Energy Proceedings
Vol 39, 2024
ISSN 2004-2965

EV Charging Load Forecasting Based on Model Driven and Data Driven

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ABSTRACT

Based on the integration of dynamic traffic information, environmental temperature, real-time traffic flow, queuing theory, and other methods, a novel deep learning architecture for predicting Origin-Destination traffic flow in urban transportation systems has been developed to forecast the spatial and temporal distribution of electric vehicle charging loads.This method begins by analyzing the impact of various factors, such as urban traffic network data, daily patterns, and weather, on the driving patterns of electric vehicles. It employs a Graph Convolutional Recursive Neural Network algorithm to separately identify the starting and ending points of private cars and taxis.Next, it introduces impedance models for road segments and nodes, which take into account dynamic traffic information, intersection flow, and an air conditioning energy consumption model that considers environmental temperature and real-time vehicle speed. The method utilizes Graph Convolutional Network to extract spatial features of traffic nodes and their neighboring nodes. Time-related features are extracted using P-Prophet, creating a traffic intersection traffic flow prediction model.To optimize the minimum cost travel routes for electric vehicles, it improves the Floyd dynamic algorithm using a sparse graph optimization strategy, thereby simulating the driving behavior of electric vehicle users. Additionally, it uses K-means clustering to analyze potential charging preferences of electric vehicle users, providing insights into characteristic charging behaviors among typical urban electric vehicle users.

Keywords: Electric vehicle, Dynamic traffic information, Charging load, Neural network, Path planning

1. INTRODUCTION

In recent years, electric vehicles have emerged as a new solution for energy industry restructuring and the development of electrified transportation [1]. However, with the sharp increase in electric vehicle users, the random driving behavior of electric vehicle users and their collective charging behavior will inevitably affect both the power grid and the transportation network [2]. The interaction between electric vehicles and the transportation and power systems will pose new challenges and opportunities [3-4].

So far, from the perspective of method modeling, there are mainly two types of research on electric vehicle charging load prediction: model-driven and data-driven. 1) Model-driven means considering the traffic conditions and analyzing and mastering the essence of electric vehicle driving and charging modes from the perspective of energy and information interaction between electric vehicles, the power grid, and traffic. For example, in literature [5], an electric vehicle charging demand prediction model was proposed, considering road topology characteristics, but it did not account for the influence of environmental temperature and speed factors on electric vehicle energy consumption. In literature [6], an electric vehicle charging demand prediction model was proposed, which considered environmental temperature and vehicle speed. It used the origin-destination matrix method to obtain the start and end points of private car and taxi trips. but there are many factors that affect the OD distribution, which cannot be accommodated by non-road traffic volume factors, and it still has a long way to go before practical application. 2) Data-driven means using artificial intelligence algorithms such as regression analysis,

This is a paper for 15th International Conference on Applied Energy (ICAE2023), Dec. 3-7, 2023, Doha, Qatar.

neural network analysis, and deep learning to achieve short-term forecasting based on historical data or long-term forecasting based on trends. For example, in literature [7], different time scales of data are integrated as input features for stacked long short-term memory neural network models. This approach fully considers the interdependencies of data from different time scales, effectively enhancing the accuracy of medium and long-term system-level load predictions.In literature [8], convolutional neural networks are employed for feature fusion, combined with long short-term memory neural networks to perform short-term predictions for regional loads.

However, the model-driven electric vehicle charging load prediction method requires the assumption of a large number of model parameters to express complex charging behavior, while the data-driven prediction method requires support from a large amount of heterogeneous data from multiple sources for training and learning, and both have their own limitations [9].

To address these issues, this paper proposes a charging demand prediction model that combines the advantages of both model-driven and data-driven methods. While fully considering the topological characteristics of road traffic and environmental temperature factors, the model uses a bidirectional Graph Convolutional Networks algorithm to analyze the regularity of user travel time and space, and accurately construct an electric vehicle charging and discharging load prediction model.

2. MODELING ROAD NETWORKS AND POWER GRIDS BASED ON GRAPH THEORY METHODS

2.1 Modeling the Road Network

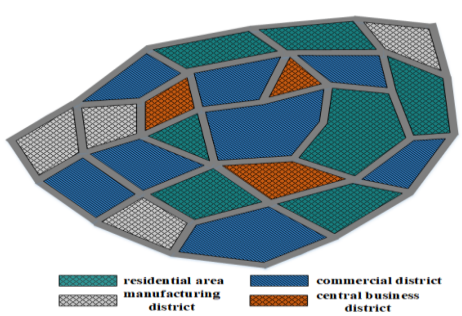

Fig. 1. Urban Traffic Network Schematic

The driving routes and times of vehicles are influenced by the road network and traffic conditions in the respective areas. Therefore, it is necessary to consider the impact of the road network and traffic information [10]. The established traffic road network model consists of 32 traffic nodes and 53 roads. It combines the distribution of residential areas, commercial areas, and industrial areas using the geographical grid modeling method based on traffic planning theory to model the corresponding urban road network structure, as shown in Figure 1, the schematic diagram of the urban traffic road network, and is expressed by Equation (1).

$$\begin{cases} G=\left(V(G),E(G),\Psi_G\right) \\ V(G)=\{v_i \mid i=1,2,\cdots,n\} \\ E(G)=\{\langle v_i,v_j\rangle \mid v_i,v_j\in V\} \\ \Psi_G=\{e_{ij} \mid \langle v_i,v_j\rangle\in E\} \end{cases} \tag{1}$$

Where, V(*G*) is the intersection node in the road network, that is, the set of road intersections, and *n* is the total number of nodes; E(*G*) is the set of road sections in the network, and e_{ij} is the length of the section; Ψ_G is the adjacency matrix of road weights, describing the connection relation of the length of each road section and nodes.

The corresponding topological structure of the road network is modeled using graph theory methods, as demonstrated by the model presented in Figure 2.

Modeling the Power Grid

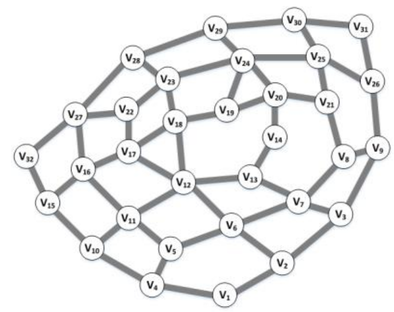

Fig. 2. Topological Structure Diagram of Traffic Network

2.2 Modeling the Power Grid

In this paper, the power grid is simplified into a network structure composed of nodes and edges, without considering switches, where nodes solely represent generators and loads. The topology of the power grid is depicted in Equation (2).

$$\begin{cases} G^d=\left(V^d(G),E^d(G),\psi_G^d\right) \\ V^d(G)=\{n_i \mid i=1,1,\cdots,n_G\} \\ E^d(G)=\{\langle n_i,n_j\rangle \mid n_i,n_j\in V^d\} \\ \psi_G^d=\{(ri,xi,ci,P_i^l) \mid \langle n_i,n_j\rangle\in E^d\} \\ B_G^d=\{(P_i^d,Q_i^d) \mid i=1,2,\cdots,n_G\} \\ F_G^d=\{f_i(t) \mid t=1,2,\cdots,T\} \end{cases} \tag{2}$$

Where, $V^d(G)$ is the node set of the power grid;nG indicates the number of network nodes. $E^d(G)$ is a collection of branches between network nodes; $\Psi_G{}^d$ is the resistance, reactance, susceptance and transmission power limit of the branch of the power grid. $B_G{}^d$ is the average active power and reactive power of each node in the power grid. F_G^d is the load variation coefficient of power network node;T is the total time of day; l_d indicates the number of branches.

2.3 The Distribution Network-Traffic Network-Vehicle Network Coupling Relationship

Urban power grids are typically constructed based on geographical location. Initially, the geographical area is divided into residential, working, and other zones (e.g., commercial areas) according to the functional zoning of urban planning, with roads from the road network serving as boundaries. Furthermore, as power grids are often divided into supply zones, the delineation of these zones is coordinated with urban planning, commonly following natural barriers such as roads and rivers. Therefore, in this paper, we assume that the nodes of the regional power grid are responsible for supplying their corresponding functional zones, as illustrated in the interaction model of the distribution network, traffic network, and vehicle network in Figure 3.

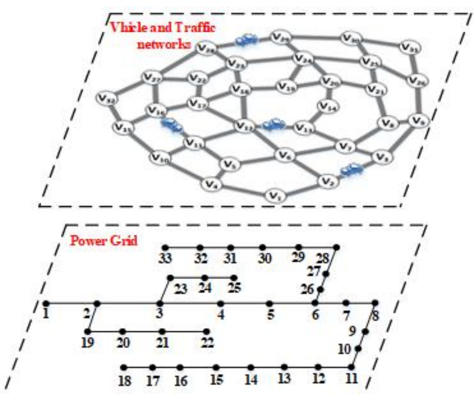

Fig. 3. Fusion Model of Distribution Network-Traffic Network-Vehicle Network

3. TRAFFIC NETWORK SIMULATION MODEL

3.1 Dynamic Traffic Road Network Modeling

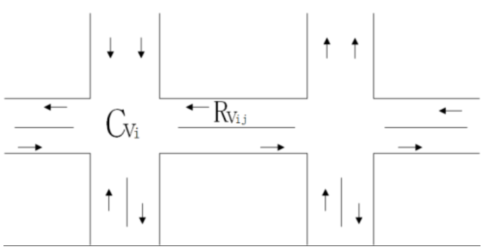

Fig. 4. Schematic Diagram of Urban Road Block

The research in this paper is focused on urban transportation networks. In urban transportation networks, the cost of electric vehicle travel (fuel consumption) is mainly affected by road length, road traffic flow, and traffic signal lights at intersections. Therefore, the time-flow model [11] is introduced to model dynamic transportation networks.

Therefore, urban road impedance can be represented as:

$$W_{ij}^k(t) = Cv_{ij}(t) + Rv_{ij}(t) \tag{3}$$

Where, $C_{vij}(t)$ is the node impedance model, and $R_{vij}(t)$ is the segment impedance model.

1) Segment impedance model

$$Rv_{ij}(t) = \begin{cases} R^1 v_{ij}(t): t_0\left(1 + a(S)^\beta\right), 0 < S \le 1.0 \\ R^2 v_{ij}(t): t_0\left(1 + a(2 - S)^\beta\right), 1.0 < S \le 2.0 \end{cases} \tag{4}$$

Where, Saturation S is the only variable, road traffic flow Q, road capacity C, zero-flow travel time t_0, impedance impact factors α and β are fixed parameters in road planning.

2) Node Impedance Model

$$Cv_i(t) = \begin{cases} C^1 v_i(t): \frac{9}{10}\left[\frac{c(1-\lambda)^2}{2(1-\lambda S)} + \frac{S^2}{2q(1-S)}\right], 0 < S \leqslant 0.6 \\ C^2 v_i(t): \frac{c(1-\lambda)^2}{2(1-\lambda S)} + \frac{1.5(S-0.6)}{1-S}, S > 2.0 \end{cases} \tag{5}$$

Where, c represents the signal cycle, λ represents the green ratio, and q represents the arrival rate of vehicles on the road segment.

3.2 Traffic Intersection Flow Prediction Based on Graph Convolutional Recursive Neural Network

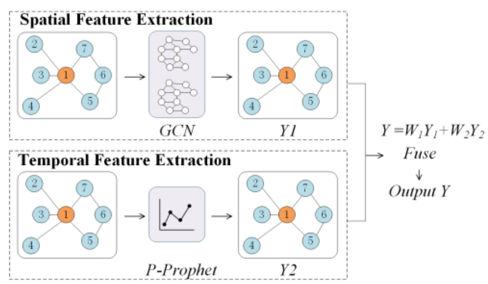

Fig. 5. Model Framework Diagram

The feature extraction of the intersection traffic prediction model proposed in this paper is divided into two parts: spatial feature extraction of intersection traffic and temporal feature extraction of intersection traffic. The model framework is depicted in Figure 5. GCN was employed to extract the spatial features of nodes and their adjacent nodes, while time features were extracted using P-Prophet to yield the prediction results Y1 and Y2, respectively. Y1 and Y2 were then combined with different weights to generate the final prediction results.The model takes into account not only temporal characteristics, such as the topological structure of the road network and traffic periodicity but also considers the influencing factors of traffic at intersections influenced by similar nodes in the temporal dimension. It identifies nodes with similarities corresponding to intersections that are not adjacent to each other in the road network. Figure 6 displays the flow prediction

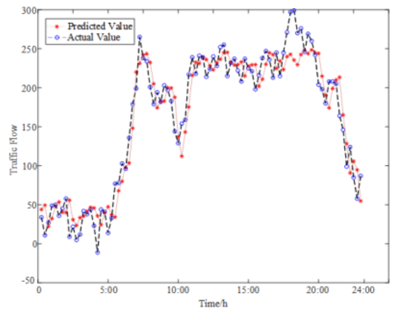

Fig. 6. Node 7 Traffic Flow Prediction Chart

results for traffic intersection 7.

3.3 Consider the Speed-Flow Model For Real-Time Traffic Flow Statistics In Road Networks

The driving speed of electric vehicles directly affects the energy consumption per unit mileage, and thus affects their charging demand [12]. Therefore, this paper constructs a practical speed-flow model based on real-time traffic flow statistics in road networks. The model can describe the vehicle speed $v_{ij}(t)$ when driving on road $R(i,j)$ at time t.

$$v_{ij(t)} = \frac{v_{ij\cdot m}}{1+\left(\frac{q_{ij}(t)}{C_{ij}}\right)^{\beta}} \tag{6}$$

$$\beta = a + b\cdot\left(\frac{q_{ij}(t)}{C_{ij}}\right)^{n} \tag{7}$$

where, $v_{ij.m}(t)$ represents the zero flow speed of the road, C_{ij} represents the maximum capacity, $q_{ij}(t)$ represents the traffic volume at time t, the saturation degree is the ratio of $q_{ij}(t)$ to C_{ij}, β is the empirical coefficient, and a, b, and n are the adaptive coefficients for different road grades.

3.4 Consider the Electric Energy Consumption Model of an Electric Vehicle with Respect to Environmental Temperature and Speed

The energy consumption per unit mileage of an electric vehicle is affected by many factors, including driving speed and environmental temperature. Changes in environmental temperature can result in additional energy consumption by the air conditioning equipment in the vehicle. In addition, a decrease in speed can increase the real-time energy consumption of an electric vehicle [13]. Therefore, a real-time energy consumption model for electric vehicles considering both environmental temperature and speed has been constructed.

$$F_{Tp} = K_{Tp} + E \tag{8}$$

$$K_{Tp} = \begin{cases} W_L \dfrac{S}{V_{ij}} & Tp > Tp_{\max} \\ W_R \dfrac{S}{V_{ij}} & Tp > Tp_{\min} \end{cases} \tag{9}$$

$$E = 0.21 - 0.01 v_{ij} + \frac{1.531}{v_{ij}} \tag{10}$$

Where, when the environmental temperature is T_p, the electric energy consumed by the air conditioning system in the vehicle when traveling S kilometers at a speed of V_{ij} is K_{Tp}. E is the real-time energy consumption per unit mileage at different speeds, and F_{Tp} is the energy consumption per unit mileage. T_{pmin} is the upper limit of the air conditioning heating temperature, and T_{pmax} is the lower limit of the air conditioning cooling temperature. W_L and W_R are the cooling and heating power of the air conditioning system.

4. MODELING OF ELECTRIC VEHICLE DRIVING AND CHARGING BEHAVIORS

Electric vehicles are typically categorized into three types: commuter private cars, taxis, and buses. Given that buses maintain a fixed departure frequency and their driving routes remain unaffected by driver subjectivity, with relatively constant charging times, this study primarily focuses on the two types: commuter private cars and taxis.

4.1 Electric Vehicle Origin-Destination Matrix Prediction based on Optimized Neural Network Algorithm

In order to obtain the flow pattern of electric vehicles, the online platform for electric vehicle charging demand load prediction needs to predict the number of cars from one area to another, which is formulated as an OD (Origin-Destination) matrix prediction problem. However, most studies assume that the origin is a residential area or derive the electric vehicle OD matrix from the OD matrix, but there are many factors that affect the OD distribution and non-road traffic volume factors cannot be accommodated, so there is still a long way to go before practical application. Therefore, this paper introduces a neural network model that can consider more factors that affect the OD distribution to predict the OD matrix of electric vehicles [14,15]. By considering multiple factors such as day type and weather, Figure 7 provides an illustrative representation of the traffic grid division in this paper and the results of the OD matrix prediction using Graph Convolutional Recursive Neural Networks.

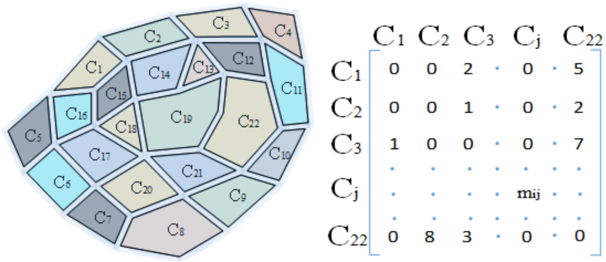

Fig. 7. Example of Grids and OD Matrix

As shown in Figure 8, the prediction scale is based on 15-minute intervals, with 96 points used for daily predictions. It represents a 24-hour electric vehicle prediction from origin C1 to destination C9.

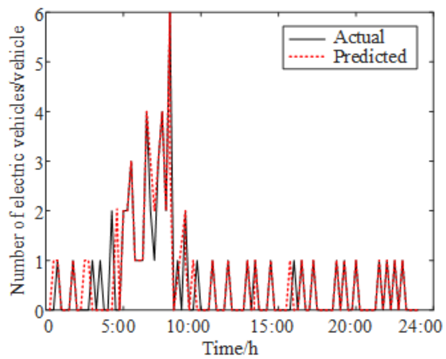

Fig. 8. GCN Prediction Results for C1 to C9

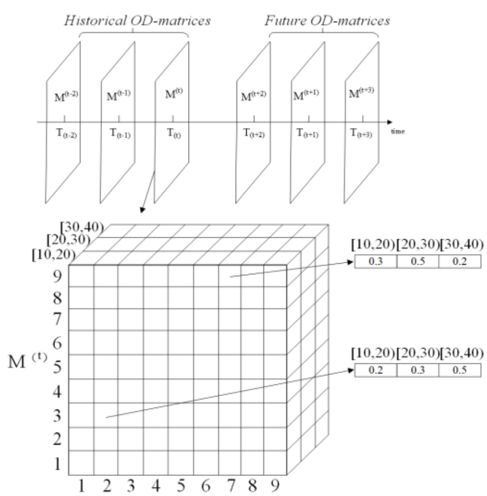

Fig. 9. Diagram of The Speed of an Electric Vehicle During a Given Time Interval

Figure 9 illustrates the electric vehicle travel speed matrix M(*t*) within a given time interval. It is represented as an $R^{9\times9\times3}$ tensor, consisting of 9 source regions, 9 destination regions, and 3 speed (*km/h*) ranges [10, 20), [20, 30), and [30, 40). The element (2, 3) in the matrix is a vector (0.2, 0.3, 0.5), indicating that the probabilities of vehicle travel speeds in the ranges 10-20 km/h, 20-30 km/h, and 30-40 km/h when traveling from region 2 to region 3 are 0.2, 0.3, and 0.5, respectively.

4.2 *Improved Floyd Algorithm for Shortest Path Search*

The driving behavior of private cars and taxis is influenced by factors such as segment length, driving speed, travel time, and fuel consumption [16]. In this paper, based on the travel cost of road segments, we improve the Floyd dynamic algorithm using a sparse graph optimization strategy to plan the driving paths for electric vehicles with the goal of minimizing travel costs. Firstly, without considering EV charging demand, we only verify the effectiveness of path search. We design experiments for path searching from the starting node 1 to the destination node 29 during the time period 07:00 to 08:00. We compare the results of the static Floyd algorithm with the real-time Floyd algorithm proposed in this paper, and the experimental results are shown in Table 1.

Table 1 Evaluation Indexes of Different Path Search Methods

Path Search Methods	Specific Paths	Driving Distance (km)	Search Time(s)	Travel Time (min)	Number of Intermediate Nodes
Static Floyd	1-2-6-7-13-14-20-24-29	14.3	0.73	29.96	9
Dynamic Floyd	1-2-3-9-8-21-25-30-29	15.4	2.53	25.55	9
Improved Floyd	1-2-3-7-13-14-20-19-24-29	16.5	2.09	24.64	10

From Table 1, it can be observed that the static Floyd algorithm plans the driving path based on road network information before departure. In contrast, the dynamic real-time Floyd algorithm uses real-time traffic information for planning. At each node, it searches and compares the real-time path impedances based on current traffic information to select the optimal next driving path. This allows for the rational avoidance of congested road segments based on the traffic flow in the road network. The sparse graph optimization-enhanced Floyd dynamic algorithm, when dealing with sparse graphs (where the number of edges is much smaller than the square of the number of nodes), reduces unnecessary computations, thus improving algorithm efficiency.

4.3 Clustering Analysis of Charging Behavior Latent Preferences

Using core indicators including initial battery charge level, mileage since the last charge, charging duration, and charging speed, a K-means clustering method was employed to perform an analysis and classification of electric vehicle users' latent charging behavior preferences. This allowed for the identification and characterization of typical charging preferences among urban electric vehicle users. The clustering results are presented in Table 2.

Tab. 2 Clustering Result

		Cluster Categories			
		1	2	3	4
Number of Clusters (%)		44.3	30.2	15.6	9.9
Cluster Centers	Initial State of Charge (SOC) (%)	23.2	44.3	49.5	23.3
	Previous Charging Distance (km)	125.2	67.4	49.7	100.5
	Charging Duration (min)	60.6	42.3	94.0	320.8
	Charging Current (A)	49.2	51.8	8.7	9.0

The analysis indicates that electric vehicle users' potential in-route charging preferences can be clustered into four modes: Low-Anxiety Fast Charging, High-Anxiety Fast Charging, Anytime Charging, and Destination Slow Charging. Using K-means, electric vehicle users' potential in-route charging preferences are clustered as follows: Low-Anxiety Fast Charging (44.3%): characterized by a lower initial state of charge (SOC), higher mileage since the last charge, a preference for fast charging, and shorter charging durations, demonstrating effective battery usage strategies; High-Anxiety Fast Charging Mode (30.2%): preferring fast charging with a higher initial SOC; High-Anxiety Anytime Charging Mode (15.6%): having a high and scattered initial SOC and a preference for slow charging; Destination Slow Charging Mode (9.9%). Characteristics of electric vehicle users' charging behavior groups are summarized in Table 3. In this study, two charging powers, fast and slow charging, are set. Based on the analysis of electric vehicle users' potential in-route charging preferences, fast and slow charging loads are allocated to electric vehicles. Slow charging power is set at 12kW, and fast charging power is set at 48kW.

Tab. 3 Summary of Cluster Characteristics of Charging Behavior

Cluster Number	Cluster Name	Initial State of Charge (SOC)	Previous Charging Distance	Charging Duration	Charging Speed
1	Low Anxiety Fast Charging Mode	Low	Long	Short	Fast
2	High Anxiety Fast Charging Mode	High	Short	Short	Fast
3	High Anxiety Anytime Charging Mode	Dispersed	Dispersed	Short	Slow
4	Destination Charging Mode	Low	Long	Dispersed	Slow

4.4 Charging Characteristics of Electric Vehicles

The state of charge (SOC) of an EV at the initial time follows a normal distribution[17]. The battery capacity of different types of electric vehicles follows a gamma distribution [18]. By combining the two, the initial electric quantity $C_0(i)$ can be obtained.

In this model, when the SOC is less than 0.2, it is considered that the electric vehicle needs to be charged and the user performs a charging operation. To prevent battery loss caused by overcharging, charging is set to end when the battery capacity reaches 0.9, and the electric quantity $C_t(i)$ and the charging duration T_c at time t are considered as:

$$C_t(i)=\eta\left(C_{t-1}(i)-\Delta l\cdot E_c\right) \tag{11}$$

$$T_c(\mathrm{i})=\frac{C_o(i)-C_t(i)}{\eta_c P_c} \tag{12}$$

In the formula: η is the energy consumption coefficient; E_c represents the power consumption per kilometer; $C_{t-1}(i)$ is the remaining electricity at time t-1; Δl is the distance traveled by the i-th vehicle from time t-1 to t; P_c is the charging power of the charging station, and c is the charging efficiency of the charging station.

This article sets two power levels, fast charging and slow charging, and allocates fast and slow charging loads for electric vehicles by analyzing charging users' uncertain behaviors such as daily mileage, departure/return time, etc.

If the process of vehicles arriving at each charging station follows a Poisson distribution [19], and the number of users charging at the charging station per unit time is used as the parameter , then the waiting time in the queue for users, W_q, is:

$$W_q=\frac{(c\rho)^c\rho}{c!(1-\rho)^2\lambda}P_0 \tag{13}$$

$$P_0=\left[\sum_{k=0}^{c-1}\frac{1}{k!}\left(\frac{\lambda}{\mu}\right)^k+\frac{1}{c!}\cdot\frac{1}{1-\rho}\cdot\left(\frac{\lambda}{\mu}\right)^c\right]^{-1} \tag{14}$$

$$\rho=\frac{\lambda}{c\mu} \tag{15}$$

$$L_s=\frac{(c\rho)^c\rho}{c!(1-\rho)^2}P_0+\frac{\lambda}{\mu} \tag{16}$$

In the formula: c represents the number of charging piles; μ represents the number of vehicles that can be charged per unit time by a charging pile; ρ represents the service intensity of the charging pile. L_s represents the queue length.

5. EXAMPLE ANALYSIS

Based on the simulation model of transportation network and the modeling of electric vehicle driving and charging behavior, predictions are made on the spatiotemporal distribution characteristics of electric vehicle charging demand. Figure 10 shows that the selected traffic plane is divided into different geographical grids as sub-areas according to residential areas, commercial areas, and industrial areas at a certain spatial scale.

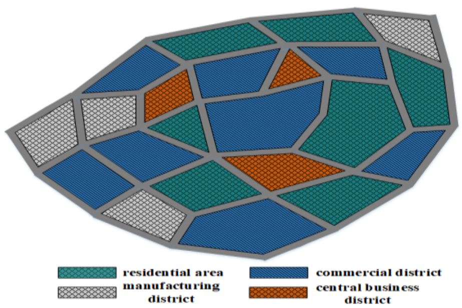

Fig. 10. Test Area Road Network Diagram

The simulation time is set to 24 hours per day, and the temporal and spatial distribution of charging demand for each node in the distribution network is shown in Figure 11.

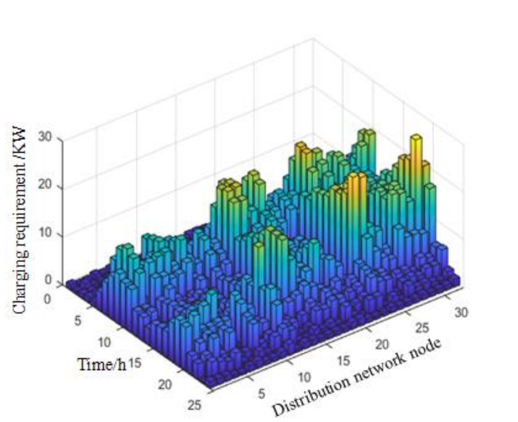

Fig. 11. Spatial and Temporal Distribution of Distribution Network Charging Demand

According to Figure 8, the overall temporal and spatial distribution characteristics of charging demand for the distribution network-transportation network-vehicle network integrated model show that user charging time is concentrated in the periods of 8:00-13:00 and 17:00-20:00, with a "double peak" distribution type that is consistent with the charging demand. Nodes 15, 16, 22, 23, 31, and other nodes have relatively high charging demand, with higher demand in residential areas than in commercial and industrial areas. The spatial distribution of charging demand is uneven, and nodes with higher charging demand are mainly concentrated near residential and commercial areas in the distribution network.

Based on the total EV charging demand in different time periods shown in Figure 12, the highest charging peak of the model is roughly distributed between 9:00-10:00.

Regarding this prediction model for the temporal and spatial distribution characteristics of charging demand, important information can be provided for developing power grid power scheduling strategies for different distribution network nodes by comparing and analyzing the charging demand of different nodes. Furthermore, analyzing the impact of charging load on the power grid is of great significance for the research on power system load scheduling or charging station presets.

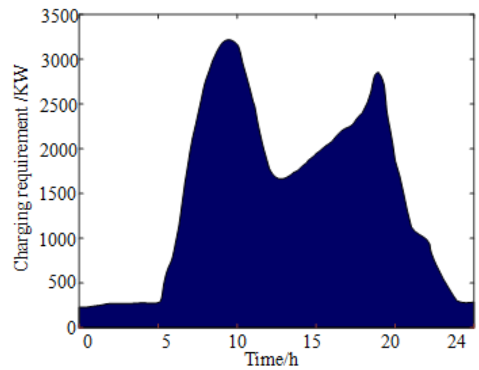

Fig. 12. 24h Electric Vehicle Charging Demand

In order to analyze the charging load characteristics of different functional areas more intuitively, Figures 13-16 provide the distribution of load demand for different vehicle types, namely commuter private cars and taxis.

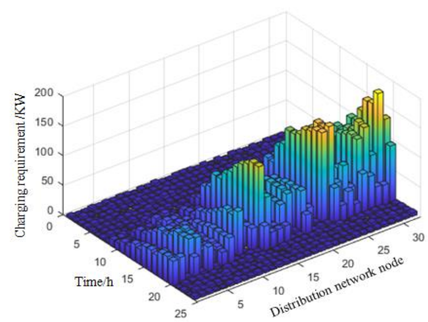

Fig. 13. Charging Demand of Commuting Private Cars at Transportation Nodes

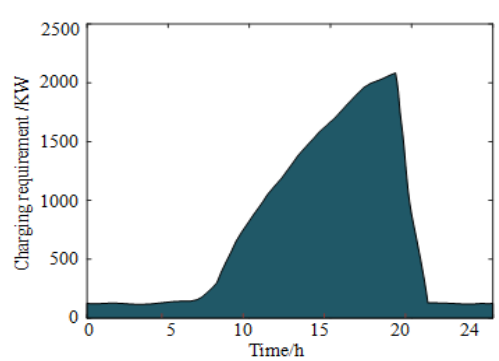

Fig. 14. Charging Demand of 24h Commuter Private Car

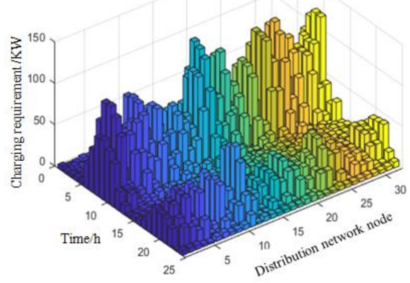

Fig. 15. Charging Demand of Taxi at Transportation Nodes

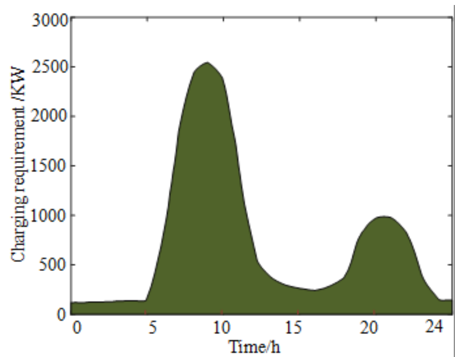

Fig. 16. Charging Demand of 24h Taxi

According to Figure 13 and 15, it can be seen that the peak period of charging load for commuter private cars has a wider span, mainly concentrated in the period from 15:00-19:30, with the highest peak period of charging demand from 18:00-19:00. The charging time distribution for taxis shows a "double peak" pattern similar to the basic residential electricity load, and the temporal and spatial distribution characteristics of charging load are consistent with the travel patterns of residents. Experimental results show that the predicted temporal and spatial distribution of charging load is consistent with the actual situation, verifying the effectiveness of the proposed load prediction method.

Finally, in response to the demand for the large-scale development of electric vehicles, Figures 17 and 18 provide the voltage changes of different transportation nodes during 24 hours and the voltage distribution of different nodes at a time section of 19:37 under different EV penetration rates. It can be seen from Figure 14 that the voltage of each node will be affected by the size of the electric vehicle charging load. Figure 15 shows that as the EV penetration rate increases, the node voltage drops with the increase of penetration rate. When the scale of electric vehicle charging further expands, the node voltage may drop below the safe voltage threshold with the increase of penetration rate.

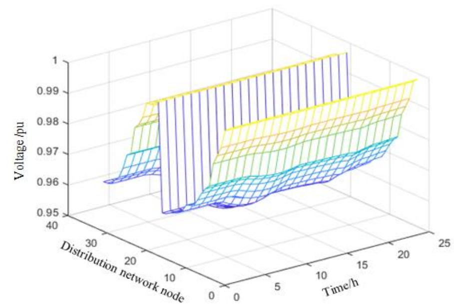

Fig. 17. Voltage of Traffic Node

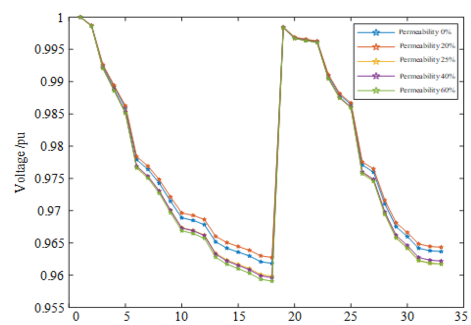

Fig. 18. Traffic Node Voltage Under Different Permeability

6. CONCLUSION

This article is based on neural networks and dynamic traffic information, fully considering the topological characteristics of road traffic to simulate driving behavior on actual roads. By analyzing the travel time and spatial relative laws of electric vehicle charging and discharging through data mining, an accurate charging and discharging load prediction model for electric vehicles is constructed. A fusion model-driven and data-driven electric vehicle charging load spatiotemporal prediction method is proposed. The following conclusions are obtained through case simulations:

1) The dynamic traffic model fully considers the topological characteristics of road traffic and environmental temperature, and introduces a speed-flow practical model for real-time traffic flow statistics of the road network to accurately simulate the characteristics of the city road network.

2) Spatial features of traffic nodes and adjacent nodes are extracted using GCN, while time features are obtained based on P-Prophet to establish a traffic intersection traffic flow prediction model.

3) By applying the Graph Convolutional Recursive Neural Network algorithm to analyze the relative patterns of user travel in both time and space, and using a Floyd dynamic algorithm improved with a sparse graph optimization strategy to plan electric vehicle driving routes with the objective of minimizing travel cost.

4) Utilizing the K-means clustering method for the analysis of potential charging preference behaviors among electric vehicle users, elucidating the characteristic charging preferences of typical urban electric vehicle users. The analysis of experimental results demonstrates that the spatiotemporal distribution predictions of charging demand align with real-world situations.

In future research, more factors that affect electric vehicle charging behavior can be integrated, considering more psychological factors that affect driving users' charging decisions, and building different scenarios to analyze the impact on charging load spatiotemporal distribution. Further analysis of experimental results can provide reference for evaluating the impact of electric vehicle charging load on the power grid, as well as research on electric vehicle charging control strategies, charging station expansion, and site selection.

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