events

FIGURE 3 shows the distribution of starting time when drivers plug in their vehicles. For Cluster A, the percent of EVSE connected begins to increase after 8:00 and maintains a steady rate during the daytime. 65% of the charging events occurred between 8:00 and 18:00. The other three groups have an obvious peak time for EVSE starting to be connected. The peak occurred between 22:00 to 23:00 for Cluster B and C, while it occurred between 8:00 to 9:00 for Cluster D. There is a smaller peak between 13:00 to 15:00 for Cluster B, presumably as individuals with long daily travel demand attempt to avoid depleting the battery and recharge vehicles to overcome the range anxiety. The start of charging can hardly be observed from 1:00 to 6:00, as most vehicles have already been plugged in before the midnight.

Place **FIGURE 3** here.

4.3 Distribution of Number of Charging Events Per Day

The distribution of the number of charging events per day when the vehicle was driven is shown in **FIGURE 4**. As for Cluster A and B, charging once per day is the frequency with the largest probability, accounting for 39.9% and 50.4%, respectively. Drivers of Cluster C do not charge the battery in 59.2% of the days. This proportion is even larger for Cluster D, accounting for 63.5% of the driving days. Since the average daily VKTs of Cluster C and D are less than one-fifth of the E50 range (i.e. 170km), it is reasonable for drivers to choose not to charge the vehicle every day.

Place **FIGURE 4** here.

4.4 Distribution of Distance Traveled Between Charges

FIGURE 5 displays the distribution of distance traveled between consecutive charging events. The travel distance between two charges is often assumed to be Gamma-distributed with different parameters in previous research (14, 17). However, the observations from **FIGURE 5** (a) may violate the assumption. That is, some conservative drivers are likely to charge the battery once they have the charging opportunity, regardless the remaining SOC. As shown in **FIGURE 5** (b), (c), and (d), the percent grows as the distance increases, until it reaches a peak. The peak occurs at the interval of 60-80km for Cluster B and D, while for Cluster C, it is observed at the interval of 40-60km, both of which are far less than the E50 range.

Place **FIGURE 5** here.

4.5 Distribution of Battery SOC Before/After Charging

FIGURE 6 shows the distribution of battery SOC at the start and the end of charging. For Cluster A, the probabilities of starting SOC are almost uniformly distributed along the range because of drivers' conservative charging behaviors. Due to the long daily VKT, the average starting SOC of Cluster B is lowest. Distributions of Cluster C and D are fairly wide but fall off quickly at each extreme, indicating that drivers are most likely to charge their vehicles when SOC is between 20% and 80%. For all the groups, it is observed that the majority of vehicles are fully or nearly fully charged at the end of each charging events.

Place **FIGURE 6** here.

4.6 Distribution of Charged Electric Energy

FIGURE 7 plots time-of-day electricity demand of the four groups. To generate these plots, first, the energy obtained from each charging event is estimated for each hour, and then the time-of-day electricity demand of different events are combined into one group. The charging demand of Cluster A and D are primarily centered in the daytime, which may add to peak load on the electric

grid. For Cluster B and C, demand mainly occurs during the off-peak period, increasing in the evening as home charging increases.

Place FIGURE 7 here.

5 CONCLUSIONS

Using the real world in-use BEV data collected from Shanghai, China, this paper studies BEV owners' driving and charging behaviors, and compares them with the observations from the EV Project. The SOM is adopted as a classifier to eliminate the interference of the intra-driver heterogeneity and capture the inter-driver diversity. The key findings from the results include: (1) similar to the observations from the EV Project, conservative charging behaviors exist in the E50 owners, resulting in short distance between charging events and averagely more than one charge per day when the vehicle was driven; (2) the charging demand in daytime is significant, potentially overlapped with the peak electricity demand from non-BEV load; (3) the distributions depicting the driving and charging patterns vary in the shape and rate parameters because of the inter-driver heterogeneity, for example, the habitual charging behaviors affects the distribution of distance between charges.

The main caveat of this paper lies in the shortage of BEV owners' socioeconomic information. For example, if the home locations are provided, the proportion of away-from-home charging events could be used to explain the high demand of daytime charging. Besides, with household vehicle ownership and job information, it would be helpful to depict the intended usage of BEVs.

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TABLE 1 Summary metrics of driving behaviors

	Mean		Med.	Max.	Min.	St.D.
	Shanghai	US EV Project				
Avg. distance traveled per day when the vehicle was driven (km)	50.7	43.0	55.4	95.3	17.5	18.8
Avg. distance traveled between charging events (km)	49.5	38.5	43.7	101.8	33.9	14.5

TABLE 2 Summary metrics of charging events

	Mean		Med.	Max.	Min.	St.D.
	Shanghai	US EV Project				
Avg. number of charging events per day when the vehicle was driven	1.1	1.1	1.3	1.6	0.2	0.5
Avg. charging power (kW)	3.8	3.3	3.8	3.9	3.6	0.1
Avg. charging time (hour)	2.6	3.3	2.5	4.4	1.8	0.5
Avg. SOC before charging (%)	45.6	44.0	45.4	61.6	18.5	8.3
Avg. SOC after charging (%)	92.9	89.6	92.3	100	87.4	3.7
Avg. start time of charging events (hh:mm)	14:14	NA	14:03	21:33	9:13	2:06

TABLE 3 Summary metrics of input components for different groups

Type	Number of vehicles	Avg. distance traveled per day when the vehicle was driven (km)			Avg. start time of charging events (hh:mm)		
		Sample size	Mean	St.D.	Sample size	Mean	St.D.
Cluster A	34	4406	58.0	42.0	4778	13:42	5:40
Cluster B	2	240	93.4	44.3	265	17:16	6:41
Cluster C	5	1059	31.7	30.1	443	18:48	5:54
Cluster D	9	1570	23.3	19.0	484	13:10	4:40

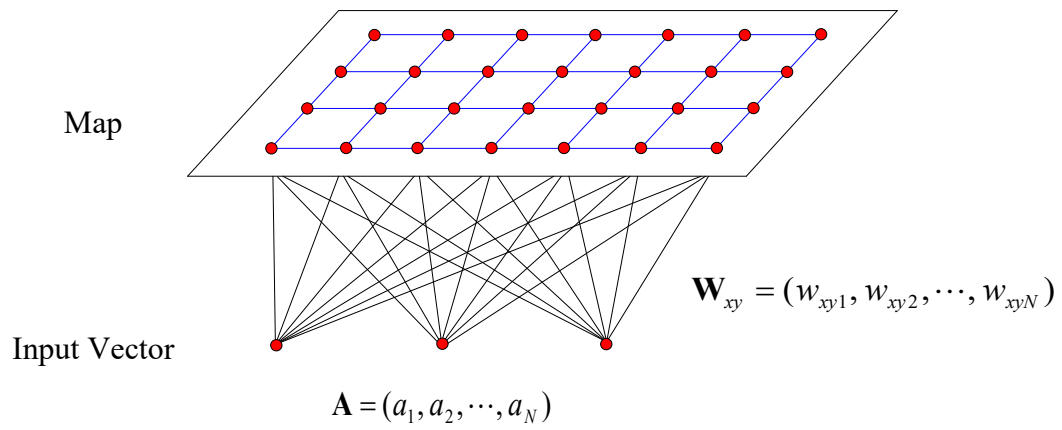
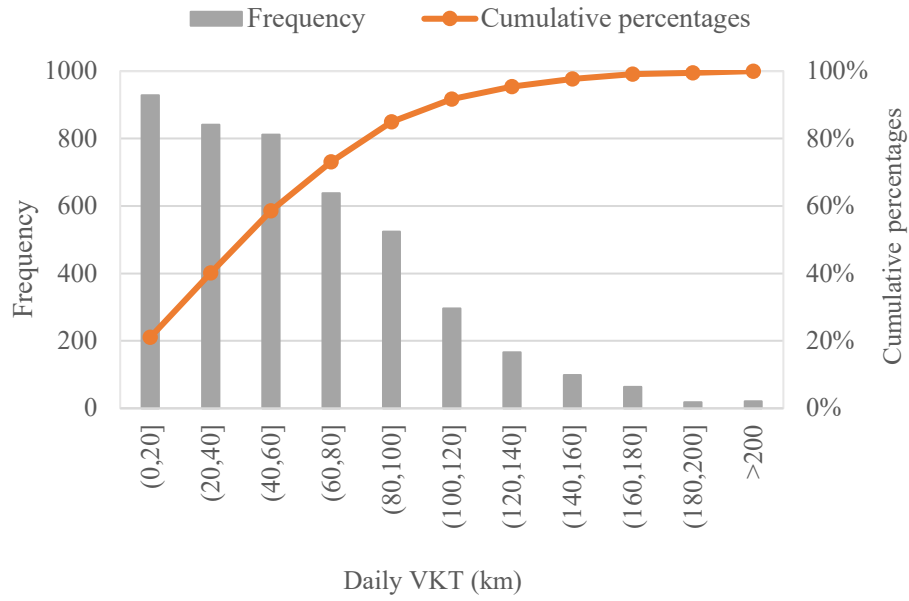
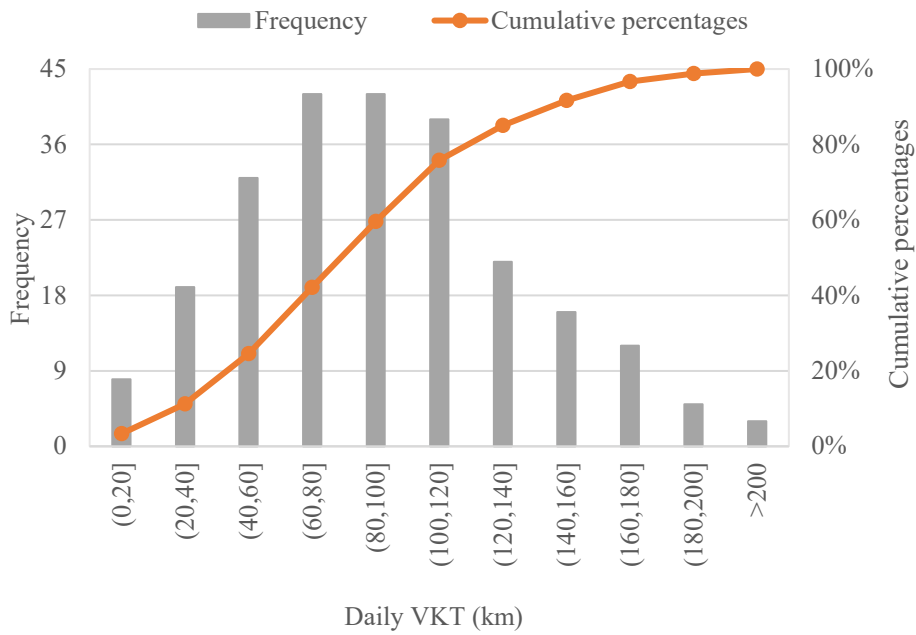


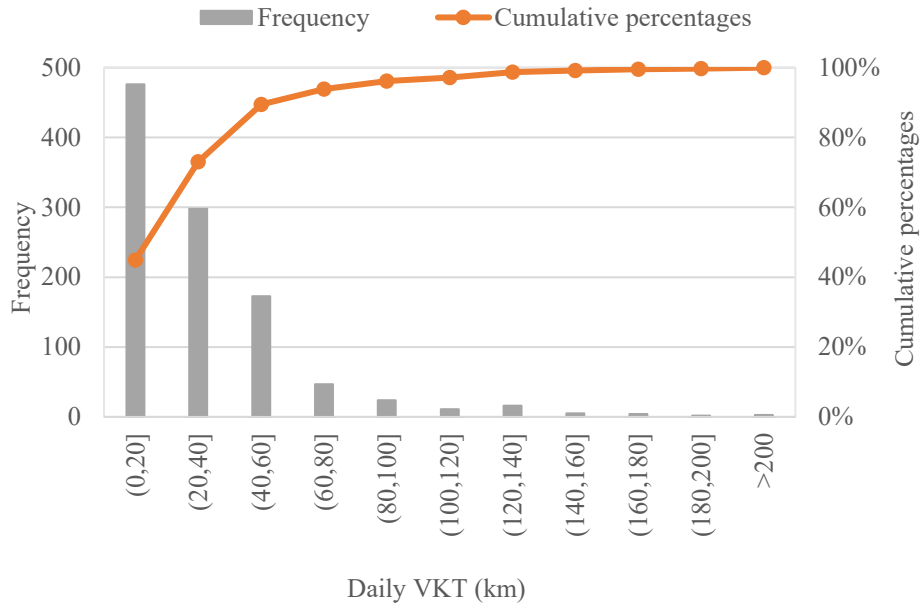
FIGURE 1 General architecture of a self-organizing feature map (26).



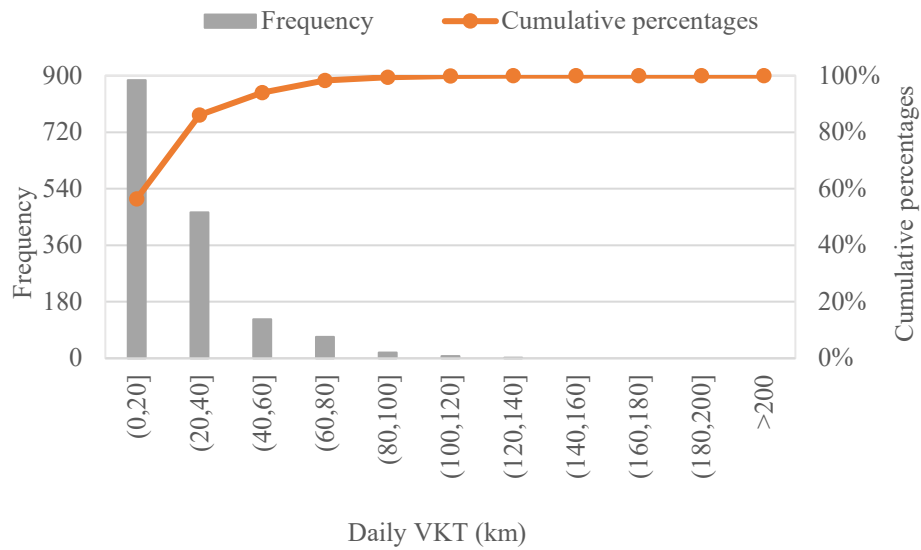
(a) Cluster A



(b) Cluster B

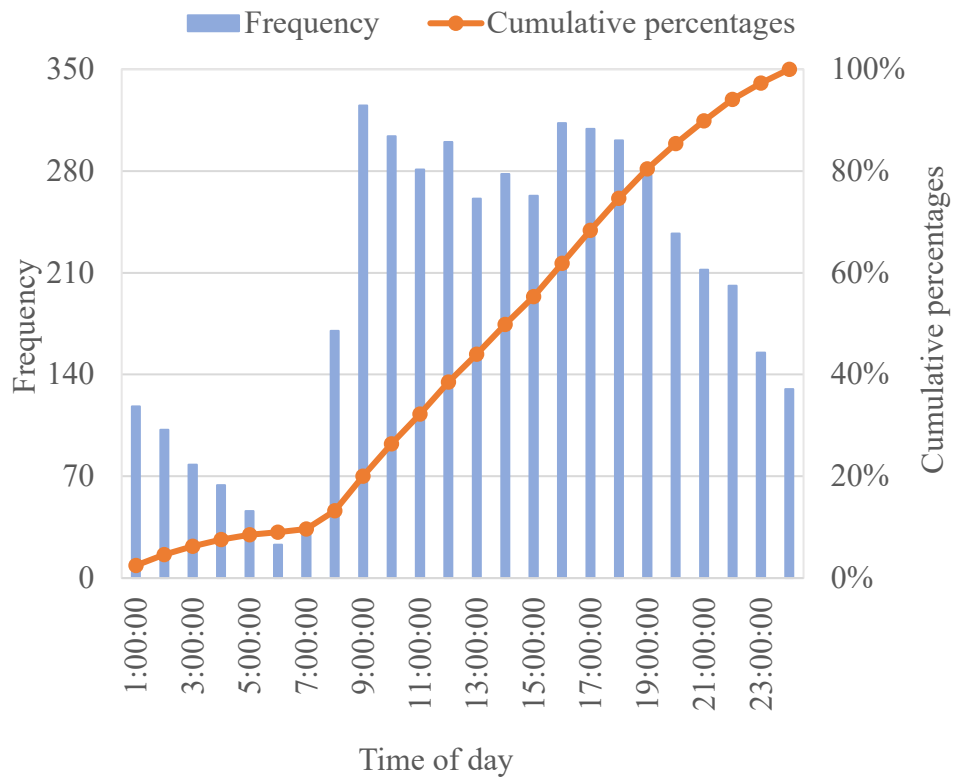


(c) Cluster C

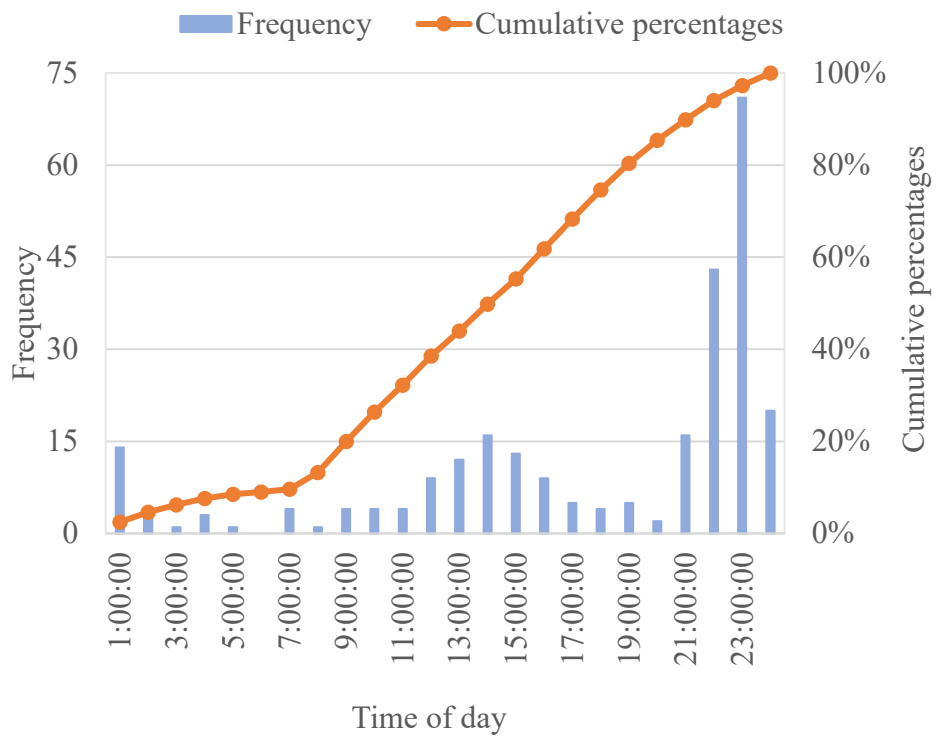


(d) Cluster D

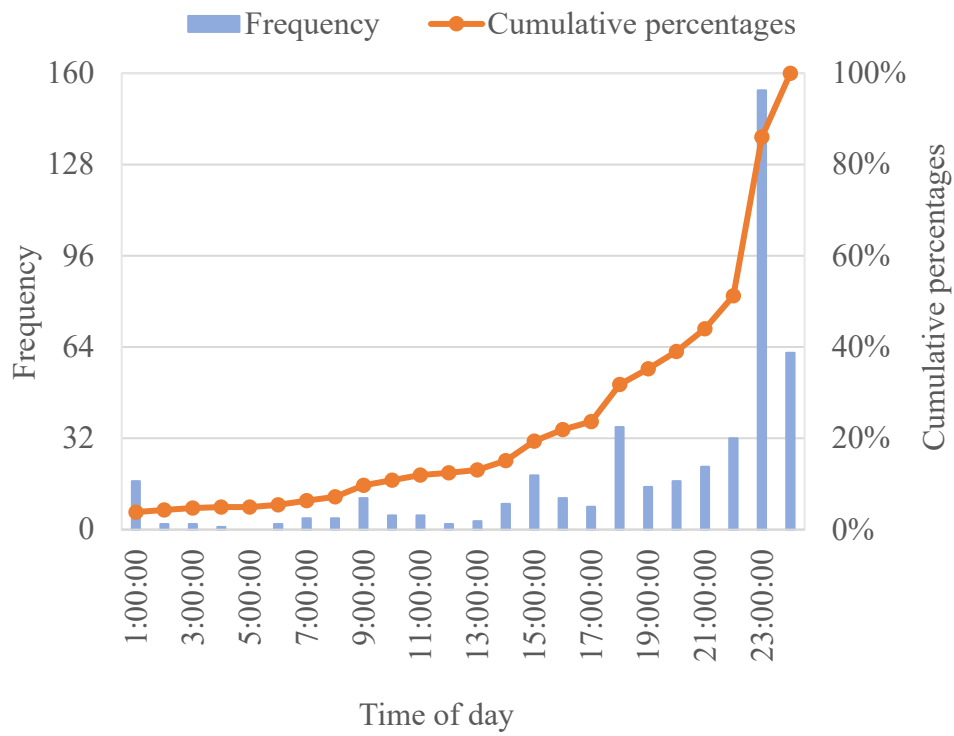
FIGURE 2 Distribution of distance traveled per day when the vehicle was driven.



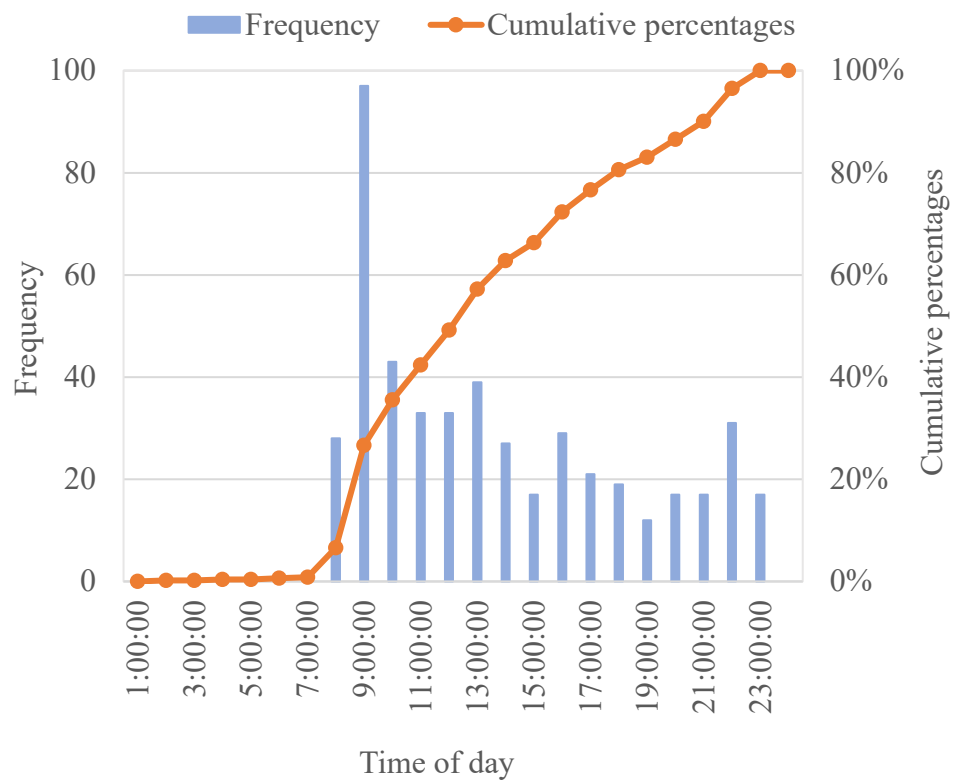
(a) Cluster A



(b) Cluster B

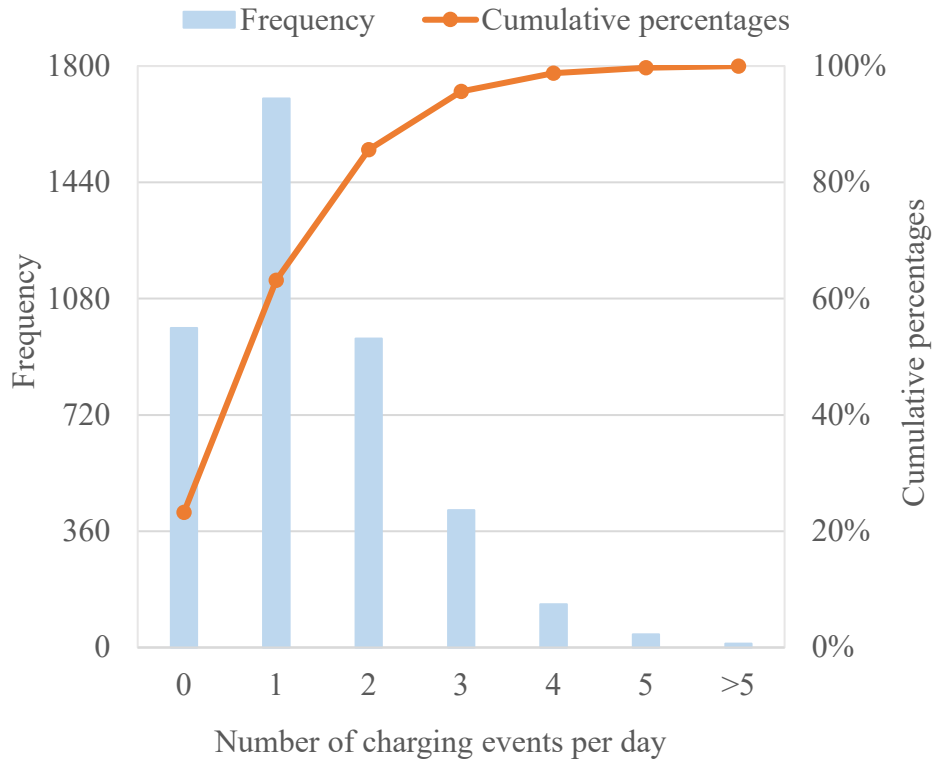


(c) Cluster C

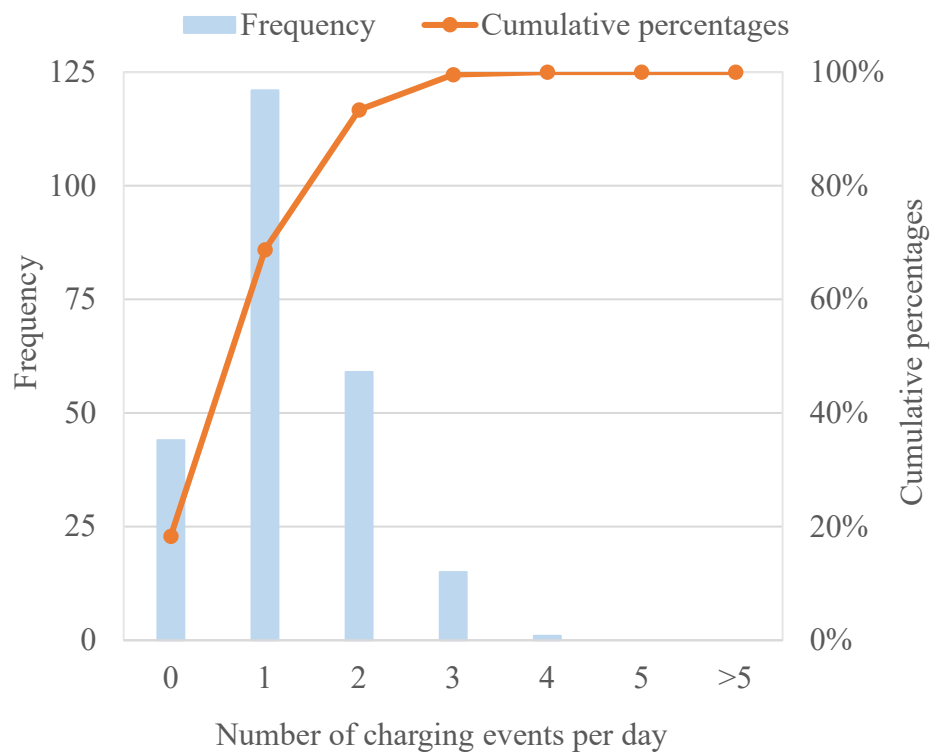


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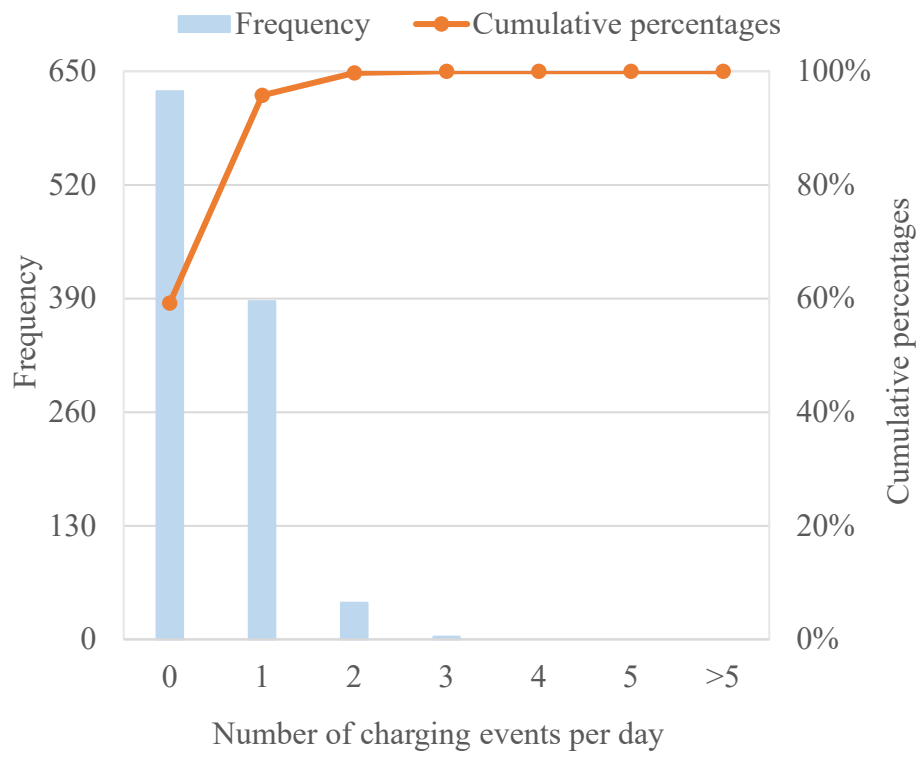
FIGURE 3 Distribution of start time of charging events.



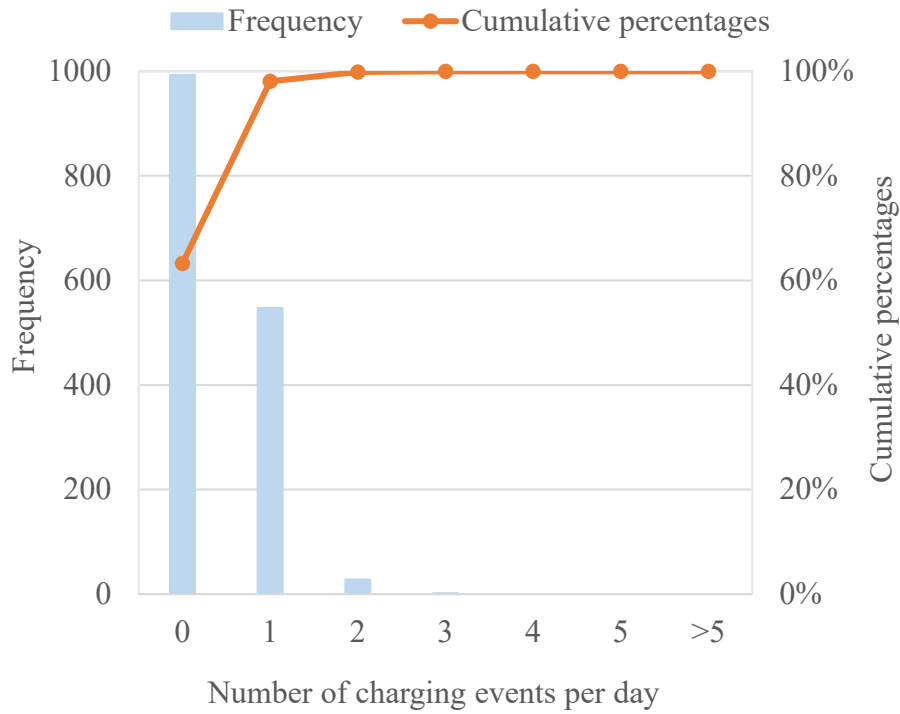
(a) Cluster A



(b) Cluster B

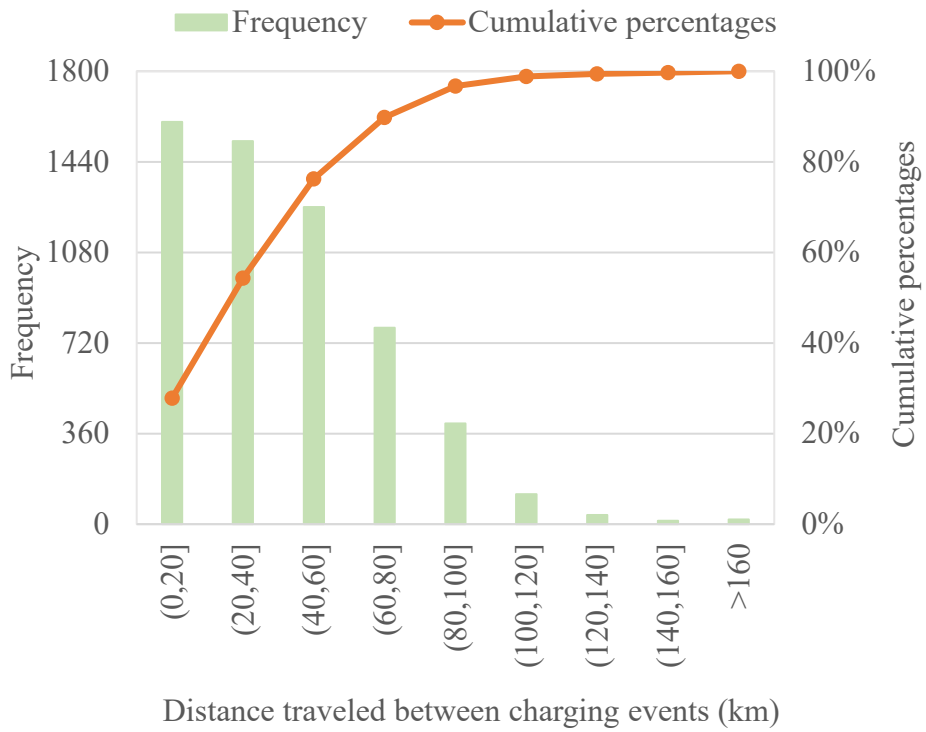


(c) Cluster C

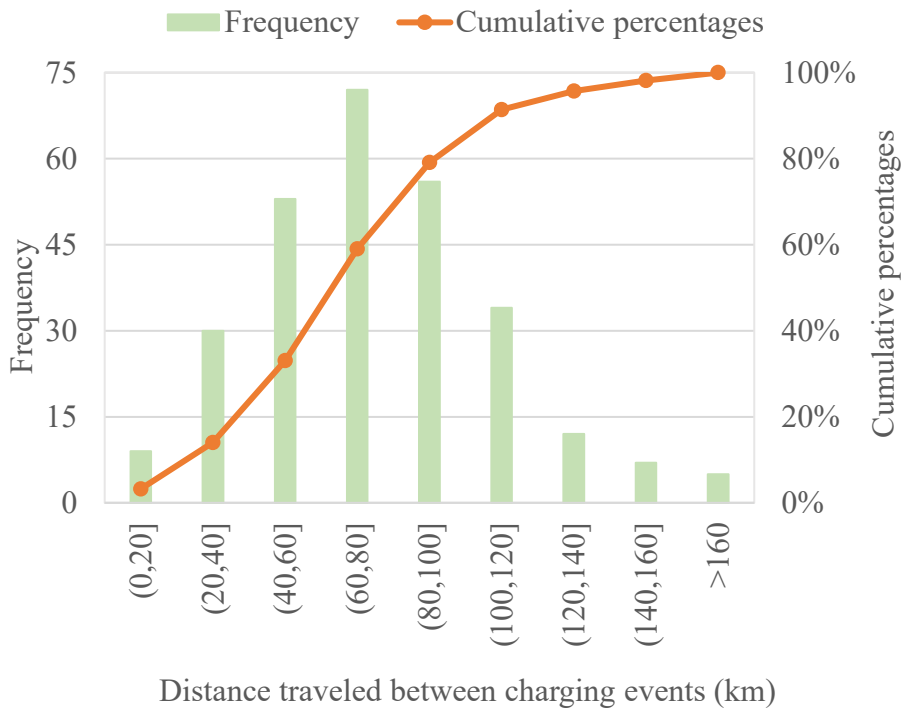


(d) Cluster D

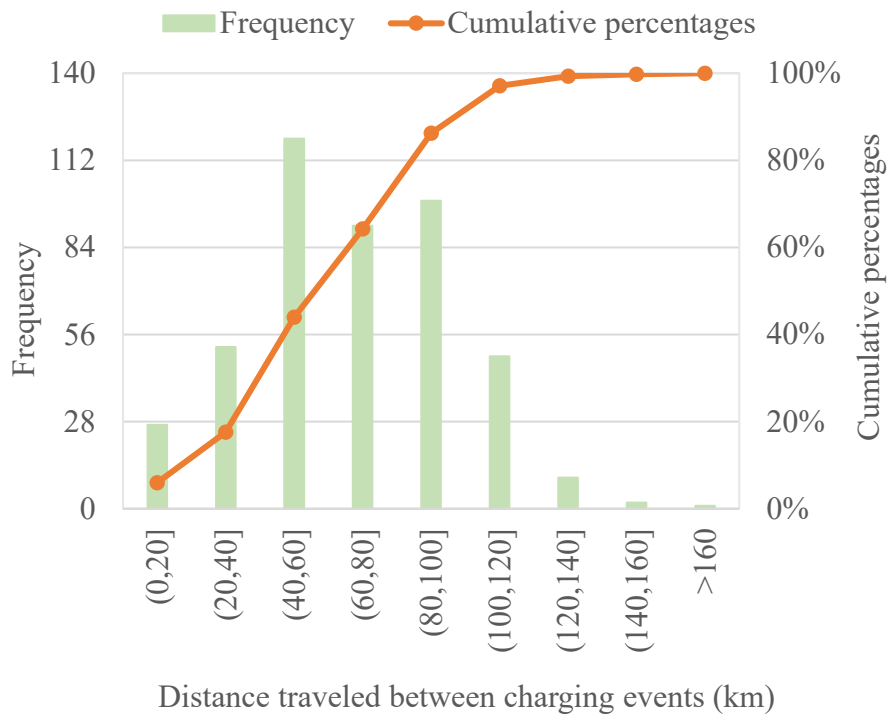
FIGURE 4 Distribution of number of charging events per day when the vehicle was driven.



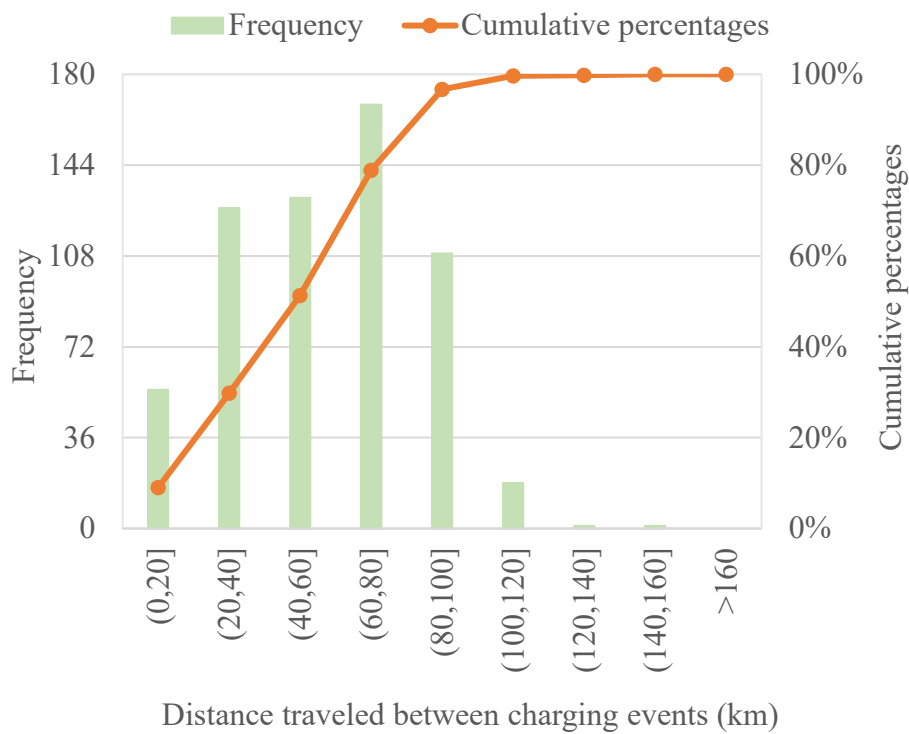
(a) Cluster A



(b) Cluster B

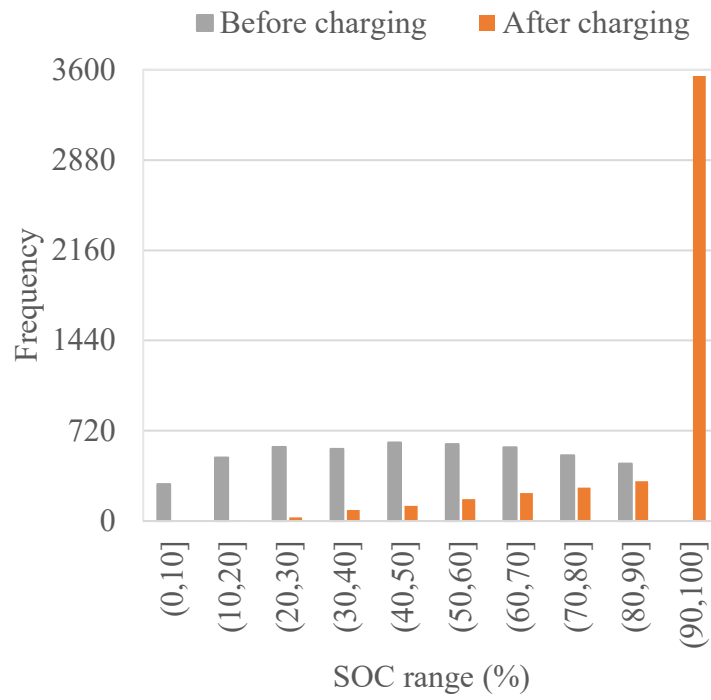


(c) Cluster C

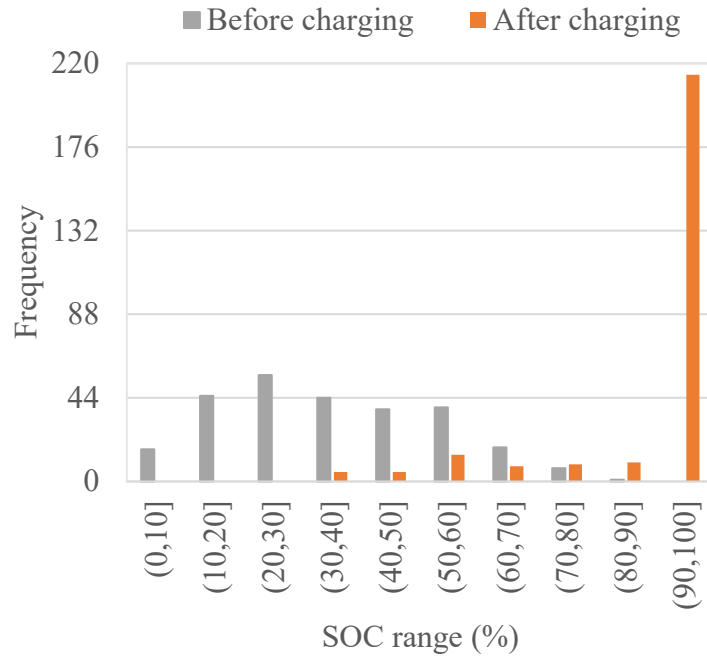


(d) Cluster D

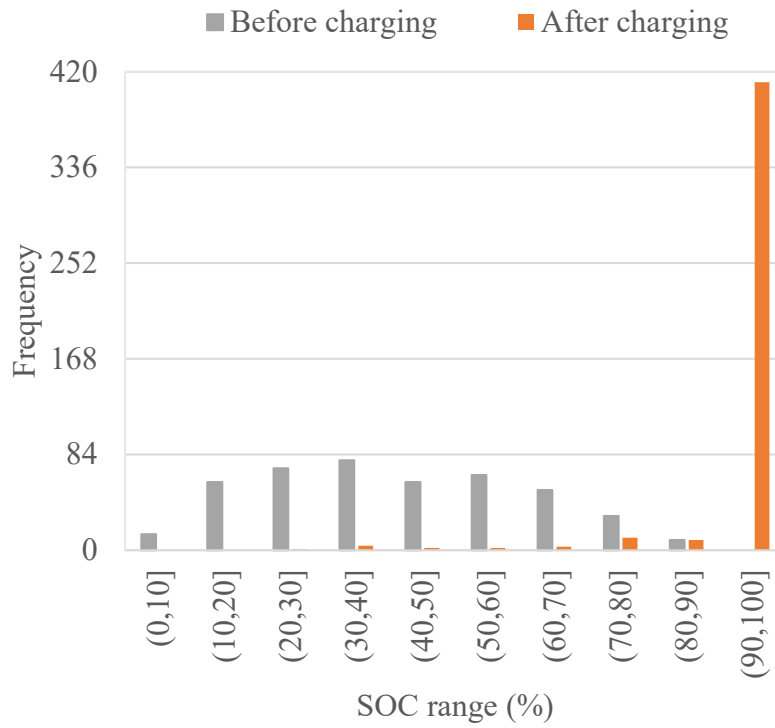
FIGURE 5 Distribution of distance traveled between charging events.



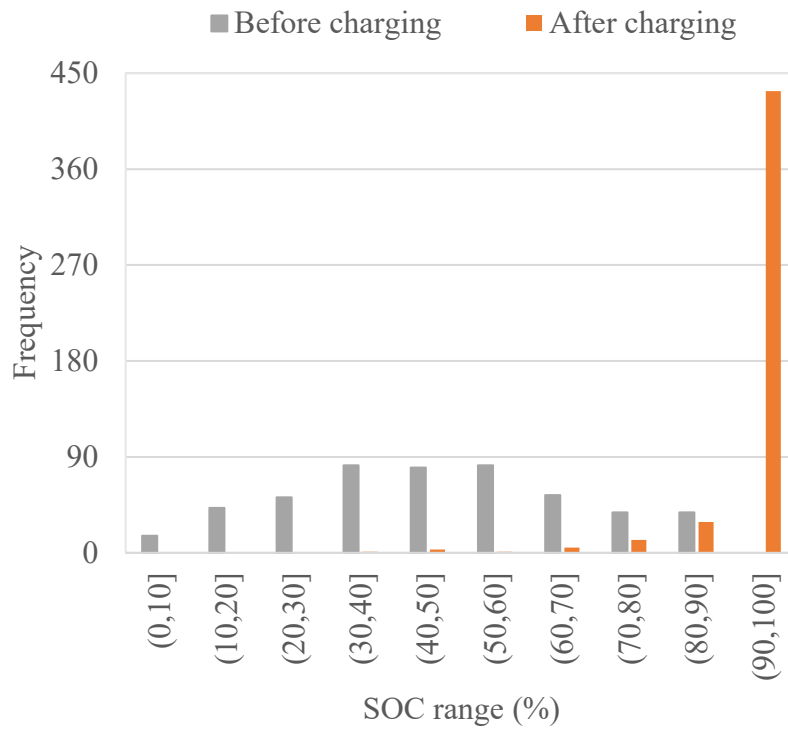
(a) Cluster A



(b) Cluster B

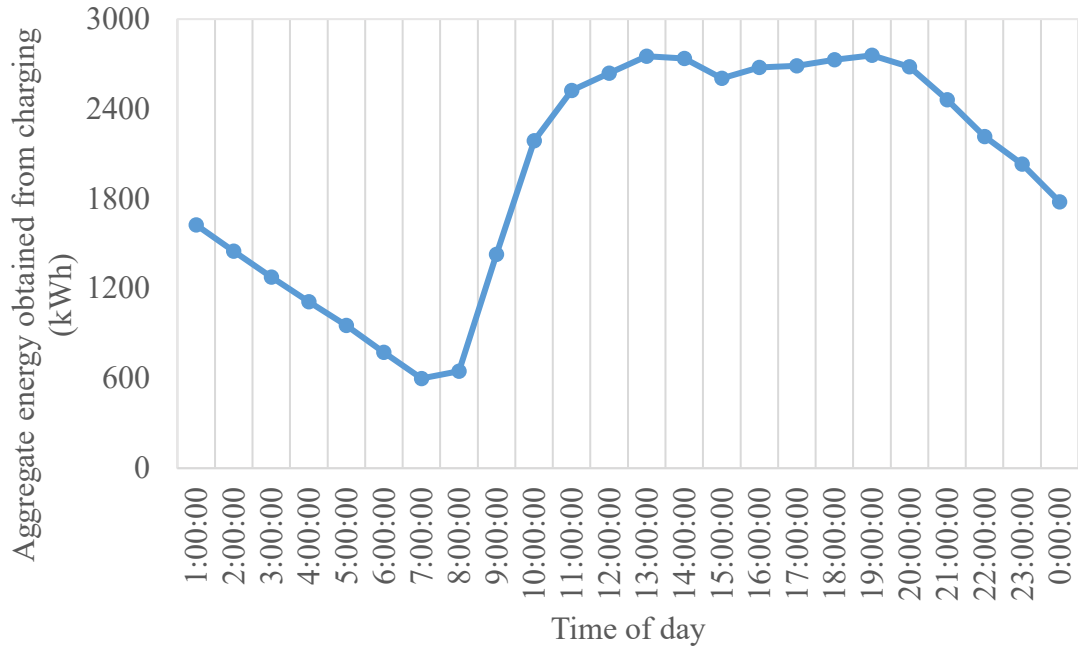


(c) Cluster C

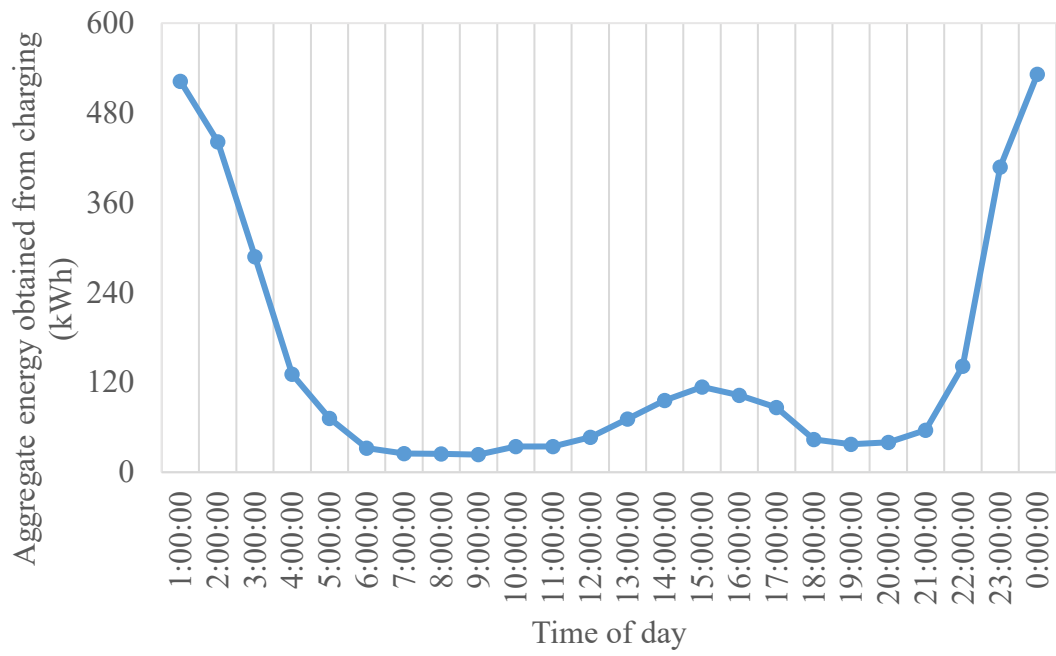


(d) Cluster D

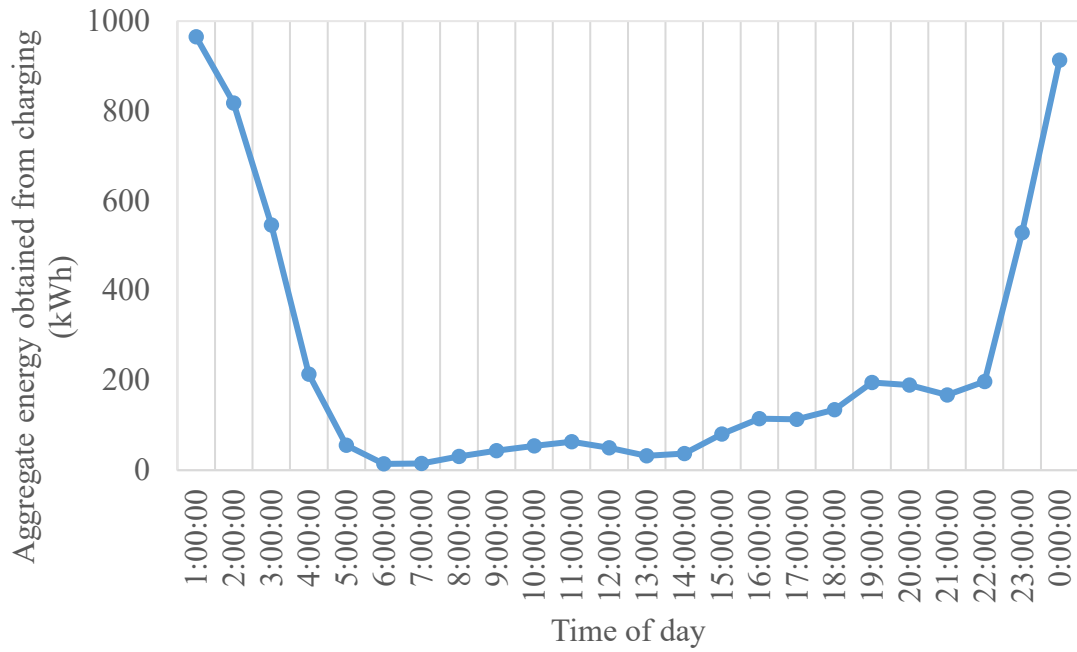
FIGURE 6 Distribution of battery SOC before/after charging.



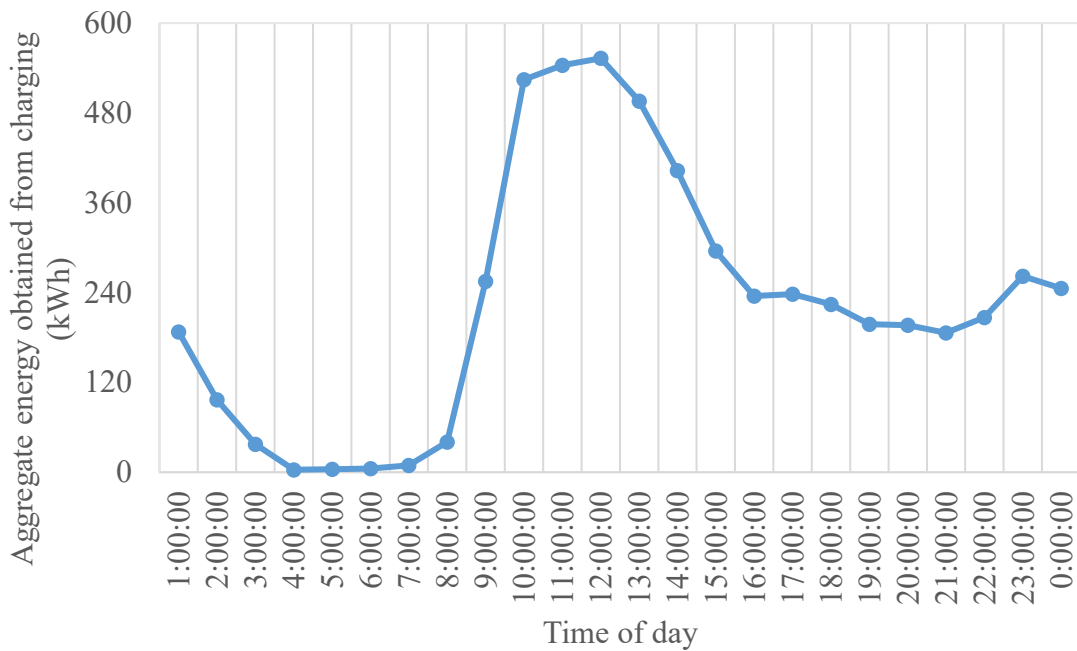
(a) Cluster A



(b) Cluster B



(c) Cluster C



(d) Cluster D

FIGURE 7 Distribution of charged electric energy.