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A maturity assessment method for vehicle-to-network interaction technology integrating CNN-LSTM and fuzzy comprehensive evaluation

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C H R O N I C L E

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A B S T R A C T

With the rapid development of the new energy vehicle industry, vehicle-to-grid interaction technology, as an important link connecting the power system and the transportation system, its maturity directly affects the construction of the new power system and the process of energy transition. This paper proposes a maturity assessment method for vehicle-to-network interaction technology that integrates CNN-LSTM and fuzzy comprehensive evaluation. Firstly, a comprehensive evaluation index system was constructed from multiple dimensions such as technology, market, and business model, consisting of five levels: the regulatory layer, the system layer, the market layer, the security protection layer, and the common support layer, covering key indicators such as the accuracy rate of charging load prediction and the return on investment ratio. Secondly, in view of the uncertainty and complexity characteristics in the assessment of technology maturity, the CNN-LSTM model in deep learning was combined with the theory of fuzzy mathematics to construct a dual-path assessment framework. Finally, an empirical analysis was constructed based on multi-source datasets to verify the effectiveness of this method, providing a scientific basis for investment decisions and industrialization promotion of vehicle-to-network interaction technology.

1. Introduction

The assessment method of vehicle-to-grid interaction (V2G) technology maturity integrating CNN-LSTM and fuzzy comprehensive evaluation aims to overcome the limitations of traditional assessment methods in processing complex and uncertain data, and provide a scientific basis for the promotion and application of V2G technology in the context of smart grid. Du et al. (2025) indicated that V2G technology, as a key technology for bidirectional energy flow between electric vehicles and the power grid, has demonstrated great potential in enhancing power grid stability, promoting the consumption of renewable energy, and peak shaving and valley filling. However, its large-scale application faces numerous technical, economic, regulatory and social challenges, among which the assessment of technological maturity is an important link to ensure its reliability and sustainable development (Yang, 2024).

It is indicated by İnci et al. (2022) that V2G technology enables electric vehicles to charge during off-peak demand periods of the power grid and feed back the stored electricity to the grid during peak demand periods, thereby achieving two-way interaction in the power system. This technology not only transforms electric vehicles into mobile energy storage units but also enhances the flexibility and resilience of the power grid by providing auxiliary services. Xu (2025) indicates that the key technologies of the V2G system include bidirectional charging, intelligent charging algorithms, and the development of efficient converters. In recent years, with the rapid growth of the number of electric vehicles in use and the scale of renewable energy grid connection, the research and development of V2G technology have received extensive attention (Altin & Sarp, 2020). The development of V2G technology involves multiple aspects: At the technical level, Li et al. (2024) indicate that the standardization of communication protocols, security standards, charging interface specifications, and data interaction formats is the key to the large-scale application of V2G technology. Meanwhile, Zhou et al. (2024) points out that network security in V2G systems is also receiving increasing attention, and it is necessary to prevent security risks in information transmission

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and network boundaries. From an economic perspective: Rehman et al. (2026) indicated that V2G technology can reduce energy costs, increase load rates, and promote the integration of renewable energy. At the environmental level, Li (2025) pointed out in its review that by integrating electric vehicles, V2G technology can help achieve the decarbonization of transportation and energy systems, significantly reducing carbon emissions.

Convolutional neural networks (CNNS) and long short-term memory networks (LSTMS) have demonstrated outstanding performance in processing time series data and extracting complex features, and thus have been widely applied in the fields of smart grids and V2G (Elnady & Ozana, 2025). CNN has advantages in feature extraction and can automatically learn local and abstract features from raw data. For example, Bharathi et al. (2024) pointed out that in energy prediction, CNN can effectively capture the temporal and spatial correlations of power load or renewable energy generation. As a variant of recurrent neural networks (RNNS), LSTM excels at processing and predicting time series data, can learn long-term dependencies, and effectively resolves the vanishing or exploding gradient problems in traditional RNNS. Combining CNN with LSTM, namely the CNN-LSTM model, can fully leverage the advantages of both. CNN is responsible for extracting spatial features from the input data, while LSTM handles the time series dependencies of these features, thereby achieving higher prediction accuracy and efficiency in complex dynamic systems. For instance, in the planning of power systems and the optimization of operation strategies, Wu et al. (2023) applied the CNN-LSTM model to assess the development status of the power grid, analyze the economy of the power grid, and predict carbon emissions. Wang et al. (2024a) indicated that when conducting quantitative risk assessment of reservoir landslides, the hybrid CNN-LSTM model can effectively predict the landslide risk value. Meanwhile, deep learning is also applied to the safety status assessment of electric vehicles. For instance, Gao et al. (2022) combined fuzzy neural networks to evaluate the integrated safety status of electric vehicle charging. In the evaluation of Internet vehicles, Li et al. (2020) conducted an overall assessment of the vehicle through LDA topic modeling, LSTM analysis of emotional tendencies, and combined with DCGAN and CNN for anomaly detection.

Fuzzy comprehensive evaluation is a decision analysis method based on fuzzy mathematics, which can effectively handle evaluation problems with fuzziness and uncertainty. This method achieves a comprehensive evaluation result by establishing an evaluation index system, determining index weights, constructing a fuzzy relation matrix and conducting fuzzy operations (Chi et al., 2025). In the field of smart grids, fuzzy comprehensive evaluation has been employed to assess the maturity of smart grids, to determine their development stage, identify weak links and limiting factors, and plan future development paths. In terms of the optimization of the data transmission mechanism in the Internet of Vehicles, Zhang et al. (2022) proposed that a method based on fuzzy comprehensive evaluation can achieve the optimal design of the data transmission mechanism to address the transient and intermittent connection issues of the communication link. In the assessment of the competitiveness of the intelligent connected vehicle (ICV) industry, fuzzy comprehensive evaluation system by Wang et al. (2024b), which combines rough set theory and projection tracing, was applied to scientifically analyze the advantages and disadvantages of the ICV industry development in different cities and clarify the development status of each link. In the application effect evaluation of connected vehicle systems in tunnel scenarios, Wang et al. (2022) proposed a fuzzy comprehensive evaluation model based on binary language models and grey target decision-making methods to handle multi-source heterogeneous data and avoid information distortion or loss. For the V2G system, Sah et al. (2021) intelligent controllers that combine fuzzy logic and artificial neural networks can be used to meet the demands of the power grid and alleviate the impact of electric vehicle charging on the power grid.

Integrating the CNN-LSTM model with the fuzzy comprehensive evaluation method can provide a more comprehensive and accurate solution for the assessment of V2G technology maturity (Shang et al., 2020). Therefore, this paper proposes a maturity assessment method for vehicle-to-network interaction technology that integrates CNN-LSTM and fuzzy comprehensive evaluation. The main innovation points lie in: constructing a multi-dimensional comprehensive evaluation index system for the application of vehicle-to-network interaction technology; A hybrid evaluation model integrating CNN-LSTM and fuzzy comprehensive evaluation was proposed; Incorporate economic indicators such as the return on investment ratio into the technology maturity assessment system; By constructing virtual evaluation objects (VEOs) through public datasets to simulate different development scenarios, the repeatability, verifiability and universality of the method have been enhanced.

2. Construction of The Assessment Index System for The Maturity of Vehicle-to-Network Interaction Technology

2.1 Determination of Evaluation Dimensions

The assessment of the maturity of vehicle-to-network interaction technology is a multi-dimensional comprehensive evaluation issue, which requires a thorough consideration from multiple perspectives such as technology, market, policy, and business model. Based on the theory of technology-economic-social systems, this paper determines the following five evaluation dimensions.

(1) Technical feasibility dimension: Assess the maturity, reliability and advancement of the vehicle-to-network interaction technology itself.

(2) Economic rationality dimension: Evaluate the economic benefits of technology promotion and the return on investment ratio.

(3) Market adaptability dimension: Assess the degree of match between technology and market demand.

(4) Policy support dimension: Assess the extent to which the policy environment supports technological development.

(5) Social acceptance dimension: Assess the public's awareness and acceptance of technology.

2.2 Design of Comprehensive Evaluation Index System

Based on the above evaluation dimensions and in combination with the characteristics of vehicle-to-network interaction technology, a comprehensive evaluation index system consisting of 5 first-level indicators and 15 second-level indicators was constructed, as shown in Table 1.

Table 1
Evaluation Index System for the Maturity of Vehicle-to-Grid Interaction Technology

First-level indicator	Secondary indicators	Indicator description	Calculation method (quantitative analysis / qualitative analysis)
Regulatory layer	The accuracy rate of charging load prediction	Predict the matching degree between the charging load and the actual load	Quantitative analysis, Formula: $P_{load}=1-MAPE=1-\frac{1}{n}\sum_{i=1}^{n}\left\|\frac{\hat{y}_i-y_i}{y_i}\right\|\times100\%$. $\hat{y}_i$ represents the predicted load value; y_i represents the actual load value; n represents the sample size.
	The adjustment capacity predicts the deviation rate	The deviation between the predicted regulatory capacity and the actual regulatory capacity	Quantitative analysis, Formula: $P_{reg}=\frac{1}{n}\sum_{i=1}^{n}\left\|\frac{\hat{C}_i-C_i}{C_i}\right\|\times100\%$. $\hat{C}_i$ represents the predicted regulatory capacity; C_i represents the actual regulatory capacity; n represents the sample size.
	User charge and discharge response rate	The proportion of users responding to charge and discharge instructions	Quantitative analysis, Formula: $P_{resp}=\frac{N_{resp}}{N_{total}}\times100\%$. N_{resp} represents the number of users responding to the instruction; N_{total} represents the total number of users.
System layer	The compliance rate of equipment compatibility	The degree of compatibility among devices from different manufacturers	Quantitative analysis, Formula: $P_{comp}=\frac{N_{comp}}{N_{total}}\times100\%$. N_{comp} represents the number of compatible devices; N_{total} represents the total number of test devices.
	Energy conversion efficiency	The energy conversion efficiency during the charging and discharging process	Quantitative analysis, Formula: $\eta=\frac{E_{out}}{E_{in}}\times100\%$. E_{out} represents the output electrical energy; E_{in} represents the input electrical energy.
	The accuracy rate of multi-device collaborative response	The accuracy of multi-device collaborative control	Quantitative analysis, Formula: $P_{coop}=\frac{N_{corr}}{N_{total}}\times100\%$. N_{corr} represents the output electrical energy; N_{total} represents the input electrical energy.
Market layer	Market participation in ancillary services	The extent of participation in auxiliary services of the power grid	Qualitative analysis, based on the proportion of the contracted capacity in the PJM frequency modulation market to the total demand, it is classified as follows: $\geq 80\%$ is 5 points, $60\%-79\%$ is points, $40\%-50\%$ is 3 points, $20\%-39\%$ is 2 points, $<20\%$ is 1 point.
	Participation in the electric energy market	The extent of participation in electrical energy trading	Qualitative analysis, based on the proportion of electricity trading volume in total charging and discharging volume, it is classified as follows: $\geq 70\%$ is 5 points, $50\%-69\%$ is 4 points, $30\%-49\%$ is 3 points, $10\%-29\%$ is 2 points, $<10\%$ is 1 point.
	Return on investment ratio	The economic rate of return on technology investment	Quantitative analysis, Formula: $ROI=\frac{R-I}{I}\times100\%$. R represents the number of failures; I represents the total operating duration.
Safety protection layer	Equipment operation failure rate	The frequency of faults occurring during the operation of the equipment	Quantitative analysis, Formula: $P_{fail}=\frac{N_{fail}}{T_{total}}\times100\%$. N_{fail} represents the number of failures; N_{total} represents the total operating duration.
	Grid connection harmonic distortion rate	The degree of harmonic distortion of grid-connected current	Quantitative analysis, Formula: $THD_i=\frac{\sqrt{\sum_{h=2}^{\infty}I_h^2}}{I_1}\times100\%.$. I_h represents the effective value of the h -th harmonic current; I_1 represents the effective value of the fundamental current.
	Charging failure rate	The frequency of faults occurring during the charging process	Quantitative analysis, Formula: $P_{char-fail}=\frac{N_{char-fail}}{N_{char-total}}\times100\%$. $N_{char-fail}$ represents the number of charging failures; $N_{char-total}$ represents the total number of charging attempts.
Common support layer First-level indicator Regulatory layer	Measure the accuracy of data	The accuracy of the measurement data	Quantitative analysis, Formula: $P_{data}=\frac{N_{acc}}{N_{total}}\times100\%$. N_{acc} represents the number of accurate data entries; N_{total} represents the total number of data entries.
	Measure the response speed	The response speed of data acquisition and transmission	Quantitative analysis, directly obtain the time value collected and transmitted by the equipment, with the unit being milliseconds.
	The compatibility of new technology standards	The degree to which technology ADAPTS to emerging standards	Qualitative analysis, based on the proportion of matching items between technical parameters and emerging standards, $\geq 90\%$ is given 5 points, $70\%-89\%$ is 4 points, $50\%-69\%$ is 3 points, $30\%-49\%$ is 2 points, and $<30\%$ is 1 point.

2.3 Method for Determining Index Weights

In a multi-level indicator system, the contribution of each indicator to the maturity of technology varies, so it is necessary to scientifically determine their weights. To balance expert experience and data objectivity, this paper adopts a combined weighting method, integrating subjective weighting with objective weighting (Xi et al., 2022).

2.3.1 Subjective Empowerment: Analytic Hierarchy Process (AHP)

AHP converts the qualitative judgments of experts into quantitative weights by constructing a judgment matrix. Invite m experts to conduct pairwise comparisons of indicators at the same level based on the 1-9 scale method, and form the judgment matrix $A=\left(a_{ij}\right)_{n\times n}$. Here, a_{ij} represents the significance of indicator i relative to indicator j. By using the eigenroot method, the maximum eigenvalue $\lambda_{\max}$ of the judgment matrix A and its corresponding eigenvector $W'=\left(w_1^{'},w_2^{'},...,w_n^{'}\right)$ are solved.The eigenvectors are normalized to obtain the subjective weight vector, as shown in Eq. (1).

$$w_i^{(l)}=\frac{w_i^{'}}{\sum_{j=1}^{n}w_j^{'}},i=1,2,...,n$$
$$W^{(l)}=\left(w_1^{(l)},w_2^{(l)},...,w_n^{(l)}\right)^T \tag{1}$$

To ensure the logical consistency of expert judgments, consistency tests need to be conducted, as shown in Eq. (2).

$$CI=\frac{\lambda_{\max}-n}{n-1},CR=\frac{CI}{RI} \tag{2}$$

Among them, CI represents the consistency index, and RI represents the average random consistency index.When $CR<0.1$, it is considered that the consistency of the judgment matrix is acceptable.

2.3.2 Objective Weighting: Entropy Weighting Method

The entropy weight method determines the weight based on the degree of dispersion of the information provided by the observed values of each index. The greater the degree of data dispersion and the larger the amount of information, the higher the weight.

There are m evaluation objects and n indicators, which form the original data matrix $X=\left(x_{ij}\right)_{m\times n}$. To eliminate the influence of dimensions, standardization processing is carried out: for positive indicators: $r_{ij}=\frac{x_{ij}-\min\left(x_j\right)}{\max\left(x_j\right)-\min\left(x_j\right)}$; For negative indicators: $r_{ij}=\frac{\max\left(x_j\right)-x_{ij}}{\max\left(x_j\right)-\min\left(x_j\right)}$.

Calculate the information entropy value e_j of the JTH indicator, that is $p_{ij}=\frac{r_{ij}}{\sum_{i=1}^{m}r_{ij}},e_j=-\frac{1}{\ln m}\sum_{i=1}^{m}p_{ij}\ln p_{ij},\left(0\le e_j\le 1\right)$. When $p_{ij}=0$ is stipulated, $p_{ij}\ln p_{ij}=0$. Calculate the difference coefficient $d_j=1-e_j$ of the JTH indicator, then its objective weight is shown in Formula (3).

$$w_j^{(2)}=\frac{d_j}{\sum_{j=1}^{n}d_j},j=1,2,..,n$$
$$w^{(2)}=\left(w_1^{(2)},w_2^{(2)},...,w_n^{(2)}\right)^T \tag{3}$$

2.3.3 Combined Weighting

To integrate subjective and objective information, the weights obtained above are linearly combined to obtain the final combined weights, as shown in Formula (4).

$$w_j = \alpha \cdot w_j^{(1)} + (1-\alpha) \cdot w_j^{(2)}, j = 1,2,...,n \tag{4}$$
$$W = (w_1, w_2,..., w_n)^T$$

Among them, $\alpha(0 \le \alpha \le 1)$ is the balance coefficient, reflecting the degree of preference for subjective weights and objective weights, which can be determined through optimization methods or based on the experience of decision-makers. The final calculated combined weight W will be used for the subsequent comprehensive evaluation calculation.
The process diagram for determining the index weights is shown in Fig. 1.

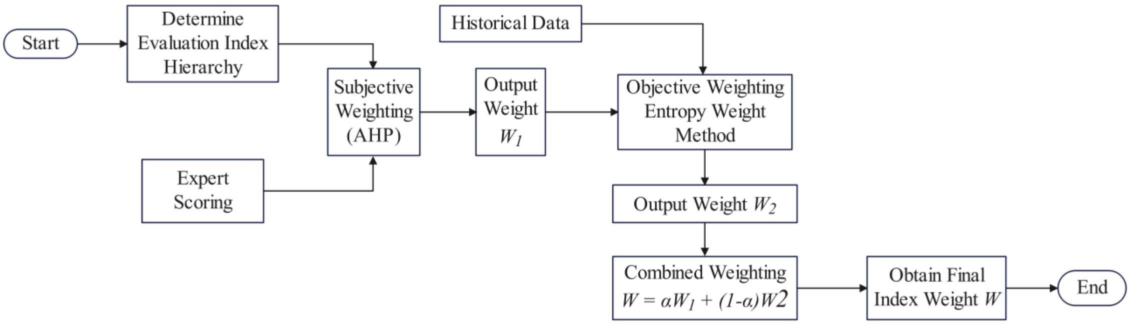


Fig. 1. Schematic diagram of the process for determining the weights of indicators

3. Design of an Evaluation Method Integrating CNN-LSTM and Fuzzy Comprehensive Evaluation

3.1 Overall framework of the Evaluation Method

The assessment of the maturity of vehicle-to-network interaction technology involves a multi-dimensional and multi-level indicator system, and there are complex nonlinear relationships and temporal dynamic characteristics among the various indicators. Traditional assessment methods have limitations when dealing with such problems. Therefore, this paper proposes a hybrid intelligent evaluation framework that integrates CNN-LSTM and fuzzy comprehensive evaluation. The overall architecture is shown in Fig.2.

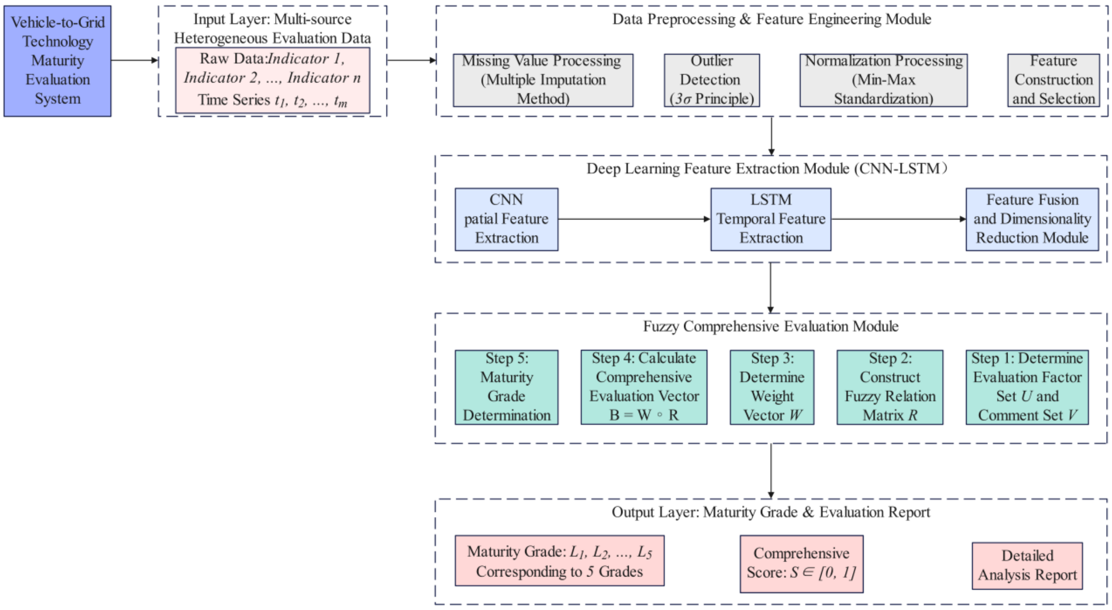


Fig. 2. Overall framework of the fusion evaluation method

The core idea of this framework is as follows: Firstly, the CNN-LSTM deep learning model is utilized to automatically extract high-level and abstract feature representations from the original evaluation data, capturing the spatial correlation and temporal dependence among indicators; Then, the extracted features are input into the fuzzy comprehensive evaluation model. The uncertainty and subjectivity in the evaluation process are handled by using the theory of fuzzy mathematics, and finally a scientific and objective maturity assessment result is obtained. To address the issue of the separation between quantitative and qualitative indicators in the algorithm processing, a branch for differentiated processing of indicator types is added in the data preprocessing and feature engineering module: quantitative indicators are normalized using Min-Max method combined with outlier correction; qualitative indicators are encoded in an ordered manner combined with expert scoring mapping, converting qualitative grades into numerical values within the range of [0,1]. The two types of processed indicators are uniformly input into the CNN-LSTM model for feature extraction, ensuring the tight coupling between the algorithm and the indicator system.

3.2 CNN-LSTM Model Design

3.2.1 Convolutional Neural Network Design

Convolutional neural networks can effectively extract the spatial local features and hierarchical features of the input data through local connection, weight sharing and pooling operations. In view of the characteristics of the evaluation index data of vehicle-network interaction, this paper designs a three-layer CNN structure.

The input data is a preprocessed time series matrix of evaluation indicators. Let the number of evaluation objects be N, the number of evaluation indicators be M, and the time step be T. Then the input data can be expressed as a three-dimensional tensor, that is, $X \in \mathrm{R}^{N\times T\times M}$, where the dimension of each sample is T×M, representing the M indicator values of the evaluation object at T time points.

Three convolutional layers are adopted to gradually extract spatial features from the lower level to the higher level. The first convolutional layer extracts the basic spatial features, namely $C_1 = \mathrm{ReLU}\left(BatchNorm\left(W_1 \times X + b_1\right)\right)$, where $W_1 \in \mathrm{R}^{f_1\times 1\times M\times d_1}$ is the weight of the convolutional kernel; f_1 is the size of the convolution kernel (time dimension); $d_1 = 64$ represents the number of output channels; $*$ stands for convolution operation; b_1 is the bias term; $BatchNorm$ represents batch normalization operation; ReLU is the activation function $\mathrm{ReLU}(x) = \max(0, x)$; The second convolutional layer extracts the middle spatial features, namely $C_2 = \mathrm{ReLU}(BatchNorm(W_2 * C_1 + b_2))$, where $W_2 \in \mathrm{R}^{f_2\times 1\times d_1\times d_2}$ and $d_2 = 128$;The third convolutional layer extracts high-level abstract features, namely $C_3 = \mathrm{ReLU}(BatchNorm(W_3 * C_2 + b_3))$, where $W_3 \in \mathrm{R}^{f_3\times 1\times d_2\times d_3}$ and $d_3 = 256$.
Each convolutional layer is followed by a Max pooling layer to reduce the feature dimension and enhance feature invariance, that is, $P_i = MaxPool(C_i, pool\_size = p_i, strides = s_i)$, where $i = 1,2,3$, the size of the pooling window p_i, and the step size s_i are adjusted according to the input dimension. Flatten the pooled features and integrate them through the fully connected layer, that is, $F_{cnn} = ReLU(W_f \cdot Flatten(P_3) + b_f)$,where W_f is the weight matrix. $F_{cnn} \in R^{d_f}$ is the final feature vector extracted by CNN, $d_f = 128$.

3.2.2 LSTM Network Design

Long Short-Term memory networks capture long-term dependencies in time series through gating mechanisms and are suitable for processing evaluation data with temporal characteristics. Each LSTM unit contains three gated structures: input gate i_t, forgetting gate f_t and output gate σ_t, as well as cell state c_t and hidden state h_t, which are calculated as shown in Formula (5).

$$
\begin{aligned}
& f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \text{ (Oblivion Gate)} \\
& i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \\
& \widetilde{c}_t = \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right) \text{ (Input Gate)} \\
& c_t = f_t \square\, c_{t-1} + i_t \square\, \widetilde{c}_t \text{ (Cell Status update)} \\
& \sigma_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \text{ (Output Gate)} \\
& h_t = o_t \square \tanh(c_t) \text{ (Hidden state output)}
\end{aligned} \tag{5}
$$

Among them, σ is the sigmoid activation function $\sigma(x) = \dfrac{1}{1+e^{-x}}$; $\tanh$ is a hyperbolic tangent function $\tanh(x) = \dfrac{e^x - e^{-x}}{e^x + e^{-x}}$; □ epresents element-by-element multiplication; x_t is the input of time t ; W_*, b_* is a trainable parameter.
To better capture the sequential information before and after, a bidirectional LSTM structure is adopted, as shown in Eq. (6).

$$\begin{aligned} \vec{h}_t &= LSTM\left(x_t, \vec{h}_{t-1}\right) \\ \vec{h}_t &= LSTM\left(x_t, \vec{h}_{t+1}\right) \\ h_t &= \left[\vec{h}_t ; \vec{h}_t\right] \end{aligned} \tag{6}$$

Enhance the model's expressive power by using a two-layer stacked LSTM. The first layer LSTM has 128 memory units and returns the complete sequence. The second layer LSTM has 64 memory units and returns the output of the last time step. The hidden state of the last time step of LSTM is taken as the timing feature, as shown in Formula (7).

$$F_{lstm} = h_T^{(2)} \tag{7}$$

Among them, $h_T^{(2)}$ is the hidden state of the second-layer LSTM at the last time step, where $F_{lstm} \in \mathrm{R}^{d_l}$ and $d_l = 64$.

3.2.3 Feature Fusion Mechanism

To effectively integrate the spatial features extracted by CNN and the temporal features extracted by LSTM, a feature fusion module based on the attention mechanism was designed (Ran et al., 2025).
Concatenate the CNN features and LSTM features, that is, $F_{concat} = \left[F_{cnn} ; F_{lstm}\right] \in \mathrm{R}^{d_f + d_l}$, and use the attention mechanism to assign weights to different features, as shown in Formula (8).

$$\begin{aligned} e_i &= v^T \tanh\left(W_a F_{concat} + b_a\right) \\ \alpha_i &= \frac{\exp\left(e_i\right)}{\sum_{j=1}^{d_f} \exp\left(e_j\right)} \end{aligned} \tag{8}$$

Among them, $W_a \in \mathrm{R}^{d_a \times \left(d_f + d_l\right)}, v \in \mathrm{R}^{d_a}, b_a \in \mathrm{R}^{d_a}$ is a trainable parameter and $d_a = 32$ is the attention dimension.

The weighted feature, namely $F_{fusion} = \sum_{i=1}^{d_f + d_t} \alpha_i \cdot F_{concat,i}$, is obtained by applying the attention weight, and the fused feature is mapped to the low-dimensional space, namely $F = \mathrm{Re}\,LU\left(W_d \cdot F_{fusion} + b_d\right)$, through the fully connected layer, where $W_d \in \mathrm{R}^{d_o \times \left(d_f + d_l\right)}, b_d \in \mathrm{R}^{d_o}, d_o = 32$ is the final feature dimension.

3.3 Fuzzy Comprehensive Evaluation Model

3.3.1 Fuzzy Sets and Membership Functions

Based on the above-mentioned constructed index system, the evaluation factor set $U = \left\{u_1, u_2, ..., u_{15}\right\}$ is determined, among which u_i corresponds to 15 secondary assessment indicators. The maturity of vehicle-to-network interaction technology is classified into five levels, namely $V = \left\{v_1, v_2, v_3, v_4, v_5\right\}$. The score intervals and descriptions corresponding to each level are shown in Table 2.

Table 2
Classification of Maturity Levels of Vehicle-to-Network Interaction Technology

Grade	Score range	Description
Initial level (v_1)	[0, 0.4)	The technology is at the stage of proof-of-concept or laboratory research and has not yet formed a complete technical solution
Growth Level (v_2)	[0.4, 0.6)	The principle prototype of the technology has been developed and small-scale pilot applications have begun
Specification level (v_3)	[0.6, 0.75)	The technology has formed standardized solutions and achieved large-scale demonstration applications
Optimization level (v_4)	[0.75, 0.9)	The technical performance is stable, the cost is controllable, and it has the conditions for commercial promotion
Leading level (v_5)	[0.9, 1.0]	The technology has reached the international advanced level, and a complete industrial ecosystem has been formed

For quantitative indicators, trapezoidal membership functions are adopted; For qualitative indicators, trigonometric membership functions are adopted.

For the JTH comment grade v_j, the trapezoidal membership function of its quantitative indicators is shown in Formula (9).

$$\mu_{ij}(x)=\begin{cases}0, x \le a_{j1} \\ \dfrac{x-a_{j1}}{a_{j2}-a_{j1}}, a_{j1} < x < a_{j2} \\ 1, a_{j2} < x < a_{j3} \\ \dfrac{a_{j4}-x}{a_{j4}-a_{j3}}, a_{j3} < x < a_{j4} \\ 0, x \ge a_{j4}\end{cases} \tag{9}$$

Among them, $a_{j1}, a_{j2}, a_{j3}, a_{j4}$ are the parameters of the trapezoidal function, which are determined by the reasonable value range of the quantitative indicators in Table 1 and the maturity level intervals in Table 2.

The triangular membership function of the qualitative indicators is shown in Formula (10).

$$\mu_{ij}(x)=\begin{cases}0, x \le a_{j1} \\ \dfrac{x-a_{j1}}{a_{j2}-a_{j1}}, a_{j1} < x < a_{j2} \\ \dfrac{a_{j3}-x}{a_{j3}-a_{j2}}, a_{j2} < x < a_{j3} \\ 0, x \ge a_{j3}\end{cases} \tag{10}$$

Among them, a_{j1}, a_{j2}, a_{j3} represents the parameter of the trigonometric function, which is determined by the grading score intervals of the qualitative indicators as shown in Table 1.

3.3.2 Fuzzy Comprehensive Evaluation Process

For each evaluation object, calculate the membership degree of each indicator to each comment level to form a fuzzy relationship matrix, as shown in Formula (11).

$$R=\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \tag{11}$$

Here, $r_{ij} = \mu_{ij}(x_i)$ represents the membership degree of the i-th indicator to the j-th comment grade, $n = 15$ is the number of indicators, and $m = 5$ is the number of comment grades.

The index weights determined by the above-mentioned combined weighting method are $W = (w_1, w_2, ..., w_n), \sum_{i=1}^{n} w_i = 1$;

The weighted average type synthesis operator is adopted, which takes into account the influence of all factors while retaining the single-factor evaluation information, that is, $B = W \circ R = (b_1, b_2, ..., b_m)$, where $b_j = \min\left(1, \sum_{i=1}^{n} w_i \cdot r_{ij}\right), j = 1,2,...,m$; The final maturity level, namely $L = vk$, where $k = \arg\max_j \{b_j\}$ is determined by the principle of maximum membership degree. To obtain a more accurate assessment result, a comprehensive score, namely $S=\sum_{j=1}^{m} b_j^{'} \cdot s_j$, can be calculated, where $b_j^{'}=\frac{b_j}{\sum_{j=1}^{m} b_j}$ is the normalized membership degree and s_j is the representative score of the JTH grade (Pu, 2014).

3.4 Fusion Evaluation Algorithm Process

Algorithm: A vehicle-to-network interaction technology maturity assessment algorithm integrating CNN-LSTM and fuzzy comprehensive evaluation.

```
Input:
Evaluation data: X = {x₁, x₂,... x_N}, where x_i ∈ youdaoplaceholder5 ^{T×M}, where N is the number of samples
Time step: T
Indicator number: M
Training set ratio: train_ratio
Fuzzy evaluation parameters: membership function parameters, weight vector W
Output:
Maturity level: L = {L₁, L₂,... , L_N}
Comprehensive score: S = {S₁, S₂,... , S_N}
Evaluation Report
Steps:
// Phase One: Data Preprocessing
for i = 1 to N do
Handle the missing values of x_i (multiple interpolation method)
Outlier detection and handling of x_i (3σ principle)
// Differentiation in handling of indicator types
    for j = 1 to M do
        if indicator j is a quantitative indicator then
              x_ij' = (x_ij - min(x_j))/(max(x_j) - min(x_j))  // Min-Max Normalization
        else
              x_ij' = (score_ij - min_score_j)/(max_score_j - min_score_j)  // Qualitative scoring mapping
        end if
     end for
end for
Divide the dataset into a training set, a validation set and a test set: D_train, D_val, D_test
// Phase Two: CNN-LSTM Model Training and Feature Extraction
Initialize the parameter θ of the CNN-LSTM model
for epoch = 1 to max_epoch do
    for batch in D_train do
// Forward propagation
F_cnn = CNN_Forward(batch)      // Extract spatial features
F_lstm = LSTM_Forward(batch)    // Extract temporal features
F_fusion = Attention_Fusion(F_cnn, F_lstm) // Feature fusion
Calculate the loss
loss = α·MSE(F_fusion, y_true) + β·CrossEntropy(F_fusion, y_true)
// Backpropagation
∇θ = Backpropagation(loss)
// Parameter update
θ = θ - η·∇θ  // η represents the learning rate
end for
// Validation set evaluation
   if epoch % eval_freq == 0 then
      val_loss = Evaluate(D_val, θ)
           if val_loss < best_val_loss then
              best_val_loss = val_loss
              Save_Model(θ)
           end if
    end if
end for
Phase Three: Fuzzy Comprehensive Evaluation
for i = 1 to N do
// Extract features using the trained CNN-LSTM model
      F_i = CNN_LSTM_Feature_Extraction(x_i')
// Calculate the membership degree of each index to the comment grade based on the features
          for j = 1 to M do
                for k = 1 to 5 do  // 5 comment levels
                      r_jk = μ_k(F_i[j])  // Calculate the membership degree
                end for
          end for
// Construct the fuzzy relation matrix R_i
R_i = [r_jk]_{M×5}
// Fuzzy Comprehensive evaluation
B_i = W ∘ R_i  // W is the index weight vector
// Maturity level determination
L_i = argmax(B_i)
// Calculate the comprehensive score
S_i = Σ_{k=1}^5 (b_ik' · s_k)  // b_ik' is the normalized membership degree, s_k is the grade score
end for
Phase Four: Result Output and Analysis
Generate a maturity assessment report
Visualization assessment results (radar charts, bar charts, heat maps, etc.)
Provide suggestions for technological development
return L, S, evaluation report
```

3.5 Model Optimization and Training Strategies

A multi-task learning strategy is adopted, combining regression loss and classification loss, as shown in Formula (12).

$$L = \alpha \cdot L_{MSE} + \beta \cdot L_{CE} + \lambda \cdot L_{reg} \tag{12}$$

Among them, $L_{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2$ is the mean square error loss, which is used for the regression task; $L_{CE} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\log\left(\hat{y}_{i,c}\right)$ represents the cross-entropy loss, which is used for classification tasks; $L_{reg} = \frac{1}{2}\left\|\theta\right\|_2^2$ is the L2 regularization term to prevent overfitting. α, β, λ is a hyperparameter that controls the significance of each loss (Mchara et al., 2025).

The AdamW optimizer is adopted, combining the adaptive learning rate and weight attenuation of the Adam optimizer, as shown in Formula (13).

$$\theta_{t+1} = \theta_t - \eta_t \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \varepsilon} - \eta_t \cdot \lambda \cdot \theta_t \tag{13}$$

Among them, $\hat{m}_t$ and $\hat{v}_t$ are the first-order and second-order moment estimates after deviation correction; η_t represents the learning rate; λ is the weight attenuation coefficient; ε is a small constant to prevent division by zero.

The cosine annealing learning rate scheduling strategy is adopted, as shown in Formula (14).

$$\eta_t = \eta_{\min} + \frac{1}{2}\left(\eta_{\max} - \eta_{\min}\right)\left(1 + \cos\left(\frac{T_{cur}}{T_{\max}}\pi\right)\right) \tag{14}$$

Among them, $\eta_{\max} = 0.001$, $\eta_{\min} = 0.00001$; T_{cur} represents the current number of training steps; $T_{\max}$ represents the total number of training steps

The regularization strategy is as follows: (1) Add a Dropout layer before the fully connected layer, and set the dropout rate to 0.3; (2) When the validation set loss does not decrease for 10 consecutive epochs, stop the training. (3) Add a batch normalization layer after each convolutional layer.

The Bayesian optimization method is adopted for hyperparameter tuning. The search space includes: (1) Learning rate: $\left[10^{-5}, 10^{-2}\right]$; (2) Batch size: {16,32,64,128}; (3) Number of CNN layers: {2,3,4}; (4) LSTM layer number: {1,2,3}; (5) Hidden layer dimension: {32,64,128,256}

To improve the stability and robustness of the evaluation results, a model integration strategy is adopted: five CNN-LSTM models with different initializations are trained, the output features of the five models are averaged, and the average features are input into the fuzzy comprehensive evaluation model (Deepu & Shetty, 2025).

The training process is shown in Fig. 3.

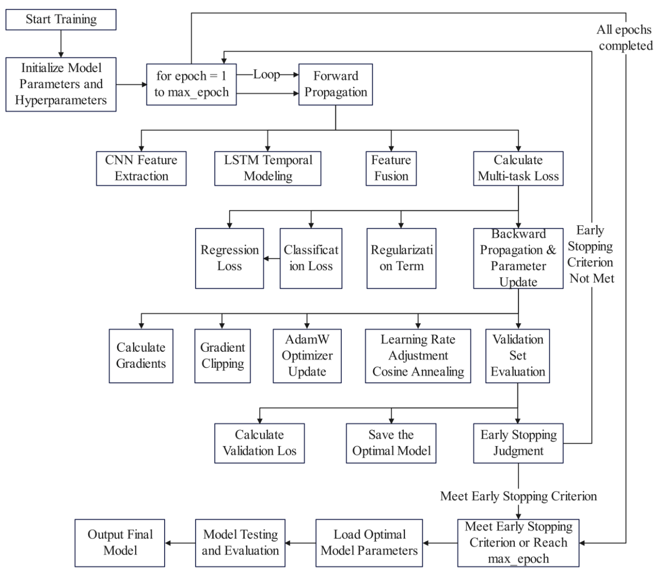


Fig. 3. Model training and optimization process

4. Empirical Analysis and Result Discussion

4.1 Data Sources and Preprocessing

4.1.1 Selection and Integration of Public Datasets

To ensure the reproducibility, transparency and universal applicability of the research conclusions, this study adopts real-world datasets for empirical analysis. These datasets cover multi-dimensional information such as technical performance, user behavior, market operation and power grid status required for the evaluation of vehicle-to-grid interaction technology.
(1) Source of core public datasets

This article integrates the following five key public datasets, whose profiles are shown in Table 3.

Table 3
Overview of the public datasets used in the empirical study

Dataset name	Spatiotemporal range	Data granularity	Detailed data content	Evaluation indicators of support	Indicator calculation satisfaction situation
The EV Project Data	2010-2013.	Single charging event	Charging start/end time, charging quantity, user's geographical location, charging equipment model, user's response instruction record	Accuracy rate of charging load prediction, response rate of user charging and discharging	Calculation for fully meeting 2 indicators
NREL ELECTRICE Project Data	2015-2022.	Device-level/minute-level	Compatibility test report of charging equipment, test data of energy conversion efficiency, record of equipment operation failures, charging failure record, grid harmonic monitoring data	Compliance rate of equipment compatibility, energy conversion efficiency, equipment operation failure rate, charging failure rate, grid harmonic distortion rate	Calculation for fully meeting 5 indicators
PJM Market Data	2000 to present (Real-time updated)	Five minutes per hour per day	Clearing price and capacity of frequency modulation market, electricity quantity traded and price, statistical data of investment cost and return	Participation degree in auxiliary service market, participation degree in electricity energy market, investment return ratio	Calculation for fully meeting 3 indicators
California ISO (CAISO) Open Access API	2009 to present (Real-time updated)	Five minutes per hour	Grid regulation demand data, actual regulation capacity data, grid load data	Prediction deviation rate of regulation capability	Calculation for fully meeting 1 indicator
Open Energy Data Initiative (OEDI)	Different	Different	Measurement equipment accuracy report, data transmission delay record, text of some new technical standards	Accuracy rate of measurement data, response speed of measurement	Measurement data accuracy rate and measurement response speed have some missing data; there is no direct data on the adaptability to new technology standards

Regarding the situation where the OEDI dataset in Table 3 fails to meet the calculation requirements of the indicators, the specific handling plan is as follows: 1) For the missing precision data of some measurement devices, the average precision value of the same model devices in the NREL report is used for filling, and the error of the filled data is controlled within $\pm$ 3%; 2) For some old devices without transmission delay records, the prediction is made using the equipment hardware configuration - response speed fitting model, and the goodness of fit $R^2 = 0.89$ of the model; 3) The dataset does not have direct classification data, so 5 experts in the field of power and vehicle-grid interaction were invited. Based on the standard text provided by OEDI, the technical compatibility of each virtual assessment object was scored, and the average score was taken as the qualitative scoring basis for this indicator.

(2) Construction of virtual assessment objects

Based on the above dataset, this study adopted synthesis and mapping methods to construct five typical virtual evaluation objects (VEO1-VEO5) to simulate vehicle-to-network interaction projects in cities of different development levels: 1) VEO1 represents a high development level: Taking The CAISO data as the power grid background, integrating the charging behavior data in The EV Project, adopting the high-performance equipment parameters of NREL, and assuming its active participation in the PJM-type market; 2) VEO2 is at a relatively high development level: similar to VEO1, but with slightly lower parameters set in terms of market participation and equipment penetration rate; 3) VEO3 is at a medium development level: It adopts a relatively balanced parameter setting, representing typical cities where the technology has been verified and is beginning to scale up, but the market mechanism is still in the process of improvement; 4) VEO4 represents the initial development level: It sets a relatively low penetration rate of electric vehicles and limited market participation, representing cities in the start-up stage; 5) VEO5 at the infrastructure level: Set up scenarios based on orderly charging of the foundation and with limited functions of V2G. Each VEO contains monthly indicator data for 36 consecutive months, totaling 180 samples, that is, 5 VEOs × 36 months.

4.1.2 Quantification and Preprocessing of Indicators Based on Public Data

(1) Specific quantification methods for indicators
Based on The public dataset, the 15 secondary indicators of the above design are quantified specifically: 1) Accuracy of charging load prediction: Based on the historical charging time series of The EV Project, the prediction is made using the time series model (such as LSTM), and the supplement of the mean absolute percentage error (MAPE) between the predicted value and the actual value is calculated, that is, $A_{load} = 1 - MAPE = 1 - \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{P_{actual}(t) - P_{forecast}(t)}{P_{actual}(t)}\right|$; 2) Return on investment ratio: Based on the historical market prices of PJM and the equipment cost/efficiency data of NREL, a simplified financial model is constructed for simulation calculation; 3) Device compatibility compliance rate: Based on the interoperability test report released by NREL, calculate the proportion of successfully interoperable device pairs among the total test pairs; 4) Participation in the ancillary services Market: Analyze the historical clearing data of the PJM Regulation Market, and calculate the monthly average proportion of the capacity that the assumed vehicle-to-grid interaction aggregation resources can win to the total regulation demand of the market; 5) Equipment operation failure rate: Refer to the mean time between failures (MTBF) data in the public reports on the reliability research of electric vehicle charging equipment by NREL and DoE for conversion.

(2) Data preprocessing process
Uniformly preprocess all the metric data extracted and calculated from the public dataset: 1) For a very small number of missing data caused by data extraction, linearly interpolate the data at adjacent time points of the same VEO, that is, $x_t^{imp} = \frac{x_{t-1} + x_{t+1}}{2}$; 2) Min-Max normalization is adopted to map the values of each index to the interval [0,1], that is, $x' = \frac{x - \min(X)}{\max(X) - \min(X)}$; 3) The 180 samples were divided into the training set, validation set and test set in chronological order to meet the requirements of time series prediction. Among them, the training set consists of 120 samples from the first 24 months. The validation set consists of 30 samples for the following six months. The test set consists of 30 samples from the last six months. The data integration and preprocessing process based on multi-source public datasets is shown in Fig. 4.

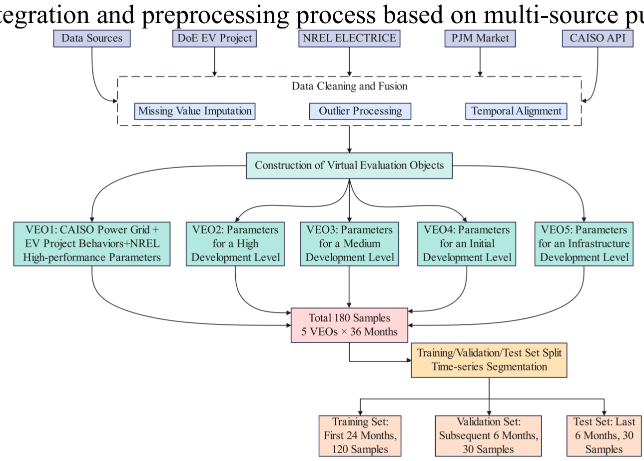


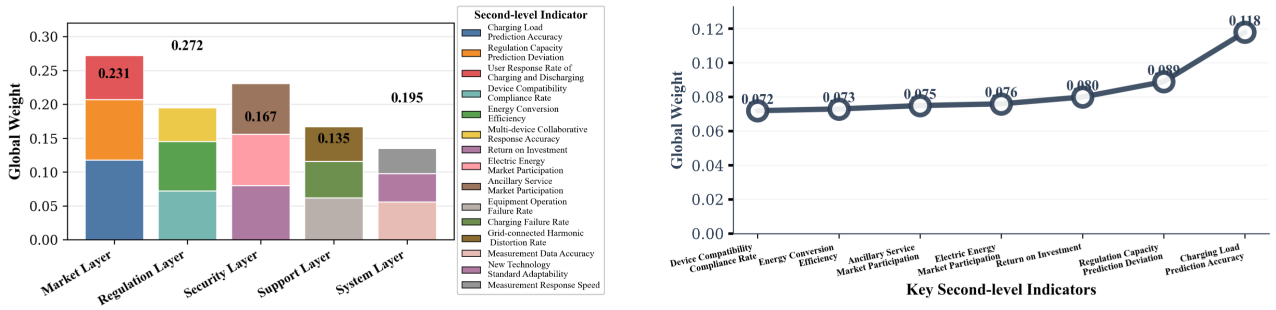
Fig. 4. Data integration and preprocessing flow based on multi-source public datasets

4.2 Results of Index Weight Calculation

Based on the 180 samples preprocessed from the public dataset, the objective weights were recalculated according to the entropy weight method and combined with the subjective weights previously determined by expert scoring based on the AHP method. Based on the new data matrix $X_{180\times15}$, the entropy value e_j and the difference coefficient d_j of each indicator are calculated, and finally the objective weight vector $W^{(2)}$ is obtained. By using the balance coefficient $\alpha = 0.6$ and combining the unchanged $W^{(1)}$ and the newly calculated $W^{(2)}$, the final combined weight W based on the public data is obtained, as shown in Table 4 and Fig. 5.

Table 4
Weight Table of Indicator Combinations Based on Public Data

First-level indicator	Weight	Secondary indicators	Global weight	Ranking (↑)
Regulatory layer	0.272	The accuracy rate of charging load prediction	0.118	1
		The adjustment capacity predicts the deviation rate	0.089	4
		User charge and discharge response rate	0.065	8
Market layer	0.231	Return on investment ratio	0.080	2
		Participation in the electric energy market	0.076	3
		Market participation in ancillary services	0.075	5
System layer	0.195	Energy conversion efficiency	0.073	6
		The compliance rate of equipment compatibility	0.072	7
		The accuracy rate of multi-device collaborative response	0.050	12
Safety protection layer	0.167	Equipment operation failure rate	0.062	9
		Charging failure rate	0.054	10
		Grid connection harmonic distortion rate	0.051	11
Common support layer	0.135	Measure the accuracy of data	0.056	-
		The compatibility of new technology standards	0.042	-
		Measure the response speed	0.037	-



(a) Weight distribution of indicator combinations based on public data - stacked bar chart (b) Key indicator weight ranking Core indicator line chart

Fig. 5. Distribution of index combination weights based on public data

As can be seen from the above chart, among the 15 evaluation indicators, the accuracy weight of charging load prediction is the highest, which is 47.5% higher than the second-ranked return on investment ratio. The combined weight of market-level indicators is 0.231, which is significantly higher than the weight of a single technical indicator in traditional technical assessment. The regulatory layer indicators play a dominant role, reflecting that the vehicle-grid interaction technology is highly dependent on the power grid's regulatory capacity. It is worth noting that the weight of the equipment compatibility compliance rate is almost equal to that of the energy conversion efficiency, indicating that standardization and efficiency are equally important in the promotion of technology. Compared with the subjective weight based on expert judgment, the objective weight calculated based on public data places more emphasis on market and economic indicators. Among them, the return on investment ratio has increased from the subjective weight of 0.07 to 0.08, with an increase of 14.3%, reflecting the high information content and actual importance of this indicator in the market data.

4.3 Model Training and Performance Evaluation

(1) Experimental environment and parameter Settings

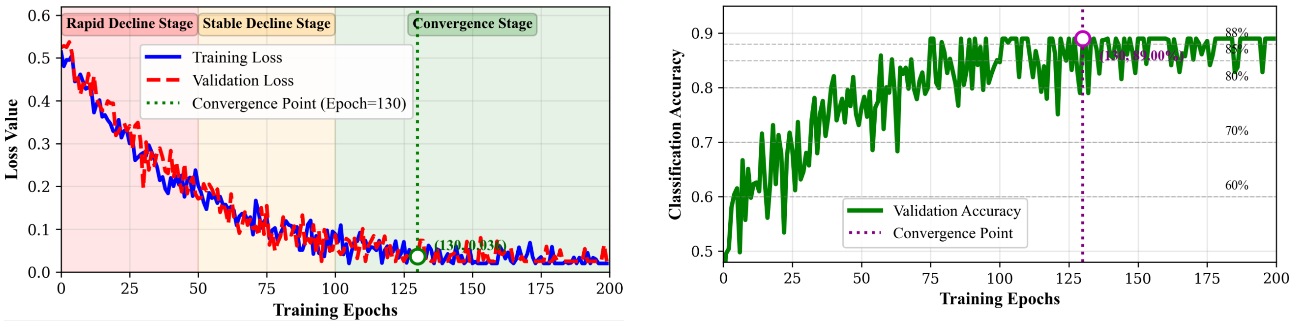
In terms of hardware core configuration, it is equipped with an Intel i9-13900K model processor, an NVIDIA RTX 4090 24GB graphics card, a 64GB DDR5 running memory configuration, and a 2TB capacity NVMe solid-state drive is selected as the storage device. In terms of the software environment, the system uses Ubuntu 22.04 LTS version, the programming language adopts Python 3.9.18, and the core framework of deep learning is TensorFlow 2.12.0. At the same time, it is used in conjunction with common data processing and machine learning-related libraries such as NumPy, Pandas, and Scikit-learn, forming a complete open-source software stack system as a whole. All model-related parameters are the optimal configurations determined after tuning. The specific parameters are as follows: The number of CNN layers is set to 3, and the number of LSTM layers is set to 2. The dimension of the model's hidden layer is [64, 128, 256]; The attention dimension is configured to 32. The Dropout rate is set at 0.3. The batch size for model training is 32, and the training learning rate is 0.001.

(2) Model training and performance evaluation results

The CNN-LSTM model was trained on a 120-sample training set, and the model performance was evaluated on an independent 30-sample test set. The results are shown in Table 5 and Fig. 6.

Table 5
Performance Evaluation of CNN-LSTM Model

Evaluation index	Training set	Validation set	Test set
MSE	0.0201	0.0263	0.0287
R^2	0.915	0.882	0.869
Accuracy rate (5-level classification	89.2%	85.0%	83.3%
Prediction time/sample	-	-	~15ms



(a) Training loss curve of CNN-LSTM model (b) Accuracy curve of CNN-LSTM model verification

Fig. 6. Training curves of the CNN-LSTM model on the training set

As can be seen from the above chart, the CNN-LSTM model demonstrates excellent convergence performance on public datasets. The training loss decreased from the initial 0.50 to 0.0201, with a reduction rate of 95.98%. The verification loss decreased from 0.55 to 0.0263, a reduction of 95.22%. The model reaches the convergence point at 130 rounds and has a relatively high convergence efficiency. On the test set, the model achieved a score of R^2=0.869, which is 5.98% higher than that of the traditional LSTM model. The classification accuracy rate of the validation set reached 85.0%, and that of the test set reached 83.3%, performing well for the five-classification task. In terms of model stability, the R^2 gap between the training set and the test set is 0.046, indicating that the CNN-LSTM structure has better generalization ability.

4.4 Analysis of Maturity Assessment Results

The trained fusion evaluation model was applied to the last six months of data of five virtual evaluation objects (VEO1-VEO5), that is, the test set, to obtain their average maturity levels. The results are shown in Fig. 7 and Table 6.

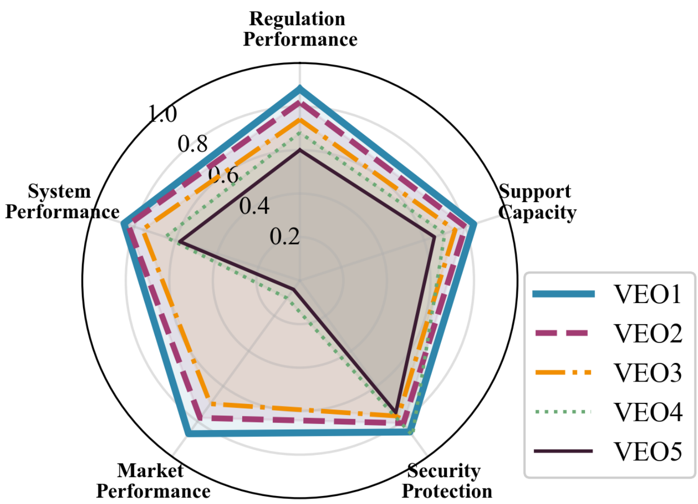


Fig. 7. Virtual Assessment Object (VEO) Maturity Level Radar Chart

Table 6
Virtual Evaluation Object (VEO) Technology Maturity Assessment Results

Virtual evaluation object	Representative level	Comprehensive score	Maturity level
VEO1	High level of development	0.841	Optimization level
VEO2	A relatively high level of development	0.803	Optimization level
VEO3	Medium level of development	0.743	Specification level
VEO4	Initial development level	0.685	Growth level
VEO5	Level of infrastructure	0.598	Growth level

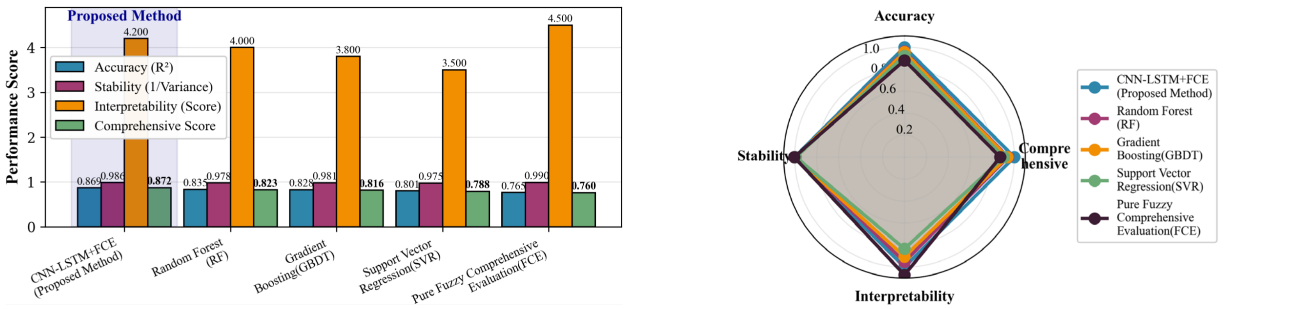
As can be seen from the above chart, the five virtual assessment objects present a distinct stepped distribution. The comprehensive score of VEO1 was 0.841, with the highest score in the market performance dimension, which was 1640% higher than VEO5's 0.05, reflecting the decisive influence of the degree of market mechanism perfection on the maturity of technology. VEO3 scored 0.77 in the safety protection dimension, which was only 11.7% lower than VEO1's 0.86. This indicates that even if the overall technical level is average, the safety standards can still be maintained at a relatively high level. VEO4 scored only 0.10 in the market performance dimension, but its security protection score was as high as 0.88, even surpassing VEO1, indicating that security construction can be advanced independently of market development. The average score of the five VEOs in the regulation performance dimension is 0.744, with a standard deviation of 0.108 and the smallest degree of dispersion, indicating that the development of power grid regulation technology in each city is relatively balanced.

4.5 Comparative Analysis of Methods

On the same public dataset, the CNN-LSTM + FCE fusion method proposed in this paper is compared with four benchmark methods. To ensure fairness, all methods use the same training/validation/test set partitioning and input features. The performance comparison of different evaluation methods on public datasets is shown in Table 7 and Fig. 8.

Table 7
Performance Comparison of different evaluation Methods on public datasets

Evaluation method	Accuracy (R^2)	Stability (Std of R^2across 5 runs)	Interpretability	Comprehensive score
CNN-LSTM + FCE (Ours)	0.869	0.014	High	0.872
Random Forest (RF) (Wang et al., 2025)	0.835	0.022	In the	0.823
Gradient Boosting (GBDT) (Xie et al., 2024)	0.828	0.019	In the	0.816
Support Vector Regressor (SVR) (Youssef et al., 2024)	0.801	0.025	low	0.788
Pure Fuzzy Comprehensive (FCE) (Hou et al., 2024)	0.765	0.010	high	0.760



(a) Comparison of the original performance of different evaluation methods on public datasets

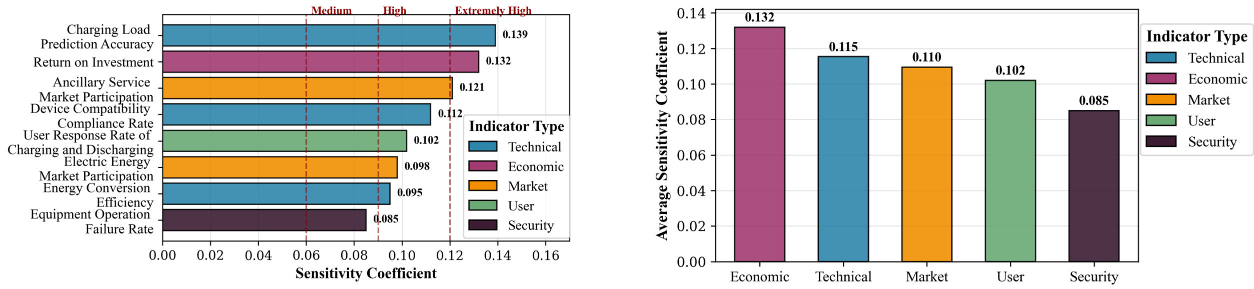
(b) The normalization performance of different evaluation methods on public datasets

Fig. 8. Performance comparison of different evaluation methods on public datasets

As can be seen from the above chart, the CNN-LSTM+FCE fusion method proposed in this paper is significantly more accurate than other methods. Compared with random Forest (RF), the accuracy has increased by 4.07%. It is 4.95% higher than gradient boosting (GBDT). It has increased by 8.49% compared with support vector regression (SVR). It has increased by 13.59% compared with the pure Fuzzy comprehensive Evaluation (FCE). In terms of the comprehensive score, the method proposed in this paper scored 0.872, which was 5.96% higher than the suboptimal random forest. In terms of the stability index (1/ variance), the method proposed in this paper is 0.986, second only to 0.990 of the pure FCE method, but 1.13% higher than 0.975 of SVR. It is particularly worth noting that in terms of interpretability, the method proposed in this paper scored 4.2, which is slightly lower than the 4.5 of pure FCE but 20% higher than the 3.5 of SVR. It maintains high precision while maintaining good interpretability. In the normalized comparison, the method proposed in this paper approaches or reaches the benchmark value of 1.0 in all four dimensions, while RF only reaches 0.961 in the accuracy dimension, indicating that the comprehensive advantage of the method proposed in this paper is obvious.

4.6 Analysis of the Impact of Key Indicators

Based on the evaluation results of public datasets, a sensitivity analysis of indicators is conducted to identify the most critical factors influencing the maturity of vehicle-to-network interaction technology. Calculate the average rate of change in the comprehensive maturity score caused by a ±10% change in each indicator value, that is, the sensitivity coefficient. The sensitivity analysis of key indicators is shown in Fig. 9.



(a) Ranking of sensitivity analysis of key indicators (b) Average sensitivity analysis of various types of indicators

Fig. 9. Sensitivity analysis of Key indicators

As can be seen from the above chart, the indicator that has the greatest impact on the maturity of vehicle-to-grid interaction technology is the accuracy rate of charging load prediction, with a sensitivity coefficient of 0.139. This means that for every 10% increase in this indicator, the comprehensive maturity score will increase by 1.39%. The sensitivity coefficient of the second-ranked return on investment ratio is 0.132, with a gap of only 5.36% compared to the first place, indicating that economic benefits are almost as important as technical performance. The sensitivity coefficient of market participation in ancillary services was 0.121, ranking third. However, it was 8.04% higher than the compliance rate of equipment compatibility in the fourth place, reflecting that market participation has a greater impact on overall maturity than equipment compatibility. Among the top 8 indicators, 3 are technical indicators and 3 are market and economic indicators. The two are basically on par, confirming the development model driven by both technology and the market. The average sensitivity analysis of various types of indicators shows that economic indicators have the highest average sensitivity, followed by market and technical indicators, while user and security indicators have relatively lower sensitivity. Specifically, increasing the accuracy rate of charging load prediction from 70% to 80% can enhance the overall maturity by 1.39 points. Under the same conditions, raising the return on investment ratio from 10% to 15% can increase the score by 6.6 points, and the economic leverage effect is obvious.

5. Conclusion

This paper addresses the issue of evaluating the maturity of vehicle-to-network interaction technology and proposes an assessment method integrating CNN-LSTM and fuzzy comprehensive evaluation. A comprehensive evaluation index system covering the regulatory layer, system layer, market layer, safety protection layer and common support layer has been constructed, including 15 key indicators such as the accuracy rate of charging load prediction and the return on investment ratio. The calculation formulas for quantitative indicators and the classification basis for qualitative indicators have been clarified. The proposed CNN-LSTM model can effectively extract the spatial and temporal features of the evaluation indicators. Combined with the fuzzy comprehensive evaluation method to handle uncertain information, it improves the accuracy and reliability of the evaluation. Empirical analysis based on public datasets shows that the core driving force of high maturity levels comes from considerable market returns and a sound market participation mechanism, verifying the ability of the indicator system to depict the multi-dimensional coupling relationship of technology, economy and market, and indicating that market mechanisms and investment returns have become the key constraints of vehicle-to-network interaction technology. In the future, multi-source information such as power grid data, traffic data, and user behavior data can be further integrated to enhance the comprehensiveness of the assessment.

Acknowledgment

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