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Charging Load Prediction of Expressway Electric Vehicles Considering Dynamic Battery State-of-Charge and User Decision

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ABSTRACT

Accurate prediction of electric vehicle (EV) charging load serves as a foundational step in the establishment of expressway charging infrastructure. This study introduces an approach aimed at enhancing the precision of expressway EV charging load predictions. The method incorporates considerations for both the battery dynamic state-of-charge (SOC) and users' charging decisions. To begin, the extraction of expressway network nodes was conducted using the open Gaode Map API, leading to the establishment of a model incorporating expressway network and traffic flow features. Subsequently, a Gaussian mixture model was employed to formulate a SOC distribution model for mixed traffic flow. An innovative SOC dynamic translation model was introduced to capture the dynamic characteristics inherent in traffic flow SOC values. Building upon this foundation, an EV charging decision model, which takes into account expressway node distinctions, was developed. The extraction of EV travel characteristics from the NHTS2017 datasets informed the construction of this model. Differentiated decision-making was achieved through the utilization of an improved Lognormal function and an improved Sigmoid function. In the final stage, the proposed method was applied to a case study involving the Lian-Huo Expressway. The analysis of EV charging power, converging with historical data, revealed that the method accurately predicts the charging load of EVs on expressways, and underscores the efficacy of the proposed approach in predicting EV charging dynamics in expressway scenarios.

KEYWORDS

Charging load prediction; electric vehicle; expressway; Gaussian mixed model; state-of-charge

1 Introduction

In light of China's steadfast commitment to the "dual carbon" strategy aimed at attaining carbon peak and neutrality, the EV industry within the country is experiencing an unprecedented surge in development opportunities. As of the conclusion of 2022, the EV number in China has soared to 10.45 million [1], leading to a substantial influx of high-capacity EV charging demands that are exerting discernible effects on the power supply infrastructure [2]. The expressway power supply system, characterized by its specific structure, is particularly susceptible to intermittent load disruptions, resulting in a compromised stability of the expressway power grid. Consequently, it becomes imperative to elucidate the spatiotemporal distribution of EVs, investigate the charging decision-making patterns of EV owners, and prognosticate the impending EV charging loads on expressways. These endeavours are prerequisites for fostering the secure functioning of the expressway power grid, which expedites the electrification of Chinese expressways and enhances the efficiency of societal electricity service [3].

Currently, research on EV charging load prediction predominantly centers on two aspects: precise characterization of the EV travel environment and the application of more accurate simulation sampling methods. Regarding the characterization of the EV travel environment, M. B. Arias et al. [4] established a model for the urban road network based on the Seoul Metropolitan Area in South Korea. They employed a Markov chain to derive the EV charging load for each city section. In [5], an urban transportation network, accounting for traffic congestion, was developed to predict EV charging loads. Additionally, [6] presented a multi-regional urban transportation network model which divided the city's traffic network into various regions. A hybrid method was proposed to predict the charging load of urban EVs.

In Italy, G. Napoli et al. [7] constructed a national expressway topology model. By integrating this model with the distribution network, they identified the optimal construction location for charging stations. In terms of simulation sampling methods, P. Zhang et al. [8] introduced the traditional Monte Carlo method to sample the EV charging load of mixed vehicle flow, yielding fundamental EV charging load values. Conversely, W. Yin et al. [9] enhanced the EV charging load calculation model by incorporating coupling characteristics using kernel density functions which enables quantitative prediction of the spatiotemporal distribution of EV charging loads.

In [10] and [11], a Markov chain model incorporating multiple random processes was formulated, starting from the perspective of user psychological decision-making, to predict the charging load of urban network EVs. To achieve more accurate predictions, deep learning methods have been employed to predict the ultra-short-term charging load of EVs [12]. This approach has demonstrated superior performance compared to traditional artificial neural networks which achieves an accuracy of 30%.

The preceding research overview highlights a prevailing emphasis on investigating the driving behaviour and charging decisions of EVs within urban transportation networks. Conversely, there is a noticeable scarcity of studies examining EV driving range and charging behaviour in the context of expressways. It is evident that accurately modelling the flow of EVs on expressways is essential for predicting the charging load of EVs in this specific environment. Consequently, this paper aims to contribute to the existing knowledge base by delving into research on EV driving energy consumption, EV charging decision-making, and expressway charging load prediction within the expressway framework. The detailed modelling process is delineated in Figure 1, illustrating the sequential steps involved in this comprehensive investigation.

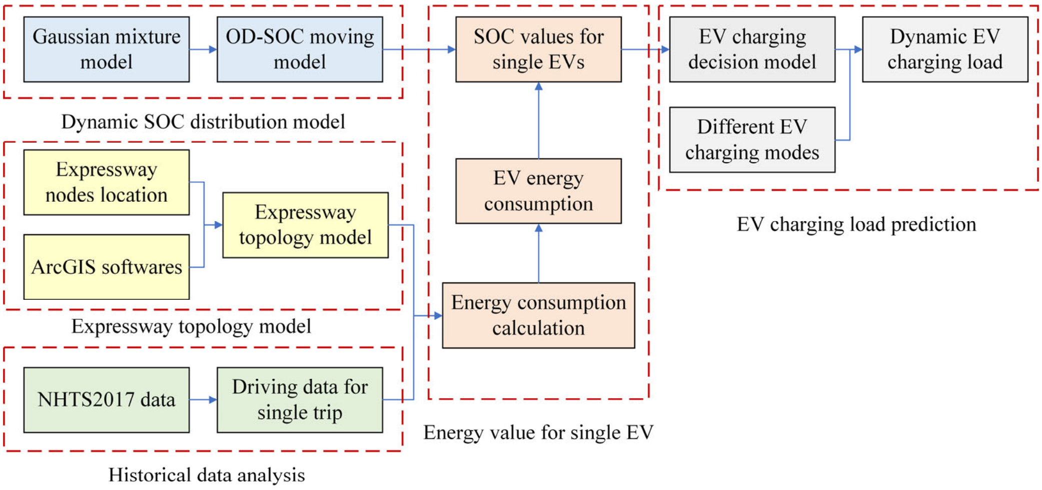

Fig. 1 Flowchart of expressway EV charging load predicting process.

This paper initiates its investigation by developing an origin-destination (OD) matrix model tailored for expressway traffic. Utilizing geographic information system (GIS) data, a road topology network is constructed, with a particular focus on extracting information from three distinct types of traffic nodes: expressway service areas, county nodes, and downtown nodes. The expressway topology model is then formulated. Subsequent to this, the modelling of SOC for EV batteries is undertaken, incorporating a Gaussian mixture model (GMM) to simulate a mixed traffic flow encompassing multiple vehicle types.

Drawing from the NHT2017 datasets, the paper establishes a charging decision model for county and downtown nodes, taking into account EV trip mileage and trip ending time characteristics. Furthermore, the Huff model is employed to discern charging decisions specifically for county and downtown nodes. In the proposed approach, an improved Sigmoid function is innovatively introduced for charging decision-making at service area nodes. Finally, the proposed method is applied to the Taohuaping-Dingyuan section of the Lian-Huo Expressway for simulating analysis and the simulation results verify the feasibility of the proposed method by comparing them with conventional methods.

2 Expressway road network and traffic characterizations model

The expressway network model mainly contains four types of nodes: service area nodes, county nodes, downtown nodes, and transportation hub nodes. Given the typically smooth traffic flow at expressway hubs, where the SOC distribution entering and exiting remains relatively equivalent, this paper exclusively focuses on modelling the expressway topology by considering service area nodes, county nodes, and downtown nodes. The omission of transportation hub nodes is deliberate, recognizing their characteristic equilibrium in SOC distribution inflow and outflow within the expressway network.

2.1 Expressway topology model

The expressway section chosen for modelling in this paper is the Taohuoping-Dingyuan section of the Lian-Huo Expressway with a total distance of 396.2 kilometers. Within this section, there are 29 nodes, comprising 17 county nodes, 4 downtown nodes, and 8 service area nodes, as shown in [13]. Each node is uniquely indexed by an integer i (i=1,2…29). The flow of EVs from one node to another is represented by the vector (i, j). Following the modelling processes detailed earlier, the resulting expressway area map is depicted in Figure 2, providing a comprehensive representation of the object expressway area under consideration.

2.2 Expressway real-time velocity-flow model

The analysis of EV driving velocity is imperative for investigating EV battery energy consumption. It is crucial to precisely determine EV velocity at each time instance [14]. Existing research often focuses on urban road networks where EV velocity tends to be low, leading to the prevalent use of linear velocity-flow models. However, there is a noticeable gap in the availability of nonlinear velocity models tailored for expressway scenarios. Recognizing this gap, this paper addresses the deficiency by developing a real-time road traffic flow-based nonlinear velocity-flow model to accurately characterize EV driving velocity within expressways. The velocity model is expressed in Eq. (1) and Eq. (2).

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

$$\beta=a+b\cdot\left(\frac{q_{ij}(t)}{C_{ij}}\right)^{n} \tag{2}$$

where $v_{ij.\max}$ is the zero-flow velocity of EVs from node i to node j, which means the maximum velocity of the expressway section. C_{ij} is the maximum mobility of the expressway section. This parameter is dependent on the railway classification of this expressway section. $q_{ij}(t)$ is the traffic flow value at the t juncture. The ratio of parameter $q_{ij}(t)$ and C_{ij} is the congestion degree of this expressway section. β is the experimental constant. a, b, n are adaptative factors for different railway classifications respectively. By referring to Expressway Traffic Survey Statistical Reporting System, it can be obtained that for Class I arterials, the factors a, b, n are 1.726, 3.15, and 3 respectively.

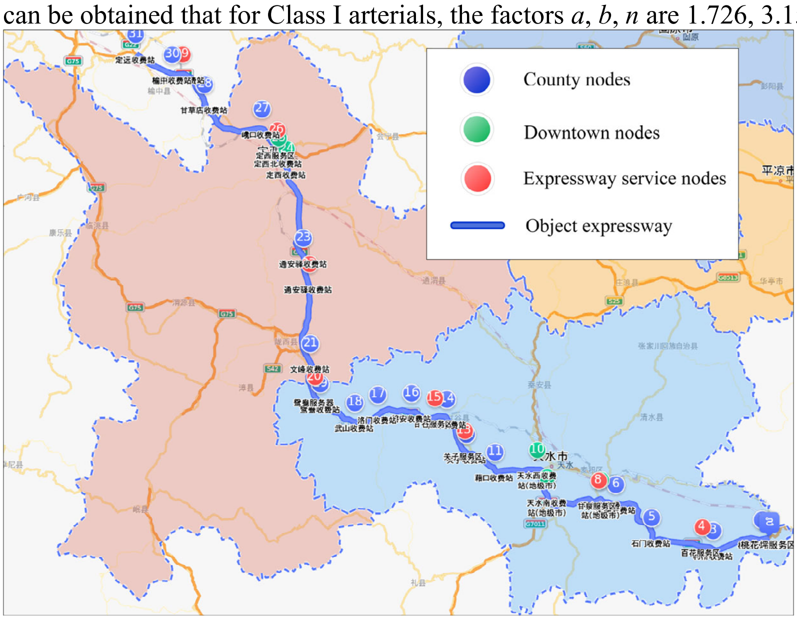

Fig. 2 Taohuoping-Dingyuan section of the Lian-Huo Expressway under investigation.

2.3 Expressway real-time velocity-flow model

Previous studies have indicated that the energy consumption of EVs is comprised of two primary components: driving energy consumption and in-vehicle air conditioning energy consumption. Inspired by these findings, this paper considers both factors when computing the overall energy consumption of EVs [15]. Building upon the aforementioned analysis, the calculation model for unit mileage power consumption is expressed in Eq. (3), (4), and (5).

$$F_{\mathrm{T}} = K_{\mathrm{T}} + E \tag{3}$$

$$K_{\mathrm{T}} = \begin{cases} W_{\mathrm{L}} \dfrac{S}{v_{ij}}, T_p > T_{p\max} \\ W_{\mathrm{R}} \dfrac{S}{v_{ij}}, T_p > T_{p\min} \end{cases} \tag{4}$$

$$E = 0.21 - 0.001 \cdot v_{ij} + \frac{1.531}{v_{ij}} \tag{5}$$

where K_{T} is the energy consumed by the air conditioner of a vehicle travelling S kilometers at speed v_{ij} when the environment temperature is T_p. The real-time velocity can be calculated through Eq. (1). $T_{p\,\min}$ and $T_{p\,\max}$ are the lower and upper temperature limits of the air conditioner, while W_{L} and W_{R} are the power of the air conditioner in cooling mode and heating mode, respectively. E is the energy consumption in different real-time velocities for unit kilometer. F_{T} is the total energy consumption of a vehicle in environment temp of T_p with velocity of v_{ij}.

3 Dynamic transfer processes of SOC of EVs

The traffic flow is conceptually treated as a particle fluid composed of traffic entities [16], with EVs representing the individual particles constituting the flow. In this conceptualization, the SOC values of a single vehicle can be characterized by the collective SOC distribution of the entire vehicle flow, leveraging the inherent characteristics of traffic flow. To capture and comprehend the dynamic evolution of SOC among EVs as they traverse different nodes, this paper introduces a dynamic transfer model. This model is designed to delineate the dynamic transfer process of SOC within the EV flow, offering valuable insights into how vehicle SOC undergoes changes across different nodes within the traffic flow.

3.1 SOC model of expressway traffic flow

In the context of widespread EV usage, the SOC distribution of EV batteries is expected to follow a normal distribution [17]. However, previous studies have predominantly focused on individual EV models, neglecting the real-world scenario of multi-EV hybrid driving. To address this limitation, this paper employs the principle of probability invariance when normal distributions are superimposed. A GMM is then utilized to model the SOC values of different vehicle types. The GMM model can be considered as a weighted superposition of multiple Gaussian models, and its mathematical expression can be described by Eq. (6) and (7).

$$f\left(x \mid \alpha, \mu, \Sigma\right) = \sum_{k=1}^{K} \alpha_k N\left(x, \mu_k, \Sigma_k\right) \tag{6}$$

$$\sum_{i=1}^{k} \alpha_k = 1 \tag{7}$$

where, the K is the fitting component value of GMM, which is an artificially set constant. If the GMM model was set by two fitting Gaussian models, then K=2. α_k is a mixture factor that is used to represent the weighting ratio for each Gaussian component model $N(x,\mu_k,\Sigma_k)$, which meets the constraints given in Eq. (7).

3.2 SOC dynamic moving model of expressway traffic flow

In this study, the modelling primarily centers on private vehicles characterized by random travelling patterns, with no consideration given to vehicles with fixed itineraries such as buses. The probability attributes of vehicle travel are elucidated through the OD matrix. Throughout subsequent sections, the subscript i signifies the origin node number in the OD matrix, while j denotes the destination node number, and l_{ij} represents the mileage between nodes i and j. It is notable that the OD matrix constructed for expressways differs from that of urban transportation networks. In expressway OD matrices, vehicle travel direction and mileage are predetermined and fixed. Therefore, when conducting vehicle flow simulation research on expressways, the focus lies in accounting for variations in charging decisions as vehicles reach different nodes. The ensuing assumptions are to be considered in modelling expressway EVs within this paper:

(1) When the vehicles drive to nodes in the expressway, the number of vehicles flowing out of the expressway is equal to the number of vehicles flowing in, which means the total number of EV traffic flow remains unchanged when the vehicles pass through the node [18].

(2) EVs driving on the expressway follow a unified energy consumption model.

(3) The proportion of vehicle types flowing into each node for charging is consistent with the proportion of vehicle

types assumed on the expressway [19].

Building upon the aforementioned assumptions, the process delineating changes in traffic flow is expounded as follows: 1) EVs with specific SOC values traverse expressway nodes; 2) EVs make decisions based on their SOC values or vehicle mileage; 3) The SOC model representing the total traffic flow on the main road is updated, excluding the SOC values of vehicles exiting the main road; 4) The SOC model of expressway traffic flow is refreshed whenever a vehicle with a new SOC value enters the traffic flow. By implementing this sequence, the simulation effectively captures the dynamics of SOC value changes within expressway traffic flow as it traverses different nodes [20]. This simulation process is illustrated in Figure 3.

It is known that the SOC distribution of an EV model in the traffic flow follows the Gaussian invariance principle, which is also reflected in the basic mathematical operation of independent Gaussian distribution, and whose main feature is computational linearity [21]. In this paper, the Gaussian invariance is extended to the SOC Gaussian mixture model of traffic flow, and the SOC translation model shown in Figure 4.

Through a comparison of the SOC value at the origin and destination of a trip as illustrated in Figure 4, it becomes apparent that the energy loss between the origin node and the destination node demonstrates linearity with the loss of vehicle mileage in the OD matrix. This observation establishes the feasibility of employing the OD-SOC translation model to effectively characterize the changes in SOC distribution within the vehicle flow on expressways.

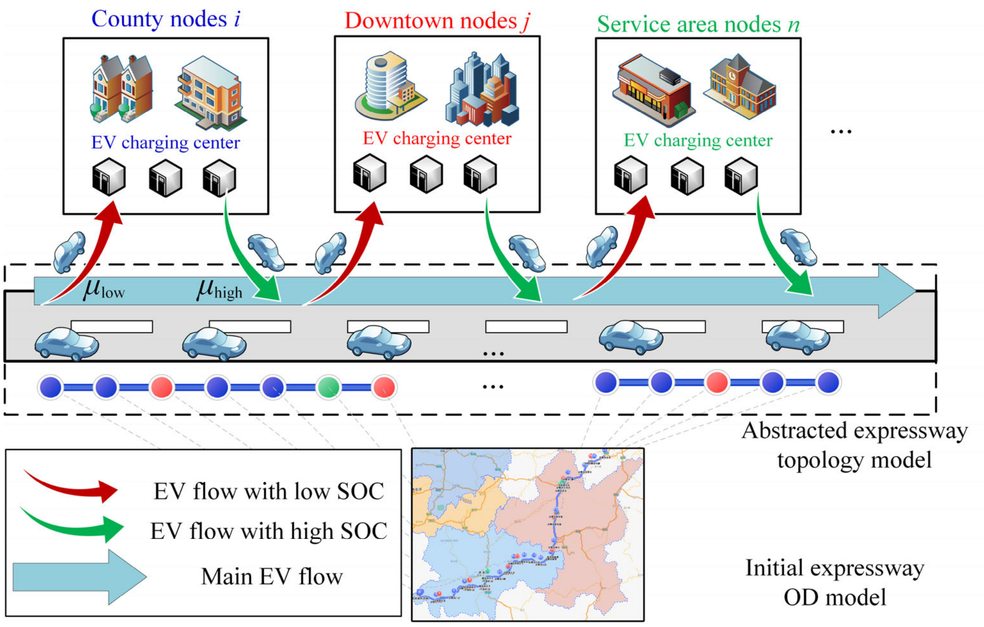

Fig. 3 Illustration of charging decision for traffic flow of expressway.

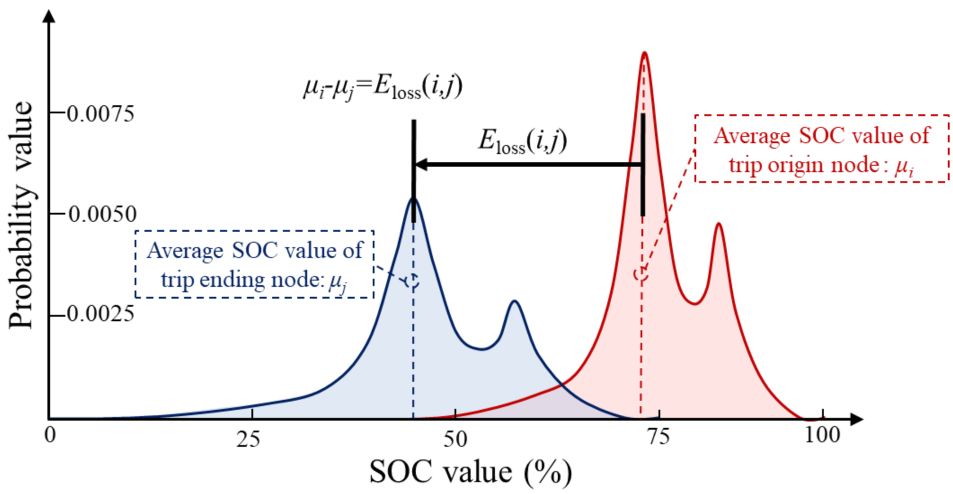

Fig. 4 Probability distribution of SOC for traffic flow of expressway.

4 EV charging decision considered expressway nodes difference

Acknowledging substantial variations in the influx of EVs entering each node and the distinct social responsibilities shouldered by these nodes, this paper adopts diverse EV charging strategies for each node in its modelling approach.

4.1 EV charging strategy for county and downtown nodes

The decisions regarding EV charging in different scenarios are commonly influenced by factors such as trip mileage and trip time. Drawing insights from NHTS2017 data and existing research [22], it is observed that the distribution of EV trip mileage adheres to the Lognormal distribution constraint. In this paper, the cumulative distribution function $F_m(x)$ derived from historical mileage data is employed as the activation function for EV charging decisions. Furthermore, the framework incorporates the dynamic characteristics of EVs as additional parameters influencing attractiveness. By employing fitting techniques on vehicle trip mileage and trip ending time data from NHTS2017, the probability distribution of EV trip is illustrated in Figure 5.

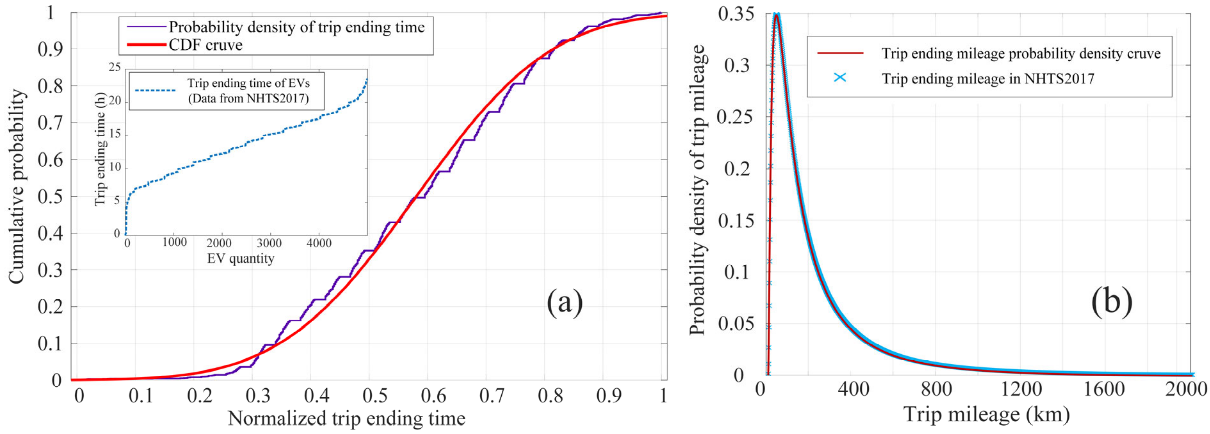

Fig. 5 Fitting curves of NHTS2017 data. (a) trip ending time. (b) trip mileage.

Subsequently, by extracting the fitting parameters of the fitting curve in Figure 5, the Lognormal probability distribution function can be obtained as shown in Eq. (8).

$$f_m(x) = \frac{1}{\sqrt{2\pi}\sigma_m x} \exp^{-\left[\frac{(\ln x - \mu_m)}{\sqrt{2}(\sigma_m)}\right]^2} \tag{8}$$

where μ_m=2.98, and σ_m=1.14 through data fitting. x stands for the mileage data of OD matrix.

While county and downtown nodes share similar social responsibilities, this paper acknowledges the substantial differences in economic scale and the scale of charging facility construction between counties and downtowns. To account for these variations, the paper employs the Huff model to emphasize distinctions in charging strategies when vehicles arrive at county and downtown nodes. The Huff model is particularly useful in capturing and illustrating the diverse factors that influence charging decisions, taking into consideration the economic and infrastructural differences between counties and downtowns.

The Huff model serves as a decision-making model to ascertain whether EV owners decide to charge based on economic benefits. Within this model, an attractiveness parameter A_i is introduced to capture variations in charging choices among users in different city regions [23]. Traditionally, the formulation of attractiveness parameters in the Huff model has predominantly focused on the psychological impact of diverse functional areas and economic levels on urban users. In this paper, the attractiveness parameter A_i is redefined by integrating a time influence parameter in conjunction with economic factors. The mathematical expression for the redesigned attractiveness parameter A_i is delineated in Eq. (9):

$$A_i = \alpha y_i + \beta c_i + \gamma \tag{9}$$

where y_i is the economic scale difference parameter of the i-th node. In this paper, the base value for the county node is set as 1, while that for downtown is set as 0.8. c_i is the time decision parameter for driving to the ith node. α, β are the economic effect influence coefficient and EV entry time influence coefficient, which can be obtained by analyzing historical data. γ is a constant [24].

By introducing the attractive parameter A_i of the Huff model into Eq. (8), an improved Lognormal function with the characteristics of economic difference of nodes and trip time difference can be obtained as Eq. (10).

$$f_{\mathrm{m}}(x)=\frac{1}{\sqrt{2\pi}\sigma_{\mathrm{m}}x}\exp^{-\left[\frac{(\ln x-A_i\cdot\mu_{\mathrm{m}})}{\sqrt{2}(\sigma_{\mathrm{m}})}\right]^2} \tag{10}$$

Based on Eq. (10), the EV charging differentiation decision at downtown and county nodes can be realized, which reflects the temporal and spatial dynamic differences of EV charging strategies.

For EVs with low SOC values, a distinct charging strategy is warranted. When a vehicle with a lower SOC value arrives at a specific node, the user must assess whether the existing SOC is sufficient to support the vehicle to the next node. In such instances, the charging decision of EVs can be succinctly characterized as follows: when the SOC of the EV is insufficient to support the vehicle's journey to the next node, the EV mandates a detour to the current node for charging. Otherwise, conventional charging decisions are adhered to [25]. The aforementioned behaviour can be mathematically expressed as Eq (11).

$$\delta_n^j=\begin{cases}1 & E_n-E_{\mathrm{loss}}^{j,j+1}<0\\ 0 & E_n-E_{\mathrm{loss}}^{j,j+1}\geq 0\end{cases} \tag{11}$$

where δ_n^j represents a decision variable in the traffic flow that determines whether the vehicle is charged when the n-th EV is marked as driving to node j. Its decision criterion is whether the EV's existing power E_n is able to support the EV drives to the next node. Considering that in the expressway scenario, EV is usually single-direction driving, therefore, this paper uses the energy consumption amount that EV drives to j+1-th node to characterise the EV decision gauge in a detailed way.

In this paper, the calculation of the charging load $P_i(t)$ at node i of the expressway is conducted based on the coupling relationship between the traffic node and the distribution network. The spatiotemporal load of each node is systematically incooperated. The charging load $P_i(t)$ is expressed as Eq (12).

$$P_i(t)=\sum_{i=1}^{N_{\mathrm{EV}}}P_i^n(t) \tag{12}$$

where N_{EV} represents the number of EVs entering the i-th node for charging, while represents the total EV charging power of the i-th node at time t.

4.2 EV charging decision for service area nodes

Given that charging facilities on expressways are centrally located in service areas, and drawing upon the earlier constructed OD-SOC translation model, it can be deduced that when vehicles reach service area nodes, some EV users with lower SOC values may choose to enter the service area for charging. To precisely characterize the decision-making behaviour of EV users entering the service area, this paper employs an improved Sigmoid function as the decision activation function. This function is utilized to model EVs whether enter service areas.

Recognizing the challenge of precisely describing the spatiotemporal distribution characteristics of EV charging decision-making using the Sigmoid function, this paper introduces an enhancement to endow the Sigmoid activation function with the capability to accurately capture the SOC value of EVs. Specifically, the average SOC value of a GMM representing traffic flow is denoted as μ and incorporated into the Sigmoid function. This ensures that the decision-making, as modelled by the improved Sigmoid function, closely adheres to the real-time SOC distribution of traffic flow on the expressway [26]. The enhanced Sigmoid function, synthesized by integrating the mentioned parameters, is expressed in Eq. (13) and Eq. (14).

$$\sigma\left[f\left(SOC_i^n\right)\right]=\frac{1}{1+e^{-f\left(SOC_i^n\right)}} \tag{13}$$

with

$$f\left(SOC_i^n\right)=\mu_i-\left(SOC_i^n\right)^{\varphi} \tag{14}$$

where $\sigma\,[f\,(SOC_i^n)]$ is the improved Sigmoid function. μ_i is the average SOC value of the Gaussian mixture model of traffic flow at the i-th node on the expressway. SOC_i^n represents the individual vehicle SOC value of the input decision model in the traffic flow. φ is the shaping parameter that controls the shape of the Sigmoid function, which is a constant.

Similar to county nodes, for vehicles with low SOC values, users will assess whether the vehicle can reach the next road section. If the current power level of the vehicle is insufficient to meet the energy consumption required for reaching the next node, the EV will be compelled to divert into the service area for charging.

5 Case study and result analysis

5.1 Case description

For the case study, it is recommended to choose expressways with stable traffic flow and consistent congestion as the data source. Upon investigation, it was determined that the traffic flow on the Taohuaping-Dingyuan section from Shaanxi to Gansu is stable, and the congestion value remains relatively fixed, strictly within the range of 0.25 to 0.3. Furthermore, the vehicles traversing this section are primarily private cars, aligning with the current types of EVs. Given these conditions, this paper selects the Taohuaping-Dingyuan section of the Lian-Huo Expressway as the case study for in-depth analysis.

This paper simplifies the traffic flow and constructs a traffic flow model that only includes private cars. To accurately simulate the real traffic flow, multiple brands of EVs were selected to construct a mixed traffic flow. In order to ensure the universality of the results, a total of 8 common vehicle brands on the market are selected to construct a mixed traffic flow, including the BYD Alto 3, BYD Han, BYD Tang, Tesla Model X, Tesla Model Y, Zeeker X, Zeeker 001, and Nissan Arria. The proportion of various vehicle types in the traffic flow, vehicle battery capacity and battery SOC value are shown in Table I.

Table 1 Description of different brands of EVs in the traffic flow on expressway.

EV types	Battery capacity (kWh)	Minimum SOC	Maximum SOC	Proportion
BYD Atto3	60.5	0.1	0.9	5%
BYD Han	85.4	0.1	0.9	25%
BYD Tang	86.4	0.1	0.9	25%
Tesla Model X	95	0.1	0.9	15%
Tesla Model Y	57.5	0.1	0.9	5%
Zeeker X	64	0.1	0.9	5%
Zeeker 001	94	0.1	0.9	5%
Nissan Ariya	87	0.1	0.9	15%

In the process of constructing traffic flow, this paper first uses the Monte Carlo method to generate an initial SOC sequence, then mixes the initial SOC values of different vehicles to construct a mixed traffic flow, and finally uses the maximum expectation algorithm to fit a Gaussian mixture model. To improve the fitting efficiency of Gaussian mixture models, this paper adopts a 4th-order Gaussian mixture model fitting that balances accuracy and efficiency [27]. The final results of the traffic flow Gaussian mixture model are shown in Figure 6.

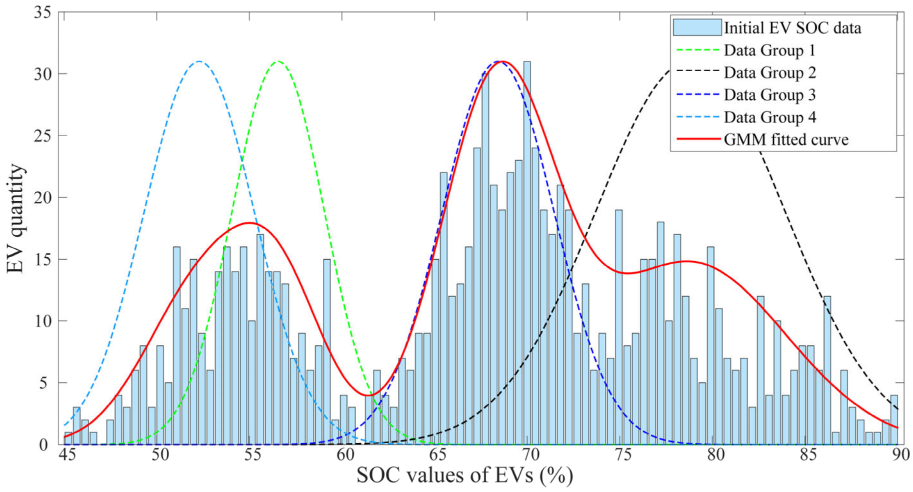

Fig. 6 GMM fitting results of traffic flow SOC on expressway.

5.2 Simulation results and discussions

In the simulation, the total number of EVs is set at 200 which is derived from the observation of vehicle data on the Taohuaping-Dingyuan section of the Lian-Huo Expressway provided by the transportation department. The Monte Carlo method is employed to conduct the experiment iteratively 5 times. The simulation results yield spatiotemporal dynamic vehicle flow patterns and line diagrams for each node of the expressway. The simulation results are shown in Figure 7.

The temperature map of vehicle flow shown in Figure 7a reflects the spatiotemporal distribution characteristics of charging vehicles. By analyzing the temperature chart data horizontally (temporal characteristics), the temporal dynamic distribution curves of charging vehicles flowing into each node can be obtained as shown in Figure 7b. From Figure 7b, it can be seen that the number of vehicles flowing into each node of the expressway on the same day has an increasing trend over time. Compared with the fitting curve obtained from NHTS2017 data, the trend of the two curves is consistent. Meanwhile, through longitudinal analysis (spatial characteristics) of the temperature map shown in Figure 7a, the spatial dynamic distribution of vehicles flowing into each node at a certain moment can be obtained, as shown in Figure 7c. Comparing the spatial distribution curve shown in Figure 7c with the distribution in Eq. (8), it is clear that the charging decisions of EV users on the expressway have similar distribution characteristics to the trip mileage described by NHTS2017 historical data. This is mainly due to the small proportion of EVs on expressways (by the end of 2022, the EVs only accounted for 5.7% in China). Based on the above results, it can be proven that the EV distribution data obtained using the method proposed in this paper has certain spatiotemporal distribution characteristics.

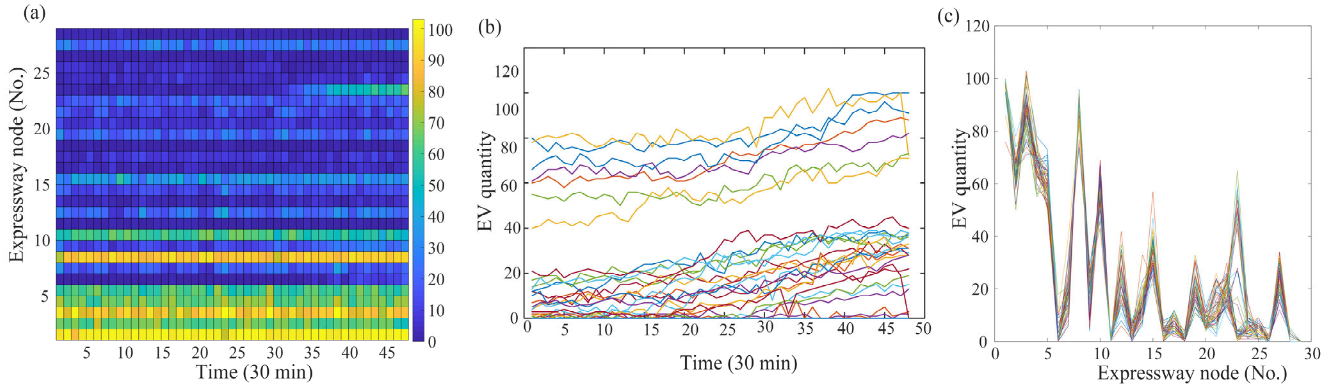

Fig. 7 Spatiotemporal distribution of expressway charging loads. (a) temperature map of EVs charging loads. (b) temporal characteristics of EVs charging loads. (c) spatial characteristics of EVs charging loads.

Upon investigating EV charging behaviour, it is evident that EV charging methods predominantly fall into two categories: ordinary charging and fast charging. Furthermore, in accordance with expressway service area planning guidelines, the current ratio of fast charging base stations to regular charging base stations is maintained at 1:4. Leveraging this charging facility data alongside the results presented in Figure 7, the spatiotemporal distribution curve of the average charging load can be derived, as illustrated in Figure 8. A more in-depth analysis of the curve in Figure 8 allows for the generation of a comparative chart between the average EV charging load and the travel data curve, as shown in Figure 9. It is apparent from this comparison that the EV charging load depicted in Figure 8 shares the same distribution characteristics as trip mileage described by Eq. (8). This consistency aligns with the distribution pattern observed in NHTS2017 data, which further validates the proposed method's ability to capture the spatiotemporal distribution characteristics of EV charging behaviour.

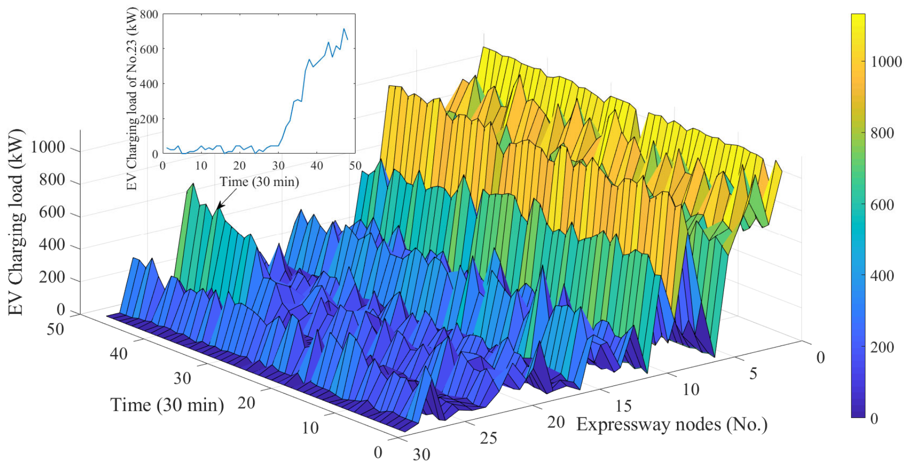

Fig. 8 Spatiotemporal distribution of EV average charging load.

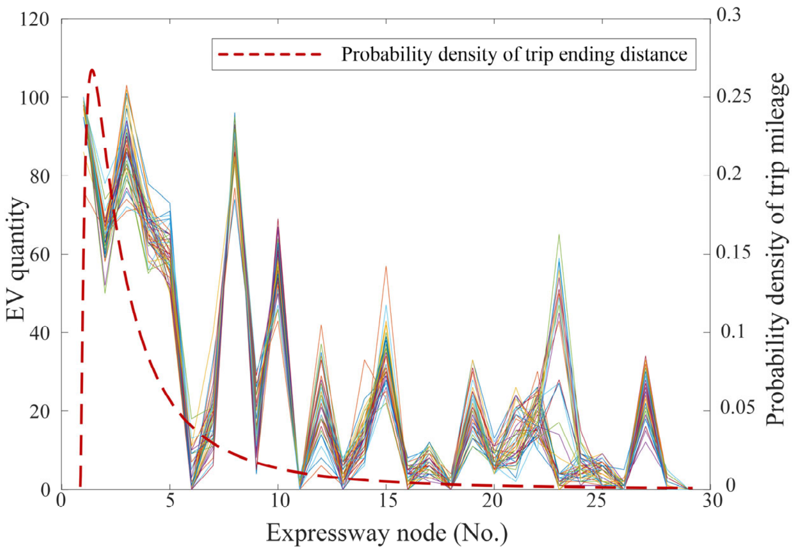

Fig. 9 Comparison of EV charging load curve and trip mileage probability distribution curve.

Furthermore, this paper takes into account extreme charging scenarios for EVs: 1) the minimum charging load scenario, where EVs exclusively utilize regular charging; and 2) the maximum charging load scenario, where all EVs exclusively opt for fast charging. The simulation analysis results in the charging load curve for expressway EVs under these extreme scenarios are depicted in Figure 10.

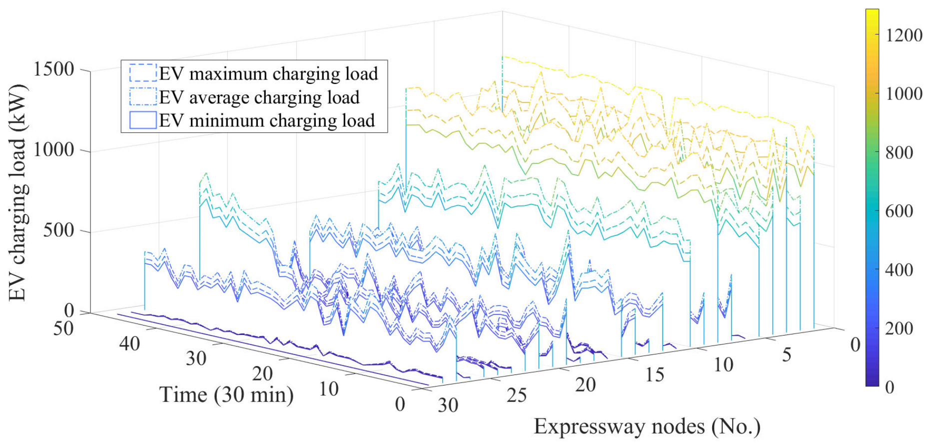

Fig. 10 EV charging load at different nodes on expressway.

The simulation results reveal that during the initial hours of each day (0:00-8:00), there is a relatively low quantity of traffic flow entering each node of the expressway, resulting in low charging load values at most charging nodes. From 9:00 to 14:00, each node on the expressway section experiences normal charging, with stable power distribution. Starting at 15:00, EVs gradually exit the expressway, leading to an increase in charging load at each node. This upward trend continues between 18:00 and 23:00. The charging load at each node of the expressway, as obtained through simulation on the same day, demonstrates a consistent upward tendency over time. This trend converges with statistical data from NHTS2017, corroborating the real-time and spatial distribution characteristics of EVs.

To validate the effectiveness of the EV charging power prediction method proposed in this paper, a comparison is conducted with the Monte Carlo simulation method, Latin hypercube sampling method, and the traditional Sigmoid function. The comparison is made against real historical data curves, demonstrating the strong practicality of the method proposed. The curve comparison between each method and real data is illustrated in Figure 11.

Considering the charging equipment for downtown nodes and county nodes is installed in city centers and requires additional urban modelling for accurate data, this paper focuses solely on comparing the node charging power in expressway service areas as the reference data. As depicted in Figure 11, the combined prediction method proposed in this paper exhibits an excellent performance with real EV charging data, which accurately describes the charging trends. In contrast, the traditional Sigmoid function proves to be overly sensitive to the SOC value of EVs, leading to an overestimation of charging vehicles and resulting in inflated load predict values. However, with the improvements made by the proposed method, the EV charging load values align more closely with the actual data.

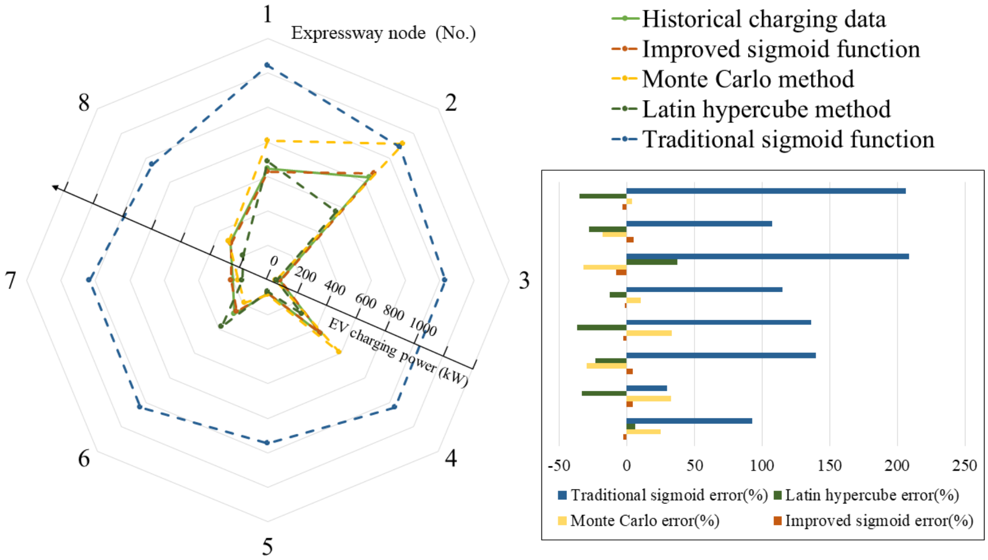

Fig. 11 EV charging load prediction results of service area nodes.

6 Conclusion

This paper introduces a combined EV charging load prediction method for expressways which incorporates dynamic SOC and user charging decisions. The effectiveness of the proposed method is validated using real expressway data and public datasets. Conclusions drawn from the simulation experiment results include:

1) Previous studies have only analyzed a single EV model, while this paper selected 8 EV models to construct a Gaussian mixture model for expressway traffic flow, and the results obtained are closer to the real situation.

2) The OD-SOC translation model constructed in this paper can truly reflect the changes in SOC during EV driving in traffic flow. This model can not only dynamically characterize the overall SOC value of EVs on expressways, but also reflect the SOC value of individual EVs, facilitating differentiated analysis of charging decisions for EVs on expressways.

3) By using an improved Lognormal decision function and Sigmoid function, differential modelling was conducted on the charging decisions of three types of nodes: county nodes, downtown nodes, and service area nodes. The accurate description of charging decisions made by EV users at different nodes made EV charging decisions more in line with real-life cases and improved the accuracy of EV charging load prediction results.

It should be noted that the conclusions drawn in this paper are based on historical data from the Lian-Huo Expressway. Further in-depth investigation is desired to assess the universality of scenarios and time, ensuring the applicability and generalizability of the findings in diverse contexts and over extended periods in the future.

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