MINISTRY OF SCIENCE AND HIGHER EDUCATION
OF THE RUSSIAN FEDERATION
Federal state autonomous educational institution of higher education
“South Ural State University (National Research University)”
Polytechnic institute
Power engineering faculty
Industrial Heat Power Engineering department
Classifier number and the name of the Master's program
13.04.01 “Heat Power Engineering and Heat Engineering”

THESIS WORK
IS VERIFIED BY
Director
of Repair & constructions Ltd.

_____________ K.A. Khasanov
«_____» ____________ 2020

ALLOW TO DEFEND
Head of department
“Industrial Heat Power Engineering”
Candidate of technical sciences,
associate professor
______________ K.V. Osintsev
«_____» ___________ 2020

Analysis of charging behavior of electric vehicles and research on optimization of charging facilities planning

THESIS WORK OF THE MASTER'S PROGRAM
“HEAT POWER ENGINEERING”
SUSU-13.04.01.2020. 298.05.EN TW

Head of the Master's program,
Candidate of technical sciences,
associate professor
______________ K.V. Osintsev
«_____» __ _______ 2020

Head of work,
Grand PhD, professor
______________ A.A. Alabugin
«____» _____________ 2020

Author of work,
Student of Master's program
of P-284 group
________________ Z. Liu
«_____» ____________ 2020

Chelyabinsk 2020

ANNOTATION

Z. Liu. Analysis of charging behavior of electric vehicles and research on optimization of charging facilities planning – Chelyabinsk: SUSU, PI, PEF; 2020, 42 p., 7 figure, references – 44, 9 slides of presentation

In TW, the method to improve the availability of clustering results and protect data security is offered (research goals, such as data clustering algorithms under differential privacy protection). And the planning method of electric vehicle charging facilities with the smallest total social cost is provided (the object of research is a charging facility planning method based on improved k-means algorithm).

TW purpose – Power system companies use methods to reduce the impact of large-scale electric vehicle access on the grid, and improve the reliability and economy of grid operations.

TW contains: charging behavior analysis model and charging facility planning model; experiments; result analysis; the analysis strengths and weaknesses of technology, opportunities and threats of its application; Gantt's schedule of actions for implementation of technology in the power industry equipment.

TABLE OF CONTENTS

ABSTRACT

Electric vehicle (EV) has the advantages of energy saving, environmental protection and clean energy. The promotion of electric vehicles helps alleviate energy shortages and environmental pollution, and has gradually received attention from countries around the world. Vigorously developing electric vehicles is very important to achieve a comprehensive energy transformation in the transportation field. In order to reduce the impact of large-scale electric vehicle access on the power grid, analysis of electric vehicle charging behavior can improve the reliability and economics of power grid operation. As the most basic supporting facilities for electric vehicles, the reasonable planning of charging facilities can accelerate the formation of the electric vehicle ecosystem and improve the economic benefits of charging facilities. The research work in this paper is mainly focused on the following aspects:

Firstly, in order to solve the problem of privacy leakage risk in the data clustering process, in order to ensure the availability of the clustering results and ensure the security of the data, an electric vehicle charging data clustering algorithm under differential privacy protection was proposed.

Secondly, in order to solve the problem that the random charging behavior of electric vehicles affects the stability of the power grid, at the same time, in order to improve the charging service, based on the real electric vehicle charging data, a charging data clustering algorithm under differential privacy protection was used to design an electric vehicle charging behavior analysis model. The classification of electric vehicle users is achieved through experiment, and the characteristics of the charging mode corresponding to each user are analyzed.

Then, according to the planning needs of electric vehicle charging facilities and the social cost of charging facilities, a method for planning charging facilities based on an improved k-means algorithm is proposed. Take the minimum overall total cost of society as the objective function of the plan. An example is used for experiments to obtain the optimal location and number of charging stations with the lowest cost in a certain area, which proves the effectiveness of the proposed method.

Finally, combining the methods of charging behavior analysis and charging facility planning, the strengths and weaknesses as well as the opportunities and threats are analyzed, and the SWOT matrix analysis is completed. Moreover, based on the work done in this article, the Gantt's schedule was determined.

1 INTRODUCTION

1.1 Research background and significance

Compared with traditional fuel vehicles, electric vehicles (EV) have the advantages of energy saving, environmental protection, and clean energy. The promotion of electric vehicles helps alleviate energy shortages and environmental pollution problems, and is gradually paid attention by countries around the world. With the popularity of electric vehicles and the improvement of charging facilities, a large amount of charging data is generated every year, which provides a data basis for the analysis and mining of charging behavior. However, the charging behavior of electric vehicles is random and intermittent, which may bring many effects to the power grid, such as increasing the peak-to-valley load difference of the power grid, reducing the power quality, and affecting the stable operation of the distribution network [1]. In order to reduce the impact of large-scale electric vehicle access on the grid, it is necessary to analyze the charging behavior of electric vehicles and improve the reliability and economy of grid operation. With the development of the competitive charging market, accurately understanding user charging behavior patterns has become a valuable asset for power service providers [2]. Therefore, analyzing and mining the charging behavior data of electric vehicle users and accurately classifying the user categories can help guide the charging behavior, lay the foundation for the charging and discharging scheduling strategy of electric vehicles, maintain the safety and stability of the power grid, and also help power service providers. Understand the personalized and differentiated service needs of each type of user.

Since the charging data of electric vehicles may contain sensitive or private information from devices and users, there is a risk of privacy leakage in the process of data analysis [3]. Therefore, on the premise of accurate analysis of user behavior data of electric vehicles, how to protect user privacy from leakage is an urgent problem to be solved. In order to protect user privacy, data can be encrypted on the user side and data exchange between the user and the data center is protected, but when data clustering and analysis are performed in the data center, an attacker may obtain sensitive data. Differential privacy helps alleviate the tension of data leakage and protects user privacy while ensuring the availability of clustering results.

Charging facilities are important facilities for providing charging services for electric vehicles. However, the difficulty of charging is the key factor restricting the further expansion of electric vehicles. Therefore, the scale of China's charging facilities is constantly expanding. According to the data released by the China Charging Union, the number of charging facilities in China has been increasing. As of June 2019, the number of charging piles in China has exceeded 1 million, of which the number of private charging piles exceeds 590,000, and public charging piles. The number of vehicles exceeds 410,000, and the pile-to-pile ratio reaches 3.5: 1. With the development of charging facilities, the acceleration of the construction of charging stations and the increase in the density of charging piles, it will drive the enthusiasm of potential electric vehicle users to purchase and promote the rapid promotion of electric vehicles. The key to the industrialization of electric vehicles is to optimize the planning of charging facilities and improve their related theories, which can provide technical and theoretical support for the actual planning work and help promote the development of electric vehicles.

1.2 Research status at home and abroad

1.2.1 Research status of electric vehicle charging behavior analysis

Charging behavior is an indispensable component of electric vehicle users' travel. Charging behavior mainly includes: charging power (including the power at the beginning of charging, the power after charging is stopped and the total charging capacity), charging time (including Charging start time, charging stop time and dwell time), charging method (slow charging or fast charging), charging frequency (average number of charging times per day) and the selected charging station location and other factors [4].

At present, there are many studies on the charging behavior of electric vehicles by scholars at home and abroad. Literature [5] based on the travel chain theory and logistic regression model research and analysis of factors that affect the charging behavior of electric vehicles, and based on single and multiple significant influencing factors to establish a prediction model. Reference [6] based on the behavior characteristics of electric vehicles, using the Monte Carlo method to simulate the driving and charging behavior of electric vehicles, obtained when and where electric vehicles will be charged in various regions, and classified electric vehicles according to the charging habits of the owners. Reference [7] proposes an analysis method of charging behavior of electric vehicle users that introduces Markov decision process. It takes the user's charging behavior as a decision set, and also analyzes the impact of different regions and different parking durations on charging behavior. There are still some studies that consider the charging behavior of electric vehicles and formulate corresponding charging strategies. Literature [8] grouped electric vehicles based on the travel end time, travel start time, maximum charging delay and required charging time, proposed an electric vehicle grouping scheduling strategy, and formulated different Charge and discharge strategy. Some foreign scholars have used pure statistical methods to study the charging behavior of electric vehicle users [9,10].

The clustering algorithm is an important algorithm in data mining. There have been some researches that apply the clustering algorithm to the analysis of the charging behavior of electric vehicles. Literature [11] proposed a two-level clustering model to determine the driving mode of electric vehicles, and obtained five daily driving modes and four multi-faceted driving modes through the model. Reference [12] uses the British travel survey data to determine five typical traditional vehicle usage conditions by k-means cluster analysis. Literature [2] on the Spark platform verified the user behavior analysis model of charging pile based on k-means algorithm through examples. Reference [13] based on the real electric vehicle charging behavior data set, proposed a k-means clustering and multi-layer perceptron combined electric vehicle user modeling technology to carry out electric vehicle parking and load forecasting. Literature [3] based on real charging data, used k-means algorithm to cluster electric vehicle users and analyzed all categories in detail, used Apriori algorithm to study the impact of weather and holidays on the charging of electric vehicle users, and also studied the temperature and number of charging through statistical methods Relationship. In summary, the use of clustering algorithms to analyze the charging behavior of electric vehicles has achieved certain results. The accurate analysis of the charging behavior data of electric vehicles can help provide users with more reliable and satisfactory services. However, the above study did not consider the randomness of the initial cluster center point selection and the impact of the outliers in the data on the clustering results, nor did it consider the risk of data leakage. Therefore, to solve this problem, this paper uses a clustering algorithm under differential privacy protection, and by detecting outliers and improving the selection of the initial clustering center point, the accuracy and availability of the clustering results are guaranteed, while protecting the user's privacy.

1.2.2 Research status of electric vehicle charging facility planning

Charging facilities are the most basic supporting facilities for electric vehicles. Therefore, there are many studies on the planning of electric vehicle charging facilities by scholars at home and abroad. Reference [14] proposes a planning method that considers the differences in urban characteristics, builds a model with the goal of maximizing the economic benefits of charging facilities, and demonstrates the availability of the method through calculations. Literature [15] based on electric logistics vehicles, built a charging and replacement facility location model, and designed an improved genetic algorithm to solve the location model and path planning. Literature [16] proposed the concept of university-based electronic car sharing to cover the energy needs of electric fleets. Using real data collected from university parking lots, build simulation models to simulate fast charging infrastructure to represent the potential utilization of electric vehicles. Reference [17] builds a model with distribution network capacity and site spacing as constraints, uses an integer programming model to achieve optimal configuration of charging station capacity, and improves quantum genetic algorithm for the location and volume planning of its charging station. Reference [18] set the goal to adapt the charging facility configuration to the existing operating characteristics of the power system, and implement the charging facility configuration according to the characteristic index. Reference [41] established an electric vehicle charging station planning model considering road network information, and proposed a charging station location method based on Voronoi diagram. It can be seen that the research on the planning method of electric vehicle charging stations has achieved certain results and formed a preliminary planning method and steps. In this paper, through an example analysis, the optimal value of the number of charging stations and the location of the lowest cost charging station in a certain area are obtained.

1.3 The main research content of article

Based on the above research status, the main research contents of this article are: electric vehicle charging behavior analysis, electric vehicle charging facility planning optimization research, SWOT analysis and Gantt's schedule.

Preprocess the real charging data; propose a charging data clustering algorithm under differential privacy protection, add Laplace noise at the center of the cluster, improve the selection of the initial clustering center and detect outliers; designed an electric vehicle charging behavior analysis model, using silhouette coefficient to determine the value of the clustering number k, and obtained the user charging mode through experiments.

Combined with the analysis of the component factors of the total social cost of electric vehicle charging stations, the optimal number of charging stations corresponding to the minimum social cost is used as the optimization goal, and the minimum overall total social cost as the objective function of the charging station planning. The improved k-means clustering algorithm is used to divide the service area of charging stations. Through an example analysis, it is proved that there are the optimal values of the number and location of charging stations in a certain area, and the effectiveness of the proposed method is verified.

On the basis of the method proposed in this article, SWOT matrix analysis is completed, including the strengths and weaknesses of technology, as well as the opportunities and threats of application. Moreover, determine Gantt's schedule according to the framework of the thesis.

1.4 The organizational structure of article

Chapter 1 Introduction. First, the research background and significance of this paper are described, then the domestic and foreign research status of electric vehicle charging behavior analysis and charging facility planning are described, and finally the research content of this paper is introduced to determine the following research direction.

Chapter 2 Related theoretical basis. First, an overview of electric vehicles is introduced. Three different types of electric vehicles are introduced from the perspective of characteristics and functions. The application scope, advantages and disadvantages of the three charging modes are also described. Secondly, it describes the current status of the construction of charging facilities in China, and introduces the charging facilities of electric vehicles from the aspects of charging stations and charging piles. Next, it analyzes the impact of the charging behavior of electric vehicles, and expounds the basic theoretical knowledge of differential privacy protection and k-means algorithm, which lays a theoretical foundation for subsequent research in this article.

Chapter 3 Analysis of charging behavior of electric vehicles. In view of the fact that the charging behavior analysis process of electric vehicles is easy to leak user privacy and the amount of data is large, an electric vehicle charging behavior analysis model and charging data clustering algorithm are proposed. By improving the selection of initial clustering centers and calculating the density of each data point to find outliers, the availability of data clustering results is ensured under the premise of safety.

Chapter 4 Research on the optimization of electric vehicle charging facilities. The charging facility planning model is given, including assumptions and objective functions. Analyze the three parts of the total social cost of electric vehicle charging stations, find the optimal number of charging stations corresponding to the smallest social cost as the optimization goal, and take the minimum total social cost as the objective function of charging station planning. Then, the solution method based on improved k-means clustering algorithm is proposed, and the steps of the algorithm are introduced.

Chapter 5 Experiment analysis. Firstly, the model and algorithm given in Chapter 3 are analyzed and tested, and the actual charging data after pre-processing is used for the experiment, and the number k of clusters is determined by the contour coefficient. Then experiment with the DP k-means algorithm on the same data set. The charging mode of electric vehicle users is also obtained, and the charging characteristics of each user mode are analyzed in detail. Moreover, the charging station planning model given in Chapter 4 is also tested. First, an example is simulated and calculated, and the optimal solution of the charging station planning in a certain area is obtained, which verifies the effectiveness of the algorithm. Then it analyzes the changing trend of institutional cost, user cost and total cost as the number of charging stations increases.

Chapter 6 Use of results of a research in the power industry equipment. On the basis of the method proposed in this article, analyze the strengths and weaknesses of the technology, as well as the opportunities and threats of application. At the same time, determine Gantt's schedule of actions for implementation of technology in the power industry equipment.

Chapter 7 Summary and outlook. Summarize the research results of this article and determine the follow-up research direction.

2 RELATED THEORETICAL BASIS

2.1 Overview of electric vehicles

2.1.1 Types of electric vehicles

An electric car is a car that uses new technologies, new structures, and has leading technology principles. It combines advanced technologies in power control and driving. Generally, electric vehicles are divided into three categories according to different internal combustion engines, namely, fuel cell vehicles (FCV), hybrid electric vehicles (HEV), and pure electric vehicles (BEV). The three types of electric vehicles are introduced below.

1. Pure electric vehicle (BEV)

The power source of a pure electric vehicle is a battery, which provides electrical energy to the motor through the battery to provide power for the vehicle. Different from traditional fuel vehicles, pure electric vehicles are mainly different in the components of power battery, speed control, on-board charging and driving motor. The cruising range of a pure electric vehicle depends on its battery capacity, its starting speed and speed depend on the performance and power of the motor, and the weight of the on-board battery depends on the choice of power battery [19].

2. Hybrid electric vehicle (HEV)

Hybrid electric vehicles are equipped with internal combustion engines on the basis of the above-mentioned pure electric vehicles, so that electric vehicles have compound power [19]. When the battery is fully charged, the hybrid electric vehicle can use the battery to drive the motor; when the battery is exhausted, the battery can be charged with fuel to ensure normal use [20].

3. Fuel Electric Vehicle (FCV)

The fuel used in fuel electric vehicles is new energy and non-polluting energy. Common fuels include methanol and hydrogen, which convert chemical energy into electrical energy to drive the vehicle [20]. Fuel electric vehicles are composed of fuel cell engines, electric motors, fuel tanks, and storage batteries [19].

2.1.2 Electric vehicle charging mode

According to the classification of commonly used charging technologies, there are three modes of charging that are often used: slow charging, fast charging, and battery pack replacement [42].

1. Slow charging

Slow charging generally uses a smaller constant current or constant voltage current for charging, the current size is generally only about 15A, and the charging time is longer, generally 5-8 hours. Therefore, slow charging is suitable for users who can travel for a full day, and is generally suitable for commercial areas and residential parking lots. Although the slow charging mode is difficult to meet the user's emergency charging needs, it also has advantages. For example, its small charging current can protect the battery and prolong the service life of the battery, and the charging current of about 15A requires the cost of power equipment and power grid Lower [20].

2. Fast charging

The charging time of fast charging facilities is very short, usually only about half an hour to two hours, but the requirements for power facilities are high, generally requiring more than 200A of current. The fast charging mode has the advantages of meeting the user's travel needs in a short time and saving the user's time cost. Therefore, the fast charging mode is suitable for the situation where special facilities for fast charging have been built, which is convenient for users to take emergency charging and complete the remaining journey. However, the fast charging mode also has some shortcomings. High current requires higher security for the power grid, and the operating costs and installation costs of charging facilities are also higher [20].

3. Replace the battery pack

Replacing the battery pack means that when the battery of the electric vehicle is exhausted, the storage battery is directly replaced with a fully charged battery. Because the battery packs of electric vehicles are relatively complex, heavy, and bulky, professionals need to maintain and replace the battery packs in the corresponding charging area [20].

2.2 Overview of electric vehicle charging facilities

2.2.1 Electric vehicle charging station

Electric vehicle charging stations have charging equipment and are places where electric vehicles can be charged. The charging station is generally composed of multiple chargers or charging piles. In addition to completing the charging function, it can also monitor the operating status of the electric vehicle.

Electric vehicle charging stations are mainly composed of five parts, namely charging system, power distribution system, security system, monitoring system and billing measurement system. There are many ways to classify charging stations. According to the charging time, they can be divided into fast charging stations and slow charging stations. According to different locations, they can be divided into public charging stations, private charging stations, and dedicated charging stations [20]. In order to facilitate research, charging stations are generally divided into different levels. In 2010, in order to improve the construction standards of charging stations, Beijing issued the "Technical Specifications for Electric Power Supply and Guarantee of Electric Vehicles", which divided charging stations into 4 levels [21], as shown in table 2.1.

Table 2.1 – Construction scale of different levels of charging stations

Charging station level	Power storage n, kWh	Area, km^2	Number of chargers
Level 1	≥ 6800	1350	16-25
Level 2	$3400 \leq n \leq 6800$	1150	8-16
Level 3	$1700 \leq n \leq 3400$	1050	6-8
Level 4	≤ 1700	950	3-5

2.2.2 Electric vehicle charging pile

As a key facility of a charging station, a charging pile is a power supply device that provides charging services for electric vehicle users. The charging piles are generally arranged in groups. Electric vehicle charging piles are generally composed of electrical modules, calculation modules, pile bodies, and so on. There are many classification methods for charging piles. According to the charging speed, they can be divided into slow charging piles and fast charging piles. According to the national grid standard, charging stations can be divided into 3 categories according to rated voltage, rated current, and frequency [20]. As shown in table 2.2.

Table 2.2 – Different charging pile types

Category	Rated voltage	Rated current	Frequency	Standart type
AC charging pile	≥6800	32A	50+1Hz	State Grid Standard
AC charging interface	3400≤n≤6800	16/32A	50Hz	State Grid Standard
DC charging interface	≤1700	125/250A	–	State Grid Standard

2.3 Relevant theories of electric vehicle charging behavior analysis

When electric vehicle users choose fast charging facilities, they pursue convenience and controllability of the charging duration, hoping that the charging time is shorter and avoid spending a lot of time on inefficient charging. Therefore, a good prediction of the duration of charging behavior is a key factor in evaluating the quality of charging services, and also a crucial factor in the planning of charging facilities [22].

According to the data in the survey results of the US Department of Energy's EERE automotive technology project, electric vehicles are charged an average of 1.05 times per day, and a maximum of 3.22 times a day [23]. The survey included 347,222 charging incidents, of which 82% completed charging in the user's home, and only 18% were charged on the way out, and most of these charging behaviors occurred in office areas, shopping centers, dining places and other urban areas. More than 70% of private cars are charged at least once when going out. A very small number of electric cars are not charged at home at all, and are only charged during the outing.

2.3.1 Analysis of factors affecting charging behavior

Literature [43] studied the charging behavior of electric vehicle users in non-residential and residential areas, and determined the occurrence probability of charging events with different SOC (State of Charge). When the electric vehicle is in the parking state, most users will charge when the battery SOC is between 20% and 80%. When the battery SOC is higher than 90%, charging behavior rarely occurs. In the non-residential area and the residential area, the battery SOC at the start of charging conforms to a normal distribution, while there is a significant difference in the distribution of battery SOC at the time of charging stop. Electric vehicle users generally end the current charge when the battery SOC is higher than 70%, and the battery SOC of the electric vehicle in the residential area at the time of charging stop is greater than the battery SOC of the non-residential area at the end of charging.

The charging behavior of electric vehicles will be affected by environmental factors such as season, temperature and meteorology [24], which mainly include the following reasons:

1. The high utilization rate of air conditioning in summer and winter seasons will increase the Electricity consumption, the charging frequency increases correspondingly, and the air conditioning utilization rate in spring and autumn is relatively low, and the charging frequency decreases accordingly. The total charging load of electric vehicles is lower than that in summer and winter.

2. Temperature The difference will affect the performance of the battery. Exceeding the upper and lower temperature limits will reduce the battery capacity, resulting in an increase in charging time.

3. Some electric vehicle users have working hours in summer and winter time. Changes in the start time of charging.

4. The impact of meteorology is reflected in the impact of different weather conditions on the user's car willingness and traffic conditions, and the charging time may change accordingly.

2.4 Differential privacy protection

Commonly used privacy protection technologies are k-anonymity, l-diversity, t-closeness, etc. However, when the attacker has sufficient background knowledge, these techniques cannot guarantee the security of the data. Dwork [25] proposed a differential privacy protection mechanism to solve the problem of traditional privacy protection.

The differential privacy mechanism [25] protects private data by adding noise, while preserving the statistical characteristics of the data, ensuring maximum data availability. Compared with other methods, differential privacy protection has the advantages of a quantifiable level of privacy protection, a solid mathematical theoretical foundation, and resistance to the largest background knowledge attacks. The basic principles of differential privacy protection are as follows:

Definition 1 [26]: Differential privacy protection. There is a random algorithm M, $\mathrm{P_M}$ is a set of all possible outputs of M. For any two adjacent data sets $\mathrm{D_1}$, $\mathrm{D_2}$ and any subset $\mathrm{S_M}$ of $\mathrm{P_M}$, if the algorithm M satisfies (2.1):

$$\mathrm{P}_r\left[M\left(D_1\right)\in S_M\right]\le e^{\varepsilon}\times \mathrm{P}_r\left[M\left(D_2\right)\in S_M\right] \quad (2.1)$$

It is said that the algorithm M provides ε - differential privacy protection, where the parameter ε is called the privacy protection budget [27].

Definition 2 [28]: Global sensitivity. Given the query function $f: D \to R^d$, the sensitivity of the function *f* is (2.2):

$$\Delta f = \max_{D_1, D_2} \left\| f(D_1) - f(D_2) \right\|_1 \qquad (2.2)$$

Among them, D_1 and D_2 are arbitrary adjacent data sets, R represents the mapped real space, and d represents the query dimension of the function f. The noise mechanism is an important mechanism to achieve differential privacy. Too much noise will affect the availability of clustering results, and too little noise will affect the security of data. Sensitivity is mainly divided into global sensitivity [28] and local sensitivity [29].

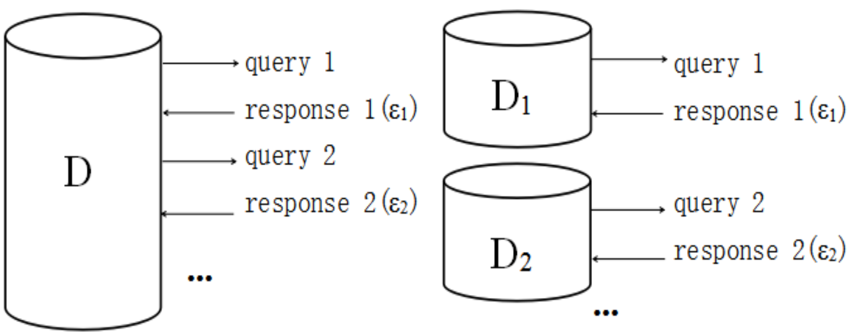
The noise mechanisms of differential privacy protection mainly include Laplace mechanism and exponential mechanism. This article uses the Laplace mechanism because it is suitable for numerical data and implements ε-differential privacy by adding random noise matching the Laplace distribution to the precise query results. The definition of the Laplace mechanism is as follows:

Definition 3[28]: Given a data set D with a function $f: D \to R^d$, then the random algorithm $M(D) = f(D) + Y$ provides ε-differential privacy protection, with a sensitivity of Δf, where $Y \sim \mathrm{Lap}(\Delta f / \varepsilon)$ is random noise and follows the Laplace distribution with a scale parameter of $\Delta f / \varepsilon$.

In definition 3, the probability density function of $\mathrm{Lap}(\Delta f / \varepsilon)$ is (2.3):

$$p(x) = \frac{1}{2\left(\Delta f / \varepsilon\right)} \exp\left[-\frac{|x|}{\left(\Delta f / \varepsilon\right)} \right] \qquad (2.3)$$

In order to ensure that the privacy protection level of the algorithm is within the budget ε, the following two combination properties need to be satisfied: sequence combination and parallel combination (figure 2.1).



a) $\sum_{i=1}^{n} (\varepsilon_i)$ – differential privacy b) $\max(\varepsilon_i)$ – differential privacy

Figure 2.1 – The combined nature of differential privacy protection algorithms

Property 1 [4]: For data set D, there is algorithm $M_1, M_2, \cdots, M_n$, whose privacy protection budget is $\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_n$, and combined algorithm $M(M_1(D), M_2(D), \cdots, M_n(D))$ provides $\sum_{i=1}^{n}(\varepsilon_i)$ – differential privacy protection.

Property 2 [4]: For the disjoint data set $D_1, D_2, \cdots, D_n$, there is an algorithm $M_1, M_2, \cdots, M_n$, whose privacy protection budget is $\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_n$, and the combined algorithm $M(M_1(D_1), M_2(D_2), \cdots, M_n(D_n))$ provides $\max(\varepsilon_i)$-differential privacy protection.

2.5 K-means clustering algorithm

Clustering algorithm is an important algorithm in data mining. It is a type of unsupervised machine learning algorithm. It can be used to discover the internal connection of things and make business decisions. The essence of the clustering algorithm is to divide according to the similarity of the data set to form independent clusters to reveal the data distribution. There is no category label in the data set of cluster analysis, and the data set processed by the data classification method has a category label. This is the main difference between the two data analysis methods of clustering and classification [30].

The k-means algorithm is one of the representative clustering algorithms based on partition, which has the advantages of simplicity, high efficiency and easy implementation. The k-means algorithm and the improved k-means algorithm have been widely used in user behavior and classification research, and there are many successful cases, such as [31,32]. In the k-means clustering process, there are two steps prone to data privacy leaks, namely the selection of the center point and the calculation of the distance between the data point and the center point. If the attacker obtains the information about the center point and the distance between a data point and the center point before the clustering calculation is completed, the value of the data point can be calculated. After the cluster analysis is completed, the value of the center point will be returned. If the attacker has the maximum background knowledge at this time, the value of the data point can also be calculated, which also has the risk of data privacy leakage. Combining the above inferences, in order to ensure user privacy and security in k-means clustering analysis, noise needs to be added.

2.6 K-means clustering algorithm under differential privacy protection

Reference [33] first proposed combining differential privacy protection and k-means clustering algorithm to provide differential privacy protection for sensitive information by adding noise to the central point during the clustering process. However, the selection of the initial center point in DP k-means has a greater impact on the clustering results. Literature [34] proposed an improved differential privacy k-means algorithm (IDP), which improves the selection of the initial center point and proves the improvement of the usability of clustering results through experiments. Literature [35] believes that differential privacy protection technology is more suitable for data mining by comparing the scope of applicable privacy protection technology. Reference [36] proposed an optimized differential privacy clustering algorithm based on k-means algorithm and k-modes algorithm for mixed data in smart grid. Reference [37] proposes a clustering analysis method of electricity consumption data for massive users under differential privacy protection, and obtains the user's electricity consumption behavior model through local and global clustering. Reference [38] proposes a privacy and usability data clustering scheme based on k-means algorithm and differential privacy, improves the selection of the initial center point and the distance calculation method from other points to the center point, and detects anomalies during the clustering process Values to reduce the effects of outliers. By analyzing the above research, it is found that the key to privacy leakage is the clustering center point, because the clustering center point is obtained by dividing the sum of all data points in the cluster by the number of data points. If you provide an approximate value for the center point of each cluster when clustering data, you will protect sensitive data while ensuring cluster accuracy. Therefore, this paper adds noise at the center of clustering and uses differential privacy protection to reduce the risk of privacy leakage.

2.7 Chapter summary

This chapter first gives an overview of electric vehicles, introduces three different types of electric vehicles from the perspective of characteristics and functions, and also describes the application scope, advantages and disadvantages of the three charging modes. Secondly, it describes the current status of the construction of charging facilities in China, and introduces the charging facilities of electric vehicles from the aspects of charging stations and charging piles. Next, it analyzes the impact of the charging behavior of electric vehicles, and expounds the basic theoretical knowledge of differential privacy protection and k-means algorithm, which lays a theoretical foundation for subsequent research in this article.

3 ANALYSIS OF ELECTRIC VEHICLE CHARGING BEHAVIOR

In order to reduce the random charging behavior of electric vehicles and the impact of large-scale access on the grid, it is necessary to analyze the charging behavior of electric vehicles in order to understand the charging behavior of users, thereby improving charging services, and providing decisions for off-peak charging and grid charging scheduling strategies stand by. With the development of data mining technology, a large number of new algorithms combining data mining technology and differential privacy protection technology have been proposed and applied in many fields. As one of the representative clustering algorithms, the k-means algorithm has the advantages of simplicity, efficiency, and ease of implementation. The k-means algorithm and its improved algorithms have been widely used in user behavior and classification research, and have the advantages in analyzing electric vehicle data Many success stories. Therefore, the improved k-means algorithm is suitable for analyzing the charging behavior of electric vehicle users.

3.1 Data sources

3.1.1 Introduction to electric vehicle charging data

The data used in this chapter comes from a 30-day charging data set of an electric vehicle charging facility in China. Data is collected every second and includes attributes such as user ID, charging start time, charging stop time, charging cost, and charging degree.

3.1.2 Data preprocessing

Next, the collected data of electric vehicles in a certain city is used as the initial data of the experiment to perform data preprocessing.

The data used in this chapter has a missing user ID. Considering that this attribute value is indispensable for obtaining the number of charging times, the data bar with missing user ID is directly deleted. Therefore, under the premise of the same user ID, multiple pieces of duplicate data are identified and deleted, and only one piece of data with the largest actual charging degree is retained. Moreover, data with extremely short charging times are excluded to avoid adversely affecting the analysis results. Then, count the number of charging times per hour for each electric vehicle user within 30 days. Then use formula (3.1) to normalize the data [37]:

$$d'_{i,j} = \frac{d_{i,j} - d_{min}}{d_{max} - d_{min}} \quad (3.1)$$

Among them, $d_{i,j}$ represents the current data, $d'_{i,j}$ represents the normalized data, d_{min} represents the minimum value in the electric vehicle data set, d_{max} represents the maximum value in the data set, i represents the number of data, and n represents the total value in the electric vehicle data set Number of items, j represents the number of attribute values in the data. Although the data set before normalization is 24 dimensions, including 24 attribute values, the unit of each attribute value is the same and all indicate the number of charging within an hour. Therefore, the normalization uses the minimum and maximum values in the entire data set as d_{min} and d_{max}.

Finally, the processed data is used as the input data of the clustering model. The input data contains n pieces of charging times data, and each piece of data has 24 attribute values, which respectively represent the corresponding charging times value of 24 hours.

3.2 Electric vehicle charging behavior analysis model

The process of analyzing electric vehicle charging behavior is shown in figure 3.1.

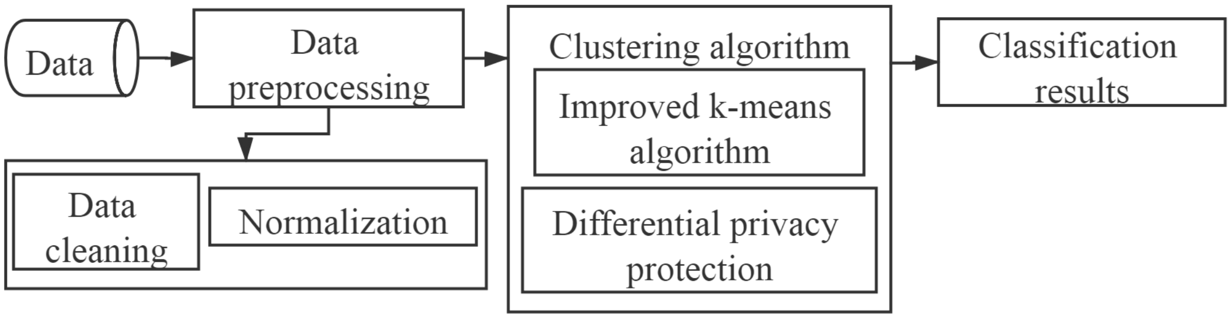


Figure 3.1 – Flow chart of electric vehicle charging behavior analysis

1. Electric vehicle charging data

The data set used in this chapter contains a large number of electric vehicle charging data, which can be used to analyze charging behavior.

2. Data preprocessing

In order to make better use of a large amount of charging data, first remove missing values and duplicate data. Then exclude the data with extremely short charging time. Then statistically calculate the number of charging per hour within 30 days. Finally, by normalizing the data, the data of the number of charging times in the time series is obtained.

3. Charging data clustering algorithm

The time series charging times data is used as the input data of the algorithm. The algorithm combines differential privacy protection and an improved k-means clustering algorithm. The k-means algorithm has the advantages of simplicity, efficiency, and ease of implementation. Moreover, the k-means algorithm and its improved algorithm have been widely used in user behavior and classification research, and there are successful cases in analyzing electric vehicle data. The model based on this algorithm has good practical application value. Considering that the k-means clustering algorithm needs to manually set the number k of clusters, therefore, the value of k needs to be determined before subsequent classification.

4. User classification results

The results can be used for charging scheduling, and provide personalized charging services for electric vehicle users.

3.2.1 Selection of the number k of clusters

The k-means algorithm needs to set the number of clusters in advance, and the value of k has a great influence on the clustering result. As the value of k increases, clustering will inevitably describe the data more accurately, but the more clustering, the fewer dimensions of the problem. In general, clustering results of low similarity between clusters and high similarity within clusters are considered good. Therefore, the method used in this chapter to evaluate the clustering results is silhouette coefficient, which is described as follows:

1. Calculation a_i

a_i is the average distance between the data d_i and other samples in the same cluster, which is called the intra-cluster dissimilarity of data.

2. Calculation b_i

Calculating the average distance of data d_i to all samples in a certain cluster is called the dissimilarity between the data and a certain cluster. b_i is defined as the inter-cluster dissimilarity of data: $b_i = min\{b_{i,1}, b_{i,2}, \cdots, b_{i,k}\}$.

3. Calculation s_i

According to the intra-cluster dissimilarity a_i and inter-cluster dissimilarity b_i of the data d_i, define the Silhouette Coefficient of the data.

4. Evaluation

When s_i is close to 1, it indicates that the data clustering is reasonable; if s_i is close to -1, the data d_i should be classified into another cluster; if s_i is approximately 0, the data d_i is located on the boundary of the two clusters. Generally, the average value of all s_i is called the contour coefficient of the clustering result, which is the final metric used to evaluate the clustering result.

3.2.2 Electric vehicle charging data clustering process

In this chapter, the clustering of electric vehicle charging data is mainly divided into two processes:

1. Calculate the density value of each electric vehicle charging data point, and determine the abnormal value according to the density value. The data is divided into k clusters in the order of density value, and the center of each cluster is used as the initial center point.

2. Use the initial central point clustering electric vehicle charging data set to obtain k charging modes for electric vehicle users.

In order to protect the safety of electric vehicle charging data during the clustering process, this chapter uses differential privacy mechanism. Since this method protects the privacy data by adding noise, the randomness of the cluster centers is increased, making each cluster center point different from the real center point. Moreover, an inappropriate initial cluster center point may reduce the usability of the results. In addition, there may be some data points far away from the central point in the charging data of electric vehicles, and these data points will affect the cluster analysis of the k-means algorithm. These factors may further lead to the uncertainty of clustering results. This chapter increases the stability of clustering results by detecting outliers and improving the selection of initial center points.

The formula for calculating the distance between the current data point and other data points is shown in formula (3.2). Suppose the data set is $D = \{d_1, d_2, \cdots, d_n\}$, n represents the number of data, the current data point is represented by d_i, other data points are represented by d_l, the number of attribute values of the data point is represented by j, the number of data used in this chapter is n, the number of attribute values is 24.

$$dist(d_i, d_l) = \sqrt{\sum_{j=1}^{24} \left(d_{i,j}, d_{l,j}\right)^2} \tag{3.2}$$

Detection of outliers [39]: Data points far from the center point in the electric vehicle charging data set are called outliers. When calculating the center point of clustering, identifying these data outliers can improve the accuracy of clustering results. The density value of each data point is expressed by the ratio of the number n of data and the square of the distance, and the calculation formula is shown in formula (3.3).

$$density(d_i) = \frac{n}{\sum_{l=1}^{n} dist^2(d_i, d_l)} \tag{3.3}$$

According to formula (3.3), the denser the points near a certain data point, the greater the density value of the point. The cluster center points are easily affected by outliers, so this chapter sorts the density values of all data points in a decreasing manner. Set the outlier parameter to q, identify the $n * (1 - q)$ data points at the end of the sequence as outliers, and use the first $n * q$ data points to calculate the cluster center point. In the following cycle, the outliers are still part of the cluster division.

The selection of the initial center point. By adding noise to the cluster center point and providing an approximate value of the center point, the privacy of electric vehicle users is protected, but it will cause the new cluster center to be different from the real cluster center and affect the stability of the clustering result. Therefore, this chapter improves the accuracy and usability of clustering results by improving the selection of the initial center point. First calculate the density of each data point to identify outliers, and then divide the data into k clusters in the order of density value, and the center of each cluster is used as the initial center point.

This chapter uses differential privacy protection to reduce the risk of privacy leakage by adding noise at the center of the cluster. The Laplacian mechanism is suitable for numerical data and achieves ε-differential privacy by adding random noise matching the Laplacian distribution to the result. Reference [25] proposed two methods for setting privacy protection budget ε under the premise of unknown and known iterations. The number of iterations of this algorithm is unknown, so we choose to adjust the value of the parameter ε during the clustering process. The value of the privacy protection budget in the first iteration is $\varepsilon/2$ and the noise is $Lap(2\,(d+1)/\varepsilon)$. The budget consumption of each iteration is half of the previous iteration until the end of the iteration.

In this algorithm, the calculation formula for updating the cluster center point is shown in formula (3.4).

$$newcenter = \frac{(sum+Lap(b))}{(\text{count}+Lap(b))} \qquad (3.4)$$

Among them, sum represents the sum of the dimensions of the data points, count represents the total number of data points, and $Lap(b)$ represents the noise. $b = \Delta f/\varepsilon$, Δf represents the sensitivity of the query function. ε is a privacy protection parameter, and represents the amount of noise. The sensitivity of the denominator is 1, and the sensitivity of the numerator is determined by the dimensions of the data set. Add or delete points in the d-dimensional data set, the sensitivity of each dimension is 1, and the sensitivity of the molecule is d, then the sensitivity of the entire query sequence is d + 1. The dimension of the data used in this chapter is 24, that is, d = 24.

3.2.3 Charge data clustering algorithm

The purpose of privacy-protected data mining [40] is to extract valuable information from large amounts of data while protecting the data privacy of users or devices. In order to better protect the privacy of electric vehicle users, this chapter uses the improved k-means clustering algorithm under differential privacy protection to ensure the availability of clustering results while protecting data privacy.

The input data of the algorithm is the data of the number of charging times of the 24-dimensional electric vehicle after data preprocessing. The output clustering result is k charging modes of electric vehicle users. The specific steps of the clustering algorithm are as follows:

1. Traverse all data points and calculate the distance from the current data point to other data points.
2. Calculate the density of data points.
3. Sort the density values of all data points in order from large to small.
4. Mark the data points at the end of the queue where density values are sorted as outliers.
5. The data points except the outliers are divided into k clusters in sorted order.
6. Calculate the initial cluster center point.
7. Calculate the distance from each point to each center point.
8. Compare the size to get the minimum distance corresponding to each point, and divide it to the corresponding center point.
9. Calculate the sum of the dimensions of the data points and the total number of data points, plus noise. Then calculate and update the center point of each cluster.
10. If the convergence condition is not satisfied, repeat steps7 to 9; otherwise, output the clustering result.

3.3 Chapter Summary

This chapter first introduces the electric vehicle charging data to be used, and preprocesses the data. In view of the fact that the analysis process of electric vehicle charging behavior is easy to leak user privacy and the amount of data is large, this chapter proposes an analysis model of electric vehicle charging behavior and a clustering algorithm of charging data. By improving the selection of initial clustering centers and calculating the density of each data point to find outliers, the availability of data clustering results is ensured under the premise of safety.

4 PLANNING AND OPTIMIZATION OF ELECTRIC VEHICLE CHARGING FACILITIES

As the most basic supporting facilities for electric vehicles, rational planning of electric vehicle charging facilities can help promote electric vehicles and improve the economic benefits of charging facilities. On the basis of satisfying the constraints of the distribution network, the most critical factor affecting the choice of electric vehicle charging facility planning options is the social cost of charging facilities. This chapter first analyzes the various costs of electric vehicle charging facilities, and then uses the minimum total cost of the whole society as the objective function of charging station planning to carry out charging station site planning.

4.1 Social cost analysis of charging facilities

The total social cost refers to the total cost of the various production sectors of the society. Considering all costs in the entire life cycle of electric vehicle charging stations, we can analyze from the perspective of each cost bearer, and the social costs of charging facilities are correspondingly divided into charging station institutional costs, user costs of electric vehicle users, and grid Line loss cost, the specific frame structure is shown in figure 4.1 [44].

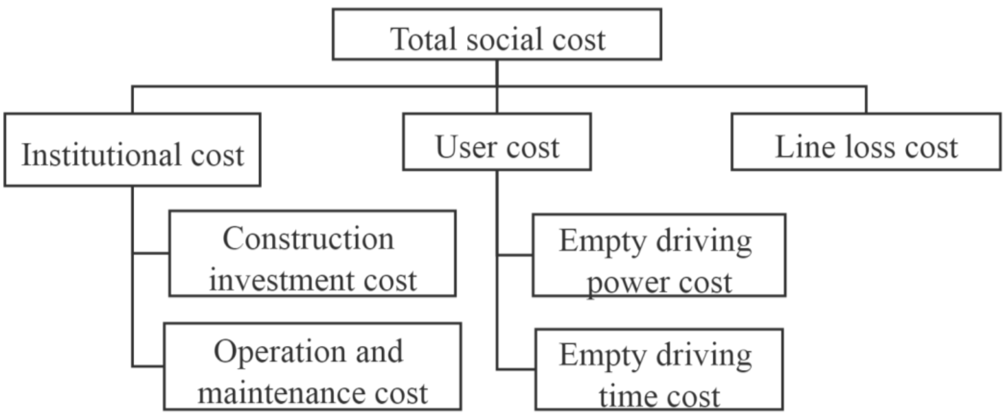


Figure 4.1 – Total social cost framework of charging facilities

Among them, the institutional cost refers to the cost borne by the construction and operation unit; the user cost refers to the cost borne by the electric vehicle user; the line loss cost is the cost caused by the power loss of the transmission line during the normal operation of the charging station.

1. Institutional cost of charging stations

Institutional costs mainly include construction investment costs and operation and maintenance costs [41]. If the institutional cost corresponding to the i-th charging station is Co_i, the annual construction investment cost is Cc_i, the annual operation and maintenance cost is Cm_i. The institutional cost is shown in formula (4.1):

$$Co_i = Cc_i + Cm_i \tag{4.1}$$

The annual construction investment cost of the i-th charging station is shown in formula (4.2):

$$Cc_i = (m_i b + w_{EV}) \frac{r_0(1+r_0)^z}{(1+r_0)^z - 1} \tag{4.2}$$

Among them, m_i represents the number of charging piles in the i-th charging station, b represents the price of each charging station, w_{EV} represents the cost of the fixed investment portion of each charging station, r_0 represents the discount rate, and z represents the operating life of the charging station.

The maintenance cost during the operation period mainly includes the maintenance cost and wage and welfare cost of various types of equipment. It is generally considered that this cost is proportional to the previous construction investment cost. The ratio is set to η_m, and the annual operation and maintenance cost of the i-th charging station is shown in formula (4.3):

$$Cm_i = \eta_m Cc_i \tag{4.3}$$

2. Cost of charging station users

The user cost is mainly composed of the cost of empty driving power and the cost of empty driving time from the point of charging demand to the charging station [41]. If the user cost of the charging station is Cu_i, it is shown in formula (4.4):

$$Cu_i = Ce_i + Ct_i \tag{4.4}$$

Among them, Ce_i represents the idling power cost of electric vehicle users, and Ct_i represents the idling time cost.

The user's annual comprehensive empty driving electricity cost of the i-th charging station is shown in formula (4.5):

$$Ce_i = \frac{\sum_{j=1}^{Nc_i}(d_{i,j} \times Nev_j)}{L_{EV}} \times p \times 365 \tag{4.5}$$

Among them, Nc_i represents the number of electric vehicle charging demand points in the service area of the i-th charging station; $d_{i,j}$ represents the distance from charging demand point j to charging station i; Nev_j represents the number of vehicles included in charging demand point j, L_{EV} represents electric The mileage traveled per unit of electricity consumed by the car, p is the charging price of the electric car.

The formula for calculating the distance from the charging demand point to the charging station is shown in formula (4.6). Among them, (x_i, y_i) represents the position of the charging station i in the road network; (x_j, y_j) represents the coordinates of the charging demand point j.

$$d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (4.6)$$

The cost of the user 's annual comprehensive empty driving time for the i-th charging station is shown in formula (4.7):

$$Ct_i = \frac{\sum_{j=1}^{Nc_i}(d_{i,j} \times Nev_j)}{v_{EV}} \times c_w \times 365 \quad (4.7)$$

Among them, v_{EV} represents the average driving speed of electric vehicles; c_w represents the cost per unit time for users to travel.

3. Line loss cost

In the transmission process of the transmission line, the energy loss caused by the impedance of the line is called line loss [44]. The calculation formula of line loss is shown in formula (4.8):

$$\Delta p = 3I^2R \times 10^{-3} \quad (4.8)$$

Among them, Δp represents the line loss, the unit is kW, I represents the current in the circuit, the unit is A, and R represents the resistance in the line, the unit is Ω (4.9):

$$R = \rho \frac{l}{S} \quad (4.9)$$

Among them, ρ represents the resistivity of the line material, l represents the length of the line, and S represents the cross-sectional area of the line material.

It can be seen from the above two formulas that when the transmission line material is determined, the resistance R is proportional to the line length l, so the line loss cost of the electric vehicle charging station is mainly determined by the distance between the charging station and the node of the local distribution network. China's power grid configuration is relatively complete, so when building a charging station, you can find the distribution network nodes with a short distance, so the impact of line losses is small.

4.2 Planning model for charging facilities

4.2.1 Assumptions

In order to facilitate research, the assumptions are as follows:

1. Demand point refers to all electric car users in a small area centered on this point. Demand refers to the number of all electric cars that need to be charged within this range.
2. Each charging facility has the same level and uses the same charging pile.
3. The vehicle type and battery type are the same.
4. Regardless of traffic delays, power consumption due to road conditions.

5. Regardless of the preferences of electric vehicle users, they will choose the charging facility with the closest starting point.

4.2.2 Objective function

The planning of charging stations mainly includes the determination of the number and the selection of the location. The institutional cost of charging stations is in contradiction with the cost of users. The relationship between institutional cost and user cost is shown in figure 4.2. From the perspective of the charging station, increasing the number can improve service efficiency, but at the same time will increase construction costs and operation and maintenance costs. If the number of charging stations is relatively small, service efficiency will be reduced, and the convenience of charging for electric vehicle users cannot be guaranteed. From the user's perspective, in order to enjoy convenient charging services, charging stations should be added, which can reduce the cost of the user's charging process. Therefore, the cost of the organization and the cost of users should be comprehensively considered to optimize the overall situation.

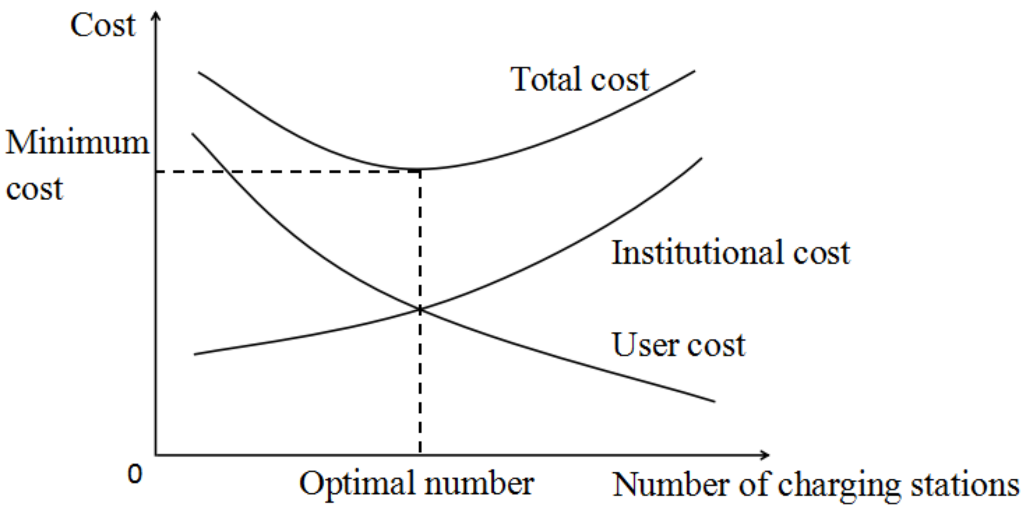


Figure 4.2 – The impact of the number of charging stations on cost

This paper considers the cost of charging station organization and the cost of electric vehicle users comprehensively, and finds the optimal number of charging stations corresponding to the minimum social cost as the optimization goal, and takes the minimum total cost of the whole society as the objective function of charging station planning [44], the calculation formula is shown in formula (4.10):

$$minC = \sum_{i=1}^{N}(Co_i + Cu_i) \qquad (4.10)$$

Among them, C represents the total social total cost converted to each year; N represents the total number of charging stations; Co_i represents the institutional cost corresponding to the i-th charging station; Cu_i represents the user cost corresponding to the i-th charging station.

4.2.3 Planning of charging facilities

The k-means clustering algorithm has the advantages of simplicity, efficiency, and ease of implementation, and is suitable for such clustering problems with large amounts of data. The k-means clustering algorithm needs to manually set the number k of clustering centers. The choice of k value in this chapter also needs to consider the influence of institutional cost, that is, the increase of k value will increase the construction investment cost and operation and maintenance cost of the charging station. Therefore, when the k value is increased for a certain time, the increase in institutional cost is greater than the decrease in user cost, and the k value at this time represents the optimal number of charging stations.

Since the clustering result is more sensitive to the selection of the initial clustering center, an inappropriate initial center point may reduce the usability of the result. Therefore, this chapter improves the usability of clustering results by improving the selection of initial center points.

The detailed steps to improve the k-means clustering algorithm are as follows:

1. Enter the relevant data of the charging demand point and initialize $k = 1$.
2. Traverse all the demand points, calculate the distance from each point to other points, and calculate the density value of each point.
3. Sort the density values of all data points.
4. Divide the sorted data points into k clusters, and calculate the center of each cluster as the initial center point.
5. Calculate the cost of charging each remaining demand point to each charging station, and classify the demand point to the corresponding charging station with the lowest cost.
6. Calculate and update the center point of each class.
7. Repeat Step 5 and Step 6 until the new center point is equal to the original center point or the gap is less than the specified value, and record the charging station coordinates and social cost at this time.
8. If $k = 1$, then $k = k + 1$, return to step 2. Otherwise, proceed to the next step.
9. If $C_k < C_{k-1}$, then $k = k + 1$, return to step 2; otherwise, output C_k and the current position coordinates of each charging station to end.

4.3 Chapter summary

This chapter analyzes the three parts of the total social cost of electric vehicle charging stations, and gives a charging facility planning model, including assumptions and objective function. The optimal number of charging stations corresponding to the smallest social cost is taken as the optimization goal, and the minimum total cost of the whole society is taken as the objective function of charging station planning. Finally, a solution method based on improved k-means clustering algorithm is proposed, and the steps of the algorithm are introduced.

5 EXPERIMENT ANALYSIS

5.1 Related experiments on charging behavior analysis of electric vehicles

5.1.1 Selection of the number k of clusters

When k takes different values, the data of electric vehicle charging times after data preprocessing is used for cluster analysis. The silhouette coefficient values corresponding to different k values are shown in table 5.1. It can be found from the data in table 5.1 that when k takes 5, the silhouette coefficient value is the largest, that is, the best clustering result is achieved. Therefore, choose k = 5.

Table 5.1 – Silhouette coefficient values with different k values, %

k	3	4	5	6	7	8
Silhouette Coefficient	55.82	56.87	57.62	55.16	55.67	32.17

5.1.2 Experimental results of electric vehicle data cluster analysis

According to the electric vehicle charging behavior analysis model mentioned above, the preprocessed data of the input data is used to use the electric vehicle charging data clustering algorithm, and the resulting clustering result is shown in figure 5.1.

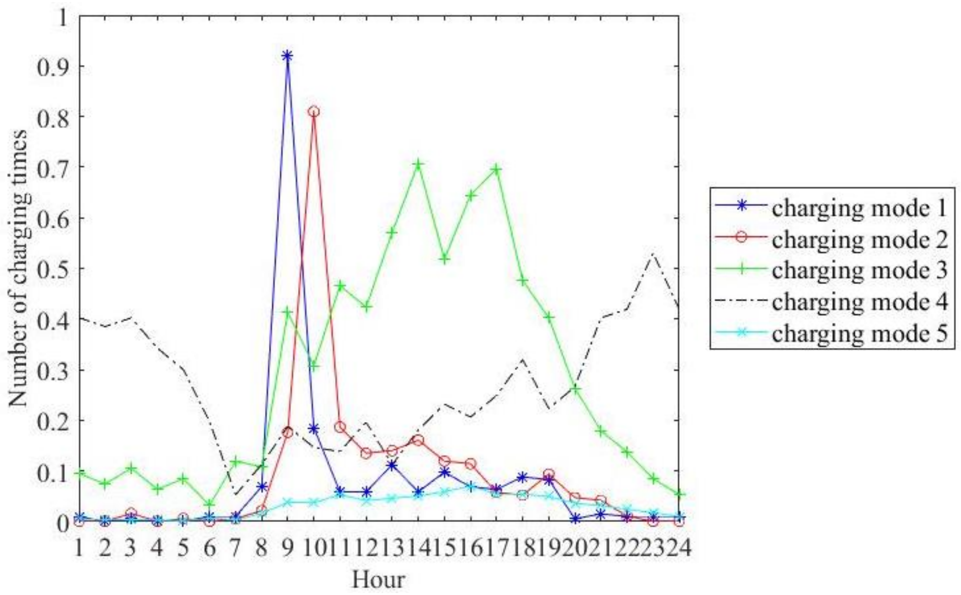


Figure 5.1 – Clustering results of the proposed algorithm for charging behavior in Chapter 3

Figure 5.1 shows that the charging times data obtained 5 user charging modes after cluster analysis of the algorithm proposed in this article. From figure 5.1, you can analyze the different charging habits of each user. It can be seen that the charging time of charging mode 1 is relatively concentrated, reaching a peak at 9 o'clock. Compared with charging mode 1, charging mode 2 has an hour delay and a lower peak value, reaching the peak at 10 o'clock. The charging time of charging mode 3 is more scattered, mainly between 9 o'clock and 20 o'clock, and there are two peaks at 14 o'clock and 17 o'clock. The charging time of charging mode 4 is mainly concentrated in the evening, reaching a peak at 23:00. Charging mode 5 has less charging, especially in the early morning hours. The charging time is evenly distributed, and the overall fluctuation is not large [3].

According to the charging behavior characteristics of each type of user, the power service provider can understand the individualized and differentiated service needs of each user, thereby providing differentiated services and marketing strategies for different types of users. For example, users corresponding to charging mode 3 have more accumulated charging times, which can provide them with more convenient and faster charging services to improve the satisfaction of such users. The charging time of the two types of users corresponding to charging mode 1 and charging mode 2 is concentrated around 9:10 in the morning. You can use time-sharing tariffs and other preferential policies to encourage electric vehicles to charge during low peak hours and support related decisions about dispatch management. The users corresponding to charging mode 4 are mostly charged at night, which is the trough period of the grid load, so it can provide some differentiated services and reduce user churn. The users corresponding to charging mode 5 have fewer charging times and belong to the potential user group. These users should be maintained, take active marketing programs, and encourage their charging to improve their charging and consumption capabilities (figure 5.2).

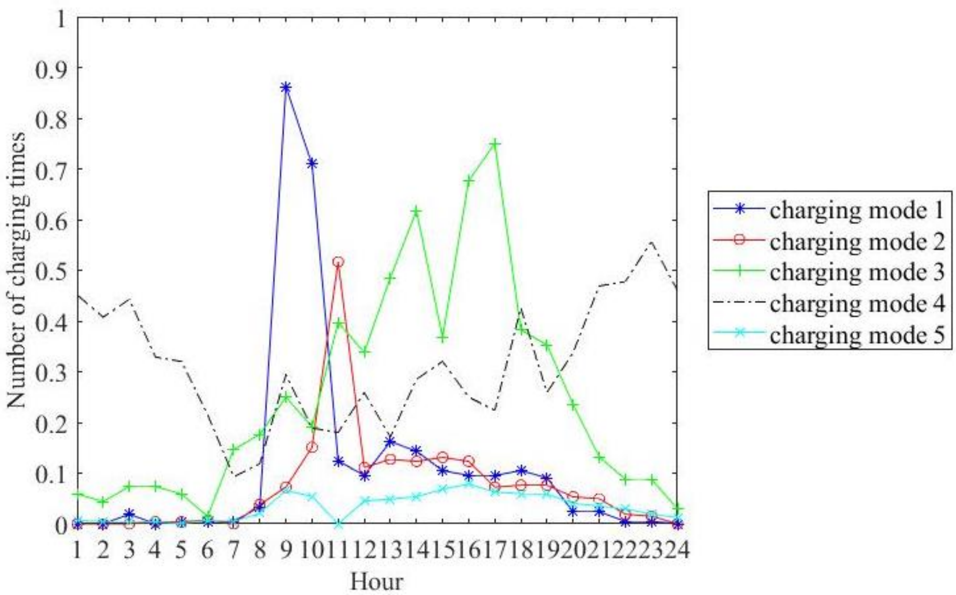


Figure 5.2 – Clustering results of k-means algorithm for charging behavior

In order to verify the effectiveness of the clustering algorithm obtained in this chapter, this chapter also uses the k-means clustering algorithm to cluster the same data. The clustering results are shown in figure 5.2. By comparing the charging behavior characteristic curves in figure 5.1 and figure 5.2, it can be seen that although the clustering algorithms used in the two figures are different, the trend of the user's charging mode can be analyzed. Reference [3] uses k-means clustering algorithm to perform cluster analysis on electric vehicle charging data, which shows the effectiveness of k-means algorithm, which also shows that the algorithm proposed in this chapter is effective.

5.2 Related experiments on electric vehicle charging facility planning

In order to verify the effectiveness of the proposed algorithm and model in Chapter 4, the area of a new district of a city is now used as a calculation example. There are 24 demand points in the 50km * 50km plane area. Table 5.2 lists the related parameters of electric vehicles and charging stations [41,44]. The horizontal and vertical coordinates of the charging demand point and the number of electric vehicles required for charging are shown in table 5.3.

Table 5.2 – Related parameters of electric vehicles and charging stations

Parameter	Symbol	Numerical value	Unit
Fixed investment cost of charging station	w_{EV}	80	Ten thousand yuan
Electricity price in the area	p	0.8	yuan
User travel time value	c_w	17	yuan/hour
The mileage of electric vehicles consuming unit electricity	L_{EV}	6.6	km
Average speed of electric vehicles	v_{EV}	36	km/h
Charging station operating years	z	20	year
Charging pile unit price	b	5	Ten thousand yuan
Number of charging piles in the i-th charging station	m_i	5-20	station
Discount rate	r_0	0.1	/
Maintenance cost scale factor	η_m	0.9	/

According to the data in table 5.2 and table 5.3, the algorithm proposed in Chapter 4 was used to conduct experiments on MATLAB to calculate the location of the charging station.

Table 5.3 – Charging demand information

Demand point number	Abscissa x_j, km	Ordinate y_j, km	Number of charging needs
1	0.5	32.6	19
2	1.1	4.9	20
3	20.1	19.8	15
4	10.6	0.5	13
5	21.0	41.9	16
6	4.1	36.4	15
7	26.8	5.0	23
8	21.5	27.2	22
9	30.5	5.4	24
10	4.6	41.7	16
11	35.1	7.8	18
12	24.9	21.9	15
13	6.5	32.3	18
14	8.0	27.3	17
15	45.6	40.4	20
16	10.1	43.8	10
17	41.8	3.9	12
18	48.2	44.3	19
19	48.5	46.2	26
20	10.8	45.5	12
21	47.2	23.8	30
22	44.8	5.3	12
23	25.2	25.5	24
24	46.4	8.1	11

The result is shown in figure 5.3.

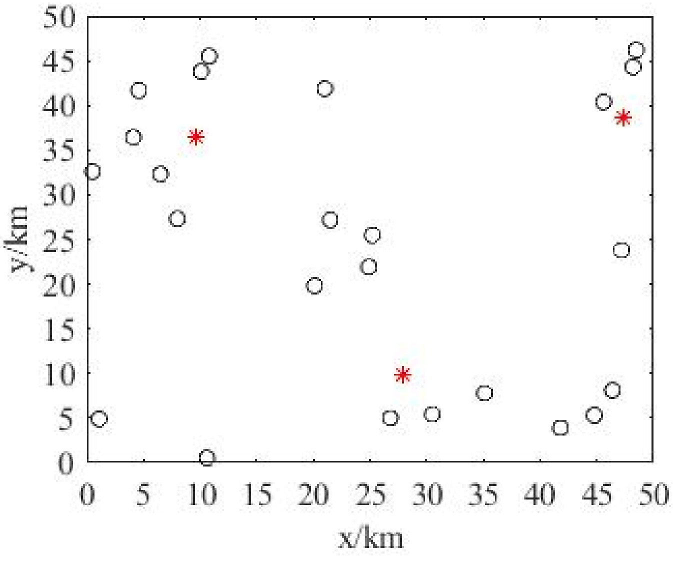


Figure 5.3 – Location and service area of electric vehicle charging stations

The social cost obtained by the improved k-means clustering algorithm is shown in table 5.4. It can be found from the data in the table that when the number of charging stations is 3, the total social cost is the smallest, which is the optimal charging station planning scheme. As the number of charging stations increases, the institutional costs (annual construction costs and annual operation and maintenance costs) of charging stations also increase, which is approximately linearly related to the number of charging stations. With the increase in the number of charging stations, the cost of charging station users (annual empty driving power cost and annual empty driving time cost) is decreasing. As the number of charging stations increases, the total social cost decreases first and then increases.

Table 5.4 – The social cost corresponding to the number of different charging stations

Number of charging stations	Annual construction cost, ten thousand yuan	Annual operation and maintenance cost, ten thousand yuan	Annual empty driving power cost, ten thousand yuan	Annual air-driving time cost, ten thousand yuan	Social cost, ten thousand yuan
1	14.10	12.69	39.06	152.18	218.03
2	28.19	25.37	29.79	116.05	199.40
3	42.29	38.06	20.73	80.74	181.81
4	56.38	50.74	17.84	69.49	194.44

5.3 Chapter summary

In this chapter, we first analyze and experiment with the models and algorithms given in Chapter 3, and use the actual charging data after preprocessing to conduct experiments, and determine the number of clusters k by the contour coefficient. Then the DP k-means algorithm is used to experiment on the same data set. This chapter also draws out the charging modes of electric vehicle users, and analyzes the charging characteristics of each user mode in detail. This chapter also conducts experiments on the charging station planning model given in Chapter 4 and performs simulation calculations on an example to obtain the optimal solution of the charging station planning in a certain area, which verifies the effectiveness of the algorithm. Then it analyzes the changing trend of institutional cost, user cost and total cost as the number of charging stations increases.

6 USE OF RESULTS OF A RESEARCH IN THE POWER INDUSTRY EQUIPMENT

6.1 The analysis strengths and weaknesses of technology, opportunities and threats of its application

SWOT is an abbreviation for Strengths, Weaknesses, Opportunities and Threats. SWOT analysis is actually a method to synthesize and summarize all aspects of internal and external conditions of the enterprise, and then analyze the advantages and disadvantages of the organization, opportunities and threats. It organically combines the company's strategy with its internal resources and external environment.

1. Strengths (S) refers to the ability of an enterprise to surpass its competitors, or refers to something unique to the enterprise that can improve competitiveness. The strengths can be in the following aspects: technical skills, tangible assets, intangible assets, etc.

2. Weaknesses (W) refers to something that a certain enterprise lacks or does not do well, or refers to a condition that will put the enterprise at a disadvantage. The factors that may lead to weakness are: lack of competitive skills and technologies, lack of competitive assets, and the loss of competitiveness in key areas.

3. Opportunities (O). Enterprise managers should identify each opportunity, evaluate the growth and profit prospects of each opportunity, and select the best opportunities that can match their own financial and organizational resources to maximize the potential of the company's competitive advantage.

4. Threats (T). In the external environment of an enterprise, there are always certain factors that pose a threat to profitability and market position. Managers should promptly identify threats that threaten the future interests of the enterprise, make evaluations and take corresponding strategic actions to offset or mitigate their impact.

The steps of SWOT analysis:

1. List the strengths and weaknesses, opportunities and threats of the enterprise.

2. Combine the advantages and disadvantages of the enterprise with the opportunities and threats of the external environment to form SO, ST, WO, and WT strategies.

3. Choose SO, ST, WO, and WT strategies and determine the specific strategies that the enterprise should adopt.

The promotion of electric vehicles helps to alleviate energy shortages and environmental pollution problems. The charging behavior of electric vehicles is characterized by randomness, which may bring many effects to the power grid [1]. With the development of the competitive charging market, accurately understanding user charging behavior patterns has become a valuable asset for power service providers [2]. Therefore, analyzing the charging behavior data can lay the foundation for the charging and discharging scheduling strategy of electric vehicles. Charging facilities are important facilities for providing charging services for electric vehicles. With the acceleration of the construction of charging facilities, it will drive the enthusiasm of potential users to purchase. The key to the industrialization of electric vehicles is to optimize the planning of charging facilities and improve their related theories, which can provide technical and theoretical support for the actual planning work and contribute to the development of electric vehicles. The SWOT matrix analysis combined with the techniques of this paper is shown in table 6.1.

Table 6.1 – SWOT matrix analysis of technology in this paper

Internal factor / External factor	Strength	Weaknes
	1. Energy saving, environmental protection and clean energy. 2. Improve the reliability and economy of power grid operation. 3. Lay the foundation for charge and discharge scheduling of electric vehicles. 4. Protect user privacy of electric vehicles. 5. Improve the economic benefits of charging facilities. 6. Promote the formation of the electric vehicle ecosystem.	1. The amount of data is insufficient. 2. The charging facility planning scheme is not perfect.
Opportunities	SO	WO
1. Electric vehicles are valued by countries all over the world. 2. China has introduced many preferential policies related to electric vehicles. 3. The number of electric vehicles in China is increasing, and the scale of charging facilities is also expanding.	1. Promote the popularity of electric vehicles. 2. Provide users with personalized services, and increase satisfaction. 3. Guide charging behavior, and maintain the safety and stability of the power grid. 4. Alleviate the tension of data leakage and protect user privacy.	1. With the popularity of electric vehicles and the improvement of charging facilities, more data can be used for analysis. 2. Speed up the construction of supporting facilities.
Threats	ST	WT
1. Electric vehicles are in the initial stage of development. 2. The application of automotive electronic technology needs further research and development 3. Imperfect supporting facilities. 4. The market recognition of electric vehicles is not high.	1. Accelerate the research of related technologies. 2. Provide convenient charging methods to drive potential users' purchase enthusiasm. 3. Innovate business operation models and build reasonable charging facilities.	1. Establish an electric vehicle technology platform. 2. Increase the research and development of electric vehicles.

Electric vehicles are now in the initial stage of development, and electric vehicles are very important for achieving energy transformation in the transportation field. At the same time, China has introduced many preferential policies related to electric vehicles, which has greatly promoted the share of electric vehicles. Moreover, the number of electric vehicles and charging facilities is increasing. The application of research and development informatization and intelligent automotive electronic technology, the improvement of the construction of charging facilities, and the provision of convenient services to users can promote the formation of an electric vehicle ecosystem and help alleviate energy shortages and environmental pollution.

6.2 Gantt's schedule of actions for implementation of technology in the power industry equipment

According to the framework of the paper, I divided the research into the following parts, as shown in table 6.2. Electric vehicles have the advantages of energy conservation, environmental protection and clean energy use, and are gradually being valued by countries all over the world. Vigorous development of electric vehicles is very important for the comprehensive transformation of energy in the transportation field. In order to reduce the impact of large-scale electric vehicle access on the grid [1], analyzing the charging behavior of electric vehicles can improve the reliability and economy of grid operation [2]. As the most basic supporting facilities for electric vehicles, charging facilities can be rationally planned to promote the formation of an electric vehicle ecosystem.

Table 6.2 – Gantt's schedule of actions for implementation of technology in the power industry equipment

Research and Project stages	Performers	Period of implementation of the project 2019 - 2020, month								
1	2	3								
		9	10	11	12	1	2	3	4	5
1. Development of introduction.	Z. Liu									
2. Search for references	Z. Liu									
3. Analysis of electric vehicle charging behavior	Z. Liu									
4. Planning and optimization of electric vehicle charging facilities	Z. Liu									
5.Experimentalize	Z. Liu									
6. Analysis of Experiment results	Z. Liu									
7. SWOT-analysis and Gant's schedule	A. Alabugin Z. Liu									
8. Prepare PPT	A. Alabugin R. Alabugina Z. Liu									
9. Finish final thesis	A. Alabugin R. Alabugina Z. Liu									
10. Registration of SUSU TW	R. Alabugina Z. Liu									

7 SUMMARY AND OUTLOOK

With the development of the electric vehicle industry and the acceleration of the construction of charging facilities, electric vehicles are connected to the power grid on a large scale, which may bring many potential risks to the power grid. The analysis of the charging behavior of electric vehicles and the optimization of charging facility planning can provide technical and theoretical support for actual analysis and planning, help improve charging services and guide charging behavior, and further promote electric vehicles. The foundation of charging and discharging scheduling can improve the economic benefits of charging facilities, accelerate the formation of an electric vehicle ecosystem, and maintain the safety and stability of the power grid. The main work completed is as follows:

1. Aiming at the adverse effect of randomly selecting the initial center point in the k-means algorithm on the clustering results, and in order to protect the privacy of data, an electric vehicle charging data clustering algorithm under differential privacy protection is proposed. The selection and detection of outliers improve the accuracy and usability of clustering results under the premise of safety.

2. For the problem that the random charging behavior of electric vehicles may affect the stability of the power grid, by analyzing the real charging data, it is understood that different users and cities have different charging behavior characteristics, and the data is preprocessed. Then, an electric vehicle charging behavior analysis model is designed, the cluster coefficient k is determined by the contour coefficient, the pre-processed charging data is clustered, and five user charging modes are obtained, and the charging characteristics of each type of user are analyzed. The k-means algorithm is also used to cluster on the same data, and the effectiveness of the algorithm is proved by the comparison results.

3. According to the planning needs of electric vehicle charging facilities, the composition factors of charging facilities' social costs are analyzed. A charging facility planning method based on improved k-means algorithm is proposed. Through the analysis experiment of the example, the optimal solution of charging facility planning is obtained, which proves the feasibility of the proposed method. Through experimental results, it is found that with the increase in the number of charging stations, the cost of the organization will increase, the cost of users will decrease, and the total social cost will decrease first and then increase.

4. Combined with the method proposed in this article, SWOT matrix analysis was carried out, which list the strengths, weaknesses, opportunities and threats. Moreover, according to the structure of this article, the Gantt timetable was established.

With the popularity of electric vehicles and the continuous expansion of the scale of charging facilities, the amount of data for analyzing charging behavior will become larger and larger, and the planning of charging facilities will have longer-term value. Subsequent research work can be carried out from the following aspects:

1) Analyze the influence of various factors such as season and temperature on the charging behavior of electric vehicles, and study the charging and discharging guidance and scheduling strategies of electric vehicles in conjunction with the charging behavior, which is of great significance for maintaining the safety and stability of the power grid.

2) In the study of charging facility planning in this paper, there is no planning related

to the capacity of charging stations. In the follow-up work, you can study the related fixed volume methods and establish a complete planning plan for charging facilities.

REFERENCES

1 Guo, J. The impact of electric vehicle charging on the power system and its countermeasures / J. Guo, F. Wen // Electric Power Automation Equipment. - 2015. - Vol. 35. - Issue 6. - P. 1-9 + 30.

2 Lin, L. Research on Clustering Analysis of New Energy Charging User Behavior Based on Spark / L. Lin, Y. Li and L. Ma // 2018 International Conference on Sensor Networks and Signal Processing (SNSP). - Xi'an, China, 2018. - P. 23-28.

3 Wang, Y. The Analysis of Electrical Vehicles Charging Behavior Based on Charging Big Data / Y. Wang et al. // 2019 IEEE 4th International Conference on Cloud Computing and Big Data Analysis (ICCCBDA). - Chengdu, China, 2019. - P. 63-67.

4 Mcsherry, F. Privacy Integrated Queries: An Extensible Platform for Privacy-Preserving Data Analysis / F. Mcsherry // Communications of the ACM. - 2010, - Vol. 53. - Issue 9. - P. 89-97.

5 Yu, H. Analysis of influencing factors of charging behavior of electric vehicles based on travel chain / H. Yu, L. Zhang, Y. Ren // Journal of Beijing University of Aeronautics and Astronautics. - 2019. - Vol. 45. - Issue 9. - P. 1732-1740.

6 Yu, H. Medium and long-term deduction model of electric private car charging load / H. Yu, Y. Zhang, A. Pan // Electric Power System Automation. - 2019. - Vol. 43. - Issue 21. - P. 80-93.

7 Pan, Y. Analysis of charging behavior of electric vehicles based on Markov decision process / Y. Pan, X. Qiu, J. Wu, J. Xiao // Electric Power Construction. - 2018. - Vol. 39. - Issue 7. - P. 129-137.

8 Huang, Y. Group scheduling strategy of electric vehicles considering user satisfaction / Y. Huang, C. Guo, L. Wang, Y. Bao, S. Dai, Q. Ding // Power System Automation. - 2015. - Vol. 39. - Issue 17. - P. 183-191.

9 Lee, J. Analysis of Data Streams in a City-Wide Electric Vehicle Charger Monitoring System / J. Lee, GL. Park, Y. Kang et al. // Proceedings of the 3rd International Conference on Communication and Information Processing. - Tokyo: ACM. 2017. - P. 28-31.

10 Quirós-Tortós, J. A statistical analysis of EV charging behavior in the UK / J. Quirós-Tortós, LF. Ochoa and B. Lees // 2015 IEEE PES Innovative Smart Grid Technologies Latin America (ISGT LATAM). - Montevideo, 2015. - P. 445-449.

11 Li, X. A data-driven two-level clustering model for driving pattern analysis of electric vehicles and a case study/ X. Li, Q. Zhang, Z. Peng et al. // Journal of Cleaner Production. - 2019. - Vol. 206. - P. 827-837.

12 Crozier, C. Clustering of Usage Profiles for Electric Vehicle Behaviour Analysis / C. Crozier, D. Apostolopoulou and M. McCulloch // 2018 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe). - Sarajevo, 2018. - P. 1-6.

13 Xiong, Y. Electric Vehicle Driver Clustering using Statistical Model and Machine Learning / Y. Xiong, B. Wang, C. Chu and R. Gadh // 2018 IEEE Power & Energy Society General Meeting (PESGM). - Portland, OR, 2018. - P. 1-5.

14 Zhou, S. Planning of charging facilities based on differences in urban characteris-

tics / S. Zhou, J. Yang, B. Gu, L. Zhu, W. Tan, H. Long // Journal of Southwest University (Natural Science Edition). - 2019. - Vol. 41. - Issue 10. - P. 133-141.
15 Yang, L. Location model of charging and power exchange facilities based on electric logistics vehicles / L. Yang, C. Hao, R. Tang // System Engineering Theory and Practice. - 2019. - Vol. 39. - Issue 7. - P. 1781-1795.
16 Genikomsakis, KN. Simulation and Design of Fast Charging Infrastructure for a University-Based e-Carsharing System / KN. Genikomsakis, I. Angulo Gutierrez, D. Thomas and CS. Ioakimidis // in IEEE Transactions on Intelligent Transportation Systems. - 2018. - Vol. 19. No. 9. P. 2923-2932.
17 Ge, S. Charging station planning considering the random probabilistic behavior characteristics of electric taxis / S. Ge, R. Li, J. Han, H. Liu, T. Li, H. Lian // Automation of Electric Power Systems. - 2016. - Vol. 40. - Issue 4. - P. 50-58.
18 Zhang, C. Configuration of electric vehicle charging facilities and two-stage optimal charging scheduling based on data mining / C. Zhang, J. Liu, Y. Xiang, Y. Liu, Y. Li, D. Liu // Chinese Journal of Electrical Engineering. - 2018. - Vol. 38. - Issue 4. - P. 1054- 1064 + 1282.
19 Liu, Z. Orderly charging strategy for electric vehicles based on user driving behavior / Z. Liu // Beijing Jiaotong University, - 2017.
20 Gao, D. Electric vehicle travel behavior analysis and charging facility layout research / D. Gao // Beijing Jiaotong University, - 2018.
21 Technical Standards for Electric Vehicle Electric Power Guarantee and Supply: Charging Stations. Beijing Standardization Guiding Technical Document, - 2010.
22 Pang, J. Research on the location layout of fast charging stations considering the duration of charging / J. Pang // Dalian University of Technology, - 2016.
23 Smart, J. Battery electric vehicle driving and charging behavior observed early in the EV project / J. Smart, S. Schey // SAE International Journal of Alternative Powertrains. - 2012. - Vol. 1. - Issue 1. - P. 27-33.
24 Zhang, L. Resident load harmonic assessment and prediction with electric vehicles / L. Zhang // Shandong University, - 2019.
25 Dwork, C. Differential Privacy / C. Dwork // International Colloquium on Automata, Languages, and Programming. Springer, - Berlin, Heidelberg, - 2006.
26 Dwork, C. A firm foundation for private data analysis / C. Dwork // Communications of the ACM. - 2011. - Vol. 54. - Issue 1. - P. 86-95.
27 Haeberlen, A. Differential privacy under fire / A. Haeberlen, B.C. Pierce and A.Narayan // Proceedings of the 20th USENIX Conference on Security. - San Francisco, USA, 2011. - 33 p.
28 Dwork, C. Calibrating noise to sensitivity in private data analysis / C. Dwork, F. Mcsherry, K. Nissim et al. // Proceedings of the Third Conference on Theory of Cryptography. - Berlin: Springer-Verlag, 2006. - P. 265-284.
29 Nissim, K. Smooth sensitivity and sampling in private data analysis / K. Nissim, S. Raskhondnikova and A. Smith // Proceedings of the Thirty-Ninth Annual ACM Symposium on Theory of Computing. - New York: ACM, 2007. - P. 75-84.
30 Krishna, K. Genetic K-means algorithm / K. Krishna and M. Narasimha Murty //

in IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics). -1999. Vol. 29, No. 3, - P. 433-439.

31 Lang, X. The Analysis of Traffic Drivers' Behavior based on Kmeans / X. Lang, Z. Zhao, G. Xiong // Proceedings of 2017 International Conference on Computer Science and Artificial Intelligence, - Jakarta: ACM, 2017. - P. 232-236.

32 Ding, D. Student Behavior Clustering Method Based on Campus Big Data / D. Ding, J. Li, H. Wang and Z. Liang // 2017 13th International Conference on Computational Intelligence and Security (CIS), - Hong Kong, 2017. - P. 500-503.

33 Blum, A. A learning theory approach to noninteractive database privacy / A. Blum, K. Ligett, A. Roth // Journal of the ACM. - 2013. - Vol. 60. - Issue 2. - 12 p.

34 Li, Y. Research on differential privacy protection k-means clustering method / Y. Li, Z. Hao, W. Wen, G. Xie // Computer Science. - 2013. - Vol. 40. - Issue 3. - P. 287-290.

35 Clifton, C. On syntactic anonymity and differential privacy / C. Clifton and T. Tassa // 2013 IEEE 29th International Conference on Data Engineering Workshops (ICDEW), - Brisbane, QLD, 2013. - P. 88-93.

36 Lv, Z. An Optimizing and Differentially Private Clustering Algorithm for Mixed Data in SDN-Based Smart Grid / Z. Lv et al. // in IEEE Access. - 2019. - Vol. 7. - P. 45773-45782.

37 Wang, B. Clustering analysis of electricity consumption data for massive users under differential privacy protection / B. Wang, H. Hu, S. Zhang // Automation of Electric Power Systems, - 2018. - Vol. 42. - Issue 2. - P. 121-127.

38 Xiong, J. Enhancing Privacy and Availability for Data Clustering in Intelligent Electrical Service of IoT / J. Xiong et al. // in IEEE Internet of Things Journal. - 2019. - Vol. 6. No. 2. - P. 1530-1540.

39 Kang, H. Overview of the application of differential privacy protection in data mining / H. Kang, Y. Ma // Journal of Shandong University (Science Edition), - 2017. Vol. 52. Issue. 3. - P. 16-23 + 31.

40 Blum, A. Practical privacy: The SuLQ framework / A. Blum, C. Dwork, F. McSherry et al // Proceedings of the twenty-fourth ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems (PODS ' 05), - New York: ACM, 2005. - P. 128–138.

41 Huang, J. Research on electric vehicle charging station planning and charging guidance strategy / J. Huang // Southwest Jiaotong University, - 2018.

42 Liu, W. Demonstration method of urban pure electric vehicle development model / W. Liu, L. Zhang, Z. Liu, J. He // Electric Power System Automation, - 2014. Vol. 38. Issue. 24. - P. 34-40.

43 Liu, Y. Research on the Synergistic Complementarity of Electric Vehicle Charging and Discharging Strategies and Renewable Energy in Microgrid/ Y. Liu // Shandong University, - 2019.

44 Yue, L. Research on Charging Strategy of Electric Vehicles and Charging Station Planning Based on Time and Space Characteristics / L. Yue // University of Science and Technology of China, - 2019.