Comprehensive Evaluation of Electric Vehicle Charging Responsiveness Based on Combined Weights and Grey-TOPSIS

Yiwei Ma, Ningying Liu, Miao Huang

Abstract—**With the rapid development of electric vehicles (EVs) in recent years, it has become an essential flexible load in microgrids, and their impact on the grid is increasingly significant. Currently, a mature and scientific evaluation scheme for EV charging responsiveness is lacking, making it difficult to utilize the potential of adjustable user-side flexible resources fully. To this end, a comprehensive EV charging responsiveness evaluation method is proposed based on improved rank correlation analysis, flexible entropy model, and a technique for order preference by similarity to an ideal solution improved by grey correlation degree (Grey-TOPSIS). Firstly, an EV charging responsiveness evaluation index system is established. The weights of each index are determined using the improved rank correlation analysis method and flexible entropy model. Then, the evaluation scores of different types of EV charging responsiveness are obtained using Grey-TOPSIS. The experimental results show that the method is more effective and applicable than the traditional multiple evaluation methods, which provide decision-making support for grid managers and improve the power system's operational and energy utilization efficiency.**

Index Terms—**Index system, Rank correlation analysis method, Flexible entropy model, Grey-TOPSIS.**

I. INTRODUCTION

With the scarcity of fossil energy and the rapid growth of new energy generation, the technological development and number of EVs are rising at an alarming rate[1]. The charging behavior of large-scale EVs will inevitably cause severe negative impacts on the power grid, increase the instability of the grid, cause line blockage, and cause serious peak-to-valley differences[2]. Therefore, it is necessary to develop a scientific evaluation system to better utilize the role of EVs in microgrid regulation, to ensure the ability to reduce the pressure on the grid by using the energy storage of EVs during the peak power hours, and to utilize the storage characteristics of EVs to absorb the excess power from renewable energy sources during the low power hours.

Reference [3] proposes a joint control and optimization strategy for EV aggregators (EVAs) to participate in grid frequency and voltage regulation based on the cloud-side cooperative hierarchical scheduling architecture. It establishes a multi-timescale EV charging pile cluster (EVC) scheduling model to maximize EVA profits. The Reference[4] establishes an EV demand response aggregation potential assessment index system containing six evaluation indices from the grid and user sides. Reference [5] establishes an EV cluster evaluation index model using the reported dispatch power, user credit, battery wear, and user participation as evaluation indices. Reference [6] established a multidimensional EV safety evaluation system consisting of ten indicators that assess component safety and dangerous driving behavior. Reference[7] takes EV real-time charging message data as the research object, analyzes and establishes the affiliation model of charging safety influencing factors, and proposes an EV real-time charging risk assessment method based on the improved generalized back-propagation and hierarchical analysis process (BBP-AHP) assessment method. Most of the above studies focus on aspects such as EV dispatch capability and safety assessment, and less consideration is given to charging responsiveness influencing factors, which makes it challenging to provide appropriate guidance for auxiliary distribution network planning. Scientific evaluation methods are essential for accurately assessing EV charging responsiveness in the grid. Reference[8] evaluates key storage technologies for EVs based on five criteria: cost, technical characteristics, compatibility, technology maturity, environment, health, and safety, and uses the AHP method to select storage for EVs. Reference[9] proposes a two-stage Multi-Criteria Decision Making (MCDM) framework that combines the Technique for Ordering Priorities of Similarity of Ideal Solutions (TOPSIS) with Binary Goal Planning (BGP) to evaluate EV charging pile locations based on geospatial, environmental, technical, and economic criteria. Reference[10] uses the hierarchical analysis method to calculate the weights of indices at each level. Then, it introduces the fuzzy comprehensive evaluation method to evaluate the integrated operation of the vehicle-pile-network-source. Reference[11] constructs a response intention assessment model based on TSK fuzzy mathematics, taking electricity prices, battery

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charge status, and temperature as key influencing factors, and establishes 27 fuzzy rules to quantify EV users' response intentions accurately. Reference [12] proposes a distributed robust real-time flexibility assessment model to accurately evaluate EVs' real-time flexibility in charging stations. This model formulates EVs' uncertain departure behavior and charging status in an online update mode.

The above studies mainly focus on EV storage technology, location selection of charging piles, vehicle–pile–network–source integrated operation, and EV flexibility evaluation. Still, few relevant research results and practical cases exist in EV charging responsiveness evaluation. Therefore, a comprehensive EV charging responsiveness evaluation method is proposed, utilizing the improved rank correlation analysis method, flexible entropy model, and Grey-TOPSIS to fully utilize the adjustable potential of user-side EVs. The method fully considers the operational purpose of the EV control system and the charging response of different EVs, in which the proposed EV charging responsiveness index system contains four core evaluation indices and 16 sub-indices. The main contributions of this paper are summarized as follows.

(i) EV is an essential flexible load. Still, the lack of a scientific EV charging responsiveness evaluation system makes it difficult to guide access to flexible resources. We propose a comprehensive evaluation method for EV charging responsiveness, based on an improved rank correlation analysis method, a flexible entropy model, and Grey-TOPSIS.

(ii) To utilize the adjustable potential of user-side flexible resources, by the principles of science, representativeness and reliability in the construction of the evaluation index system, and based on the charging response characteristics of different types of EVs, an EV charging responsiveness evaluation index system is proposed, which contains four core evaluation criteria and 16 evaluation indices.

(iii) Combining the improved rank correlation analysis method of the subjective assignment method and the flexible entropy model of the objective assignment method can complement the influence of subjective and objective factors to make the weight allocation more comprehensive.

(iv) Combined with the grey correlation degree, the traditional TOPSIS method is improved, and the new model uses the weighted grey correlation degree as the distance measure to replace the original Euclidean distance. The improved model reflects the proximity and ideal value of the target in terms of both curve similarity and positional distance, which can more accurately reflect the internal changes of each evaluation object and make up for the shortcomings of the Euclidean distance in the traditional TOPSIS.

The remainder of the paper is organized as follows. Section II outlines the evaluation methods used in this study. Section III presents the evaluation model for EV charging responsiveness. Section VI introduces the case study results and discussions. Finally, Section V summarizes the work of the paper.

II. Evaluation Methodology

The proposed EV charging responsiveness evaluation method can be categorized into three main stages, as shown in Fig. 1. It integrates the improved rank correlation analysis method, the flexible entropy model, and Grey-TOPSIS. The following is a brief description of these evaluation methods.

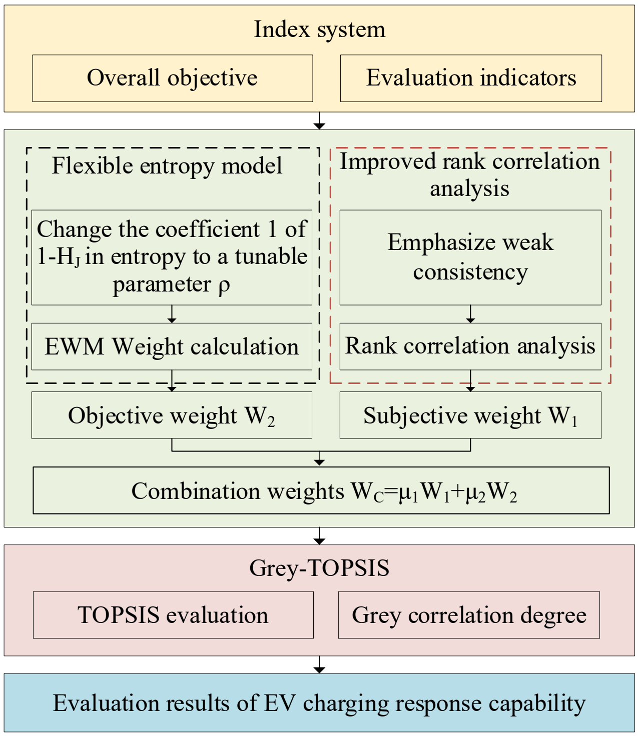

Fig. 1. EV charging responsiveness evaluation framework

A. Improved Rank Correlation Analysis Method

In current research, the rank correlation analysis method, known as the G1 method, is widely used to establish the subjective weights of evaluation criteria. This method stems from a reimagining of the hierarchical analysis method (AHP). Compared with AHP, the G1 method is more concise and efficient in calculation and avoids the difficulty of the consistency test, overcoming the limitations of AHP[13]. First, experts qualitatively rank the importance of evaluation indices. Then, the ranking results are compared to determine the importance of adjacent indices. Finally, the weight of evaluation indices is obtained, simplifying the calculation of weight coefficients[14]. However, the sequential relationship analysis technique necessitates strong consistency among evaluation indices and employs the proportional scale approach. Under strong consistency, ensuring that the evaluation indices do not violate people's thinking isn't easy. Thus, within this study, the subjective index weights are derived through the improved rank correlation analysis method. Under the hierarchical relationship between indices assumed, this analysis focuses on weak consistency rather than strong, employing a distinct scalar methodology. The steps for determining subjective weights via the improved rank correlation analysis method include the following stages[15]:

Step 1: The expert gives the ordinal relation $t_1^* \succ t_2^* \succ \ldots \succ t_n^*$ in the set of contribution rates $\{t_1, t_2, \ldots, t_n\}$, which is still expressed $t_1 \succ t_2 \succ \ldots \succ t_n$ for the convenience of writing. The intuitive meaning of the contribution rate t_j is the ratio of the sum of the evaluation values contributed by the jth index to the composite evaluation magnitude, calculated as shown in Eq. (1).

Assuming that there are m evaluation samples $\{s_1,s_2,\ldots,s_m\}$, n evaluation indices $\{b_1,b_2,\ldots,b_n\}$. A normalized evaluation matrix denoted $B=\left[b_{ij}\right]_{m\times n}$, and b_{ij} is the standardized measure of the ith evaluation sample concerning the jth index. The contribution of each evaluation index b_j is:

$$t_j=\frac{w_j\sum_{i=1}^{m}b_{ij}}{\sum_{i=1}^{m}x_i},j=1,2,\ldots,n \tag{1}$$

Where, w_j is the individual significance of each metric, and $\sum_{i=1}^{m}w_i=1$. x_i denotes the holistic assessment score for the subject s_i under review, determined in accordance with Eq. (2).

$$x_i=\sum_{j=1}^{n}w_jb_{ij},i=1,2,\ldots,m \tag{2}$$

Denote the sum of the m evaluation data in the b_j as l_j, $l_j=\sum_{i=1}^{m}b_{ij}$, then:

$$t_j=\frac{w_jl_j}{\sum_{j=1}^{n}w_jl_j} \tag{3}$$

Step 2: A reasonable judgment of the relative contribution between t_{k-1} and t_k should be provided, based on a judicious assessment of the proportion of the extent of contribution of the experts to the evaluation indices is shown in Eq. (4).

$$r_k=\frac{h_{k-1}}{h_k} \tag{4}$$

The assignment of r_k is shown in Table I.

TABLE I
ASSIGNMENT OF r_k

r_k	Meaning
1.0	t_{k-1} and t_k contribute equally
1.2	The contribution of t_{k-1} is slightly higher than that of t_k
1.4	The contribution of t_{k-1} is higher than that of t_k
1.6	The contribution of t_{k-1} is obviously higher than that of t_k
1.8	The contribution of t_{k-1} is definitely higher than that of t_k

Step 3: Calculation of the contribution rate t_j.

$$maxf=\sum_{k=2}^{n}\left(t_{k-1}-t_k\right)=t_1-t_n$$
$$s.t.\begin{cases}t_{k-1}-t_kr_k\le 0,k=2,3,\ldots,n\\ t_k-t_{k-1}\le 0,k=2,3,\ldots,n\\ t_1-1.8t_n\le 0\\ \sum_{k=1}^{n}t_k=1\end{cases} \tag{5}$$

The significance of the objective function is the sum of the distances between the contribution rates t_j of neighboring indices. The purpose of maximizing f under the condition of satisfying the scale of proportionality is to expand the distance between the contribution rates of neighboring indices, reflecting as much as possible the reasonable assessment of the experts regarding the ratio of the evaluation metrics' impact. $t_k-t_{k-1}\le 0$ reflecting the need for evaluation indices to meet the weak consistency requirements of $t_1\ge t_2\ge\ldots t_n$. Under scaling, the meaning of $t_1-1.8t_n\le 0$ is to avoid the situation that $w_1/w_3=2.56$ does not align with human cognitive patterns when $w_1/w_2=1.6$ and $w_2/w_3=1.6$ satisfy the strong consistency requirement.

Step 4: Calculation of weighting factors.

$$w_n=\left[1+\frac{l_n}{t_n}\sum_{k=2}^{n}\frac{t_{k-1}}{l_{k-1}}\right]^{-1} \tag{6}$$

$$w_{k-1}=w_k\frac{l_kt_{k-1}}{t_kl_{k-1}},k=n,n-1,\ldots,3,2 \tag{7}$$

Where, $\sum_{k-1}^{n}w_k=1$.

B. Flexible Entropy Model

Entropy weighting method (EWM) is a widely applied technique for determining the objective weights of indices. Still, its shortcomings in calculating the objective weights of indices are that it cannot reflect the small changes in the evaluation matrix, which can easily lead to a large gap in the distribution of weights of the indices[16]. It only considers the degree of variation of a single index and can't deal with the correlation between indices. Compared with EWM, the flexible entropy model transforms the coefficient 1 of $1-H_j$ in the entropy weights into a system parameter ρ, enhancing the adaptability of the weight distribution and effectively avoiding the shortcomings of EWM. Meanwhile, before calculation, the relationship among indices is analyzed by the Pearson correlation coefficient method, and by using the calculation of its average similarity value to process each index with high correlation, the comprehensive indices vector with high independence can be obtained, which improves the problem that EWM can't deal with the correlation between indices. The steps are as follows[17].

The data's objective allocation informs the application of Pearson correlation coefficient technique for determining index correlations. If indices show a strong correlation with the objective data, they are treated as a single index for calculating the objective weights. This paper uses the optimization model for minimizing distance to integrate highly correlated indices, as shown in Eq. (8), and the centroid of the strongly independent indices is determined. Following the integration of highly correlated indices, the EV charging responsiveness evaluation indices set is denoted as $C=\{c_1,c_2,\ldots,c_l\}$ and the normalization matrix is denoted as $R=\left[r_{ij}\right]_{m\times l}$.

$$\min z'=\sum_{f=1}^{g}\sqrt{\sum_{i=1}^{m}\left(b_i-b_{ip}\right)^2}$$
$$\begin{cases}\sqrt{\sum_{i=1}^{m}\left(b_i-b_{ip}\right)^2}=\sqrt{\sum_{i=1}^{m}\left(b_i-b_{iq}\right)^2}\\ 0\le b_i\le 1\\ p=1,2,\ldots,g\\ q=1,2,\ldots,g,p\ne q\end{cases} \tag{8}$$

Where, g denotes the number of indices with high correlation in the objective indices, b_i denotes the centroid vector of indices with high correlation after the fusion process. b_{ip} and b_{iq} are the standardized magnitudes of the ith sample concerning the pth and qth indices.

$$R=\begin{bmatrix} r_{11} & \cdots & r_{1l} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{ml} \end{bmatrix}$$

Where, r_{ij} is the normalized value of the ith sample concerning the jth index.

Step 2: For $R=\left[r_{ij}\right]_{m\times l}$, the entropy associated with the jth index is computed as:

$$E_j=-k\sum_{i=1}^{m}p_{ij}\ln p_{ij}, j=1,2,\ldots,l \tag{9}$$

Where, $k=1/\ln m$, $p_{ij}=r_{ij}/\left(\sum_{i=1}^{m}r_{ij}\right)$; $0\le E_j\le 1$, and if $p_{ij}=0$, $p_{ij}\ln p_{ij}=0$.

Step 3: Based on the entropy figures for each index, the variation coefficient H_j is derived.

$$H_j=\rho-E_j \tag{10}$$

Where, ρ is the parameter $\left(\rho\ge max\left\{E_1,E_2,\ldots,E_n\right\}\right)$.

Subsequently, as per Eq. (11), the flexible entropy model with weights γ can be solved.

$$\begin{cases} minz=\gamma^T H\gamma \\ s.t.e^T\gamma=1 \\ \gamma\ge 0 \end{cases} \tag{11}$$

Where, H is the diagonal matrix of $n\times n$ with diagonal elements $h_{jj}=\rho-E_j$, $h_{jj}>0, j=1,2,\ldots,l$, and the rest of the elements are zero.

Suppose $L=\gamma^T H\gamma-\lambda\left(e^T-1\right)$, and $\frac{\alpha L}{\alpha\gamma_j}=2h\gamma-\lambda=0$, $\frac{\alpha L}{\alpha\lambda}=e^T\omega-1=0$. The flexible entropy weights of the indices can be calculated according to Eq. (12).

$$\gamma=\frac{H^{-1}e}{e^T H^{-1}e} \tag{12}$$

Step 4: To assign weights to each relevant index, we use the Pearson correlation coefficient method to assess the degree of association among each pertinent index and various standalone variables. By analyzing the correlation coefficient, the autonomous objective weight for each pertinent indicator is derived.

C. Grey-TOPSIS

Krohling and Pacheco proposed the Technique of Ranking Preferences by Similarity to Ideal Solutions (TOPSIS)[18]. The method is based on ideal solutions; an alternative is considered optimal if it is closer to a positive ideal solution. However, the traditional TOPSIS method uses Euclidean distance to calculate the distance between the evaluation object and the positive and negative ideal solutions. The Euclidean distance can only reflect the positional relationship between the data curves, but not the trend changes of the data series, which affects the accuracy of the evaluation results[19].

To address the issues above, the traditional TOPSIS method is enhanced by integrating the grey correlation degree to assess EV charging responsiveness. The grey correlation degree measures the magnitude of the correlation between two systems concerning factors that vary over time or across different objects[20]. The grey correlation degree is used as a distance measure, replacing the original Euclidean distance. The improved model reflects the proximity and ideal value of the target in terms of both curve similarity and positional distance, which can more accurately reflect the internal changes of each evaluated country and make up for the shortcomings of the Euclidean distance in the traditional TOPSIS. The specific steps of the new model Grey-TOPSIS are as follows.

Step 1: Construct the evaluation matrix. For m evaluation samples and n indices, construct the evaluation index matrix C as follows:

$$C=\begin{bmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{m1} & \cdots & c_{mn} \end{bmatrix} \tag{13}$$

Where, c_{ij} is the evaluated value of the jth index for the ith sample.

Step 2: The evaluation matrix is standardized and normalized. Indices standardization is shown in Eq. (14), which transforms all negative and interval-type indices into positive indices to maintain consistency; normalization is shown in Eq. (15), which finally obtains the standardization matrix C' and the normalization matrix U.

$$c'_{ij}=\begin{cases} c_{ij} & positive\ indices \\ \frac{1}{c_{ij}} & negative\ indices \\ 1-\frac{\left|c_{ij}-c_{best,j}\right|}{M} & interval\ indices \end{cases} \tag{14}$$

$$u_{ij}=\frac{c'_{ij}}{\sqrt{\sum_{i=1}^{m}{c'_{ij}}^2}} \tag{15}$$

Where, c'_{ij} denotes the positive standardized index value of the jth index for the ith sample. u_{ij} denotes the standardized value of the jth index for the ith sample. $c_{best,j}$ denotes the optimal value of the jth index. M is the maximum value of the jth index at a distance of $c_{best,j}$, and $M=max\left\{\left|c_{ij}-c_{best,j}\right|\right\}$.

Step 3: Construct the weighted normalization matrix Z, calculated as shown in Eq. (16).

$$z_{ij}=w_j^* * u_{ij} \tag{16}$$

Where, z_{ij} denotes the weighted normalized value of the jth index for the ith sample, and w_j^* is the composite weight of the jth index.

Step 4: Determine the positive ideal solution Z^+ and negative ideal solution Z^-, as shown in Eq. (17) and Eq. (18). Calculate the grey correlation coefficients γ^+ and γ^- as shown in Eq. (19) and Eq. (20).

$$Z^{+}=\left\{\max_{j} z_{ij}\right\}=\left\{z_1^{+},z_2^{+},\ldots,z_n^{+}\right\} \quad (17)$$

$$Z^{-}=\left\{\min_{j} z_{ij}\right\}=\left\{z_1^{-},z_2^{-},\ldots,z_n^{-}\right\} \quad (18)$$

Where, $z_1^{+},z_2^{+},\ldots,z_n^{+}$ denotes the positive ideal solution for each index, $z_1^{-},z_2^{-},\ldots,z_n^{-}$ denotes the negative ideal solution for each index.

$$\gamma_{ij}^{+}=\frac{\min_i \min_j \left|z_{ij}-z_j^{+}\right|+\rho \max_i \max_j \left|z_{ij}-z_j^{+}\right|}{\left|z_{ij}-z_j^{+}\right|+\rho \max_i \max_j \left|z_{ij}-z_j^{+}\right|} \quad (19)$$

$$\gamma_{ij}^{-}=\frac{\min_i \min_j \left|z_{ij}-z_j^{-}\right|+\rho \max_i \max_j \left|z_{ij}-z_j^{-}\right|}{\left|z_{ij}-z_j^{-}\right|+\rho \max_i \max_j \left|z_{ij}-z_j^{-}\right|} \quad (20)$$

Where, ρ is the resolution factor, $\rho \in [0,1]$. $\rho = 0.001$ is taken in this paper.

Step 5: Calculate the Grey-TOPSIS distance measures S_i^{+} and S_i^{-}. The weighted grey correlation degree calculated by the weighted sum of grey correlation coefficients is used as the distance measure because the matrix Z has been weighted normalized, so the grey correlation degree is obtained by directly summing the grey correlation coefficients. The calculation is shown in Eq. (21) and Eq. (22).

$$S_i^{+}=\sum_{j=1}^{n}\gamma_{ij}^{+} \quad (21)$$

$$S_i^{-}=\sum_{j=1}^{n}\gamma_{ij}^{-} \quad (22)$$

Where, S_i^{+} is the distance from the ith sample to the positive ideal solution, S_i^{-} is the distance from the ith solution to the negative ideal solution.

Step 6: Calculate the composite evaluation value of the sample S_i^{*}, as shown in Eq. (23).

$$S_i^{*}=\frac{S_i^{+}}{S_i^{+}+S_i^{-}} \quad (23)$$

Where, S_i^{*} takes a value in the range of 0 to 1. The larger its value, the closer the evaluation object is to the positive ideal solution.

III. Evaluation Model and Strategy

In order to comprehensively evaluate the charging responsiveness of EVs, we first determine the evaluation indices affecting the response of EVs, then establish a two-level evaluation index system of EV charging responsiveness, and solve the subjective and objective weights of the evaluation index system by using the improved rank correlation analysis method and the flexible entropy model. Finally, a comprehensive evaluation of different types of EVs is carried out using the Grey-TOPSIS method.

A. EV Charging Responsiveness Evaluation Index System

The comprehensive evaluation index system for charging guidance of EV charging stations fully considers the demand of EV charging stations and the characteristics of different types of EVs. It guides the charging of different types of EVs from EV battery charging characteristics, EV charging spatiotemporal characteristics, EV charging response characteristics, and EV charging economic cost characteristics[21].

Fig. 2 shows the EV charging responsiveness evaluation index system. EV battery charging characteristics include capacity of battery, charging efficiency, rechargeable capacity, state of battery health, and monitoring of battery charging temperature. EV charging spatiotemporal characteristics include the distance to the charging station, the charging duration, the charging level during off-peak periods, and the peak charging level. EV charging response characteristics include timeliness of charging response, frequency of EV charging response, interruptibility of charging in emergencies, and planned charging capacity. EV charging economic cost characteristics include rationality of charging price, level of price compensation, and charging cost.

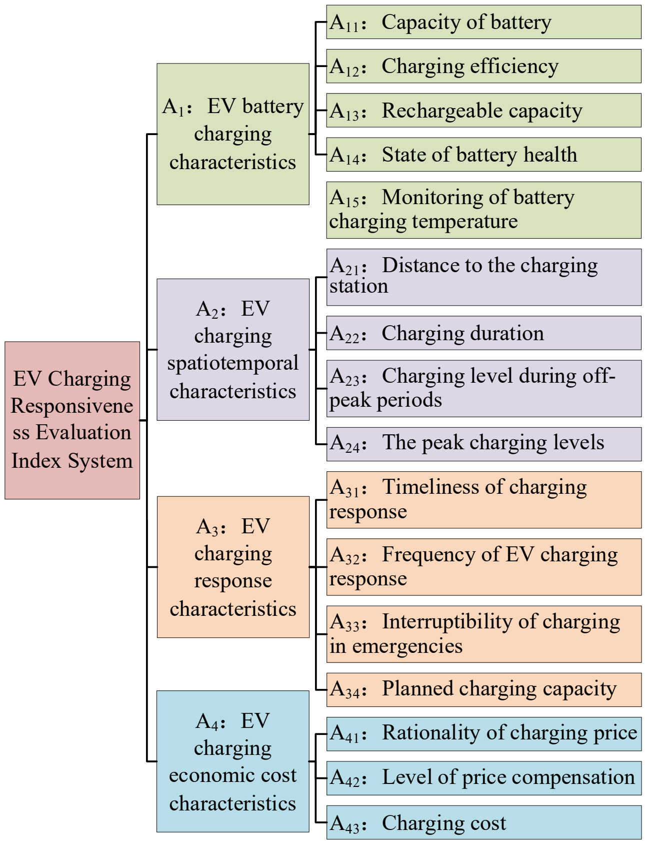

Fig. 2. EV charging responsiveness evaluation index system

The hierarchical structure of EV charging responsiveness evaluation index system is divided into three layers. The first layer is the target layer, the second layer is the criterion layer, and the third layer is the index layer, which has 16 indices in total.

B. EV Charging Responsiveness Evaluation Process

In order to accurately evaluate the charging responsiveness of different types of EVs and give full play to the adjustable potential of user-side flexible resources, a method is proposed to utilize the improved rank correlation analysis and the flexible entropy model to solve the subjective and objective weights of the evaluation index system, and utilize the Grey-TOPSIS method to conduct a comprehensive evaluation of different types of EVs. Fig. 3 illustrates the specific evaluation flowchart.

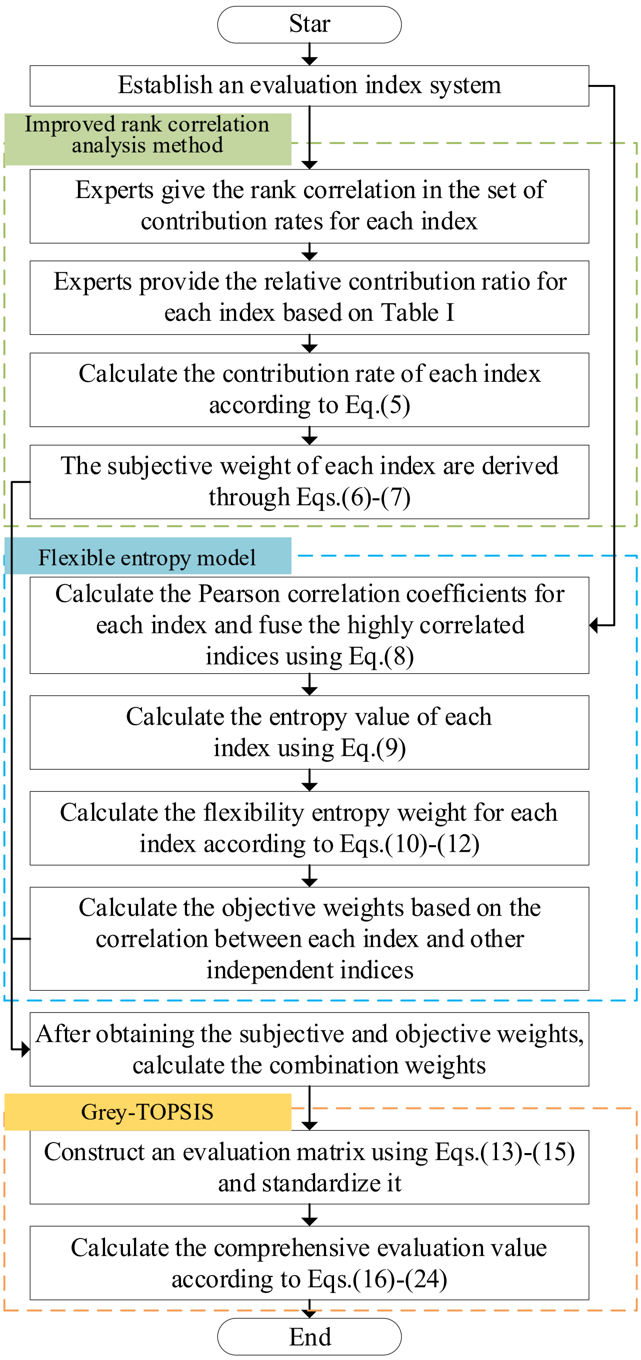

Fig. 3. EV charging responsiveness evaluation process

As shown in Fig. 3, the main steps of the evaluation are summarized below.

Step 1: Construct the EV charging responsiveness evaluation index system and analyze each index quantitatively and qualitatively.

Step 2: Calculate the subjective weight of each index using the improved ordinal relationship analysis.

Firstly, the expert establishes the ordinal relationship and the ratio of relative contribution degree within the set of contribution rates for each index. Then, the expert analyzes the hierarchical structure relationship of the constructed index system and calculates the subjective weight of each index using the Eqs. (5)-(7).

Step 3: Calculate the objective weight of each index using the flexible entropy model.

Prior to determining each index's objective weight, the Pearson correlation coefficient technique is applied to examine the relationships among indices based on data distribution. The correlation coefficients of the evaluation indices are calculated as shown in Eq. (24), and the evaluation metrics' correlation matrix E is then calculated.

$$E=\begin{bmatrix} e_{11} & \cdots & e_{1n} \\ \vdots & \ddots & \vdots \\ e_{n1} & \cdots & e_{nn} \end{bmatrix}$$

Where, e_{uk} is the correlation coefficient between y_u and y_k, a greater value indices, a stronger association between the indices. In this study, the correlation cutoff is established at 0.9, which means that y_u has a strong correlation when $e_{uk} \geq 0.9$. Otherwise, their association is slight and not contingent on one another.

$$e_{uk}=\frac{\sum_{i=1}^{m}\left(b_{iu}-\overline{b_u}\right)\left(b_{ik}-\overline{b_k}\right)}{\sqrt{\sum_{i=1}^{m}\left(b_{iu}-\overline{b_u}\right)}\sqrt{\sum_{i=1}^{m}\left(b_{ik}-\overline{b_k}\right)}} \tag{24}$$

Where, $\overline{b_u}$ and $\overline{b_k}$ are the average of the data of the uth and kth indices within the adjusted assessment array; m represents the comprehensive count of chosen EV categories.

Using the Pearson correlation coefficient method, indices with high correlations to objective data are treated as a single index for calculating objective weights. Eq. (8) combines the elevated correlation coefficients. It also determines the centroid vector from highly independent measures. Following the integration of the strongly correlated indices, the objective weights of each index are calculated by Eqs. (9)-(12).

Step 4: The obtained subjective and objective weights are combined. Ultimately, the EV charging responsiveness of each type is evaluated comprehensively by Grey-TOPSIS.

The portfolio weights are calculated as shown in Eq. (25).

$$W_c=\mu_1 W_1+\mu_2 W_2 \tag{25}$$

Where, W_1 denotes the subjective weighting derived from by improved rank correlation analysis method, W_2 denotes the objective weight determined through flexible entropy model, which is combined by Eq. (25) to get its combined weight W_c. μ_1 and μ_2 denote the subjective and objective coefficients of the combined weights, and satisfy $0<\mu_1,\mu_2<1$, $\mu_1+\mu_2=1$. This paper ensures that both subjective and objective factors are considered equally in the evaluation process to avoid over-reliance on one aspect of information, so $\mu_1=\mu_2=0.5$ is taken.

Finally, the comprehensive evaluation values of the charging responsiveness of different types of EVs are calculated by Eqs. (13)-(24).

IV. Case Study

To verify the effectiveness of the proposed evaluation method, data related to EV charging responsiveness are collected. Typical EV types include: electric buses (EV_1), electric cabs (EV_2), electric trucks (EV_3), and electric private cars (EV_4). The responsiveness of these four types of EVs is evaluated using the proposed method.

A. Data Acquisition and Organization

The charging performance data collected for different types of EVs are shown in Table II. Typical EV types can be represented as: electric buses (EV_1), electric cabs (EV_2), electric trucks (EV_3), and electric private cars (EV_4).

TABLE II
INDEX PERFORMANCE INFORMATION FOR DIFFERENT TYPES OF EVS

Indices		EV_1	EV_2	EV_3	EV_4
A_1	A_{11}	180kWh	90kWh	200kWh	100kWh
	A_{12}	Lower	High	Low	Higher
	A_{13}	170kWh	80kWh	160kWh	70kWh
	A_{14}	Moderate	Better	Moderate	Poorer
	A_{15}	Higher	Moderate	Higher	Moderate
A_2	A_{21}	Near	Moderate	Far	Farther
	A_{22}	Short	Shorter	Long	Moderate
	A_{23}	Moderate	Lower	Low	Lower
	A_{24}	Moderate	Higher	High	Higher
A_3	A_{31}	Low	High	Low	Higher
	A_{32}	0-1	3-5	0-1	1-2
	A_{33}	Moderate	Higher	Low	High
	A_{34}	150kWh	70kWh	160kWh	60kWh
A_4	A_{41}	More reasonable	Moderate	Less reasonable	Reasonable
	A_{42}	Low	High	Low	Higher
	A_{43}	Low	Higher	Lower	Higher

The qualitative indices are quantified according to the scoring rules and then normalized by Eqs. (13)-(15), where A_{15}, A_{21}, A_{22}, and A_{23} are negative indices, and the rest are positive indices. Tables III and IV show the quantitative and normalized data for the four EVs and 16 indices.

TABLE III
QUANTITATIVE DATA ON INDICES FOR DIFFERENT TYPES OF EVS

Indices		EV_1	EV_2	EV_3	EV_4
A_1	A_{11}	180	90	200	100
	A_{12}	65	85	60	80
	A_{13}	170	80	160	70
	A_{14}	75	80	70	85
	A_{15}	75	70	80	60
A_2	A_{21}	40	60	90	65
	A_{22}	40	45	90	50
	A_{23}	35	40	20	25
	A_{24}	60	65	85	80
A_3	A_{31}	50	90	40	85
	A_{32}	45	95	40	80
	A_{33}	60	65	40	90
	A_{34}	150	70	160	60
A_4	A_{41}	50	75	30	80
	A_{42}	40	90	70	85
	A_{43}	60	85	70	85

TABLE IV
INDICES NORMALIZED DATA FOR DIFFERENT TYPES OF EVS

Indices		EV_1	EV_2	EV_3	EV_4
A_1	A_{11}	0.5983	0.2992	0.6648	0.3324
	A_{12}	0.4438	0.5804	0.4097	0.5462
	A_{13}	0.6627	0.3119	0.6237	0.2729
	A_{14}	0.4826	0.5148	0.4504	0.547
	A_{15}	0.4668	0.5001	0.4376	0.5835
A_2	A_{21}	0.7035	0.469	0.3127	0.4329
	A_{22}	0.6169	0.5484	0.2742	0.4935
	A_{23}	0.3838	0.3358	0.6717	0.5373
	A_{24}	0.4097	0.4438	0.5804	0.5462
A_3	A_{31}	0.3587	0.6457	0.287	0.6099
	A_{32}	0.326	0.6883	0.2898	0.5796
	A_{33}	0.4532	0.491	0.3022	0.6799
	A_{34}	0.6305	0.2942	0.6725	0.2522
A_4	A_{41}	0.4026	0.6039	0.2416	0.6441
	A_{42}	0.2708	0.6092	0.4738	0.5754
	A_{43}	0.3961	0.5611	0.4621	0.5611

B. Determination of Weights

After obtaining the normalized data of the indices of different types of EVs, the subjective and objective weights of each index are calculated using the improved rank correlation analysis method and the flexible entropy model.

1) Subjective weights determined based on the improved rank correlation analysis method

This segment employs the improved rank correlation analysis method for determining the individual subjective importance of each evaluation criterion. Five invited experts in the electric vehicle field provided a tiered evaluation accordingly. They play a decisive role in determining subjective weights, and the accuracy and consistency of their judgments directly impact the scientific validity and credibility. The results are shown in Table V.

TABLE V
EVALUATION OF EXPERT SERIAL RELATIONSHIPS

Expert	Primary indices	A_1	A_2	A_3	A_4
$Expert_1$	3412	23451	3421	4123	132
$Expert_2$	3421	32451	3412	2413	312
$Expert_3$	3421	23145	3241	1243	123
$Expert_4$	3142	25341	3421	1423	321
$Expert_5$	3412	23541	3421	4123	132

Table VI delineates the assigned proportions for each index, as indicated by the hierarchical correlation analysis findings in Table I.

TABLE VI
RATIO OF RELATIVE CONTRIBUTION OF EVALUATION INDICES

Expert	Primary indices	A_1	A_2	A_3	A_4
$Expert_1$	1.6-1.4-1.0	1.0-1.4-1.0-1.2	1.4-1.4-1.0	1.0-1.0-1.6	1.0-1.2
$Expert_2$	1.8-1.4-1.0	1.2-1.4-1.0-1.0	1.4-1.4-1.0	1.2-1.0-1.6	1.2-1.2
$Expert_3$	1.6-1.2-1.0	1.2-1.2-1.4-1.2	1.2-1.2-1.0	1.2-1.2-1.4	1.0-1.2
$Expert_4$	1.2-1.2-1.0	1.4-1.0-1.2-1.2	1.6-1.2-1.0	1.2-1.0-1.2	1.0-1.2
$Expert_5$	1.8-1.2-1.2	1.0-1.4-1.0-1.0	1.4-1.4-1.0	1.2-1.0-1.6	1.2-1.4

Referencing Eq. (5), the rate of influence for each evaluation metric is ascertainable. For better understanding, the spatio-temporal feature layer of Expert$_1$ serves as a case for computational demonstration.

$$maxf=\sum_{k=2}^{4}\left(t_{k-1}-t_k\right)=t_1-t_4$$

$$s.t.\begin{cases} t_1-1.4t_2\le 0\\ t_2-1.4t_3\le 0\\ t_1-t_2\le 0\\ t_4-t_3\le 0\\ t_3-t_2\le 0\\ t_2-t_1\le 0\\ t_1-1.8t_4\le 0\\ \sum_{k=1}^{4}t_k=1 \end{cases}$$

By solving the planning problem, Expert$_1$'s contribution rate to the indices of the time-space characteristics layer is $t_4^*=1966$, $t_3^*=1966$, $t_2^*=2528$, $t_1^*=3539$. Based on $l_j=\sum_{i=1}^{m}b_{ij}$, we can calculate $l_1=7.5608$, $l_2=5.8016$, $l_3=9.7289$, $l_4=7.7598$. According to $t_1\succ t_1\succ\ldots\succ t_n$, therefore $l_1^*=5.8016$, $l_2^*=7.5608$, $l_3^*=7.7598$, $l_4^*=9.7289$. Finally, the subjective weights of each of the four indices are derived from Eqs. (6)-(7) as $w_1=0.3560, w_2=0.2477, w_3=1974, w_4=0.1989$. Repeating the above steps, the expert's assigned weighting for each index is computed. Based on the following Eq. (26), the subjective weights assigned by five experts to each index are derived. The results are presented in Fig. 4.

$$\beta_{jt}=\frac{w_i^* w_j^*}{\sum_{i=1}^{k}\sum_{j=1}^{q}w_i^* w_j^*} \tag{26}$$

Where, w_i^* is the weight of the primary indices, w_j^* is the weight of the secondary indices, and β_{jt} is the subjective weights by the t th expert.

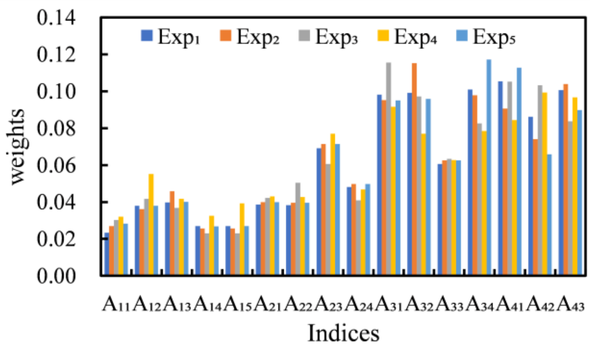

Fig. 4. Subjective weights determined by the five experts

The subjective weights of the EV charging responsiveness evaluation indices can be calculated using the arithmetic average of five experts as [0.0282, 0.0417, 0.0408, 0.0270, 0.0284, 0.0408, 0.0421, 0.0699, 0.0471, 0.0991, 0.0969, 0.0624, 0.0954, 0.0997, 0.0857, 0.0950].

From the calculation results, it can be seen that the EV planned charging capacity (A$_{34}$), rationality of charging price (A$_{41}$), timeliness of charging response (A$_{31}$), frequency of EV charging response (A$_{32}$), and EV charging cost (A$_{43}$) account for the highest weighting values. These indices are often important factors for EV charging stations to guide charging. On the other hand, the distance required for EVs to reach the charging station (A$_{21}$), capacity of battery (A$_{11}$), monitoring of battery charging temperature (A$_{15}$), expected charging waiting time (A$_{22}$), and state of battery health (A$_{14}$) are spatial-temporal characteristics of the EVs and their intrinsic attributes, which are less influential to the charging guidance decision, and thus their weights are also smaller.

2) Objective weights determined based on the flexible entropy model

Before calculating the objective weights of each evaluation index, the correlation between the indices is analyzed using the Pearson correlation coefficient method based on the analysis of the gathered data. The correlation coefficient of the evaluation indices is calculated according to Eq. (24). The correlation matrix for the assessment metrics is derived E. This step helps to identify potential multicollinearity issues, aiming to eliminate resulting weight estimation biases, thereby guaranteeing the robustness and reliability of the final weighting outcomes. Subsequently, the correlation coefficient between indices is computed, as depicted in Table VII.

As shown in Table VII, the associations among A$_{11}$, A$_{13}$, A$_{34}$, A$_{12}$, A$_{31}$, A$_{32}$, A$_{41}$, A$_{14}$, A$_{15}$, A$_{33}$, A$_{23}$, A$_{24}$, A$_{42}$, and A$_{43}$ exceed 0.9. There is a strong correlation exists between EV capacity of battery, rechargeable capacity and planned charging capacity; there is a high correlation between EV charging efficiency, timeliness of charging response, frequency of EV charging response and rationality of charging price; there is a high correlation between state of battery health, monitoring of battery charging temperature and interruptibility of charging in emergencies; there is a high correlation between charging level during off-peak periods and peak charging level; there is a high correlation between level of price compensation and charging cost.

Based on the correlation coefficient calculations for each index, the vector of integrated indices with high independence $\{c_1,c_2,c_3,c_4,c_5\}$ can be obtained from the analysis of indices with strong correlations using Eq. (8). The set of EV charging responsiveness evaluation indices after fusion of the highly correlated indices can be expressed as $C=\{c_1,c_2,\ldots,c_7\}$. The values of the fused evaluation indices are shown in Table VIII.

Using the flexible entropy model, target weights were derived for the indices listed in Table II. The system parameters of this model serve as variables, whose values were set and validated according to Eq. (11). The corresponding results are summarized in Table IX. The table structure is as follows: the first row displays the fused evaluation indices, the second row shows entropy values, and the remaining data records the changes of each index's weight.

Table IX shows that the maximum entropy value calculated using EWM is 0.9850. When $\rho<0.9850$, the value of $\rho-E$ is negative, it isn't very meaningful to use it as the numerator to represent the weight ratio of each index. Therefore, the value of $\rho<0.9850$ is not reasonable. In this paper, the objective weight of each evaluation index is determined by changing from $\rho=1$.

TABLE VII
PEARSON CORRELATION COEFFICIENTS BETWEEN INDICES

Indices	A_{11}	A_{12}	A_{13}	A_{14}	A_{15}	A_{21}	A_{22}	A_{23}	A_{24}	A_{31}	A_{32}	A_{33}	A_{34}	A_{41}	A_{42}	A_{43}
A_{11}	1.0000	0.9948	0.9632	0.9055	0.7974	0.0490	0.4394	0.4922	0.1637	0.9998	0.9853	0.7834	0.9861	0.9646	0.7494	0.8811
A_{12}	0.9948	1.0000	0.9374	0.8677	0.7358	0.0129	0.4727	0.5584	0.2353	0.9959	0.9938	0.7320	0.9642	0.9494	0.7313	0.8575
A_{13}	0.9632	0.9374	1.0000	0.8890	0.8428	0.2835	0.2064	0.2402	0.1071	0.9580	0.9407	0.7751	0.9878	0.9058	0.8643	0.9631
A_{14}	0.9055	0.8677	0.8890	1.0000	0.9642	0.0996	0.5134	0.3810	0.1085	0.9052	0.8198	0.9730	0.9383	0.9726	0.5451	0.7379
A_{15}	0.7974	0.7358	0.8428	0.9642	1.0000	0.0298	0.3377	0.1373	0.1157	0.7933	0.6872	0.9762	0.8723	0.8785	0.5324	0.7105
A_{21}	0.0490	0.0129	0.2835	0.0996	0.0298	1.0000	0.8750	0.7292	0.8827	0.0313	0.1007	0.1869	0.1312	0.1470	0.6908	0.5152
A_{22}	0.4394	0.4727	0.2064	0.5134	0.3377	0.8750	1.0000	0.9084	0.8871	0.4555	0.3915	0.5265	0.3538	0.5922	0.2552	0.0378
A_{23}	0.4922	0.5584	0.2402	0.3810	0.1373	0.7292	0.9084	1.0000	0.9365	0.5085	0.5161	0.3041	0.3603	0.5441	0.0826	0.0684
A_{24}	0.1637	0.2353	0.1071	0.1085	0.1157	0.8827	0.8871	0.9365	1.0000	0.1823	0.1831	0.0851	0.0268	0.2562	0.4201	0.2858
A_{31}	0.9998	0.9959	0.9580	0.9052	0.7933	0.0313	0.4555	0.5085	0.1823	1.0000	0.9853	0.7834	0.9835	0.9666	0.7383	0.8724
A_{32}	0.9853	0.9938	0.9407	0.8198	0.6872	0.1007	0.3915	0.5161	0.1831	0.9853	1.0000	0.6660	0.9527	0.9113	0.7886	0.8896
A_{33}	0.7834	0.7320	0.7751	0.9730	0.9762	0.1869	0.5265	0.3041	0.0851	0.7834	0.6660	1.0000	0.8371	0.9028	0.3827	0.5956
A_{34}	0.9861	0.9642	0.9878	0.9383	0.8723	0.1312	0.3538	0.3603	0.0268	0.9835	0.9527	0.8371	1.0000	0.9607	0.7793	0.9110
A_{41}	0.9646	0.9494	0.9058	0.9726	0.8785	0.1470	0.5922	0.5441	0.2562	0.9666	0.9113	0.9028	0.9607	1.0000	0.5780	0.7616
A_{42}	0.7494	0.7313	0.8643	0.5451	0.5324	0.6908	0.2552	0.0826	0.4201	0.7383	0.7886	0.3827	0.7793	0.5780	1.0000	0.9677
A_{43}	0.8811	0.8575	0.9631	0.7379	0.7105	0.5152	0.0378	0.0684	0.2858	0.8724	0.8896	0.5956	0.9110	0.7616	0.9677	1.0000

TABLE VIII
EVALUATED VALUES OF HIGH CORRELATION INDICES AFTER FUSION TREATMENT

	c_1	c_2	c_3	c_4	c_5	c_6	c_7
EV_1	0.6286	0.5312	0.5192	0.3967	0.3334	0.7035	0.6169
EV_2	0.3032	0.6673	0.5535	0.3898	0.5851	0.4690	0.5484
EV_3	0.6504	0.1852	0.3049	0.6260	0.4679	0.3127	0.2742
EV_4	0.2958	0.3814	0.5541	0.5418	0.5682	0.4329	0.4935

TABLE IX
DISTRIBUTION OF WEIGHTS FOR DIFFERENT VALUES OF ρ

	c_1	c_2	c_3	c_4	c_5	c_6	c_7
E	0.9515	0.9354	0.9817	0.9850	0.9840	0.9694	0.9720
$\rho=1$	0.2194	0.2925	0.0830	0.0677	0.0724	0.1383	0.1267
$\rho=1.5$	0.1474	0.1517	0.1393	0.1384	0.1387	0.1426	0.1419
$\rho=2$	0.1452	0.1474	0.1410	0.1406	0.1407	0.1427	0.1424
$\rho=2.5$	0.1444	0.1459	0.1416	0.1413	0.1414	0.1428	0.1425
$\rho=3$	0.1440	0.1452	0.1419	0.1417	0.1418	0.1428	0.1426

When $\rho=1$ corresponds to the traditional EWM, it often results in significant drawbacks in weight distribution. As Table IX shows, the weight value of c_2 is 0.2925, and the weight value of c_4 is 0.0677. The weight value of c_4 is only 23% of that of c_2 , and the difference between them is 0.2248, which means that c_2 contributes about 22.48% more weight than c_4 in the total evaluation. The over-emphasis of high informative index (c_2) and the weakening of low informative index (c_4) in decision making may lead to bias and reduce the comprehensiveness and fairness of decision making.

When $\rho=1.5$, the unreasonable situation of traditional entropy weight is avoided, and when $\rho>1.5$, there is no significant difference in the distribution of weights compared with $\rho=1.5$. From Fig. 5, it can be more intuitively seen that the objective weight distribution of each index when ρ is varied, and the weight of each index tends to be consistent with the increase of ρ . As ρ increases, each index's weight approaches 0.14.

The flexible entropy model employs $\rho=2$ as its parameter, with the weight vector γ computed. These findings are depicted in Fig. 6.

Of the seven weighting values calculated from the calculation, the value of c_1 denotes the combined weights of A_{11}, A_{13}, and A_{34} after the fusion process. The value of c_2 represents the combined weights of A_{12}, A_{31}, A_{32}, and A_{41}. The value of c_3 represents the combined weights of A_{14}, A_{15}, and A_{33}. The value of c_4 represents the combined weights of A_{23} and A_{24}. The value of c_5 represents the combined weights of A_{42} and A_{43}. The values of c_6 and c_7 indicate the weights of A_{21} and A_{22}.

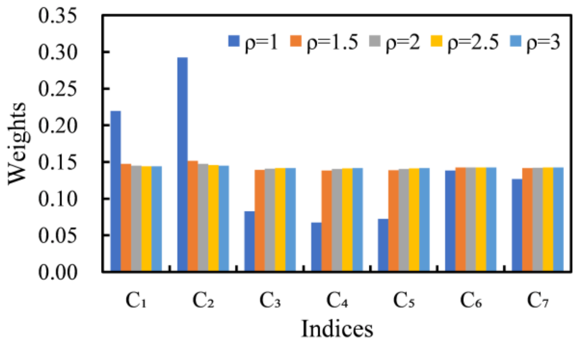

Fig. 5. Distribution of weights for different values of ρ

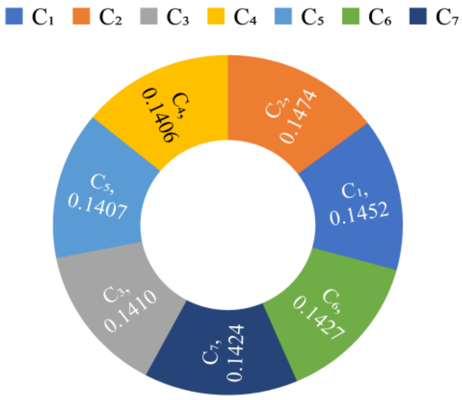

Fig. 6. Indices' flexible entropy weights after processing

Then, the weights of c_1 to c_5 are reassigned, and the weights of the synthesized vectors c_1 to c_5 are assigned to the indices other than A_{21} and A_{22} to obtain the final objective weights in Table II.

According to Eq. (24), the correlations of A_{11}, A_{13}, and A_{34} with the other 13 evaluation indices have been determined. The results of these calculations are presented in Table X. The average correlation for other evaluation indices can also be obtained.

The higher the interplay among an index and various other indices, the less pertinent info the index offers for gauging EV charging promptness, and the less weight should be given to that index. On the flip side, it should carry more significance.

Based on the above, objective weights can be assigned to A_{11}, A_{13}, A_{34}, A_{12}, A_{31}, A_{32}, A_{41}, A_{14}, A_{15}, A_{33}, A_{23}, A_{24}, A_{42}, and A_{43}. The value of A_{11} equals $0.1452\times(1-(-0.5997))/[(1-(-0.5997))+(1-(-0.6051))+(1-(-0.6180))]\approx 0.0482$; the value of A_{13} equals $0.1452\times(1-(-0.6051))/[(1-(-0.5997))+(1-(-0.6051))+(1-(-0.6180))]\approx 0.0483$; the value of A_{34} equals $0.1452\times(1-(-0.6180))/[(1-(-0.5997))+(1-(-0.6051))+(1-(-0.6180))]\approx 0.0487$. The value of other indices can be obtained by similar methods.

Finally, the objective weights of the 16 indices are calculated as [0.0482, 0.0373, 0.0483, 0.0465, 0.0470, 0.01427, 0.1424, 0.0736, 0.0670, 0.0367, 0.0378, 0.0475, 0.0487, 0.0357, 0.0729, 0.0678].

From the calculation results, it can be seen that the distance required for the EV to reach the charging station (A_{21}), the expected charging waiting time (A_{22}), the charging level during off-peak periods (A_{23}), and the peak charging levels (A_{24}) account for the highest value of the weights, which indicates that the data of these indices have a greater degree of variability, provide more information, and have high weights. The other indices are relatively less informative and therefore have smaller weights.

TABLE X
CORRELATION OF INDICES A_{11}, A_{13} AND A_{34}

Indices	A_{11}	A_{13}	A_{34}
A_{12}	-0.9948	-0.9374	-0.9642
A_{14}	-0.9055	-0.889	-0.9383
A_{15}	-0.7974	-0.8428	-0.8723
A_{21}	0.049	0.2835	0.1312
A_{22}	-0.4394	-0.2064	-0.3538
A_{23}	0.4922	0.2402	0.3603
A_{24}	0.1637	-0.1071	0.0268
A_{31}	-0.9998	-0.958	-0.9835
A_{32}	-0.9853	-0.9407	-0.9527
A_{33}	-0.7834	-0.7751	-0.8371
A_{41}	-0.9646	-0.9058	-0.9607
A_{42}	-0.7494	-0.8643	-0.7793
A_{43}	-0.8811	-0.9631	-0.911
Average value	-0.5997	-0.6051	-0.618

3) Assignment of subjective and objective weight combinations

In complex decision problems, it is often difficult for a single type of weight to adequately capture the importance of all relevant factors. For this reason, we adopt a weight combination method that combines subjectivity and objectivity, incorporating both the improved rank correlation analysis method and the flexible entropy model.

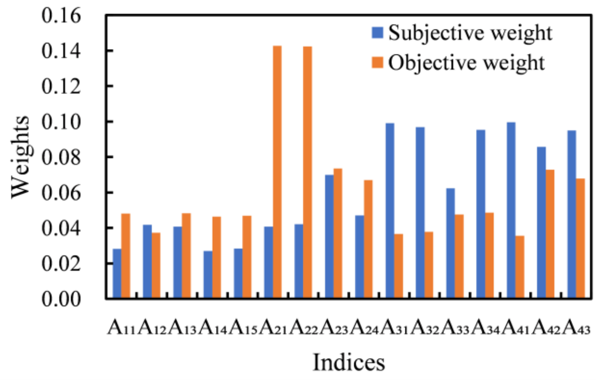

Fig. 7. Subjective and objective index weightings

The improved rank correlation analysis method depends on expert opinions. It assigns the weights by constructing the rank correlation evaluation matrix, which fully reflects the preferences and experience of decision makers. However, the flexible entropy model is based on the distribution characteristics of the data itself, which reflects the objectivity of the data. Combining the weights obtained by these two methods by a certain ratio or rule takes into account both the subjective will of the decision maker and the objective information of the data.

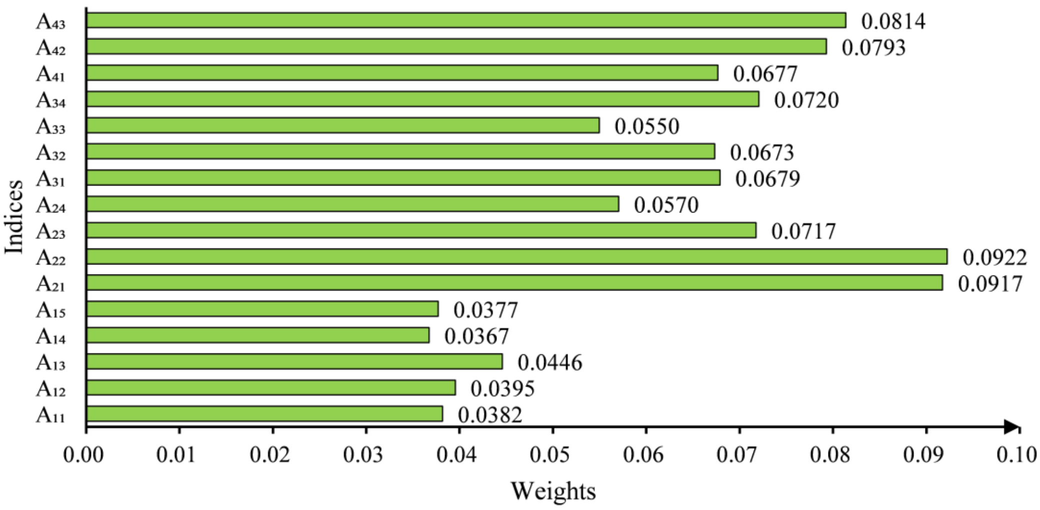

Fig. 8. Combined weights of indices

Fig. 7 shows the final subjective and objective weights of the indices.

Referencing Eq. (25), the subjective and objective weightage values are determined to get the comprehensive weights of EV charging responsiveness evaluation indices. The calculation results are [0.0382, 0.0395, 0.0446, 0.0367, 0.0377, 0.0917, 0.0922, 0.0717, 0.0570, 0.0679, 0.0673, 0.0550, 0.0720, 0.0677, 0.0793, 0.0814]. And the combined weights of the indices are shown in Fig. 8.

From the final combination of weights, it can be seen that the five indices that have the greatest impact on EV charging responsiveness are the distance required to reach the charging station (A_{21}), the expected charging waiting time (A_{22}), the EV charging cost (A_{43}), level of price compensation (A_{42}), and the planned charging capacity (A_{34}) with corresponding weights of 0.0922, 0.0917, 0.0814, 0.0793, and 0.0720.

C. EV Charging Responsiveness Evaluation Based on Grey-TOPSIS

There are four typical types of EVs, including electric buses (EV_1), electric cabs (EV_2), electric trucks (EV_3), and electric private cars (EV_4). Based on the weighted normalization matrix, the combined evaluation values of the four different types of EVs are calculated using the Grey-TOPSIS method. The final score of the evaluation is calculated using Eq. (23), where the weights in the equation are the combined weights calculated in the previous section, and the results are shown in Table XI. The EV charging responsiveness is ranked based on the score.

TABLE XI
EV CHARGING RESPONSIVENESS RESULTS BASED ON GREY-TOPSIS

EV types	EV_1	EV_2	EV_3	EV_4
Score	0.4935	0.7090	0.3103	0.7118
Sorting	3	2	4	1

From the comprehensive evaluation scores and rankings, it can be seen that the charging responsiveness of different types of EVs is ranked as electric private cars (EV_4) > electric cabs (EV_2) > electric buses (EV_1) > electric trucks (EV_3).

As can be seen from the index values in Table II, electric private vehicles (EV_4) rank first in six indices as the type with the highest EV charging response capability, and three of these indices have high weights: charging cost, charging level during off-peak periods, and rationality of charging price. The charging responsiveness of electric cabs (EV_2) is also relatively high, with all indices of charging response characteristics performing better than other types of EVs. In contrast, electric trucks (EV_3) and electric buses (EV_1) are less responsive. Therefore, when EVs are utilized to regulate the electric load of the grid through EV aggregators, electric private cars and electric cabs can be prioritized, which in turn effectively shaves the peaks and fills the troughs of the electric loads that have different modal performances at different times of the day.

To authenticate the efficacy of this approach, the methods AHP[22], AHP-EWM[23], AHP-TOPSIS[24], AHP-EWM-TOPSIS[25], AHP-Grey-TOPSIS[26], and AHP-EWM-Grey-TOPSIS[27] are compared. Table XII and Table XIII represent scores and ranking results of the four different types of EVs after applying different evaluation methods. And F_6 is the improved rank correlation analysis (IRCA), flexible entropy model (FEM), and Grey-TOPSIS proposed in this paper.

TABLE XII
SCORES OF THE FOUR DIFFERENT TYPES OF EVS

Method	Type	EV_1	EV_2	EV_3	EV_4
F_1	AHP	0.4617	0.5001	0.4436	0.5003
F_2	AHP-EWM	0.4635	0.5170	0.4052	0.5369
F_3	AHP-TOPSIS	0.5799	0.4881	0.5244	0.4669
F_4	AHP-EWM-TOPSIS	0.5669	0.4934	0.5101	0.4732
F_5	AHP-Grey-TOPSIS	0.4736	0.7010	0.3145	0.6938
F_6	IRCA-FEM-Grey-TOPSIS	0.4935	0.7090	0.3103	0.7118

TABLE XIII
RANKING RESULTS OF THE FOUR DIFFERENT TYPES OF EVS

Method	Type	EV_1	EV_2	EV_3	EV_4
F_1	AHP	3	2	4	1
F_2	AHP-EWM	3	2	4	1
F_3	AHP-TOPSIS	1	3	2	4
F_4	AHP-EWM-TOPSIS	1	3	2	4
F_5	AHP-Grey-TOPSIS	3	1	4	2
F_6	IRCA-FEM-Grey-TOPSIS	3	2	4	1

Fig. 9 and Fig. 10 show comparisons of scores and ranking results of the different evaluation methods.

In order to compare the ranking differences between the methods in this paper and other methods, the mean absolute error (MAE) of each method is calculated. The ranking vectors of the six methods in Table XIII are denoted as M_1, M_2, M_3, M_4, M_5, and M_6. The MAE among sorting sequences is given by:

$$MAE\left(M_i, M_k\right) = \frac{\sum_{j=1}^{m}\left|M_{ij} - M_{kj}\right|}{m} \tag{27}$$

Where, M_{ij} denotes the jth magnitude of the sequence M_i and m denotes the length of the sequence.

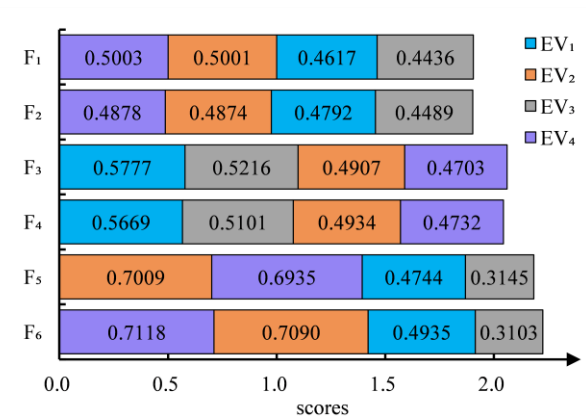

Fig. 9. Scores of different evaluation methods

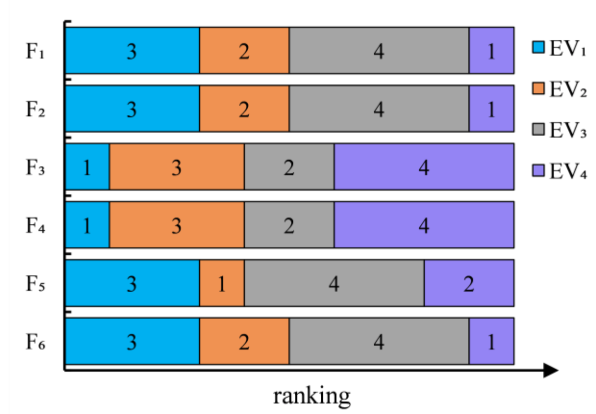

Fig. 10. Ranking results of different evaluation methods

The results are shown in Table XIV. The lower the MAE, the better the performance of the method. The MAE value of the method in this paper is less than AHP-TOPSIS, AHP-EWM-TOPSIS, and AHP-Grey- TOPSIS, so the sorting accuracy is better than them. Compared with AHP and AHP-EWM, which have equal MAE value, as shown in Table XII, the top two ranking scores calculated by them differ only by 0.0002 and 0.0004. In contrast, the proposed method significantly magnifies this gap to 0.0028, which is equivalent to a magnification of about 10 times. The same applies to the last two ranked scores. Therefore, this method can more clearly distinguish the subtle differences in regulation responsiveness among different types of EVs, enhance the sensitivity of the model, and provide a more reliable basis for formulating clear priority strategies. In summary, the overall sorting accuracy of the proposed method is better than that of AHP, AHP-EWM, AHP-TOPSIS, AHP-EWM-TOPSIS, and AHP-Grey-TOPSIS.

TABLE XIV
MAE VALUES FOR DIFFERENT METHODS

Sorting vector	M_1	M_2	M_3	M_4	M_5	M_6	Average value
M_1	0	0	2	2	0.5	0	0.75
M_2	0	0	2	2	0.5	0	0.75
M_3	2	2	0	0	2	2	1.33
M_4	2	2	0	0	2	2	1.33
M_5	0.5	0.5	2	2	0	0.5	0.92
M_6	0	0	2	2	0.5	0	0.75

Different evaluation methods lead to different scores and rankings in EV charging responsiveness evaluation. The main reasons for this are: (i) The improved rank correlation analysis and flexible entropy model in this paper have respectively improved the AHP and EWM methods. There are differences in the distribution of weights when calculating the weights of indices in different evaluation methods, and the results of the evaluations are different. (ii) We improve the Euclidean distance in TOPSIS through grey correlation degree, which also makes the evaluation results of Grey-TOPSIS and traditional TOPSIS significantly different. (iii) Compared with AHP-TOPSIS, AHP-EWM-TOPSIS, and AHP-Grey-TOPSIS, etc., the improved rank correlation analysis method, flexible entropy model, and Grey-TOPSIS selected make full use of the advantages of each of AHP, EWM, and TOPSIS, improve their deficiencies, and obtain new evaluation results. The evaluation index system combines various EVs' natural and physical characteristics and the adjustable capacity as flexible loads. The proposed improved rank correlation analysis method, flexible entropy model, and Grey-TOPSIS evaluation method fully consider the significant differences between evaluation indices and EV charging characteristics, which are more suitable for guiding flexible resource access in practical applications.

V. CONCLUSION

To fully utilize the adjustable potential of user-side flexible resources, a comprehensive evaluation method for EV charging responsiveness is proposed, utilizing the improved rank correlation analysis method, flexible entropy model, and Grey-TOPSIS. This approach can obtain quantifiable EV charging evaluation data. The experimental results show that, compared with the traditional methods such as AHP, AHP-EWM, AHP-TOPSIS, AHP-EWM-TOPSIS, and AHP-Grey-TOPSIS, this evaluation method guides the access of flexible resources. On the other hand, it can also assist with the distribution network planning.

The evaluation method facilitates grid operators to accurately grasp the ability of flexible loads to regulate their response to the grid, so that they can reduce the pressure on the grid by guiding users to reduce electricity consumption through demand response during peak hours, and make full use of the energy storage characteristics of flexible loads to absorb excess electricity from renewable energy sources during the low hours of the power, thus optimizing the allocation of power resources.

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