iEnergy

ARTICLE

https://doi.org/10.23919/IEN.2024.0011

Charging load prediction method for expressway electric vehicles considering dynamic battery state-of-charge and user decision

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ABSTRACT

Accurate prediction of electric vehicle (EV) charging loads is a foundational step in the establishment of expressway charging infrastructures. This study introduces an approach to enhance the precision of expressway EV charging load predictions. The method considers both the battery dynamic state-of-charge (SOC) and user charging decisions. Expressway network nodes were first extracted using the open Gaode Map API to establish a model that incorporates the expressway network and traffic flow features. A Gaussian mixture model is then employed to construct a SOC distribution model for mixed traffic flow. An innovative SOC dynamic translation model is then introduced to capture the dynamic characteristics of traffic flow SOC values. Based on this foundation, an EV charging decision model was developed which considers expressway node distinctions. EV travel characteristics are extracted from the NHTS2017 datasets to assist in constructing the model. Differentiated decision-making is achieved by utilizing improved Lognormal and Sigmoid functions. Finally, the proposed method is applied to a case study of the Lian-Huo expressway. An analysis of EV charging power converges with historical data and shows that the method accurately predicts the charging loads of EVs on expressways, thus revealing the efficacy of the proposed approach in predicting EV charging dynamics under expressway scenarios.

KEYWORDS

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

In light of China's steadfast commitment to the "dual carbon" strategy aimed at achieving carbon peak and neutrality, China's electric vehicle (EV) industry is experiencing an unprecedented surge in development opportunities. At the end of 2022, the numbers of EVs in use in China had soared to 10.45 million[1], leading to a substantial influx of high-capacity EV charging demands that have had noticeable effects on power supply infrastructures[2]. Expressway power supply systems are particularly susceptible to intermittent load disruptions, which compromise the stability of expressway power grids. Consequently, elucidating the spatiotemporal distribution of EVs, investigating the charging decision-making patterns of EV users and predicting impending EV charging loads on expressways are critical. These endeavors are prerequisites for establishing the secure functioning of expressway power grids, thereby expediting the electrification of Chinese expressways and enhancing the efficiency of electricity services[3].

Current research on EV charging load prediction has primarily focused on two aspects: precise characterization of EV travel environments and the application of more accurate simulation sampling methods. Regarding the characterization of EV travel environments, Arias et al.[4] established a model for urban road networks based on the Seoul Metropolitan Area in South Korea. They employed a Markov chain to derive EV charging loads for each city section. In Ref. [5], an urban transportation network that considers traffic congestion was developed to predict EV charging loads. The study in Ref. [6] presented a multi-regional urban transportation network model that divided the city's traffic network into various regions. A hybrid method was proposed to predict the charging loads of urban EVs.

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

The studies in Refs. [10] and [11] formulated a Markov chain model incorporating multiple random processes, starting from the perspective of user psychological decision-making, to predict the charging loads of urban network EVs. Deep learning methods have also been employed to achieve more accurate predictions of ultra-short-term charging loads of EVs[12]. This approach has demonstrated superior performance as compared with traditional artificial neural networks that achieve only an accuracy of 30%.

This overview highlights the prevailing emphasis in existing research on investigations into the driving behaviors and charging decisions of EVs in urban transportation networks. By contrast, studies examining EV driving ranges and charging behaviors on expressways are noticeably lacking. Accurately modeling the flow of EVs on expressways is essential for predicting the charging loads of EVs. Consequently, this study contributes to the existing knowledge base by examining EV driving energy consumption and charging decision-making as well as expressway charging load prediction under the expressway framework. The modeling process is delineated in Figure 1.

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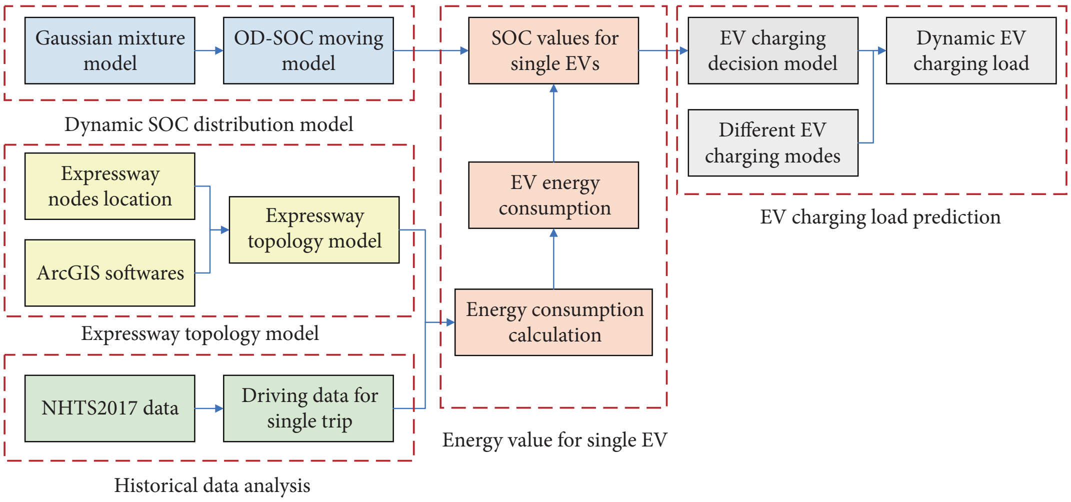

Figure 1 Flow of expressway EV charging load prediction process.

This study first develops an origin-destination (OD) matrix model tailored for expressway traffic. Utilizing geographic information system data, we constructed a road topology network with a focus on extracting information from three types of traffic nodes: expressway service areas, county nodes, and downtown nodes. The expressway topology model is then constructed. The modeling of the state-of-charge (SOC) for EV batteries is then conducted, incorporating a Gaussian mixture model (GMM) to simulate a mixed traffic flow that considers multiple vehicle types.

From the NHT2017 datasets[13], the study establishes a charging decision model for county and downtown nodes considering EV trip mileage and trip ending-time characteristics. The Huff model is also employed to discern charging decisions for county and downtown nodes. In the proposed approach, an improved Sigmoid function is 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 simulation analysis. The simulation results verify the feasibility of the proposed method based on a comparison with those of conventional methods.

1 Expressway road network and traffic characterization modeling

The expressway network model mainly includes four types of nodes: service-area, county, downtown, and transportation-hub nodes. Given the typically smooth traffic flow at expressway hubs, where SOC-distribution inflow and outflow are relatively equivalent, this study focuses on modeling the expressway topology by considering only the first three nodes. Transportation-hub nodes are purposely omitted due to their characteristic equilibrium in SOC-distribution inflow and outflow in the expressway network.

1.1 Expressway topology modeling

The Taohuoping-Dingyuan section of the Lian-Huo expressway, with a total distance of 396.2 km, was used for modeling in this study. This section contains 29 nodes consisting of 17 county, four downtown, and eight service-area nodes, as shown in Ref. [14]. 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 modeling processes previously detailed, the resulting expressway area map is depicted in Figure 2, which provides a full representation of the object expressway area under consideration.

1.2 Expressway real-time velocity-flow modeling

An analysis of EV driving velocity is necessary for investigating EV battery energy consumption, where precisely determining EV velocity at each instance is crucial[15]. Existing research often focuses on urban road networks where EV velocities tends to be low, leading to the predominant use of linear velocity-flow models. However, a noticeable gap exists in the availability of nonlinear velocity models tailored for expressway scenarios. This study addresses this gap by developing a real-time road traffic flow-based nonlinear velocity-flow model to accurately characterize EV driving velocity in expressways. The velocity model is expressed by the following equations.

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

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

where $v_{ij.\max}$ is the zero-flow velocity of EVs from node i to j, which refers to the maximum velocity of the expressway section. In addition, C_{ij} is the maximum mobility of the expressway section, which is dependent on the railway classification of this expressway section, and $q_{ij}(t)$ is the traffic flow value at the t juncture. The ratio of parameter $q_{ij}(t)$ to C_{ij} is the degree of congestion of this expressway section. In addition, β is the experimental constant, a, b, and n are adaptive factors for different railway classifications, where a is the basic capacity of the road, b is the adaptative weight parameter, and n is the expressway road level. All parameters are set by government management institutions via the Expressway Traffic Survey Statistical Reporting System. As expressways are Class I arterials, the values of factors a, b, and n are 1.726, 3.15, and 3, respectively.

1.3 EV energy consumption modeling

Previous studies have shown that the energy consumption of EVs consists of two primary components: driving energy consumption and in-vehicle air conditioning energy consumption. Accordingly, this study considers both factors when computing the overall energy consumption of EVs[16]. Based on the previous analysis, the calculation model for unit mileage power consumption is

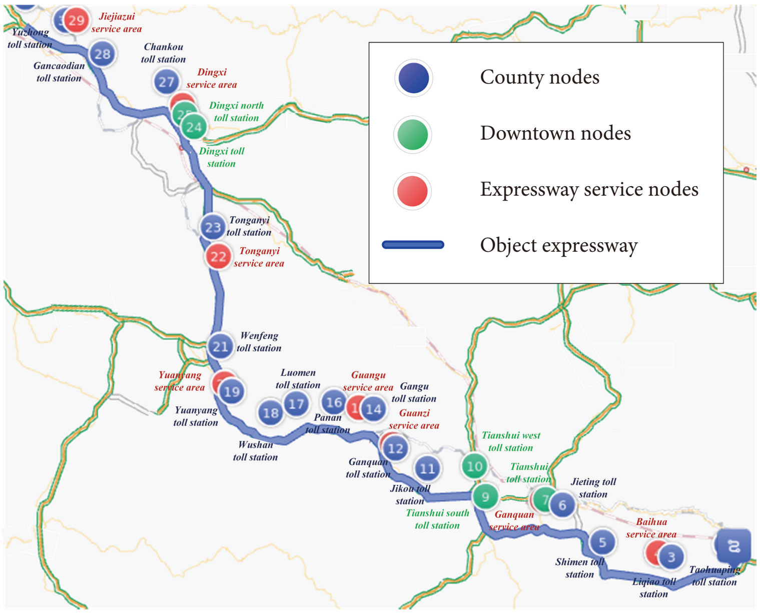

Figure 2 Taohuoping-Dingyuan section of the Lian-Huo expressway.

expressed by the following equations.

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

$$E = 0.21 - 0.001 \cdot v_{ij} + \frac{1.531}{v_{ij}} \tag{4}$$

$$K_{\mathrm{T}} = \begin{cases} W_{\mathrm{C}} \dfrac{S}{v_{ij}}, & T_{\mathrm{p}} > T_{\mathrm{p\,max}} \\ W_{\mathrm{H}} \dfrac{S}{v_{ij}}, & T_{\mathrm{p}} > T_{\mathrm{p\,min}} \end{cases} \tag{5}$$

where K_{T} is the energy consumed by the vehicle air conditioner under a travel distance of S km at speed v_{ij} and environment temperature T_{p}, wherein v_{ij} can be calculated using (1). In addition, $T_{\mathrm{p\,min}}$ and $T_{\mathrm{p\,max}}$ are the lower and upper temperature limits of the air conditioner, respectively, and W_{C} and W_{H} are the power of the air conditioner in cooler and heater modes, respectively. According to statistics presented in Ref. [17], the energy consumption K_{T} can be set by (5). Finally, E is the energy consumption in different real-time velocities per km and F_{T} is the total energy consumption of a vehicle with a velocity of v_{ij}. To simulate an EV driving environment, the environment temperature T_{p} is set to 20 °C.

2 Dynamic transfer processes of the SOC of EVs

A traffic flow is conceptually treated as particle fluid composed of traffic entities[18], 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 the dynamic evolution of the SOC among EVs as they traverse different nodes, this study introduces a dynamic transfer model. This model is designed to delineate the dynamic transfer process of the SOC in the EV flow, offering valuable insights into how a vehicle SOC undergoes changes across different nodes in the traffic flow.

2.1 SOC model of expressway traffic flow

In terms of widespread EV usage, the SOC distribution of EV batteries is expected to follow a normal distribution[19]. However, previous studies have mostly focused on individual EV models, neglecting the real-world scenarios of multi-EV hybrid driving. To address this limitation, this study 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 is a weighted superposition of multiple Gaussian models, where its mathematical expression can be expressed by

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

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

where K is the fitting component value of GMM, which is an artificially set constant. If the GMM is set by two fitting Gaussian models, then $K = 2$. In addition, α_k is a mixture factor used to represent the weighting ratio for each Gaussian component model $N(x,\mu_k,\Sigma_k)$, which meets the constraints given in (6), and μ_k and Σ_k are the positional and dispersion measure parameters, respectively, for the k-th Gaussian distribution.

2.2 SOC dynamic moving model of expressway traffic flow

In this study, the modeling focuses on private vehicles characterized by random traveling patterns, without considering vehicles with fixed itineraries, such as buses. The probability attributes of vehicle travel are elucidated through the OD matrix. In the sections that follow, the subscript i is the origin node number in the OD matrix, j is the destination node number, and l_{ij} is the mileage between nodes i and j. Notably, the OD matrix constructed for expressways differs from that of urban transportation networks. For OD matrices for expressways, vehicle travel direction and mileage are predetermined and fixed. Therefore, vehicle flow simulation research on expressways must consider variations in charging decisions as vehicles reach different nodes. Accordingly, the following assumptions must be considered in modeling expressway EVs:

(1) When EVs drive to nodes on an expressway, the numbers of vehicles that flow both in and out of the expressway are equal, which means the total number of EV traffic flow remains

unchanged when the vehicles pass through a node[20].

(2) EVs driving on an 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[21].

Based on these assumptions, the process delineating changes in traffic flow is 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 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 updated whenever a vehicle with a new SOC value enters the traffic flow. Through this process, the simulation effectively captures the changes in SOC values in expressway traffic flow as EVs traverse different nodes[22]. This simulation is illustrated in Figure 3.

The SOC distribution of an EV model in the traffic flow is known to follow the Gaussian invariance principle, which is also reflected in the basic mathematical operation of independent Gaussian distribution, and whose main feature is computational linearity[23]. In this study, the Gaussian invariance is extended to the SOC GMM of traffic flow. Figure 4 shows the SOC translation model.

A comparison of the SOC values at the origin and destination of a trip, as illustrated in Figure 4, reveals that the energy loss between the origin and destination nodes is linear with the loss of vehicle mileage in the OD matrix. This observation enables the OD-SOC translation model to characterize the changes in SOC distribution in the vehicle flow on expressways. The dynamic variation of the SOC GMM can be calculated using the following equation, which reflects the linear and spatial variation characteristics of the SOC.

$$\forall[\Gamma(SOC_i^n)] - \forall[\Gamma(SOC_{i-1}^n)] = E_i^n$$
$$\text{s.t.}\begin{cases} n \in N_{EV} \\ i \in N_{node} \end{cases} \tag{8}$$

where $\Gamma(.)$ represents the GMM. Note that (8) shows that the SOC value for the nth EV at the i-th expressway node follows the GMM. Subtracting the SOC values of two adjacent nodes allows us to determine that the energy consumption of EVs is based on the value of E, which is calculated by (4).

3 EV charging decision considering expressway node differences

Because of the significant variations in the influx of EVs entering each node and the distinct social responsibilities shouldered by these nodes, the modeling approach in this study adopts diverse EV charging strategies for each node.

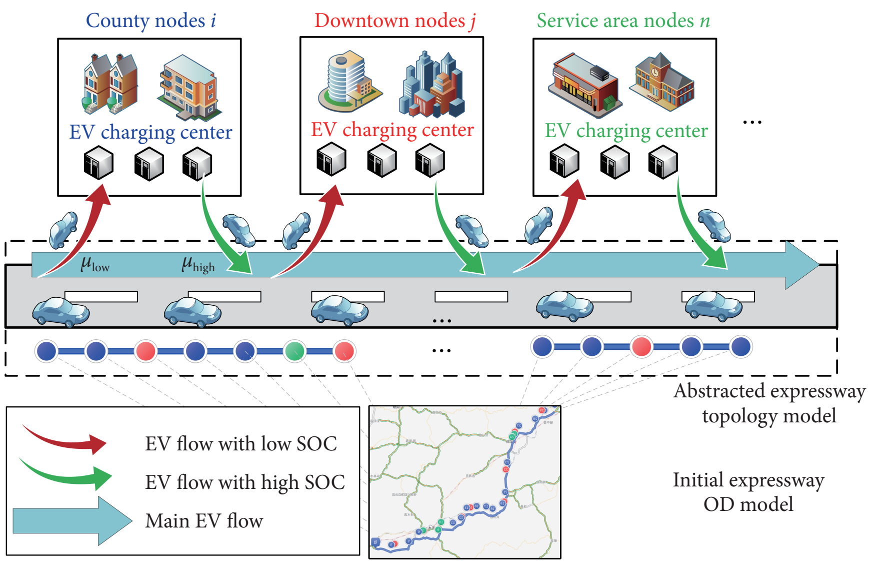

Figure 3 Charging decisions in expressway traffic flow.

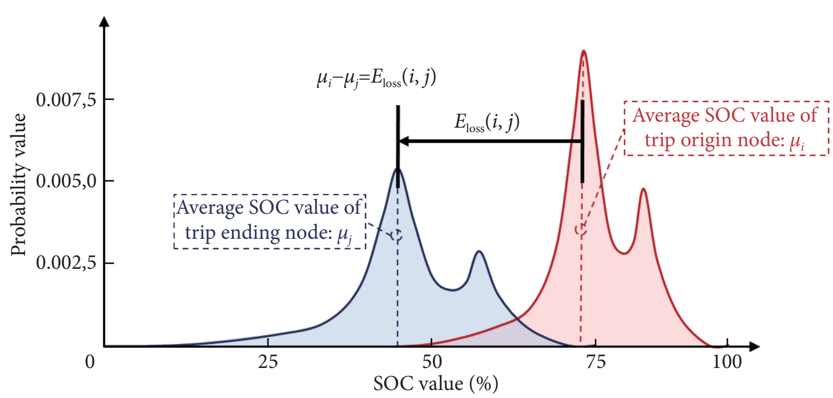

Figure 4 Probability distribution of the SOC for expressway traffic flow.

3.1 EV charging strategy for county and downtown nodes

The decisions regarding EV charging in different scenarios are affected by factors such as trip mileage and trip time. Based on NHTS2017 data and existing research[24], we observed that the distribution of EV trip mileage adheres to the Lognormal distribution constraint. In this study, the cumulative distribution function $F_m(x)$ derived from historical mileage data is employed as the activation function for EV charging decisions. The framework also incorporates the dynamic characteristics of EVs as additional parameters that influence attractiveness of a city. Fitting techniques on vehicle trip mileage and trip ending time data from NHTS2017 are used to illustrate the probability distribution of EV trips in Figure 5.

When the fitting parameters are extracted from the fitting curve in Figure 5, the Lognormal probability distribution function can be expressed as

$$f_m(x) = \frac{1}{\sqrt{2\pi}\sigma_m x}\exp^{-\left[\frac{(\ln x - \mu_m)}{\sqrt{2}(\sigma_m)}\right]^2} \tag{9}$$

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

Although county and downtown nodes share similar social responsibilities, this study acknowledges the significant differences in economic scale and the scale of construction of charging facilities between counties and downtowns. To account for these variations, the study 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 affect charging decisions particularly the economic and infrastructural differences between counties and downtowns

The Huff model serves as a decision-making model to determine whether EV owners decide to charge based on economic benefits. In this model, an attractiveness parameter A_i is introduced to capture variations in charging choices among users in different city regions[25]. Traditionally, the formulation of attractiveness parameters in the Huff model has mostly focused on the psychological effects of diverse functional areas and economic levels on urban users. In this study, the attractiveness parameter A_i is redefined by integrating a time influence parameter in conjunction with economic factors. The redesigned attractiveness parameter A_i is calculated by

$$A_i = \alpha y_i + \beta c_i + \gamma \tag{10}$$

where y_i is the economic scale difference parameter of the i-th node. In this study, the base values for the county and downtown nodes are set as 1 and 0.8, respectively. In addition, c_i is the time decision parameter for driving to the i-th node, and α and β are the economic influence and EV entry-time influence coefficients, respectively, which can be obtained by analyzing historical data. Finally, γ is a constant obtained from[26].

When the attractiveness parameter A_i of the Huff model is introduced into (8), an improved Lognormal function with the characteristics of economic difference of nodes and trip time difference can be obtained as

$$f_m(x) = \frac{1}{\sqrt{2\pi}\sigma_m x}\exp^{-\left[\frac{(\ln x - A_i \cdot \mu_m)}{\sqrt{2}(\sigma_m)}\right]^2} \tag{11}$$

From (11), the EV charging differentiation decision at downtown and county nodes can be determined, which reflects the temporal and spatial dynamic differences of EV charging strategies.

For EVs with low SOC values, a distinct charging strategy is necessary. 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's journey to the next node. In these instances, the charging decisions 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, as described in Ref. [27]. The aforementioned behaviors can be expressed by

$$\delta_n^j = \begin{cases} 1 & E_n - E_{\text{loss}}^{j,j+1} < 0 \\ 0 & E_n - E_{\text{loss}}^{j,j+1} \geqslant 0 \end{cases} \tag{12}$$

where δ_n^j is 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 can support the EV's journey to the next node. Based on the fact that in an expressway scenario, an EV is usually single-direction driving, this study uses the energy consumption amount in the EV's journey to the j+1-th node to characterize the EV decision in a more detailed manner.

In this study, the charging load $P_i(t)$ at node i of the expressway is calculated based on the coupling relationship between the traffic node and distribution network. The spatiotemporal load of each node is systematically incorporated. The charging load $P_i(t)$ is expressed as

$$P_i(t) = \sum_{i=1}^{N_{\text{EV}}} P_i^n(t) \tag{13}$$

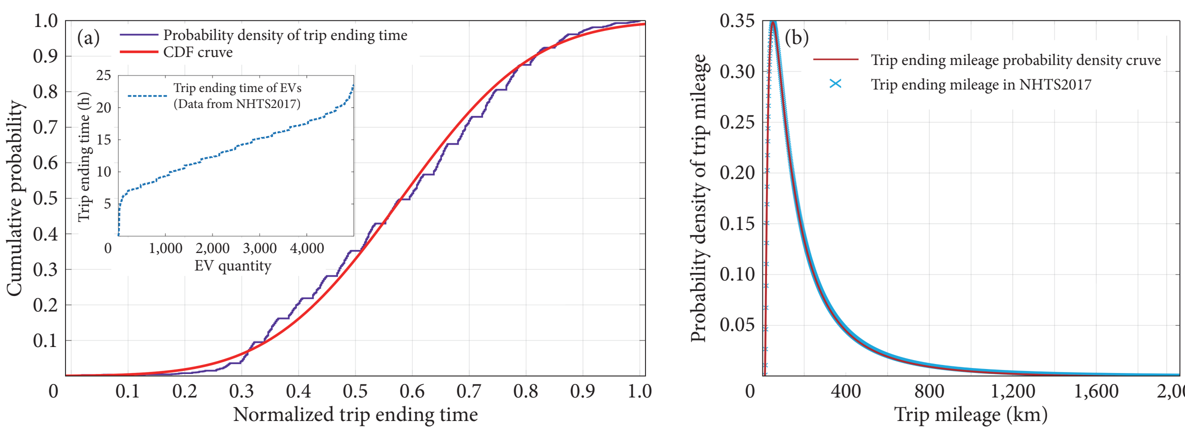

Figure 5 Fitting curves of NHTS2017 data: (**a**) trip ending time, (**b**) trip mileage.

where N_{EV} is the number of EVs entering the i-th node for charging, and $P_i(t)$ is the total EV charging power of the i-th node at time t.

3.2 EV charging decision for service area nodes

Given that charging facilities on expressways are centrally located in service areas and based on the OD-SOC translation model, we can deduce that when vehicles reach service-area nodes, some EV users with lower SOC values may choose to enter the service-area for charging. To characterize more precisely the decision-making behaviors of EV users entering service areas, this study employs an improved Sigmoid function as the decision activation function. This function is used to model EVs entering service areas.

Recognizing the challenge of precisely describing the spatiotemporal distribution characteristics of EV charging decision-making using the Sigmoid function, this study introduces an enhancement to enable the Sigmoid activation function to accurately capture the SOC values of EVs. 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 modeled by the improved Sigmoid function closely adheres to the real-time SOC distribution of traffic flow on an expressway[28]. The enhanced Sigmoid function, which is synthesized by integrating the aforementioned parameters, is expressed by the following equations.

$$\sigma[f(SOC_i^n)] = \frac{1}{1+e^{-f(SOC_i^n)}} \tag{14}$$

$$f(SOC_i^n) = \mu_i - (SOC_i^n)^{\varphi} \tag{15}$$

where $\sigma[f(SOC_i^n)]$ is the improved Sigmoid function, μ_i is the average SOC value of the GMM of traffic flow at the i-th node on the expressway, SOC_i^n is the individual vehicle SOC value of the input decision model in the traffic flow, and 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 decide 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 must divert into the service-area for charging.

4 Case study and analysis of results

4.1 Case description

For the case study, choosing expressways with stable traffic flow and consistent congestion as the data source is recommended. We determined that the traffic flow on the Taohuaping-Dingyuan section from Shaanxi to Gansu is stable, where the congestion values remain relatively fixed, i.e., strictly within the range of 0.25 to 0.3. In addition, the vehicles traversing this section are primarily private cars, aligning with the current types of EVs. Given these conditions, this study used the Taohuaping-Dingyuan section of the Lian-Huo expressway as a case study for in-depth analysis.

For an accurate simulation of real traffic flow, multiple brands of EVs were selected to construct a mixed traffic flow. However, many EV brands exist, and the proportion of EV brands on the EV market is not the same. Therefore, based on market statistical data[29], this study uses the top eight EV brands with a market share of 78.4% to construct a mixed traffic flow. This ensures the reality of traffic flow while avoiding excessive complexity. These brands are BYD Alto 3, BYD Han, BYD Tang, Tesla Model X, Tesla Model Y, Zeeker X, Zeeker 001, and Nissan Arria. Table 1 lists the proportions of vehicle types in the traffic flow, vehicle battery capacities, and battery SOC values. Based on (6), the positional parameters of independent Gaussian distribution μ can be represented by battery capacity parameters. Here, Σ is the dispersion measure parameter, where its value is set as the multiplied value of the minimum SOC and battery capacity to measure the SOC distribution evenly.

In the process of constructing traffic flow, this study first uses the Monte Carlo method to generate an initial SOC sequence. It then mixes the initial SOC values of different vehicles to construct a mixed traffic flow. Finally, it uses the maximum expectation algorithm to fit a GMM. To improve the fitting efficiency of GMMs, this study adopts a fourth-order GMM fitting that balances accuracy and efficiency[30]. The simulation platform is set in MATLAB 2018b, where the final results of the traffic flow GMM are shown in Figure 6.

4.2 Simulation results and discussion

In the simulation, the total number of EVs was set at 200, which was derived from the observation of vehicle data on the Taohuaping-Dingyuan section of the Lian-Huo expressway as provided by the Transportation Department. The Monte Carlo method was employed for a five-iteration experiment. The simulation results yielded spatiotemporal dynamic vehicle flow patterns and line diagrams for each node of the expressway. Figure 7 shows the simulation results.

The temperature map of vehicle flow shown in Figure 7(a) reflects the spatiotemporal distribution characteristics of charging vehicles. When the temperature chart data are analyzed horizontally (i.e., temporal characteristics), the temporal dynamic distribution curves of charging vehicles flowing into each node can be obtained as shown in Figure 7(b). Figure 7(b) reveals that the numbers of vehicles flowing into each node of the expressway on the same day increase over time. The number of charging EVs may decrease over a short-term analysis (15 min), which may be explained by the randomness of EV charging decisions, This phenomenon may therefore be considered a normal fluctuation. If the analytical time scale is placed within the full day, the number of charging EVs increases over time. Compared with the fitting curve obtained from NHTS2017 data, the trend of the two curves is consistent. In addition, through longitudinal analysis (i.e., of the spatial characteristics) of the temperature map shown in Figure 7(a), the spatial dynamic distribution of vehicles flowing into each node at a certain time can be obtained, as shown in Figure 7(c). A comparison of the spatial distribution curve shown in Figure 7(c) with the distribution in (8) shows that the charging decisions of EV users on an expressway clearly have similar distribution char-

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

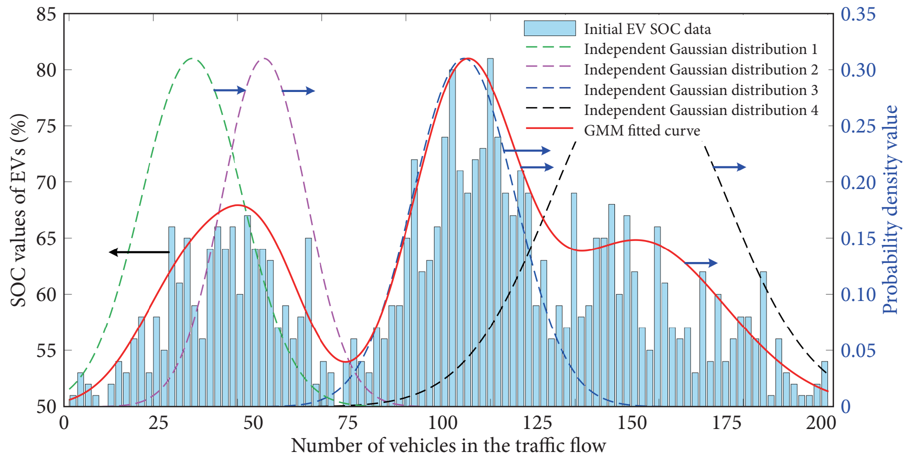

Figure 6 GMM fitting results of traffic flow SOC on the expressway.

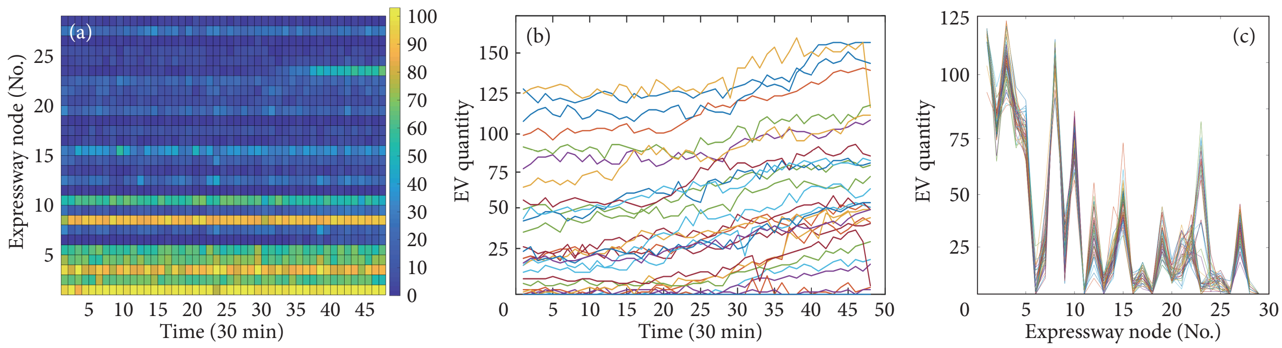

Figure 7 Spatiotemporal distribution of expressway charging loads: (**a**) temperature map of EV charging loads, (**b**) temporal characteristics of EV charging loads, (**c**) spatial characteristics of EV charging loads.

acteristics to the trip mileage described by NHTS2017 historical data. This is mainly due to the fact that the proportion of EVs on expressways is small (e.g., by the end of 2022, all categories of EVs only accounted for 5.7% in China). These results prove that the EV distribution data obtained using the proposed method have certain spatiotemporal distribution characteristics.

Investigation of EV charging behaviors reveals that EV charging methods primarily fall into two charging categories: ordinary and fast. In addition, in accordance with expressway service-area planning guidelines, the current ratio of fast to regular charging base stations is maintained at 1:4. When these charging facility data are leveraged against 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 this curve enables us to generate a comparative chart between the average EV charging load and travel data curve, as shown in Figure 9. This comparison shows that the EV charging load presented in Figure 8 shares the same distribution characteristics as the trip mileage described by (9). This consistency aligns with the distribution pattern observed in NHTS2017 data, further validating the proposed method's ability to capture the spatiotemporal distribution characteristics of EV charging behaviors.

Furthermore, when (1) and (3) are combined, vital EV driving information can be derived, which is presented in Figure 10. Figure 10(a) show the energy consumption per unit km for EVs across varying driving speeds, and Figure 10(b) shows the EV charging probability curve at different nodes. Leveraging historical congestion data from the Lian-Huo expressway enables us to determine the typical EV driving speeds at 60–80 km/h. Notably, energy consumption remains relatively consistent across different expressway sections. The probability curve presented in Figure 10(b) reveals a clear pattern: as energy consumption increases, the likelihood of EVs requiring charging also increases, which is attributed to a rapid decline in EV storage energy levels. Consequently, as vehicles with a low SOC are absorbed at previous nodes, the demand for EV charging diminishes, thereby reducing the charging probabilities at subsequent nodes. By contrast, when energy consumption is low, EVs delay charging, leading to an accumulation of vehicles with low SOCs in the traffic flow and resulting in a rapid increase in EV charging probabilities at subsequent nodes.

This study considers the following extreme charging scenarios for EVs: (1) the minimum charging load scenario, in which EVs exclusively utilize regular charging, and (2) the maximum charging load scenario, in which all EVs exclusively opt for fast charging. Figure 11 shows the simulation analysis results via a charging load curve for expressway EVs under these extreme scenarios.

The simulation results reveal that during the initial hours of each day (0:00–8:00), a relatively low amount of traffic flow enters 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 loads at each node. This upward trend continues from 18:00 to 23:00. The charging loads at each node of the expressway, as obtained through simulation on the same day, demonstrate a consistent upward trend over time. This trend converges with statistical data from NHTS 2017, corroborating the real-time and spatial distribution characteristics of EVs.

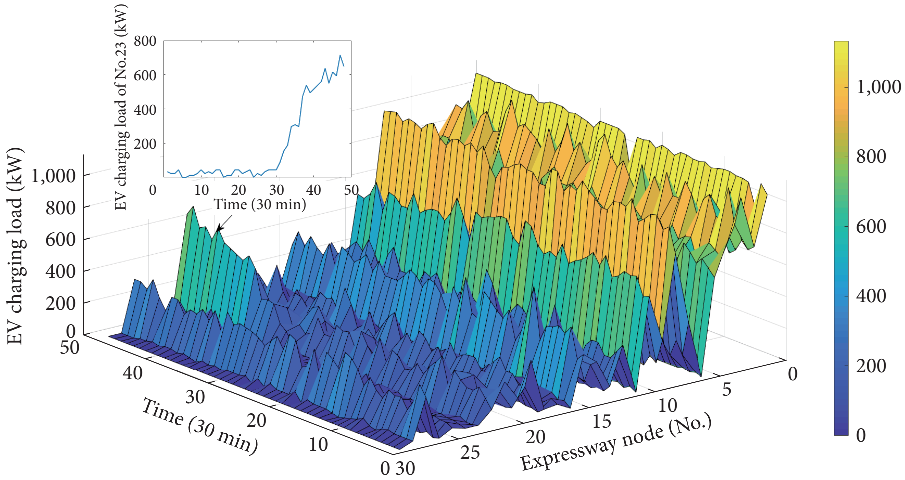

Figure 8 Spatiotemporal distribution of EV average charging load.

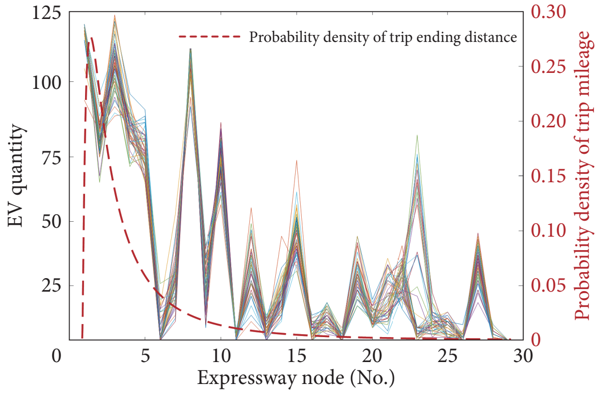

Figure 9 Comparison of the EV charging load curve and trip mileage probability distribution curve.

To validate the effectiveness of the proposed EV charging power prediction method, a comparison is conducted with the Monte Carlo simulation and Latin hypercube sampling methods and the traditional Sigmoid function. The comparison is made against real historical data curves, demonstrating the strong practicality of the proposed method. The comparison curves for the methods and real data are presented in Figure 12.

Because the charging equipment for downtown and county nodes is installed in city centers and requires additional urban modeling for accurate data, this study uses as reference data the comparison of the different node charging power in expressway service areas. Figure 12 shows that the proposed combined prediction method performs exceptionally well with real EV charging data, accurately describing the charging trends. By contrast, the traditional Sigmoid function proves to be overly sensitive to the SOC values of EVs, leading to an overestimation of charging vehicles and inflated load prediction values. However, with the improvements made by the proposed method, the EV charging load values align more closely with the actual data.

In addition, compared with other similar power prediction methods, the proposed method has higher prediction accuracy, and the predicted power curve fits the historical curve more closely, reflecting the psychological characteristics of actual EV charging decisions. In terms of improvement effectiveness, similar methods require historical data training and are based on power prediction methods driven by historical data, whereas the proposed method is constructed based on a probability distribution function, which frees the predicted power from historical data limitations.

The data listed in Table 2 show that, compared with the other methods, the proposed method has clear advantages in terms of data prediction accuracy. In terms of global data prediction, the proposed method can adaptively adjust the prediction mode based on specific spatiotemporal environments and obtain accurate EV charging loads.

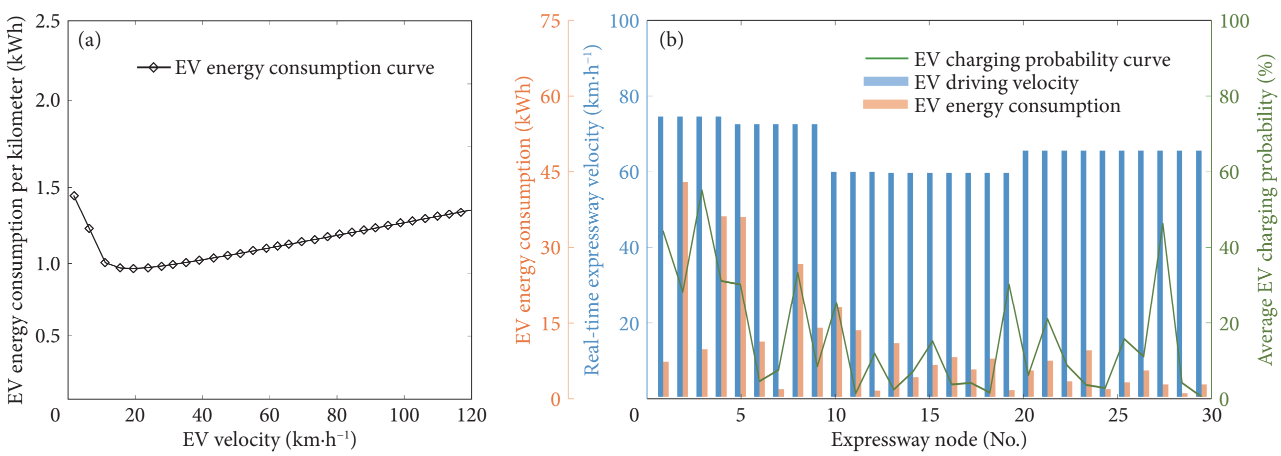

Figure 10 EV driving information: (**a**) EV energy consumption curve for different velocities, (**b**) EV driving data for the different expressway nodes.

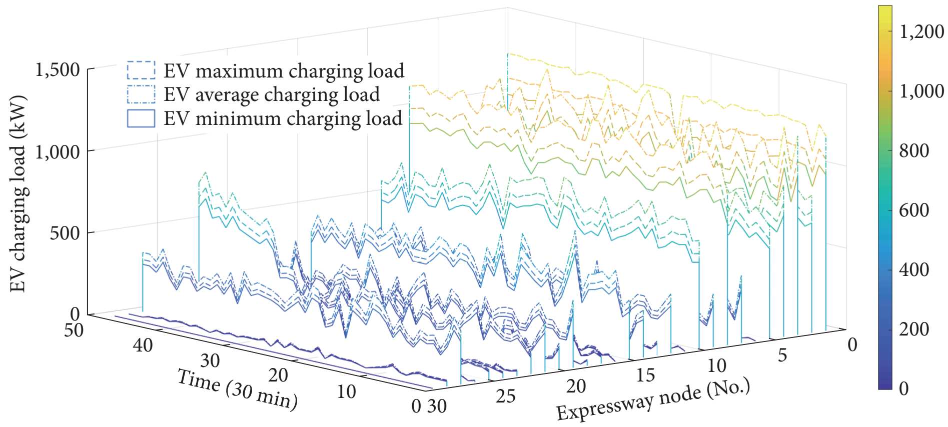

Figure 11 EV charging load at different nodes on the expressway.

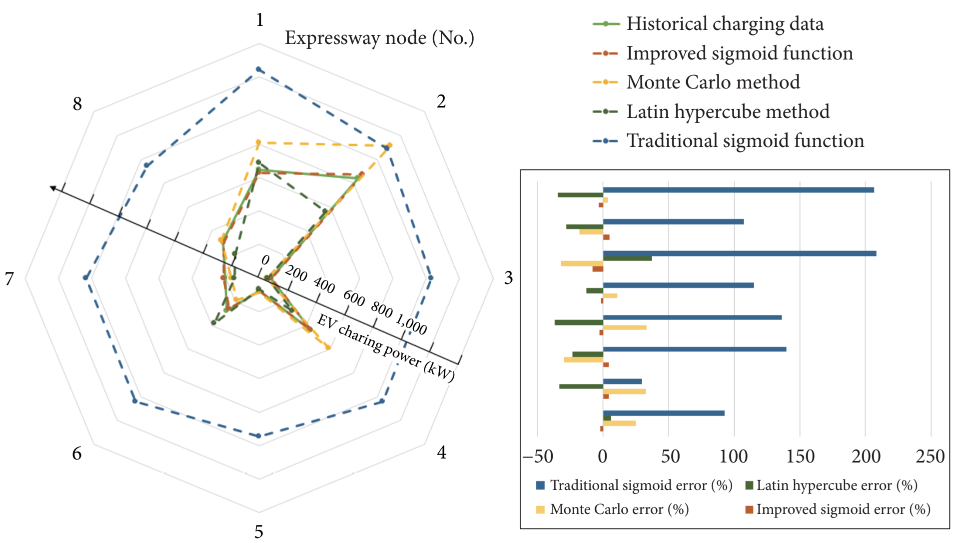

Figure 12 EV charging load prediction results of service-area nodes.

Table 2 Comparison data table of similar methods

Data / Methods	Mean value of charging power (kW)	Predicting average variance (%)	MAE	RMSE
Historical data	357.83	0	0	0
Traditional sigmoid sampling	1047.75	129.43	610.23	684.53
Latin hypercube sampling	296.65	−15.63	47.78	122.68
Monte Carlo method sampling	414.74	3.16	55.45	128.43
Improved sigmoid (proposed method)	384.57	2.09	4.75	21.31

5 Conclusions

This study introduced a combined EV charging load prediction method for expressways that incorporates dynamic SOC and user charging decisions. The effectiveness of the proposed method is validated using real expressway data and public datasets. Conclusions derived from the simulation results are as follows:

(1) Previous studies have analyzed only single EV models, whereas this study used eight EV models to construct a Gaussian mixture model for expressway traffic flow, with the results being closer to real situations.

(2) The study showed that the developed OD-SOC translation model can accurately reflect the changes in the SOC during EV driving in traffic flow. This model not only dynamically characterizes the overall SOC values of EVs on expressways, it also reflects the SOC values of individual EVs, thus facilitating unique analysis of charging decisions for EVs on expressways.

(3) Using improved Lognormal decision and Sigmoid functions, this study conducted differential modeling on the charging decisions of three types of nodes, namely, county, downtown, and service-area nodes. An accurate description of the charging decisions of EV users at different nodes enables EV charging decisions to be more consistent with real-life cases and improves the accuracy of EV charging load prediction results. Comparison data of the Monte Carlo and Latin hypercube sampling methods and traditional Sigmoid functions showed that the proposed prediction method effectively reduces the prediction range, improving the median predicted power. Compared with historical data, the proposed method reduces the mean absolute error (MAE) values between the simulating results and historical data, accurately pre-

dicted EV charging load.

Because the conclusions derived from this study are based on historical data from the Lian-Huo expressway, further in-depth investigations should be conducted to assess the universality of scenarios and periods, ensuring the applicability and generalizability of the findings in diverse contexts and over extended periods.

Acknowledgements

This work was supported by the Unveiling and Leading Projects of Gansu Provincial Department of Transportation (JT-JJ-2023-008).

Article history

Received: 29 January 2024; Revised: 27 May 2024; Accepted: 3 June 2024

Additional information

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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