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Research on Resource Allocation Optimization of Smart City Based on Big Data

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ABSTRACT The resource allocation of charging stations is an important part of promoting the development of renewable energy in modern cities. It can promote the scientific and modern construction of urban resource allocation and promote the intelligent transformation of cities. In view of the existing problems in the resource allocation process of urban charging stations, such as a single planning method, considering the actual travel demand. Based on the smart city transportation network information, this article will consider the impact of charging station construction costs, user driving and waiting costs on the location of charging stations, construct a charging station configuration optimization model, and introduce charging convenience coefficients to modify the model. Secondly, this paper establishes a systematic clustering model based on principal component analysis, selecting factors such as per capita GDP, population, and civilian car ownership as indicators, clustering analysis of different regions and assigning different charging convenience coefficients. Finally, the shortest distance matrix between any two nodes is calculated by the Voronoi diagram to concentrate the regional charging load to the traffic node, and the Floyd algorithm is used to analyze and evaluate the effect of the established charging station configuration optimization model. This technology provides a basis for promoting the modernization of urban green transportation.

INDEX TERMS Smart city, charging station, configuration optimization, big data.

I. INTRODUCTION

With the increasing demand of social development and scientific and technological progress, the fossil energy crisis and environmental pollution are becoming worse and worse. While the traditional fuel vehicles consume a lot of fossil energy, they also produce serious vehicle exhaust pollution [1], [2]. Therefore, many countries are vigorously developing new energy vehicles, among which the development of electric vehicles is the most concerned. As the basis of the promotion of electric vehicles, the construction of charging stations is very important. There are problems in the layout of existing charging stations, such as single configuration method, mismatch with the actual travel demand of the city and so on [3], [4]. How to choose the right location of charging station and how to configure the reasonable number of charging piles are the hot issues concerned by the current society and many scholars. The in-depth development of high-tech technologies such as smart cities and the Internet of Things provides information research ideas for the construction of smart city charging station resource allocation optimization technology based on big data [5].

At present, some scholars have studied and discussed the optimization of charging station resource allocation. McPherson *et al.* Compared the applicability of different location models in the location of charging stations, and selected FRLM as the location model, and studied how to select the optimal geographical location to build battery

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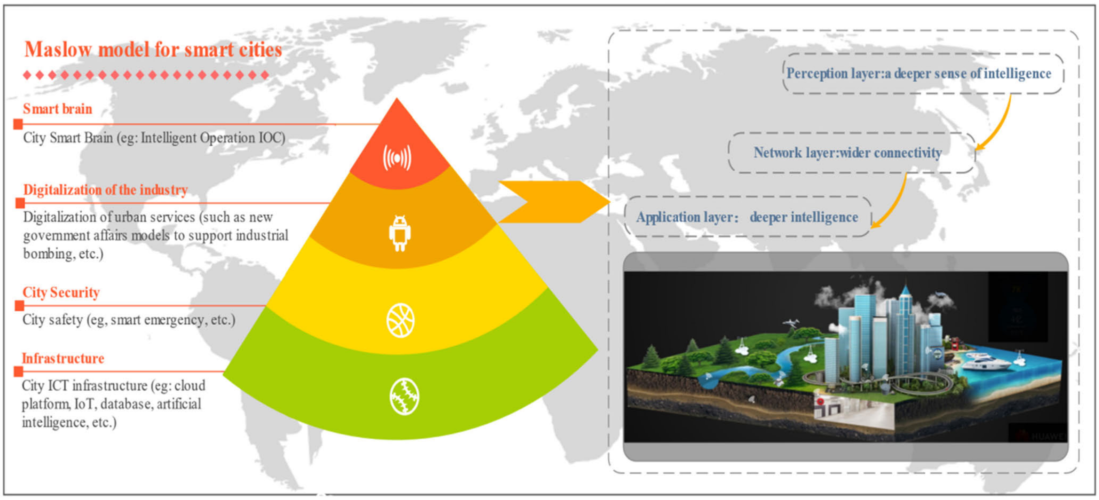

FIGURE 1. Smart city technology integration map.

switching stations in Australia [6]. Frade *et al*. Proposed a location model to maximize demand coverage within a given distance, and solved the model with Lisbon as an example [7]. Mak *et al*. Studied the location problem of electric vehicle switching station by establishing two kinds of robust optimization models with the lowest cost and the highest service level, and then solved it with CPLEX software [8]. Andrew *et al*. Considered that under the limitation of charging station capacity and charging time, aiming at the minimum driving distance between electric vehicle and charging station, established a MIP location optimization model [9]. Chung *et al*. Take Korean expressway as an example, based on the FRLM model, proposed a multi-stage charging station location model. Zhang Guoliang and others proposed a multi-level charging station location model to minimize the user's charging cost and the initial construction cost of the charging station, and improved the taboo search algorithm to solve the model [10]. Li Ruqi *et al*. Established the optimal model of charging facility cost aiming at the minimum cost in charging facility service system by using queuing theory [11].

By analyzing the research of domestic and foreign scholars on the planning of charging stations, we find that the current methods basically stay in the theoretical stage, not in the actual data or just based on the assumption of actual calculation examples, ignoring the application requirements of the planning of charging stations in reality [12], [13]. There is no research on the driving track data and POI data which reflect the travel behavior in practice, only based on the theoretical models such as point demand or closure model, without considering the practicability of the model in practice. Therefore, from the perspective of smart city, this paper proposes a big data-driven model based on the actual data, using the real urban traffic data to explore and solve the charging station planning problem and establish the corresponding optimization system, in order to inject new scientific power into the modernization of urban green traffic.

II. OVERVIEW OF SMART CITY TECHNOLOGY

Smart city technology can use the advantages of cloud computing technology and Internet of Things technology. This technology can effectively change the way the public and enterprises interact. These interactive methods can create a better life for people and enjoy the charm of smart cities happily [14].

The definition of ‘‘smart city’’ comes from the vision of ‘‘smart earth’’ [15]. ‘‘Smart Earth’’ actually refers to the full use of IT technology in various industries, to embed and equip sensors in hospitals, power grids, railways, bridges, tunnels, roads, buildings and other objects in every corner of the world. Various objects are connected to form the Internet of Things, and the Internet is being used to integrate the Internet of Things. Andrea Cargile and others believe that a smart city is an investment in social capital, human capital, and traditional and modern communication infrastructure, using participatory governance to achieve resource management and improve the quality of life of residents [16], [17]. As an important component of urban transportation and daily life, the resource allocation of charging stations needs to be analyzed based on real-time indicators such as urban transportation network information. Smart city technology can provide dynamic and real information about the urban transportation network and other related factors. Therefore, this article will rely on smart cities to explore a charging station configuration optimization model driven by urban transportation network big data.

III. DEMAND ANALYSIS OF INTELLIGENT CITY CHARGING STATION CONFIGURATION OPTIMIZATION SYSTEM

First of all, as the design concept of the smart city charging station configuration optimization system, relevant requirements and design analysis should be carried out first. Through analysis and demand collection and negotiation, a better experience and design effect can be provided for charging configuration optimization system design. The relevant

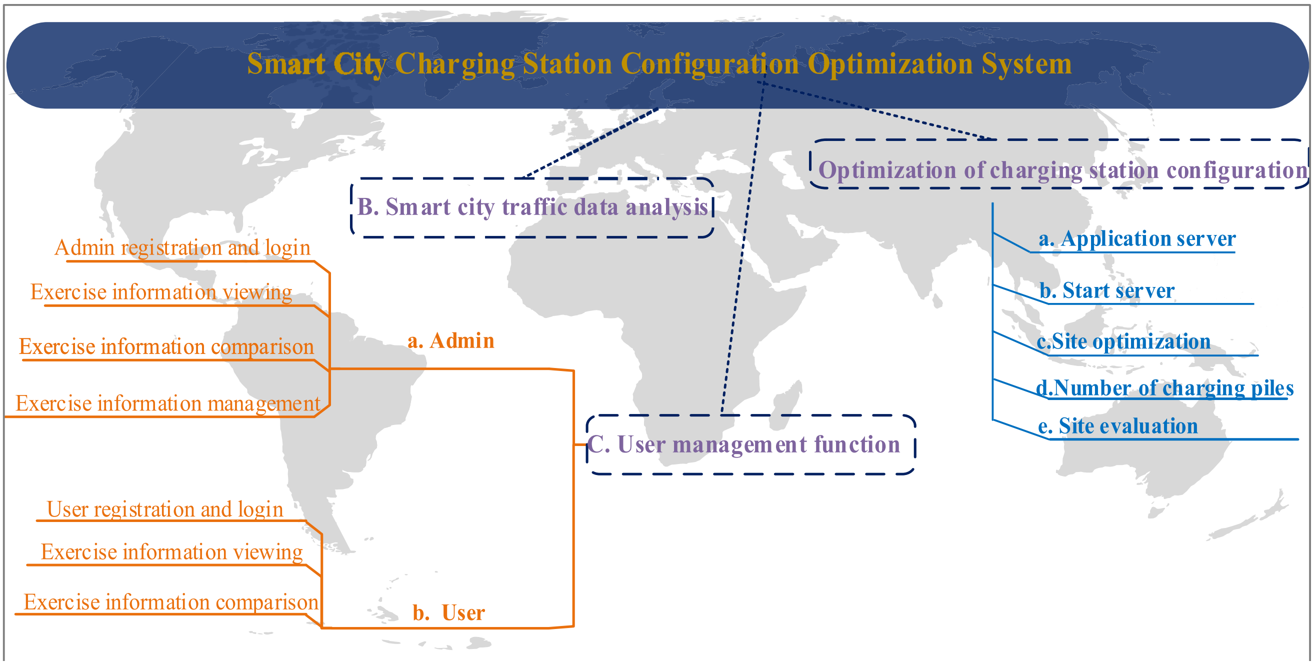

FIGURE 2. Demand analysis of smart city charging station configuration optimization system.

theoretical basis and design principles in the design process are embodied in other explanations in this section.

The ultimate goal of this system is to realize a resource optimization system integrating smart city traffic big data analysis and charging station resource allocation optimization. The system has many components, including several medium-sized computers and EMC storage, as well as related equipment, such as ATM optical fiber lines, DDN dedicated lines and trunk lines, which provide the equipment basis for the operation of the system [18].

IV. OPTIMIZATION METHOD OF CHARGING STATION CONFIGURATION IN SMART CITY

As an important part of urban traffic and daily life, the planning of charging station should focus on the practical application needs. In this paper, based on the traffic network information of smart city, considering the influence of the construction cost of charging station, the cost of user driving and queuing on the location of charging station, the optimization model of charging station configuration will be built, and the charging convenience coefficient will be introduced to modify the model. Secondly, this paper establishes a system clustering model based on the principal component analysis, and selects the factors such as per capita GDP, population and the ownership of civil vehicles as indicators to cluster different regions and give different charging convenience coefficients. Finally, the shortest distance matrix between any two nodes is calculated by Voronoi diagram, from charging load to traffic node and Floyd algorithm, and the effect of the optimization model is analyzed and evaluated.

A. CONVENIENCE FACTOR

The distribution of EV affects the construction cost of charging stations, the driving cost of car owners and the waiting cost of car owners in the charging stations. According to Voronoi diagram theory, the driving cost of car owners is significantly related to the number of electric vehicle charging stations. A large number of charging stations will reduce the driving cost, but at the same time increase the cost of building charging stations [19]. Therefore, it is necessary to comprehensively consider the driving cost and the construction cost of the charging station of the vehicle owner, so as to ensure that the vehicle owner can find the charging station for charging at any position in the city within a maximum distance of l, which is related to the driving mileage l of the electric vehicle and the charging convenience coefficient α. The relationship between them is as follows:

$$l = L \times \alpha \tag{1}$$

The value of α is determined by the principle of the minimum sum of the construction cost of charging station, the driving cost of car owners and the waiting cost of car owners queuing in charging station. The total cost is expressed as follows:

$$C_{all} = C_c(\alpha) + C_d(\alpha) + C_w(\alpha) \tag{2}$$

Among them, $C_c(\alpha)$ is the construction cost of the charging station;$C_d(\alpha)$ is the power consumption cost and time-consuming cost of the electric vehicle on the way to the charging station; $C_w(\alpha)$ is the waiting cost of the electric vehicle during the charging process of the charging station.

The construction cost of charging station includes fixed investment and operation cost. The fixed investment is mainly the cost of land occupation and equipment investment such as charger [20]. The operation cost mainly includes staff salary, equipment maintenance and overhaul, etc. The total cost of the charging station is converted to the following per day:

$$C_c(\alpha) = \frac{1}{365}\sum_{i=1}^{h}\left[f_1(Q_i)\frac{r_0(1+r_0)^m}{(1+r_0)^m-1}+f_2(Q_i)\right] \tag{3}$$

$$Q_i = f(\alpha) \tag{4}$$

Among them, $f_1(Q_i)$ is the fixed investment related to the *i-th* charging station and its number of chargers Q_i; $f_2(Q_i)$ is the annual operating cost of the *i-th* charging station related to the number of chargers it is equipped with; m is the depreciation life of the charging station, Take 20α; r_0 as the discount rate, take 0.08; h as the total number of charging stations to be built. Equation (3) shows that the number of chargers in the charging station is a function of charging convenience coefficient α.

The fixed investment of the charging station is represented by the second-order multi model of the number of chargers in the station:

$$f_1(Q_i) = a_1 + a_2Q_i + a_3Q_i^2 \tag{5}$$

$$f_2(Q_i) = 0.5a_1 + 0.5a_2Q_i + 0.5a_3Q_i^2 \tag{6}$$

Among them, a_1 is the fixed constant investment in business buildings, a_2 is the related cost of charger purchase cost which is proportional to the number of chargers, a_3 is the related cost of transformer, cable, etc. which is proportional to the square of the number of chargers. The annual operation cost is taken as 50% of the fixed investment cost.

The driving cost of electric vehicle charging is related to the distance to the charging station and the time spent in this period.

$$C_d(\alpha) = \sum_{i=1}^{h}[\overline{d_i}(\alpha)k_1c + \beta\overline{d_i}(\alpha)/v] \times V_i(\alpha) \tag{7}$$

Among them, $\bar{d}_i(\alpha)$ is the average distance from the electric vehicle to the a-th charging station, which is related to the charging convenience coefficient; k_1 is the power consumption per 100 km of electric vehicle; c is the electric charge paid by the electric vehicle in charging station 1kw$\cdot$h; v is the average speed of the electric vehicle on the way to charging station. $V_i(\alpha)$ is the number of electric vehicles that need to be charged to the a-th charging station every day? For the owner of super charging, queuing charging at the charging station will generate queuing cost, which is related to the average waiting time.

$$C_w(\alpha) = \sum_{i=1}^{h} w_{qi} \times \gamma_i(\alpha) \times 24 \tag{8}$$

Among them, w_{qi} is the average waiting time of the i-th charging station for fast charging; $\gamma_i(\alpha)$ is the number of vehicles that go to the a-th charging station for fast charging every hour.

It is assumed that the time interval between electric vehicles arriving at the charging station is independent of each other and obeys the negative exponential distribution of parameter γ. It is assumed that the charging time of EV charging process is independent and distributed in the same way, obeying the negative exponential distribution of parameter μ [21]. It can be seen from the analysis that the process of electric vehicle charging at the charging station is a typical $M/M/S$ waiting queue model. When the system is stably distributed, the relationship between the average waiting time of car owners and the number of fast chargers in the charging station S is as follows.

$$W_q = \frac{\rho_s}{S!(1-\rho_s)}p_0\int_0^{\infty} td(-e^{-(1-\rho_s)S\mu t}) \tag{9}$$

$$\rho_s = \frac{\gamma}{S\mu}, p_0 = \left[\sum_{i=0}^{s-1}\frac{\rho^i}{i!} + \frac{\rho_s}{S!(1-\rho_s)}\right]^{-1} \tag{10}$$

Among them, is the arrival rate of electric vehicles, γ μ is the average service rate of the charging station, S is the number of fast chargers in the charging station, ρ is the service intensity, and ρ_s is the service intensity of the queuing model when the number of service desks is S.

The functional relationship between the construction cost of charging station, the driving cost of charging, the waiting cost of charging queue and the charging convenience coefficient α can be obtained by using the urban traffic network information data of smart city, as shown in Figure 3. It can be seen from the figure that the total cost of α is relatively low between 0.05-0.12, so the recommended value range of charging convenience coefficient α is [0.06, 0.10].

The value of charging convenience coefficient α is directly related to urban traffic and economic conditions. In the planning of charging station, the values of different cities α with similarity can be the same, which is conducive to the standardized construction of charging station and saves the design cost of charging station.

B. REGIONAL DIFFERENCE CLASSIFICATION BASED ON CLUSTER ANALYSIS

Hierarchical clustering, also known as system clustering, regards the final level as a hierarchical mapping model from data objects to data classes. The idea of this method is to construct the data object into a clustering tree, and the sum of squares of the deviation is widely used in the clustering hierarchical method. Principal component analysis is carried out on the original factors, which are integrated into a few representative factors from multiple factors. These factors can represent the vast majority of the original information and are not related to each other [22]. Because the value of α is not only related to the regional traffic level but also to the regional economic level, in the regional division, six evaluation indexes are selected to reflect the regional socio-economic and traffic development level, such as per capita GDP, population, civil vehicle ownership, passenger turnover, freight turnover and road area density.

By calculating the correlation coefficient matrix among the factors, it is determined that there is a significant correlation. Based on the principal component analysis, two public factors are selected as the principal component, among which population, car ownership, passenger turnover and road area

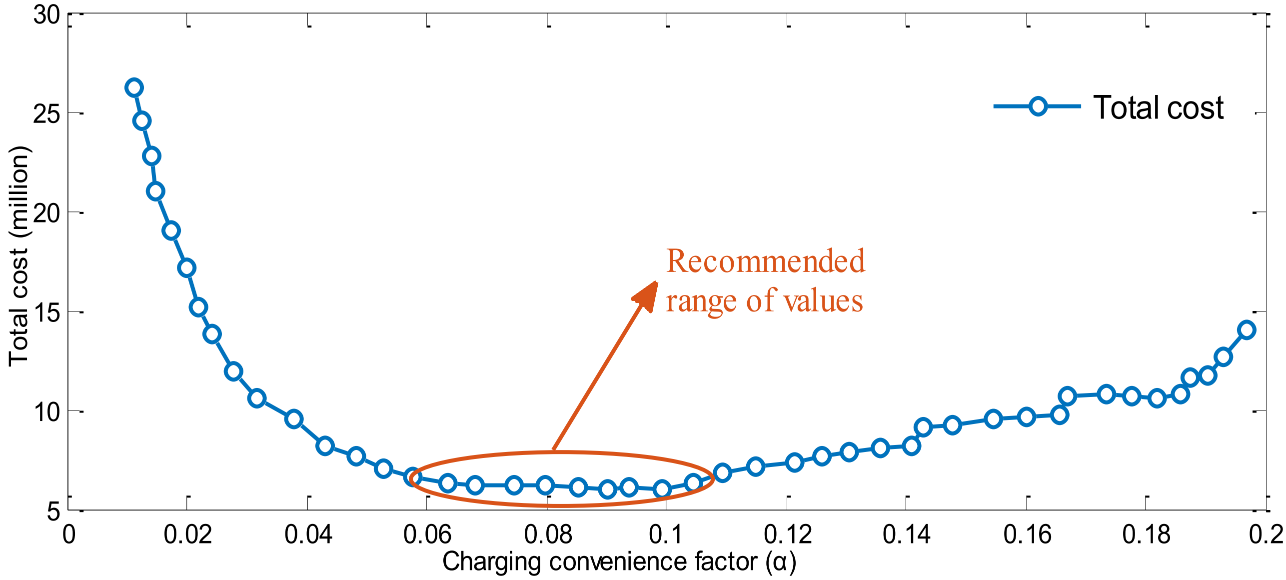

FIGURE 3. Total cost and charging convenience coefficient function diagram.

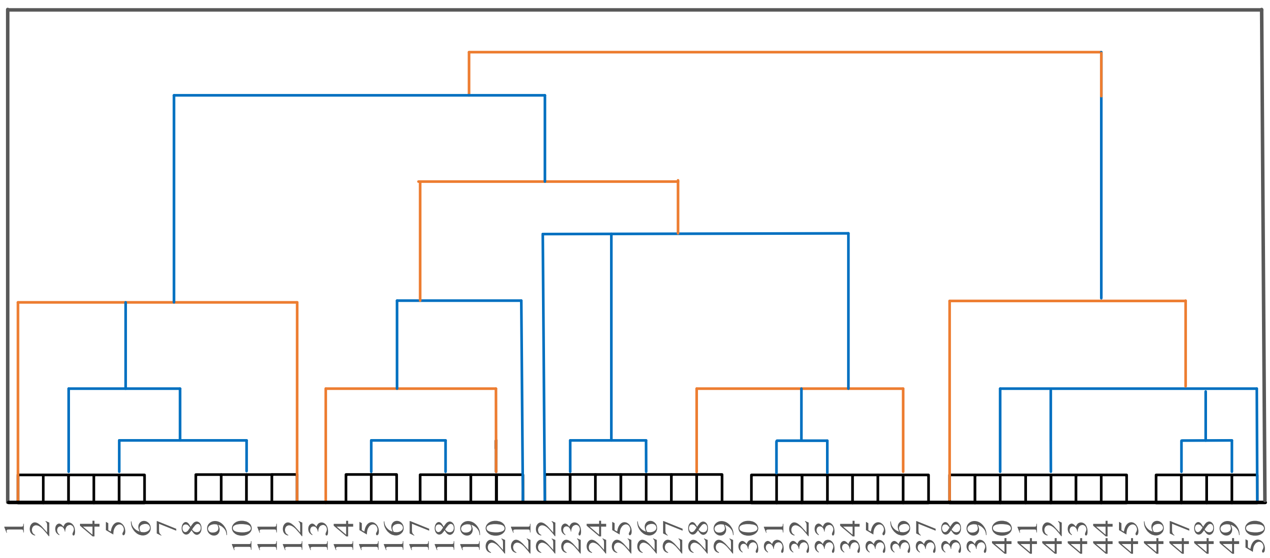

FIGURE 4. System tree diagram of cluster analysis in a certain place.

density have higher load on the first principal component, named as traffic index ZF_1, and per capita GDP has higher load on the second principal component, named as economic index ZF_2. Under the above principles, the correlation coefficient matrix of each factor, the variance interpretation table of each factor, the initial load matrix of each factor and other process results are calculated. The expressions of the two principal components are as follows:

$$\begin{aligned} ZF_1 &= 0.484ZX_1 + 0.477ZX_2 + 0.473ZX_3 \\ &\quad + 0.39ZX_4 + 0.374ZX_5 + 0.15ZX_6 \\ ZF_1 &= -0.166ZX_1 - 0.274ZX_2 + 0.116ZX_3 \\ &\quad + 0.298ZX_4 + 0.414ZX_5 + 0.789ZX_6 \end{aligned} \tag{11}$$

Among them, $ZX_1, ZX_2, ZX_3, ZX_4, ZX_5.ZX_6$ are the passenger turnover, population, civil vehicle ownership, freight turnover, road area density and per capita GDP after standardization; ZX_1, ZX_2 are the new comprehensive traffic and economic indicators.

Using ZF_1, ZF_2 as a new comprehensive index, hierarchical cluster analysis is carried out. Firstly, each region is regarded as a class, and the sum of its dispersion squares is calculated. Try to combine class C_i and class C_j into a new class C_h, and calculate the sum of the square deviation of the new class G_h. Define the square distance between Class C_i and class C_j as:

$$U_{ij}^2 = G_h - (G_i + G_j) \tag{12}$$

From the tree view, it can be seen that it is appropriate to divide the clustering results into three categories, as follows:

Category 1: developed areas of highway transportation economy, including 13 regions such as region 1, region 2

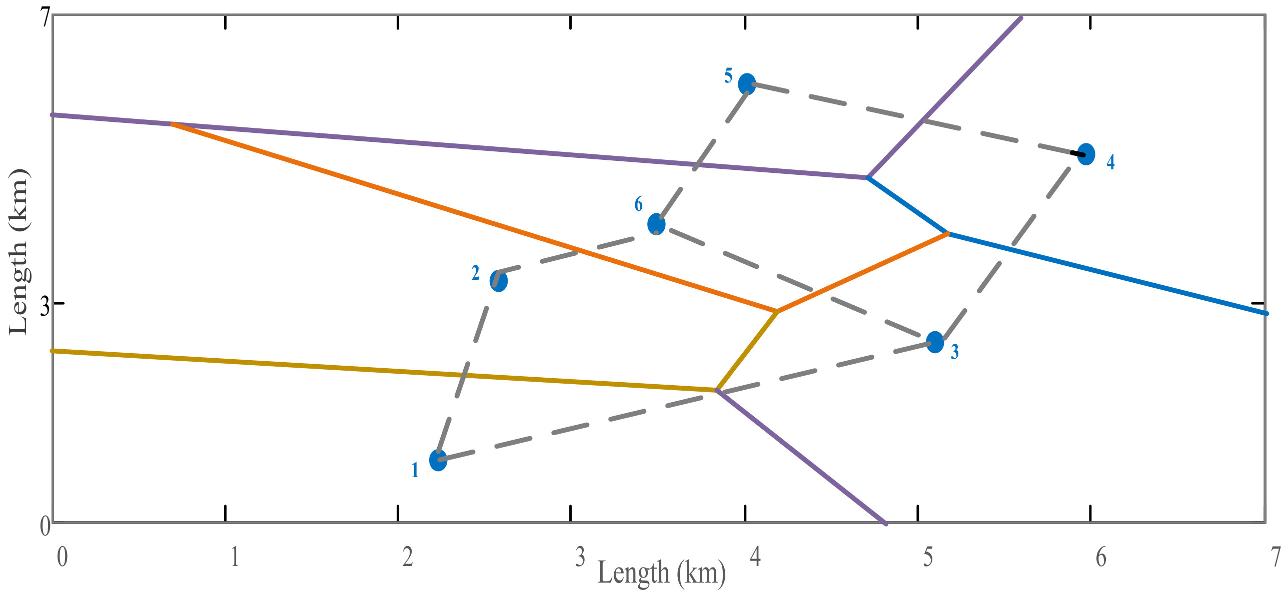

FIGURE 5. Schematic diagram of centralized processing of regional traffic load.

and region 4. These 13 regions have convenient transportation and developed economy, large demand for electric vehicle charging stations and high demand for charging convenience. The value of α should be smaller within the reference range.

Category 2: moderately developed areas of highway transportation economy, including 34 regions such as region 13, region 15 and region 18. These states have relatively convenient transportation, rapid economic development and good development potential, but their economic strength is slightly weaker than that of the first category of regions, so the value of α should be within the range of reference and suggestions.

Category 3: primary developed areas of highway transportation economy, including 14 regions such as region 24, region 31 and region 45. These states have weak local economy and underdeveloped highway transportation. In the design and planning of charging station, considering more economy, the value of α should be larger in the range of reference recommendations.

C. OPTIMIZATION MODEL OF CHARGING STATION LOCATION

According to the Voronoi diagram principle, all the electric vehicle loads in the city are concentrated at the intersection of the city road [23]. As shown in Figure 5, the load of area labeled 6 is treated as the load of point labeled 6. In this way, the driving distance of electric vehicle charging becomes the distance from the traffic intersection of the area to the candidate charging station.

According to the principle of set covering, the location of charging station needs to make the number of charging station construction as small as possible on the premise of satisfying the constraints. The constraint condition is: the distance from each traffic intersection to the nearest charging station $d \leq l$. In order to avoid waste of resources, the distance between the two charging stations should not be too close, so the distance between the two charging stations should meet the following requirements: Where, A is the distance between two adjacent charging stations; L is the driving range of electric vehicle.

$$\min(length(N)) \\ \begin{cases} \min(d_{ij}) \leq l & \forall i \in N, j \in M \\ \min(d_{it}) \leq L/2 & \forall i, t \in N \end{cases} \tag{13}$$

Among them, length (N) is to find the set length function; N is the construction node set of charging station; M is the load node set of non-charging station; L is the driving mileage of electric vehicle; d_{ij} is the distance between the construction node of any charging station and the construction node of non-charging station; d_{it} is the distance between the construction nodes of any two charging stations.

The shortest path is calculated by Floyd algorithm and the optimal location is calculated by charging station location selection algorithm, as shown in Figure 6.

D. OPTIMIZATION MODEL OF CHARGE PILE QUANTITY ALLOCATION

The above content explains the optimization technology of charging station location configuration based on intelligent traffic information network data. In this section, after the location of the charging station is selected, the area covered by the charging load nodes served by each charging station will be calculated according to the Voronoi diagram [24]–[26]. Assuming that the population of the city is evenly distributed, according to the population density of the city and the share of electric vehicles, the number of electric vehicles served by the charging station is calculated, and then the number of chargers configured for each charging

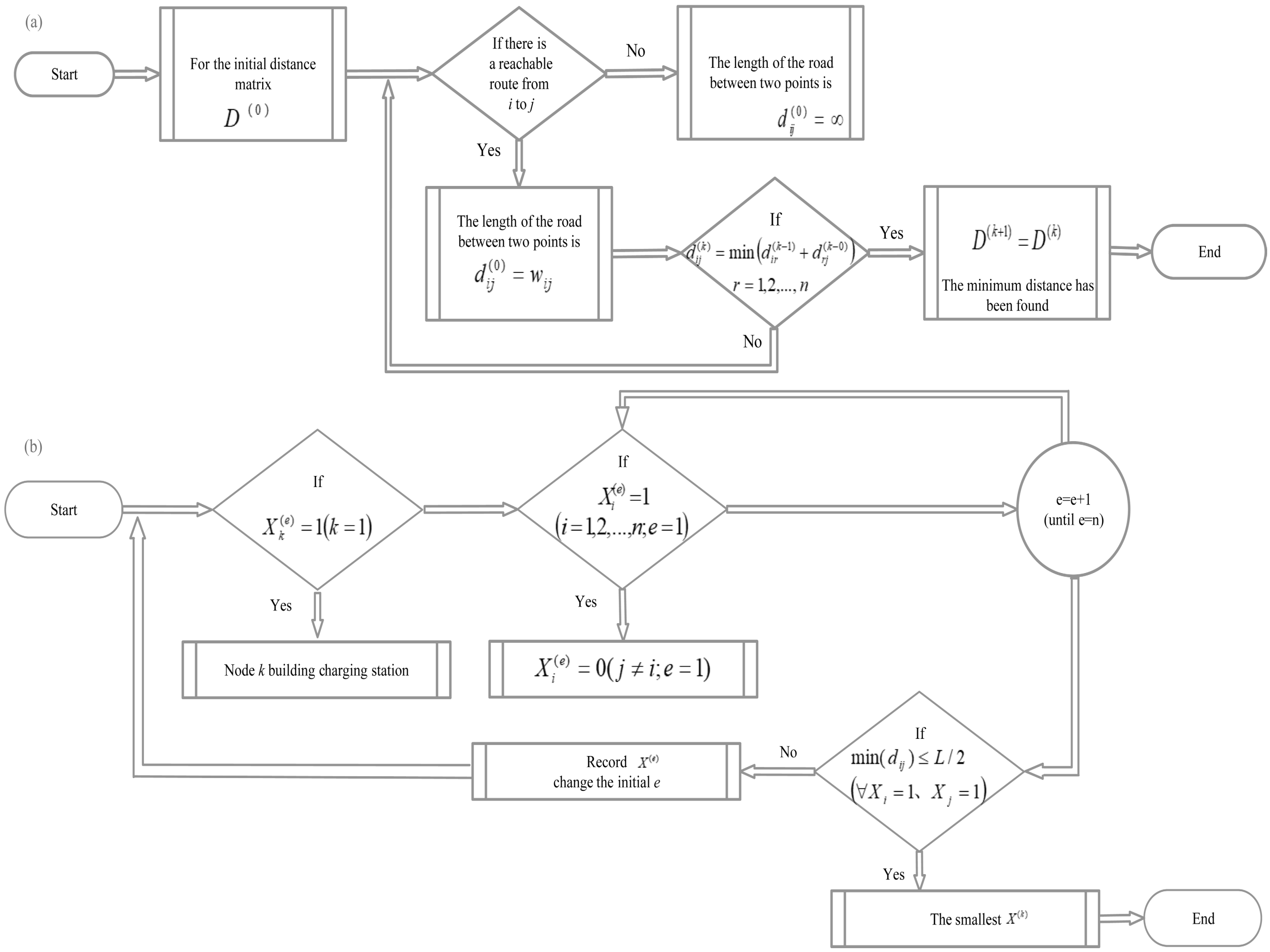

FIGURE 6. Algorithm flow chart (a) Floyd algorithm to calculate the shortest path (b) Charging station location selection algorithm.

station is calculated. Finally, the configuration capacity of the charging station is calculated according to the situation of the equipped chargers [27], [28]. The number of destination charging stations is allocated according to charging time, and the number of super charging stations is solved by queuing theory.

The number of charging stations at the destination shall be configured according to the following formula:

$$R_i = \frac{V_i n_{cha} w_i T}{t_0} \tag{14}$$

Among them, R_i is the number of destination charging piles configured for the i-th charging station; n_{cha} is the average charging times of each vehicle per day;. ω_i is the proportion of destination charging piles used from the day to the I charging station; T is the average charging time of the destination charging piles; t_0 is the daily working time of the destination charging piles [29], [30].

According to the theory of queuing theory, the number of super charging stations is optimized, the expectation of the queuing time of each super charging station is calculated, and the minimum number of charging piles is used to meet the requirement that the waiting time of car owners is not more than T_0.

The total input capacity of the charger in the charging station is:

$$S_{\sum} = K\left(\frac{p_1}{\eta_1 \cos\phi_1} + \frac{p_2}{\eta_2 \cos\phi_2} + \cdots + \frac{p_k}{\eta_k \cos\phi_k}\right) \tag{15}$$

Among them, $S_{\sum}$ is the total capacity of the charging station; p_k, η_k, $\cos\phi_k$ is the simultaneous coefficient of the charger; K is the power, charging efficiency and power factor of the K-th charger respectively.

V. SYSTEM APPLICATION ANALYSIS AND EVALUATION

Based on the traffic information network data of smart city, this paper establishes the optimization model of the location of charging station and the optimization model of the number of charging piles in the corresponding area. In order to discuss the effect of the model, the paper selects the taxi track data and POI data of some regions of Georgia and California to verify and analyze. According to the clustering analysis mentioned above, the two places are the areas with developed highway traffic economy. The charging convenience coefficient is $\alpha = 0.08$. First, the shortest distance matrix

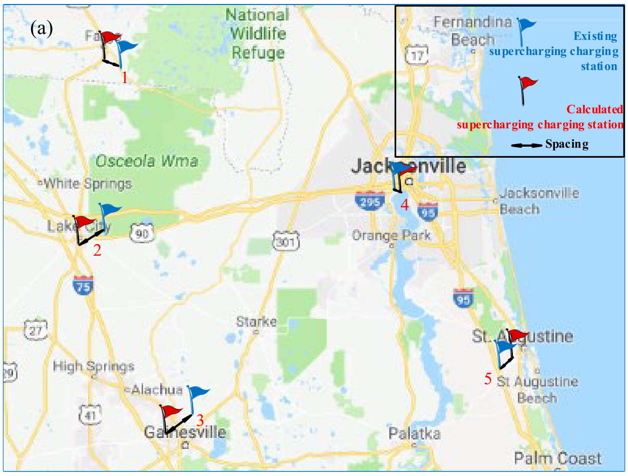

FIGURE 7. Distribution of supercharging stations in parts of Georgia.

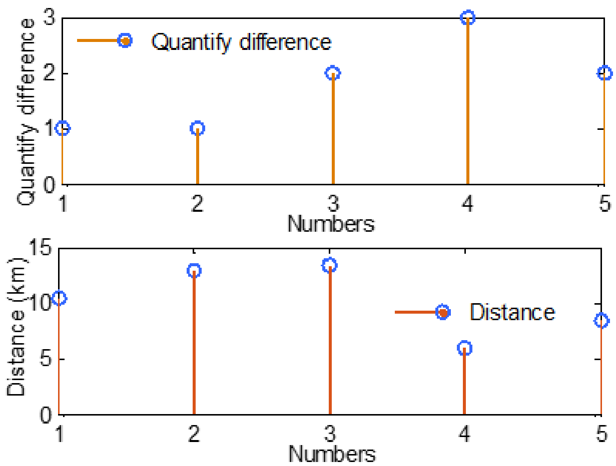

FIGURE 8. The distance between the location of Georgi's existing supercharging stations and the calculation results.

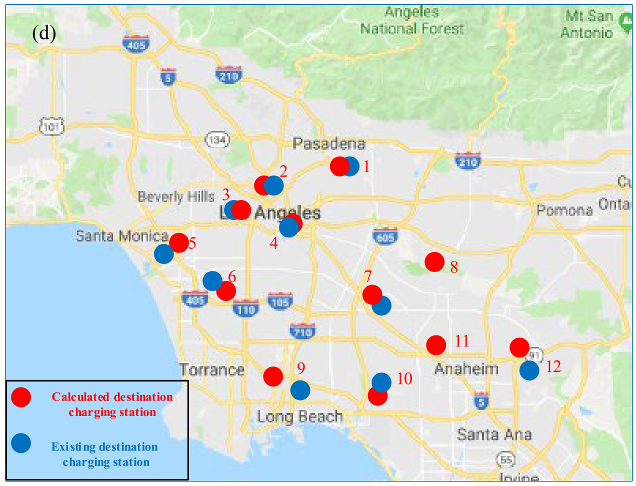

FIGURE 9. Distribution of destination charging stations in some areas of California.

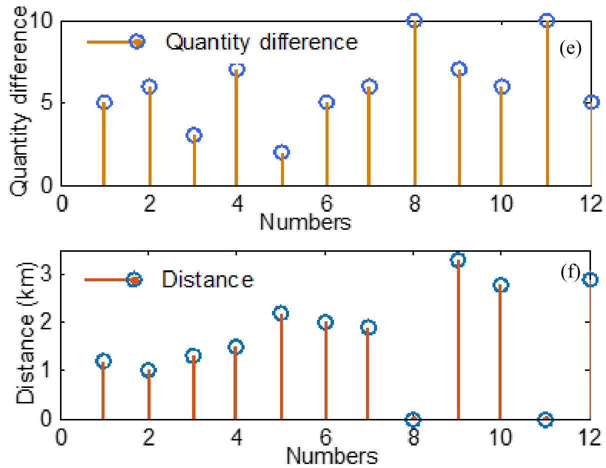

FIGURE 10. The distance between the location of the existing charging stations in California and the calculated results.

between any two intersections is calculated according to the Floyd algorithm, and then the optimal location is selected according to the charging station location algorithm. The calculated optimal location and existing location distribution of the destination charging and super charging stations are shown in Figure 7.

It can be seen from Figure.7, Figure.8 that the number of super charging stations calculated by the model is the same as the existing number, and the distance between the two is not more than 3km, which is mainly distributed along the expressway of adjacent cities and near hotels, restaurants and shopping centers, indicating that the number of charging stations in this area is reasonable. In addition, the number of charging piles in charging stations is calculated, and the results show that It is similar to the existing number, but lower than the calculation results, indicating that the number of charging piles in this area needs to be improved. From Figure.9, Figure.10, it can be seen that the number of charging stations and charging piles calculated by the model are similar to the existing number, but both are lower than the calculation results, indicating that the number of charging stations and charging piles in this area needs to be improved; the distance between the two is not more than 3km, mainly distributed near hotels, restaurants and shopping centers, indicating that the distribution in this area is reasonable. Through the case study of other states, it is found that the location and layout of charging stations in the current region are more reasonable, and the construction cost, user driving and waiting cost of charging stations are fully considered. However, compared with the number of existing electric vehicles, the number of charging stations still needs to be further improved. In order to reduce the use of fossil fuels and develop a green economic society, some countries have announced that they will ban the use of fuel vehicles in the future and promote the conversion to electric vehicles. The location and convenience of charging stations during the conversion process are very important for consumers to purchase cars and electric cars to become the mainstream. The country needs to consider the final distribution of charging stations and the key factors that affect the final ban or drastically reduce the use of fuel vehicles.

VI. CONCLUSION

Smart city charging station resource allocation optimization system can effectively promote the process of smart transformation of urban development. In this paper, the resource allocation technology of smart city charging station based on big data is studied. From the perspective of smart city, we propose a big data driven model based on the actual data, and use the real urban traffic data to explore and solve the charging station planning problem and establish the corresponding optimization system. Through the actual case test and performance test analysis, the implementation of the charging station resource allocation system is proved to be effective. In addition, considering the current energy development, this paper has achieved some research results. However, in view of the increasing and in-depth demand for charging station configuration in the future, there are still many aspects not considered in this paper, which is worth further study. We will continue to explore and improve the existing configuration optimization system to provide scientific reference for high-tech such as big data in the process of Urban Smart transformation.

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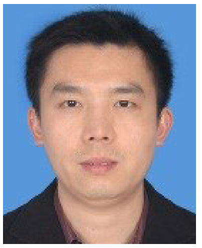

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