An Integrated Evaluation Approach for Charging Guidance of Electric Vehicle Charging Stations

Yiwei Ma, Xingzhen Li, Miao Huang

Abstract—**With the increasing penetration rate of electric vehicles (EVs), there are some prominent problems in EV charging guidance at EV charging stations such as poor charging arrangement, low charging satisfaction, etc. These problems are mainly caused by the lack of a scientific EV charging guidance scheme. Therefore, this paper proposes an integrated evaluation approach for charging guidance of EV charging stations based on the analytic hierarchy process (AHP), entropy weight method (EWM), and grey correlation evaluation (GCE). AHP is used to establish a set of EV charging response evaluation index system, and then EWM and GEM are used to improve the weights and evaluation functions of AHP to obtain quantitative evaluation scores for the charging response capabilities of different types of electric vehicles. The experiment results indicate that the proposed method has better effectiveness and applicability than the conventional AHP, and it provides an effective theoretical basis and beneficial contribution to the charging guidance of EV charging stations.**

Index Terms—**Analytic hierarchy process (AHP), electric vehicle, entropy weight method (EWM), grey correlation evaluation (GCE).**

I. INTRODUCTION

Due to technological advancements, environmental requirements, and the foreseeable shortage of fossil energy in the future, the demand for electric vehicles has continued to grow globally in recent years, especially in China, Europe, and the United States, where electric vehicle sales account for the majority of the world's total [1]. In order to meet the growing demand for electric vehicles, EV charging stations have been rapidly expanded in recent years. The planning, construction, and operation of electric vehicle charging stations require a scientific evaluation system as guidance. Therefore, developing a reasonable performance evaluation system is of great significance to electric vehicle charging stations (EVCSs) [2], [3].

In recent years, scholars around the world have proposed various analytic hierarchy process (AHP) based evaluation methods [4] for EV charging stations to solve prominent issues such as low charging efficiency, poor charging service quality, low economic benefits of charging, and low charging response of electric vehicles, such as AHP [5], FAHP [6], EWM [7], grey correlation evaluation [8], [9]. Ref. [9] presents a fuzzy evaluation model based on the fuzzy comprehensive evaluation and analytic hierarchy process to evaluate the energy efficiency of EV charging stations. Ref. [10] proposes an AHP-entropy method to evaluate the operational energy efficiency of electric vehicle charging stations from the aspects of power supply system reliability, charging equipment efficiency, power quality, operational status, and the auxiliary services to the power grid. Ref. [11] presents a method of AHP and fuzzy evaluation to assess the comprehensive performance of the electric vehicle charging stations from the aspects of power supply capacity, utilization efficiency, supply reliability, load characteristics, and user satisfaction. Ref. [12] evaluated the operational capability of EV charging stations from the aspects of charging facility configuration, service capacity, service range, and annual construction cost. In addition, some studies focused on the site evaluation and selection of electric vehicle charging stations [13], [14]. Ref. [15] employs AHP to assess suitable locations for EV charging station deployment, which presents three core evaluation criteria: environmental, physical, and economic-social aspects, and introduces nine sub-criteria. Ref. [16] utilizes AHP, Fuzzy AHP (FAHP), and Technique for Order Preference by Similarity to TOPSIS to present a method for finding suitable locations for electric vehicle charging stations from the perspectives of accessibility, environment, and economy. It first uses AHP and FAHP to calculate the weights of criteria, and then employs the technique for order preference by similarity to ideal solution to rank the alternative locations of EVCSs for suitable solution selection. Ref. [17] presents an AHP-based fuzzy comprehensive evaluation model for the location selection of electric vehicle charging stations, which selects traffic flow, economic cost, and charging convenience as the main influencing factors.

The above-mentioned research schemes mainly focus on the operational energy efficiency, charging capability, and site/location selection of electric vehicle charging stations, but do not consider EV charging response factors for suitable charging guidance of EV charging stations. To fill this research gap, this paper proposes an integrated evaluation approach of AHP, entropy weight method (EWM), and grey correlation evaluation (GCE) for EV charging guidance of EV charging stations. This method fully considers the operational purpose of EVCS and the charging response of

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different types of EVs and then proposes four core evaluation criteria and eleven sub-criteria for EV charging response, such as battery charging capacity, spatiotemporal charging convenience, charging response performance, and charging economy. The main contributions of this work are summarized as follows.

(i) To our best knowledge, this is the first work in an integrated EV charging guidance evaluation approach based on AHP, EWM, and GCE proposed for EVCSs to solve the prominent problems of low charging efficiency, poor charging service, low charging economic benefits, and low EV charging response.

(ii) Based on the operational objectives of EVCSs and the charging response characteristics of different types of EVs, a two-level evaluation index system for EV charging guidance is proposed, which includes four core evaluation criteria and eleven evaluation indices.

(iii) EWM is used to modify the weights of AHP in order to improve its disadvantages of singular subjective weights and gain advantages in both subjective and objective weights.

(iv) GCE is used to improve the conventional evaluation method of AHP by effectively extracting the objectivity and subjectivity of the evaluation object, and combining them to make the evaluation results more objective and accurate.

The remainder of the paper is organized as follows. Section II outlines the basic methodology that is used in this research, and Section III proposes the integrated evaluation model for EV charging guidance of EVCSs. Section IV presents the case study results and discussions. Finally, Section V concludes the study and provides some suggestions for future studies.

II. BASIC METHODOLOGY

The proposed EV charging guidance evaluation method can be divided into three main stages: (i) establish the index system; (ii) calculate the index weight; (iii) conduct grey evaluation, as shown in Fig. 1. It comprehensively utilizes various theoretical methods such as AHP, EWM, and GCE. The introduction of these methods used is as follows.

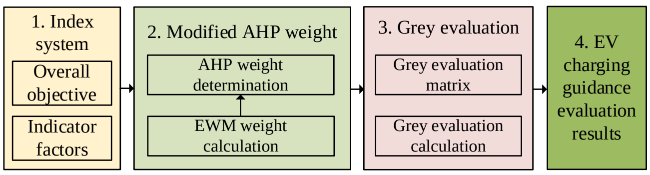

Fig. 1. The framework of EV charging guidance evaluation.

A. Analytic Hierarchy Process

The analytic hierarchy process (AHP) is a classical systematic analysis method to deal with multi-level and multi-objective decision-making problems [16]. It was proposed by Professor Saty of the University of Pittsburgh in the 1970s [18] and has significantly progressed over the years. As one of the data tools for system analysis, AHP adopts the idea of "decomposition first and then synthesize". Firstly, it divides various index factors in complex problems into interconnected and ordered levels and transforms multi-objective and multi-criteria decision-making into pairwise comparisons of multi-level single objectives. Then, it uses mathematical methods to calculate the weight of each index factor and finally evaluates different solutions based on the weight values between all elements. In general, the basic steps of AHP are summarized as follows [19].

Step 1: Establish a multi-level network structure system based on the overall decision-making objective of the evaluation object, considering factors and their related relationships.

Step 2: Construct pairwise comparison judgment matrix A by Eq. (1), where a_{ij} is the element in row i and column j of the n-dimensional matrix A, and meet three conditions: (i) $a_{ij} > 0$, (ii) $a_{ij} = 1/a_{ji}$, (iii) $a_{ii} = 1$.

$$A = \left(a_{ij}\right)_{n\times n} \tag{1}$$

Step 3: Calculate the relative weights of the judgment matrices by Eq. (2) and complete consistency checks by Eqs. (3)- (5).

$$\omega_i = \frac{1}{n}\sum_{j=1}^{n}\left(a_{ij}\Big/\sum_{k=1}^{n}a_{kj}\right) \tag{2}$$

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{3}$$

$$\lambda_{\max} = \sum_{i=1}^{n}\left(\sum_{j=1}^{n}a_{ij}\omega_j \Big/ n\omega_i\right) \tag{4}$$

$$CR = \frac{CI}{RI} \tag{5}$$

Where, ω_i is the relative weight of the compared element to the criterion, $\lambda_{\max}$ is the maximum eigenvalue, CI is the consistency index, CR is the consistency ratio, and RI is the average random consistency index.

Step 4: Calculate the evaluation score of each alternative solution according to Eq. (6).

$$S = W_l \cdot G_l^T \tag{6}$$

Where, $W_l = \left(w_1, w_2, \cdots, w_n\right)$ is the weight vector of the l-th layer, w_n is the weight of the n-th element, $G_l = \left(g_1, g_2, \cdots, g_n\right)$ is the evaluation vector of the l-th layer, g_n is the evaluation value of the n-th element.

B. Entropy Weight Method

The entropy weight method (EWM) is a commonly used method for multi-criteria decision analysis based on information entropy theory [20]. It is considered an objective-weighted data analysis method that can quantify the importance of different indices and apply them to various fields such as multi-objective decision-making, evaluation, and ranking. When calculating the weights of indices, EWM uses entropy from information theory to evaluate the relative strength of indices in a competitive sense [21]. When there is a large difference in the index values of the evaluation object, the entropy value is small, and the information provided by the index is large, so the weight of the index is also large.

The calculation of EWM mainly consists of three steps as below.

Step 1: Normalization. To eliminate the influence of different index dimensions and differences in data range, the raw data should be standardized, as shown in Eq. (7).

$$x_{ij}^{'} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}\ (i = 1, 2, \cdots, n) \tag{7}$$

Step 2: Calculate the information entropy of each index, which is used to reflect the amount of information provided by that index. Therefore, the information entropy of index i

can be calculated by Eq. (8).

$$h_i = -\frac{1}{\ln n}\sum_{i=1}^{n} x_{ij}^{'} \ln x_{ij}^{'} \tag{8}$$

Step 3: Calculate the entropy weight of the index *i*, as shown in Eq. (9).

$$v_i = \frac{1-h_i}{n-\sum_{i=1}^{n} h_i} \tag{9}$$

C. Grey Correlation Evaluation

The grey correlation evaluation (GCE) is a new evaluation method based on grey system theory, which can effectively deal with problems such as data shortage and uncertainty [22]. This GCE method calculates the grey evaluation weight coefficients of multiple indices through different grey types to handle the fuzzy evaluations of various experts. Then, the grey evaluation matrix is organically combined with the scoring criteria to obtain the comprehensive evaluation value [23], [24].

The main steps of GCE are summarized as follows:

Step 1: Set the evaluation comment set as shown in Eq. (10) and determine the grey category in Eq. (11).

$$K = \{K_1, K_2, \ldots, K_m\} \tag{10}$$

$$C = (C_1, C_2, \ldots, C_m) \tag{11}$$

Where, K is the evaluation comment set, which is generally divided into five grades such as very poor, poor, medium, good, and excellent; C is the grey category that is usually set to 5, so $C = \{1,3,5,7,9\}$.

Step 2: With m experts, each index is grated, and then an evaluation sample matrix D as shown in Eq. (12).

$$D = \begin{bmatrix} d_{11} & d_{21} & \cdots & d_{p1} \\ d_{12} & d_{22} & \cdots & d_{p2} \\ \vdots & \vdots & \ddots & \vdots \\ d_{1q} & d_{2q} & \cdots & d_{pq} \end{bmatrix} \tag{12}$$

Where, d_{pq} is the score of the *p*-th expert to the *q*-th index.

Step 3: Determine the whitening weight function. The whitening function is shown in Eq. (13).

$$f_\alpha\left(C_\alpha, d_{pq}\right) = \begin{cases} \dfrac{d_{ij}}{C_\alpha} & d_{ij} \in \left[0, C_\alpha\right] \\ \max\left(\dfrac{2C_\alpha - d_{ij}}{C_\alpha}, 1\right) & d_{ij} \in \left[C_\alpha, 2C_\alpha\right] \\ 0 & d_{ij} \notin \left[0, 2C_\alpha\right] \end{cases} \tag{13}$$

Where, f_α is the whitening function with the α-th grey category.

Step 4: Calculate the evaluation weight and matrix of grey assessment according to Eqs. (14)- (16).

$$R = \left(r_1, r_2, \ldots, r_q\right)^T \tag{14}$$

$$r_q = \left(r_q^1, r_q^2, \ldots, r_q^m\right) \tag{15}$$

$$r_q^\alpha = \frac{s_q^\alpha}{s_q} = \frac{\sum_{\partial=1}^{p} f_\alpha\left(d_{\partial q}\right)}{\sum_{\alpha=1}^{m}\sum_{\partial=1}^{p} f_\alpha\left(d_{\partial q}\right)} \tag{16}$$

Where, *R* is the grey evaluation weight matrix, and r_q is the vector of the matrix; r_q^α is the grey evaluation weight of the α-th grey category for the *q*-th evaluation index; s_q^α is the grey statistics number of the *q*-th evaluation index belonging to the α-th grey category; s_q is the sum of the gray statistics number for the *q*-th evaluation index.

Step 5: Use the weights *W* to calculate the grey evaluation matrix and the comprehensive assessment value according to Eqs. (17)- (18).

$$Q = WR \tag{17}$$

$$Z = QC^T \tag{18}$$

Where, *Q* is the grey evaluation matrix, and *Z* is the comprehensive assessment value.

III. The Proposed Integrated Evaluation Method

In order to comprehensively evaluate the charging guidance capability of EVs, this article first determines the evaluation indices that affect the response of EVs, then establishes a two-level evaluation index system for EV charging guidance, and uses the EWM method to improve the weights of the two-level evaluation index system solved by the AHP method. Finally, the GCE method is used to evaluate different types of EVs comprehensively.

A. Two-level Evaluation Index System for EV Charging Guidance

The comprehensive evaluation index system for EV charging guidance established in this paper fully considers the needs for EVCS and the characteristics of different types of EVs. It guides the charging of various types of EVs from four aspects: the battery charging capability, the charging spatiotemporal characteristics, the charging response, and the charging economical.

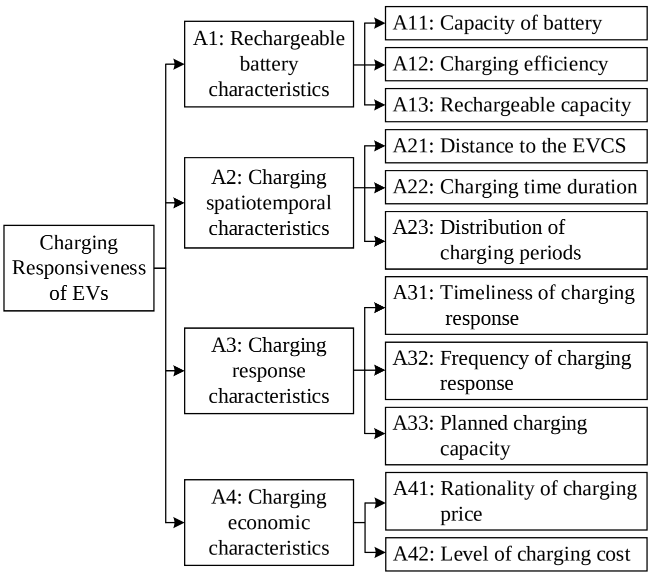

Fig. 2. Comprehensive evaluation index system for EV charging guidance.

As shown in Fig. 2, the battery charging capability includes the capacity of battery, the charging efficiency, and the rechargeable capacity. The charging spatiotemporal characteristics include the distance to the EVCS, the charging time duration, and the distribution of charging periods. The charging response includes the timeliness of the charging response, the frequency of the charging response, and the planned charging capacity. The charging economical includes the rationality of charging price and the level of charging cost.

A. Evaluation process of EV charging guidance

In order to accurately evaluate the charging response capability of different types of EVs and arrange the charging guidance of EVs reasonably, this paper proposes an AHP-EWM-GCE method. Fig. 3 shows the specific evaluation flowchart.

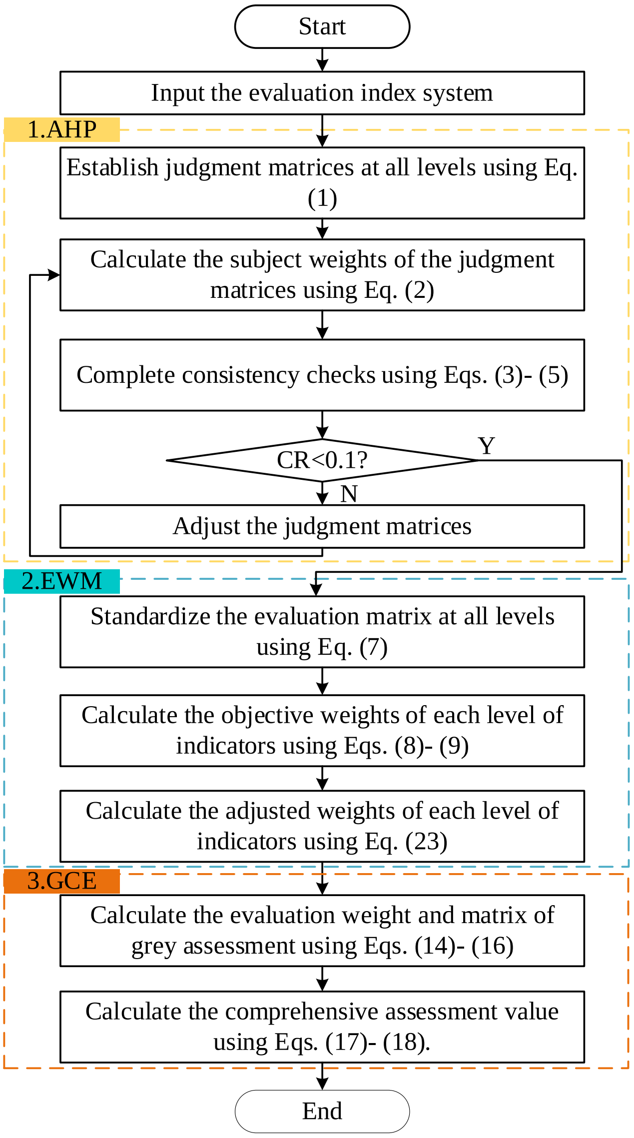

Fig. 3. Evaluation flowchart based on AHP-EWM-GCE.

The main steps of the AHP-EWM-GCE method are summarized as follows.

Step 1: Use the AHP method to calculate the weights of the evaluation index system for EV charging response.

For the evaluation index system of two-level electric vehicle charging guidance, the weights of the main and secondary indices are shown in Eqs. (19) - (20), which are calculated and verified for consistency through Eqs. (1) - (5).

$$W_1 = \left(w_1, w_2, w_3, w_4\right) \tag{19}$$

$$W_2 = \left(w_{11}, w_{12}, \ldots, w_{42}\right) \tag{20}$$

Where, W_1 is the subjective weight of the primary indices; W_2 is the subjective weight of the secondary indices.

Step 2: Use the EWM method to determine the objective weights of the index system.

Similarly, use Eqs. (7) - (9) to calculate the entropy weight for each layer index, where Eqs. (21)- (22) represent the objective weight expressions for the primary and secondary indices. Then, the subjective weights are adjusted using Eq. (23), where Eqs. (24)- (25) represent the adjusted weights of the primary and secondary indices.

$$V_1 = \left(v_1, v_2, v_3, v_4\right) \tag{21}$$

$$V_2 = \left(v_{11}, v_{12}, \ldots, v_{42}\right) \tag{22}$$

$$u_\sigma = \frac{w_\sigma v_\sigma}{\sum_{j=1}^{n} w_j v_j} \tag{23}$$

$$U_1 = \left(u_1, u_2, u_3, u_4\right) \tag{24}$$

$$U_2 = \left(u_{11}, u_{12}, \ldots u_{42}\right) \tag{25}$$

Where, V_1 is the objective weight of the primary indices; V_2 is the objective weight of the secondary indices; u_σ is the adjusted weight of the σ -th index; U_1 is the adjusted weight of the primary indices; U_2 is the adjusted weight of the secondary indices.

Step 3: Use the GCE method to evaluate different types of EVs comprehensively.

The adjusted weights U_1 and U_2 of each index in the GCE method are obtained from steps 1 and 2.

IV. Case Study

To verify the proposed AHP-EWM-GCE evaluation method, a comparative experiment was designed to evaluate different types of EVs, such as electric buses (EB), electric cabs (EC), electric trucks (ET), and electric private vehicles (EPV).

A. AHP-EWM-based Adjusted Weight Calculation

1) AHP-based subjective weight calculation

Taking into account the physical characteristics of various EVs and the charging demands of owners, an evaluation index system for EV charging guidance was constructed as shown in Fig. 2. According to the evaluation process as shown in Fig. 3, the first and second level indices were evaluated, and different levels of index judgment matrix were established by comparing each index pairwise. Table I shows the paired judgment matrix for the primary index, and its consistency verification result is good, as CR=0.0115 which is less than 0.1.

TABLE I
THE PAIRED JUDGMENT MATRIX FOR THE PRIMARY INDEX

	A_1	A_2	A_3	A_4
A_1	1	2	1/3	1/2
A_2	1/2	1	1/4	1/3
A_3	3	4	1	2
A_4	2	3	1/2	1

In the paired comparison matrix, different numerical values indicate varying levels of relative importance among different indices. As shown in Table I, index A_3 is considered more important than the other three indices. For the secondary indicators under each primary index, a similar judgment matrix can be constructed in the same format as in Table I. All of these matrices pass the consistency test.

By establishing judgment matrices at different levels, the weights of indices at each level can be obtained. Finally, the comprehensive subjective weights are obtained by integrating the weights of various levels of indices. Table II shows the subjective weights of each index.

TABLE II
THE SUBJECTIVE WEIGHTS OF INDICES

Primary indices	Primary indices weights	Secondary indices	Secondary indices weights	Subjective weights of indices
A_1	0.1601	A_{11}	0.1095	0.0175
		A_{12}	0.5816	0.0931
		A_{13}	0.3090	0.0495
A_2	0.0954	A_{21}	0.1365	0.0130
		A_{22}	0.2385	0.0228
		A_{23}	0.6250	0.0596
A_3	0.4673	A_{31}	0.3090	0.1444
		A_{32}	0.1095	0.0512
		A_{33}	0.5816	0.2718
A_4	0.2772	A_{41}	0.8000	0.2218
		A_{42}	0.2000	0.0554

As shown in Table II, the weights of the first level /primary indices are 0.4673 for the charging response index 0.2772 for the charging economy index, 0.1601 for the battery charging capacity index, and 0.0954 for the charging spatiotemporal characteristic index. Obviously, the charging response index is the most important, followed by the charging economy index, the battery charging capacity index, and the charging spatiotemporal characteristic index. In the second level /secondary indices, the weights of the planned charging capacity, the rationality of charging price, and the timeliness of charging periods are all above 0.1, which indicates that these indices have a significant impact on the charging guidance sequence of EVs. The weights of the capacity of battery and the distance to the EVCS are less than 0.02, which shows a relatively small impact.

2) EWM-based weight calculation

In order to ensure comparability and consistency of data, the evaluation results of different experts on primary and secondary indices were standardized and transformed into standardized scoring matrices at various levels, and the weight values of each level index were obtained, as shown in Table III.

TABLE III
FIRST-LEVEL STANDARDIZED SCORING MATRIX

	A_1	A_2	A_3	A_4
1	0	0.3333	0.5000	0.1667
2	0	0.5000	0.6667	0.1667
3	0.1667	0.5000	0.8333	0.3333
4	0.3333	0.1667	0.6667	0.3333
5	0.3333	0.5000	0.8333	0.5000
6	0.3333	0.6667	1	0.3333
7	0.16667	0.3333	0.8333	0.5000
8	0	0.6667	1	0.1667

According to the entropy weight calculation steps shown in Fig. 3 (2), the information entropy of the scoring matrix and the objective weight values corresponding to each index were calculated, as shown in Table IV. Similarly, the rating matrices for each secondary index and their information entropy and corresponding objective weight values were standardized and obtained the corresponding objective weights of each index, as shown in Table V.

TABLE IV
WEIGHTS OF THE PRIMARY INDICES

	A_1	A_2	A_3	A_4
Information entropy	1.8049	2.0697	2.0605	2.0722
Objective weights	0.0857	0.0915	0.0913	0.0916

TABLE V
THE OBJECTIVE WEIGHTS OF INDICES

Primary indices	Primary indices weights	Secondary indices	Secondary indices weights	Objective weights of indices
A_1	0.2283	A_{11}	0.3148	0.0719
		A_{12}	0.3461	0.0790
		A_{13}	0.3391	0.0774
A_2	0.2567	A_{21}	0.2868	0.0737
		A_{22}	0.3348	0.0859
		A_{23}	0.3784	0.0971
A_3	0.2596	A_{31}	0.3492	0.0906
		A_{32}	0.3314	0.0861
		A_{33}	0.3194	0.0829
A_4	0.2554	A_{41}	0.5354	0.1367
		A_{42}	0.4646	0.1187

The weights presented in Table V are obtained using information entropy, which is a method of minimizing the subjective influence of experts. By applying information entropy to various indices, the weights are objectively calculated, ensuring that the evaluation results are more accurate and reasonable. Using the objective weights from Table V, as specified in Eq. (23), the subjective weights in Table II are adjusted. The updated weights are displayed in Table VI.

TABLE VI
THE ADJUSTED WEIGHTS OF INDICES

Primary indices	Primary indices weights	Secondary indices	Secondary indices weights	Adjusted weights of indices
A_1	0.1444	A_{11}	0.1012	0.0146
		A_{12}	0.5911	0.0854
		A_{13}	0.3077	0.0444
A_2	0.0967	A_{21}	0.1101	0.0106
		A_{22}	0.2246	0.0217
		A_{23}	0.6653	0.0644
A_3	0.4792	A_{31}	0.3270	0.1567
		A_{32}	0.1100	0.0527
		A_{33}	0.5630	0.2698
A_4	0.2797	A_{41}	0.8217	0.2298
		A_{42}	0.1783	0.0499

Table VI shows that among the primary indices, the charging response of EVs has the greatest impact on the guidance of EV charging, accounting for 0.4792; Secondly, the charging economical accounts for 0.2797; The third is the rechargeable characteristic, accounting for 0.1444; The smallest impact is on the charging spatiotemporal characteristics, accounting for 0.0967. In the secondary indices, the adjusted weights of the planned charging capacity, the rationality of charging price, the timeliness of charging response, and the charging efficiency are 0.2698, 0.2298, 0.1567, and 0.0854, respectively. These indices have the greatest impact on the guidance of electric vehicle charging.

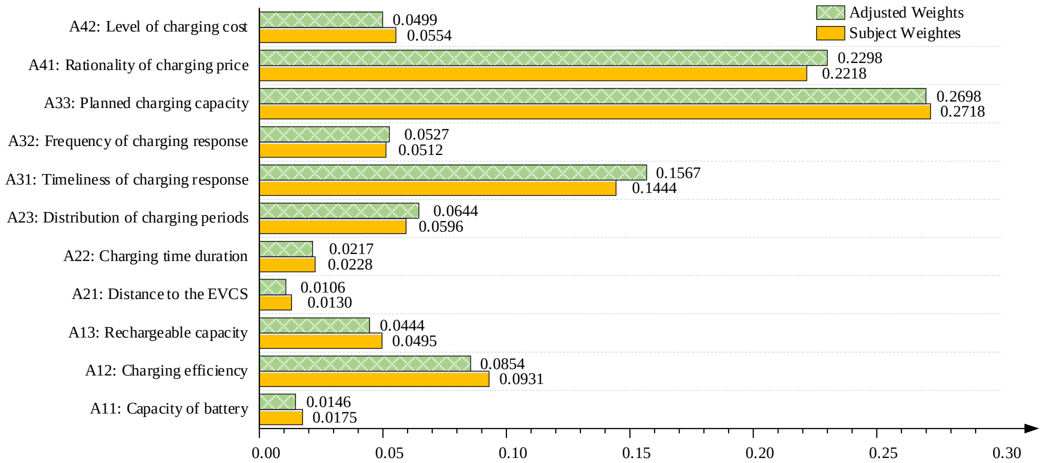

Fig. 4. The comparison between subjective weights and modified weights of secondary indices.

Fig. 4 shows the comparison between subjective weights and modified weights of secondary indices. It intuitively reflects the difference between subjective weight and modified weight. The correction of weights is influenced by objective weights and has subtle changes based on subjective weights.

B. GCE-based EV Charging Guidance Evaluation

For different types of EVs, different experts have different ratings through the evaluation system. Table VII shows the evaluation sample matrix for EB.

TABLE VII
EVALUATION SAMPLE MATRIX FOR EB

Indices	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
A_{11}	6	5	7	5	6
A_{12}	3	2	4	5	3
A_{13}	4	5	5	3	4
A_{21}	6	5	7	5	6
A_{22}	3	3	4	2	2
A_{23}	6	5	4	5	6
A_{31}	2	3	3	2	2
A_{32}	1	2	2	1	2
A_{33}	5	6	4	4	6
A_{41}	5	5	3	4	3
A_{42}	4	3	4	3	2

The grey evaluation matrix can be obtained by the whitening function, as shown in Table VIII.

TABLE VIII
THE GREY EVALUATION MATRIX FOR EB

Indices	Grey evaluation weight				
	r_q^1	r_q^2	r_q^3	r_q^4	r_q^5
A_{11}	0.2634	0.3387	0.3434	0.0545	0.0000
A_{12}	0.1659	0.2133	0.2987	0.3221	0.0000
A_{13}	0.1862	0.2394	0.3351	0.2394	0.0000
A_{21}	0.2634	0.3387	0.3434	0.0545	0.0000
A_{22}	0.1502	0.1931	0.2704	0.3863	0.0000
A_{23}	0.2342	0.3011	0.3567	0.1081	0.0000
A_{31}	0.1411	0.1815	0.2540	0.4234	0.0000
A_{32}	0.1071	0.1377	0.1928	0.3213	0.2410
A_{33}	0.2274	0.2924	0.3438	0.1364	0.0000
A_{41}	0.1840	0.2365	0.3311	0.2484	0.0000
A_{42}	0.1578	0.2029	0.2841	0.3551	0.0000

Based on the weights obtained in Table VI and the grey evaluation matrix obtained in Table VIII, the evaluation vectors of the primary level indices and the overall evaluation vector can be obtained separately, and the comprehensive evaluation score of EB can be obtained. The calculation process is as follows.

$$Q_1 = W_1 \cdot R_1 = (0.1820, 0.2340, 0.3144, 0.2695, 0)$$

$$Q_2 = W_2 \cdot R_2 = (0.2185, 0.2810, 0.3358, 0.1647, 0)$$

$$Q_3 = W_3 \cdot R_3 = (0.1860, 0.2391, 0.2978, 0.2506, 0.0265)$$

$$Q_4 = W_4 \cdot R_4 = (0.1793, 0.2305, 0.3228, 0.2674, 0)$$

$$M = W \cdot [Q_1; Q_2; Q_3; Q_4] = (0.1867, 0.2400, 0.3109, 0.2497, 0.0127)$$

$$Z = M \cdot C = 5.6765$$

Similarly, the above evaluation steps also apply to other types of electric vehicles, such as EC, ET, and EPC. In order to verify the superiority of the proposed AHP-EWM-GCE method, some benchmarking methods such as AHP, FAHP, AHP-EWM, FAHP-EWM, and AHP-GCE were given to compare. Table IX shows the detailed evaluation scoring results for different types of electric vehicles and different evaluation methods.

TABLE IX
THE SCORING OF FOUR EVS UNDER SIX METHODS

Methods	EB	EC	ET	EPV
AHP	4.6198	5.5694	4.6319	5.5628
AHP-EWM	4.6132	5.5791	4.6042	5.5824
FAHP	4.8045	5.2736	4.7665	5.3257
FAHP-EWM	4.8132	5.3144	4.8326	5.2215
AHP-GCE	5.6765	6.3346	5.6932	6.1834
AHP-EWM-GCE	5.6855	6.3487	5.6745	6.1935

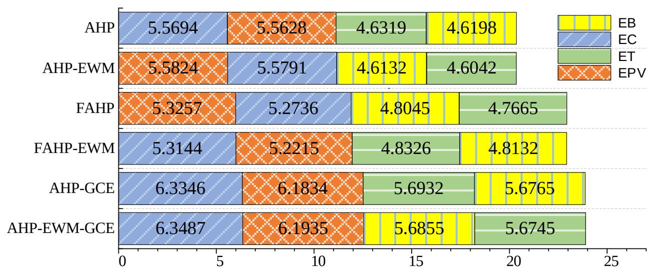

Fig. 5. The comparison between different methods.

In order to clearly demonstrate the charging guidance effect, the evaluation scores of the six different EVs evaluated by each method are arranged in descending order, and then the corresponding EV charging guidance sequences were obtained as shown in Fig. 5.

Refs. [5] - [8] are some improved evaluation methods, which are applied to the index system established in this paper for evaluation, and compared with these methods. The comparison results are shown in Table X and Fig. 6.

TABLE IX
THE SCORING OF FOUR EVS UNDER SIX METHODS

Methods	EB	EC	ET	EPV
Ref. [5]	4.7289	5.5724	4.6923	5.5526
Ref. [6]	4.8449	5.7236	4.7125	5.7956
Ref. [7]	4.8332	5.7112	4.8623	5.5231
Ref. [8]	5.6224	6.3125	5.6352	6.1723
AHP-EWM-GCE	5.6855	6.3487	5.6745	6.1935

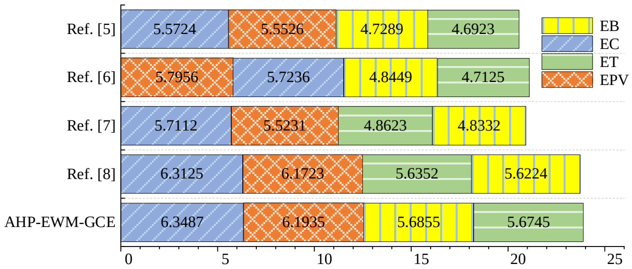

Fig. 6. The comparison between different references methods.

The evaluation results obtained by different literature methods are different. For the evaluation index system in this paper, we can get good evaluation results, which are more in line with the actual situation. Obviously, different evaluation methods have led to varying scores and orders of EV charging guidance evaluation. The main reasons are: (i) EWM caused variations in various evaluation indices, which resulted in significant differences in the evaluation results between AHP-EWM and AHP. (ii) Similarly, GCE led to significant differences in the evaluation results between AHP-GCE and AHP. (iii) AHP-EWM-GCE obtained a new evaluation result compared to AHP, AHP-EWM, and AHP-GCE, because it fully utilized the respective advantages of AHP, EWM, and GCE, and improved the unilateral evaluation results of EWM or GCE on the weights of each evaluation index. (iv) Compared with FAHP-EWM, AHP-EWM-GCE fully improves the evaluation results of the fuzzy method on index weight, gives full play to the advantages of the GCE method, and makes the weight index more in line with the actual situation. Combined with the natural and physical characteristics of various EVs with the charging demands of EV owners, as well as the evaluation index system given in Fig. 2, it is evident that the proposed AHP-EWM-GCE evaluation method is more suitable for practical applications in EVCSs, as it fully considered the significant differences between different evaluation indices and EV charging characteristics.

V. CONCLUSION

In order to improve the guidance performance of electric vehicle charging stations, this paper proposes a comprehensive evaluation method for electric vehicle charging guidance based on the Analytic Hierarchy Process, EWM, and GCE theoretical methods, which can obtain quantifiable electric vehicle charging evaluation data. The experimental results show that compared with conventional methods, such as AHP, AHP-EWM, FAHP, FAHP-EWM, and AHP-GCE, the proposed AHP-EWM-GCE evaluation method obtained the more reasonable guidance results for EVs charging.

Such EV charging guidance evaluation method is a necessary foundation for EVCSs to improve the service level of EV charging and more economic benefits. The future work will include EV charging integration, scheduling, and control management.

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