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ORIGINAL RESEARCH

Service capability evaluation of electric vehicle charging and battery swapping stations: A game theory-based combination weighting method

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Abstract

The rapid development of electric vehicles (EVs) has made the construction and service capability evaluation of EV charging and battery swapping stations (CBSSs) more important. A comprehensive evaluation indicator system for the service capability evaluation of EV-CBSSs is established, meticulously outlining the critical aspects of operational efficiency, economy, convenience, and reliability, each with multiple indicators for thorough assessment. To address the shortcomings of individual evaluation methods in evaluating the service capability of EV-CBSSs, the game theory-based combination weighting (GTCW) method is adopted, which integrates the advantages of the analytic hierarchy process method, entropy weight method, and grey relation analysis method. Specifically, the weights for each indicator are obtained separately using these three evaluation methods, and then combined using the GTCW method to calculate the final weights. In case studies, the service capability for each EV-CBSS is calculated and compared between these three individual methods and the proposed GTCW method. Simulation results validate that the proposed evaluation indicator system and GTCW method can offer a more comprehensive evaluation of the service capability for EV-CBSSs, providing guiding suggestions for future construction plans.

KEYWORDS

distribution networks, electric vehicles, energy consumption, game theory

1 | INTRODUCTION

The charging demand for urban electric vehicles (EVs) is continuously increasing with the rapid growth in the number of EVs [1]. As crucial locations for EV charging, the service capability evaluation of EV charging and battery swapping stations (CBSSs) is of paramount importance [2].

The current evaluation indicators for the service capabilities of EV charging stations mainly focus on aspects such as the charging utilisation rate, charging income, average queue waiting time for EVs, and investment cost. Ucer et al. in ref. [3] consider the customer service quality and the charging utilisation rate in the modelling and analysis of an EV charging station. Zenginis et al. in ref. [4] take into account the mean waiting time of EVs in the queue, as well as their stochastic arrival process and the stochastic recharging requirements, in the analysis of service evaluation of an EV fast charging station. Khaksari et al. [5] include the peak-to-average power consumption ratio for the EV charging station and the investment cost of charging station operators when evaluating service quality. Zhang et al. [6] develop a multi-criteria evaluation system to assess the service capability of EV charging infrastructure concerning its planning rationality and service capacity. Vosooghi et al. [7] explore the impacts of EV charging station placement and charging types of EVs, including normal and rapid charging, on service efficiency evaluation. However, to comprehensively evaluate the service capabilities of EV charging stations, the above indicators still seem insufficient. Taking the queue waiting time for EVs as an example, existing research typically analyses the average waiting time. However, during peak periods of EV charging, the waiting time may significantly increase [8]. This is also a crucial indicator for evaluating the service capabilities of EV charging stations, which should be considered. Moreover, current research on evaluating service capabilities primarily focuses on EV charging stations, with relatively limited attention given to EV battery swapping stations. This is mainly due to the insufficiency in battery swapping demand and the limited construction of EV battery swapping stations in the past years [9]. However, with the continuous growth in the number of EVs, there is a rising trend in the demand for battery swapping services [10]. Therefore, enhancing research on the evaluation of service capabilities for EV battery swapping stations is becoming increasingly essential. Currently, the evaluation methods for the service capabilities of EV battery swapping stations are relatively simple, primarily confined to using swapping speed as the sole evaluation criterion [11]. Therefore, it is necessary to conduct a more comprehensive analysis of the factors influencing the service capabilities of EV-CBSSs.

For the multiple indicators, determining the appropriate weights to evaluate their impact on the service capabilities of EV charging stations is a crucial research question. If the weights are not set properly, it may lead to certain less important indicators occupying significant influence, thus affecting the comprehensive assessment results of the service capabilities of each EV charging station. In ref. [12], the analytic hierarchy process (AHP) method is used to calculate the weights of criteria for the suitable location selection of EV fast charging stations. Xu et al. [13] propose an entropy-based method for the location selection of EV charging stations. Zhao et al. [14] use the grey relation analysis (GRA) method to make group multi-criteria decisions for locating EV charging stations. The TOPSIS method is utilised in ref.[15] to assign ranks based on suitability index values for appraising EV charging station suitability zones in Mumbai, India. However, each of the above-mentioned methods has its limitations. For example, the AHP supports decision-making by establishing a hierarchical structure and generating weight vectors through pairwise comparison matrices [16]. However, the limitation of the AHP method lies in its dependence on decision-makers to provide judgement matrices, introducing subjective judgements that may lead to bias and inconsistency. The entropy weight (EW) method is an objective evaluation method based on the information entropy theory, used to determine indicator weights [17]. However, the EW method considers indicators as mutually independent, overlooking potential relationships between indicators, which could affect the accuracy of evaluations. The GRA method explores the mutual correlation among system factors based on the grey system theory, which is relatively simple in terms of weight allocation [18]. To conclude, subjective methods, such as the AHP method, overly rely on the subjective opinions of the evaluator, which can lead to poor objectivity. Objective methods, such as the EW method and GRA methods, may overlook the inherent importance of individual indicators, resulting in significant deviations from expected results. In practical situations, complex relationships may exist among various indicators, and relying solely on correlation coefficients for weight distribution may not be accurate enough. To address this issue, this study proposes a game theory-based combination weighting (GTCW) method. The GTCW method is a process of linear combination of weights obtained by different methods to seek the most reasonable indicator weight [19]. In this paper, by integrating the subjective AHP method with the objective EW method and GRA methods through the proposed GTCW method, the weights of indicators for the service capabilities of EV charging stations can be allocated.

Based on the above analysis, the main contributions of this paper are twofold:

1) A comprehensive evaluation indicator system is developed to assess the service capability of EV-CBSSs. This system encompasses primary indicators including operational efficiency, economy, convenience, and reliability. Each aspect is meticulously outlined with multiple secondary indicators for thorough evaluation.
2) A GTCW method is proposed, integrating the AHP method, the EW method, and the GRA method, to provide a more rational weight allocation for the service capability evaluation of EV-CBSSs. The proposed GTCW method can substantially minimise the shortcomings introduced by relying solely on a single evaluation method.

The paper is organised as follows. Section 2 details the established comprehensive evaluation indicator system. Section 3 introduces the GTCW method, along with other evaluation methods. Section 4 presents the service capability evaluation results for several EV charging stations and EV battery swapping stations. Finally, Section 5 provides the conclusions and outlines future directions.

2 | THE COMPREHENSIVE EVALUATION INDICATOR SYSTEM

The established comprehensive evaluation indicator system for EV-CBSSs includes operational efficiency indicators, economic indicators, convenience indicators, and reliability indicators, which are introduced in detail in this section.

2.1 | Operational efficiency indicators

The operational efficiency indicators include the charging utilisation rate [20], peak charging period rate [21], idle charging period rate [22], and battery swap satisfaction rate [10].

$$s_o^1 = \frac{\sum_{i=1}^{m} t_i}{mT} \tag{1}$$

$$s_o^2 = \frac{\sum_{i=1}^{m} t_i^{\text{peak}}}{mT} \tag{2}$$

$$s_o^3 = \frac{\sum_{i=1}^{m} t_i^{\text{idle}}}{mT} \tag{3}$$

$$s_o^4 = \frac{1}{T}\sum_{k=1}^{T_u} \frac{N_k}{N_k + N_k^{\text{fail}}} \tag{4}$$

where s_o^1 is the charging utilisation rate, with the unit of percentage (%); m is the number of charging piles; t_i is the length of the charging period for the ith charging pile; T is the length of the total period, which is considered a day in this study; s_o^2 is the peak charging period rate, with the unit of percentage (%); t_i^{peak} is the average daily peak charging period for the ith charging pile; s_o^3 is the idle charging period rate, with the unit of percentage (%); t_i^{idle} is the average daily idle charging period for the ith charging pile; s_o^4 is the battery swap satisfaction rate, with the unit of percentage (%); N_k is the average daily number of battery-swapped EVs; N_k^{fail} is the number of EVs that had a demand for battery swapping but failed to swap due to the unavailability of batteries.

2.2 | Economic indicators

The revenues of an EV-CBSS can be characterised by their charging income and battery-swapping income. For the evaluation of the charging income of an EV-CBSS, this study uses the average charging revenue for each charging pile.

$$s_e = \begin{cases} \dfrac{\sum_{i=1}^{m}\sum_{t=1}^{T} \lambda_t P_{i,t}}{m}, \text{charging} \\ \sum_{k=1}^{N_{\text{swap}}} c(E - E_k), \text{swapping} \end{cases} \tag{5}$$

where s_e is the charging income and battery-swapping income, with the unit of RMB (¥); λ_t is the charging electricity price at the tth time slot; $P_{i,\,t}$ is the charging power of the ith charging pile at the tth time slot; N_{swap} is the number of battery-swapped EVs; c is the unit price per kWh for battery swapping; E is the rated capacity of battery; E_k is the remaining capacity for the kth battery-swapped EV.

2.3 | Convenience indicators

The convenience indicators for an EV-CBSS include the average queue waiting time for EVs, the peak queue period rate, the maximum queue waiting time, and the traffic congestion time near the EV-CBSS.

$$s_c^1 = \frac{\sum_{i=1}^{N} t_{\text{wait},i}}{N} \tag{6}$$

$$s_c^2 = \frac{n_{\text{wait}}}{T} \tag{7}$$

$$s_c^3 = \max\left\{t_{\text{wait},i}\right\}_{i=1}^{N} \tag{8}$$

$$s_c^4 = \sum_{i=1}^{n_b} t_{\text{cong}} \tag{9}$$

where s_c^1 is the average queue waiting time for EVs, with the unit of minute (min); N is the number of EVs arriving at the EV-CBSS; $t_{\text{wait},\,i}$ is the waiting time for the kth EV; s_c^2 is the peak queue period rate, with the unit of percentage (%); n_{wait} is the length of the peak charging period; s_c^3 is the maximum queue waiting time, with the unit of minute (min); s_c^4 is the traffic congestion time near the EV-CBSS, with the unit of hour (h); n_b is the number of roads connected to the EV-CBSS; t_{cong} is the traffic congestion time for the ith road.

2.4 | Reliability indicators

The reliability indicators for an EV-CBSS include the maximum voltage deviation and the overload rate at the EV-CBSS node.

$$s_r^1 = \max\left\{\left|\frac{U_t - U_{\text{rate}}}{U_{\text{rate}}}\right| \times 100\%\right\}_{t=1}^{T} \tag{10}$$

$$s_r^2 = \frac{t_{\text{over}}}{T} \tag{11}$$

where s_r^1 is the maximum voltage deviation, with the unit of percentage (%); U_t is the voltage of the EV-CBSS node at the tth time slot; U_{rate} is the rated voltage; s_r^2 is the overload rate, with the unit of percentage (%); t_{over} is the length of the overload period for the EV-CBSS node.

Figure 1 presents the structure of the comprehensive evaluation indicator system, which includes primary indicators such as operational efficiency, economy, convenience, and reliability, as well as multiple secondary indicators.

3 | GAME THEORY-BASED COMBINATION METHOD

In this section, different methods, including the AHP method, the EW method, and the GRA method, are introduced first, and subsequently, the GTCW method based on these three methods is proposed for evaluating the service capability of EV-CBSSs.

3.1 | The AHP method

The AHP method is a method to determine the weights of various indicators, particularly suitable for decision problems

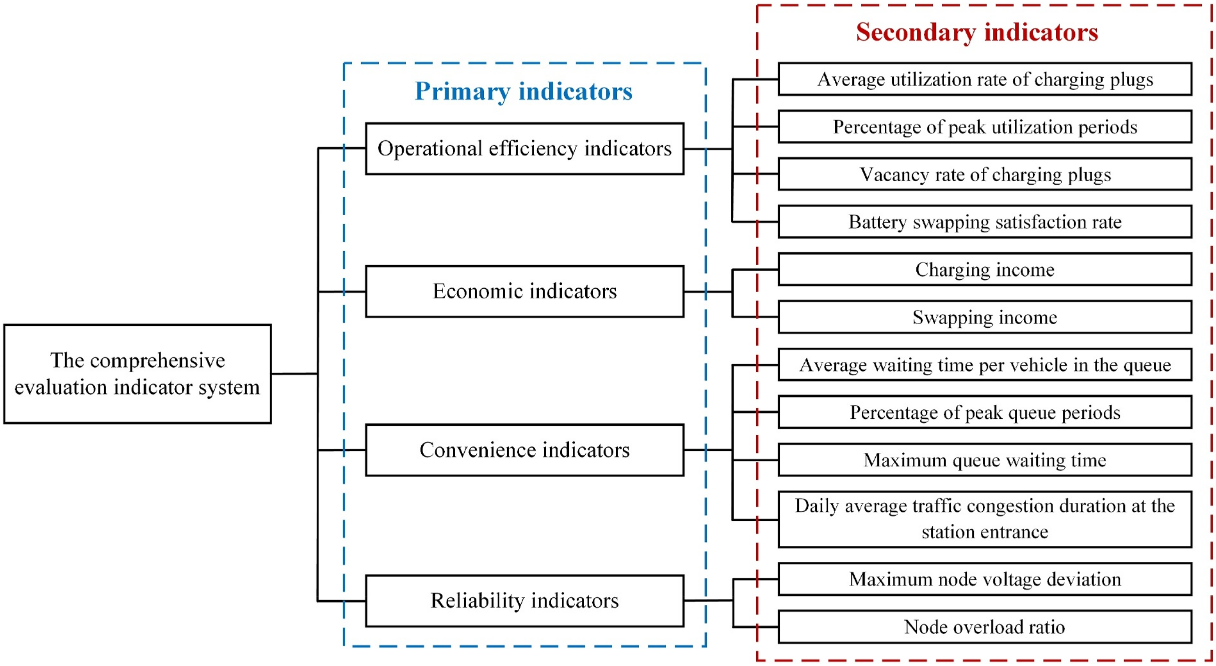

FIGURE 1 Structure of the comprehensive evaluation indicator system.

with a hierarchical structure [23]. Firstly, the problem hierarchy is divided into different levels, and hierarchical relationships between indicators are established to form a hierarchical structure. This typically includes the goal level, criteria level, and alternative level [24]. In each level, construct pairwise comparison matrices through expert judgement or data analysis. For each pair of indicators, use a scale '1–9' to make comparisons, where 1 indicates equal importance, and 9 indicates extreme importance difference. In order to appropriately reduce the subjectivity of this method, this paper considers the uncertainty in the evaluation process. It introduces interval numbers to represent elements in the judgement matrix.

$$\boldsymbol{A} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 1 \end{bmatrix} \tag{12}$$

$$\frac{1}{9} \leq a_{ij,\min} \leq a_{ij,\max} \leq 9 \quad i,j \in [1,n] \tag{13}$$

where $a_{i,\,j} = [a_{ij,\,\min}, a_{ij,\,\max}]$ is the importance of the ith indicator relative to the jth indicator.

Next, weight vectors are calculated, consistency checks are performed, and then the weight vectors at different levels are synthesised to obtain the ultimate comprehensive weight vector.

3.2 | The EW method

The EW method, as an objective weighting approach, primarily involves processing and analysing observed data to calculate the entropy values of indicators, thereby determining the weights of various evaluation indicators [25].

$$p_{i,j} = \frac{x_{i,j}}{\sum\limits_{i=1}^{n} x_{i,j}}, \quad i = 1,2,\cdots,n \ \ j = 1,2,\ldots,m \tag{14}$$

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{i,j} \ln p_{i,j} \tag{15}$$

$$g_j = 1 - e_j \, j = 1,2,\ldots,m \tag{16}$$

$$\omega_j = \frac{g_j}{\sum\limits_{j=1}^{m} g_j} \ j = 1,2,\ldots,m \tag{17}$$

where $p_{i,\,j}$ is the characteristic weight of the jth indicator for the ith evaluation object; $x_{i,\,j}$ is the normalised value of the jth indicator for the ith evaluation object; n is the number of evaluation objects; m is the number of indicators; e_j is the entropy value for the jth indicator; g_j is the coefficient of variation for the jth indicator; ω_j is the weight for the jth indicator.

In the entropy method, the observed data is initially normalised to ensure that the values of each indicator fall within the range of 0–1. For each indicator, the characteristic weight is computed in (14). This weight represents the proportion of the indicator in the overall composition. The entropy value, calculated in equation (15), is used to measure the uncertainty or fluctuation of each indicator. The coefficient of variation for each indicator is calculated in (16) to quantify the variation of the indicator across different samples. Finally, the weight for each indicator is computed in (17).

3.3 | The GRA method

The GRA method is a technique used to assign weights to various indicators, which enables the determination of the contribution of each indicator to decision-making in multi-indicator scenarios [26]. This method assigns weights to various indicators based on their correlation degrees, and the specific steps are as follows:

$$r_{i,j} = \frac{\min\left(\xi_i, \xi_j\right) + \rho \max\left(\xi_i, \xi_j\right)}{\xi_i + \xi_j + \rho}, i, j = 1, 2, \ldots, m \tag{18}$$

$$\overline{r}_i = \frac{1}{m}\sum_{j=1}^{m} r_{i,j} \tag{19}$$

$$\omega_i = \frac{\overline{r}_i}{\sum_{k=1}^{m} \overline{r}_k} \tag{20}$$

where $r_{i,j}$ is the correlation between the ith and jth indicators; ξ_i and ξ_j are the normalised value of the ith and jth indicators; ρ is a resolution coefficient, which is typically set to 0.5; $\overline{r}_i$ is the comprehensive correlation value for the ith indicator.

In the GRA method, the data for each indicator needs to be normalised to bring them onto the same scale. Next, a correlation matrix is created using the normalised data. The elements in the matrix represent the correlation between different indicators, calculated as (18). For each indicator, equation (19) calculates the comprehensive correlation value by averaging its correlations with other indicators. Finally, equation (20) determines the weights of each indicator based on its comprehensive correlation value. The weights are usually calculated as the proportion of the comprehensive correlation value compared to the sum of all comprehensive correlation values.

3.4 | The GTCW method

The above has described the steps of the AHP methods, the EW method, and the GRA method, and obtained the weights of each evaluation indicator under these three assessment methods. Since using a single method for evaluation has limitations, and combining weighting allows for leveraging strengths and avoiding weaknesses of each method, thereby improving the accuracy of the evaluation results. Therefore, this paper adopts a GTCW method to comprehensively allocate the weights of evaluation indicators obtained from these three methods, resulting in integrated assessment indicator weights. The specific steps of the proposed GTCW method are as follows:

$$L(i) = \frac{\sum_{j=1}^{n}\left[W_j(i) - \overline{\boldsymbol{W}(i)}\right]\left[W_j(k\_i) - \overline{\boldsymbol{W}(k\_i)}\right]}{\left\{\sum_{j=1}^{n}\left[W_j(i) - \overline{\boldsymbol{W}(i)}\right]^2\right\}^{\frac{1}{2}}\left\{\sum_{j=1}^{n}\left[W_j(k\_i) - \overline{\boldsymbol{W}(k\_i)}\right]^2\right\}^{\frac{1}{2}}} \tag{21}$$

$$\boldsymbol{W}(3\_i) = \begin{cases} \dfrac{\boldsymbol{W}(2) + \boldsymbol{W}(3)}{2} & i = 1 \\ \dfrac{\boldsymbol{W}(1) + \boldsymbol{W}(3)}{2} & i = 2 \\ \dfrac{\boldsymbol{W}(1) + \boldsymbol{W}(2)}{2} & i = 3 \end{cases} \tag{22}$$

$$\boldsymbol{W}' = \sum_{i=1}^{k} \boldsymbol{W}(i) L(i) \tag{23}$$

where $L(i)$ is the consistency correlation coefficient; $W_j(i)$ is the weight calculated for the jth indicator using the ith method; $\overline{\boldsymbol{W}(i)}$ is the average weight vector calculated by the ith method; For example, when the number of evaluation methods is 3, the calculation of $W(3\_i)$ can be represented as (22). $W(k\_i)$ is the combined weight for the remaining k methods, excluding $W(i)$; W' is the combined weight vector. The final step involves normalising the combined weight vector W' to obtain the weights assigned to various evaluation indicators based on the proposed GTCW method.

3.5 | Service capacity level division

By calculating the weights of various evaluation indicators based on the proposed GTCW method, they are used to compute the comprehensive service capacity assessment value in a specific scenario.

$$P_u = \sum_{i=1}^{n} \omega_i v_{i,u} \tag{24}$$

where P_u is the comprehensive service capacity assessment value of the uth EV-CBSS; $v_{i,u}$ is the normalisation value of the ith indicator for the uth EV-CBSS.

4 | CASE STUDIES

Case studies are conducted in this section to examine the effectiveness of the proposed service capability evaluation method for EV charging stations and EV battery swapping stations separately in Xuanwu District, Nanjing, China. Each EV charging station typically has 4 to 10 charging piles installed. The ratio of fast-charging piles to slow-charging piles is approximately 3:1. The rated power of fast-charging piles is 35 kW, while that of slow-charging piles is 7 kW. The statistical data for various indicators are sourced from the State Grid Nanjing Power Supply Company.

4.1 | Indicator weighting results for the EV charging station

The statistical values for various indicators at each EV charging station are shown in Table 1.

TABLE 1 Statistical values of various evaluation indicators for the EV charging stations.

Charging station nodes	1	2	3	4	5	6	7	8	9
Average utilisation rate of charging piles (%)	31.72	49.39	52.75	49.52	37.02	66.43	57.09	41.21	47.99
Percentage of peak utilisation periods (%)	25.15	41.96	43.90	38.10	23.21	59.08	50.74	27.83	35.42
Vacancy rate of charging piles (%)	55.51	31.25	25.89	36.16	56.55	2.08	20.09	41.37	37.05
Charging incomes (¥)	1015.71	1889.96	1956.70	1768.08	1057.93	2217.41	2069.92	1340.28	1605.17
Average waiting time per EV in the queue (min)	9.18	11.79	12.62	13.61	10.81	7.68	8.84	8.60	8.70
Percentage of peak queue periods (%)	6.85	8.78	9.97	13.99	8.63	9.38	8.78	8.33	8.48
Maximum queue waiting time (min)	53	57	60	75	71	75	62	66	76
Daily average traffic congestion duration at the station entrance (h)	0	0	0	0	3.36	1.79	18.17	0	0
Maximum node voltage deviation (%)	7.84	5.45	2.27	2.23	8.65	3.17	3.82	4.81	6.86
Node overload ratio (%)	25.60	8.93	0	0	33.18	0	0	18.30	0

By employing the proposed service evaluation method, it is possible to allocate weights to each indicator, thereby evaluating the service capabilities of each EV charging station. Utilising individual evaluation methods to assign weights to each indicator in the service evaluation of EV charging stations and employing the proposed ETCW method to combine the weights obtained from these three methods, resulting in composite weights.

4.1.1 | Results of the AHP method

Through interviews with 30 students and professionals in the same field, the study employed the '1–9 scale' to initially rank the importance of each primary indicator, resulting in the interval judgement matrix as follows:

$$\boldsymbol{K}_A = \begin{bmatrix} [1,1] & [2,3] & [1,1] & [1,2] \\ [1/3,1/2] & [1,1] & [1/2,1] & [1/2,1] \\ [1,1] & [1,2] & [1,1] & [1,3] \\ [1/2,1] & [1,2] & [1/3,1] & [1,1] \end{bmatrix} \tag{25}$$

The weight vectors for each primary indicator based on the AHP method with uncertainty are denoted below.

$$\omega_1{}^{(1)} = [0.3283, 0.1613, 0.3002, 0.2102] \tag{26}$$

Subsequently, the importance of each secondary indicator is ranked, leading to respective interval judgement matrices. Since only the charging cost is selected as the secondary indicator for the economic indicator, there is no need to construct a judgement matrix for it. The interval judgement matrices for the secondary indicators under the other three primary indicators are denoted as follows:

$$\boldsymbol{K}_{A1} = \begin{bmatrix} [1,1] & [1/4,1/2] & [1/3,1/2] \\ [2,4] & [1,1] & [1,2] \\ [2,3] & [1/2,1] & [1,1] \end{bmatrix} \tag{27}$$

$$\boldsymbol{K}_{A3} = \begin{bmatrix} [1,1] & [1/3,1/2] & [1/2,1] & [1/2,1] \\ [2,3] & [1,1] & [1,3] & [1,2] \\ [1,2] & [1/3,1] & [1,1] & [1/2,1] \\ [1,2] & [1/2,1] & [1,2] & [1,1] \end{bmatrix} \tag{28}$$

$$\boldsymbol{K}_{A4} = \begin{bmatrix} [1,1] & [1/3,1/2] \\ [2,3] & [1,1] \end{bmatrix} \tag{29}$$

The respective corresponding weight vectors are denoted as follows:

$$\omega_{11}{}^{(1)} = [0.1583, 0.4792, 0.3625] \tag{30}$$

$$\omega_{13}{}^{(1)} = [0.1602, 0.3726, 0.2077, 0.2596] \tag{31}$$

$$\omega_{14}{}^{(1)} = [0.2899, 0.7101] \tag{32}$$

Combining the weight calculations for both the primary and secondary indicators, the weight vectors for each indicator based on the AHP with uncertainty are obtained as follows:

$$\begin{aligned} \omega^{(1)} = [&0.0520, 0.1573, 0.1190, 0.1613, 0.0481, \\ &0.1118, 0.0623, 0.0779, 0.0609, 0.1492] \end{aligned} \tag{33}$$

4.1.2 | Results of the EW method

The Min-Max normalisation method [27] is employed to scale each statistical indicator to a range of 0–1. The normalised values are shown in Table 2.

By calculating the feature weights, the feature weight matrix is obtained as follows:

The weight vectors for each indicator based on the entropy method are obtained as follows:

$$\boldsymbol{P}=\begin{bmatrix} 0.002 & 0.510 & 0.607 & 0.514 & 0.154 & 1.000 & 0.731 & 0.275 & 0.470 \\ 0.056 & 0.524 & 0.578 & 0.416 & 0.002 & 1.000 & 0.768 & 0.131 & 0.342 \\ 0.021 & 0.466 & 0.564 & 0.376 & 0.002 & 1.000 & 0.670 & 0.280 & 0.359 \\ 0.002 & 0.728 & 0.783 & 0.627 & 0.037 & 1.000 & 0.878 & 0.272 & 0.492 \\ 0.748 & 0.308 & 0.169 & 0.002 & 0.473 & 1.000 & 0.805 & 0.845 & 0.828 \\ 1.000 & 0.730 & 0.564 & 0.002 & 0.751 & 0.646 & 0.730 & 0.793 & 0.772 \\ 1.000 & 0.826 & 0.696 & 0.045 & 0.219 & 0.045 & 0.609 & 0.436 & 0.002 \\ 1.000 & 1.000 & 1.000 & 1.000 & 0.815 & 0.902 & 0.002 & 1.000 & 1.000 \\ 0.128 & 0.499 & 0.994 & 1.000 & 0.002 & 0.854 & 0.753 & 0.599 & 0.280 \\ 0.230 & 0.731 & 1.000 & 1.000 & 0.002 & 1.000 & 1.000 & 0.450 & 1.000 \end{bmatrix} \tag{34}$$

$$\omega^{(2)}=[0.0943, 0.1232, 0.1182, 0.1098, 0.0932, 0.0666, 0.1456, 0.0639, 0.1002, 0.0851] \tag{35}$$

4.1.3 | Results of the GRA method

The obtained grey correlation coefficient matrix is denoted as follows:

$$\boldsymbol{R}=\begin{bmatrix} 0.3333 & 0.5046 & 0.5592 & 0.5065 & 0.3711 & 1.0000 & 0.6501 & 0.4076 & 0.4848 \\ 0.3458 & 0.5116 & 0.5416 & 0.4609 & 0.3333 & 1.0000 & 0.6826 & 0.3646 & 0.4312 \\ 0.3376 & 0.4828 & 0.5335 & 0.4442 & 0.3333 & 1.0000 & 0.6019 & 0.4094 & 0.4378 \\ 0.3333 & 0.6473 & 0.6974 & 0.5721 & 0.3413 & 1.0000 & 0.8029 & 0.4065 & 0.4953 \\ 0.6641 & 0.4191 & 0.3751 & 0.3333 & 0.4865 & 1.0000 & 0.7188 & 0.7632 & 0.7440 \\ 1.0000 & 0.6491 & 0.5336 & 0.3333 & 0.6673 & 0.5852 & 0.6491 & 0.7069 & 0.6865 \\ 1.0000 & 0.7419 & 0.6216 & 0.3433 & 0.3898 & 0.3433 & 0.5610 & 0.4694 & 0.3333 \\ 1.0000 & 1.0000 & 1.0000 & 1.0000 & 0.7300 & 0.8354 & 0.3333 & 1.0000 & 1.0000 \\ 0.3639 & 0.4992 & 0.9877 & 1.0000 & 0.3333 & 0.7735 & 0.6688 & 0.5544 & 0.4094 \\ 0.3932 & 0.6501 & 1.0000 & 1.0000 & 0.3333 & 1.0000 & 1.0000 & 0.4755 & 1.0000 \end{bmatrix} \tag{36}$$

The weight vectors for each indicator based on the GRA method are calculated and represented as follows:

$$\omega^{(3)}=[0.0863, 0.0837, 0.0821, 0.0949, 0.0986, 0.1041, 0.0860, 0.1415, 0.1001, 0.1227] \tag{37}$$

4.1.4 | Results of the proposed GTCW method

By calculating and normalising the consistency correlation coefficients, the weights obtained from the proposed GTCW method for these three individual evaluation methods are represented as follows:

$$\omega=[0.0781, 0.1194, 0.1051, 0.1204, 0.0810, 0.0946, 0.0976, 0.0968, 0.0879, 0.1190] \tag{38}$$

A comparison of the weights obtained from the three individual weighting methods and the combination weighting method is shown in Figure 2. It can be observed that solely relying on subjective weighting methods may lead to the loss of distinctive characteristics of each indicator obtained from the data. On the other hand, solely relying on objective weighting methods often overlooks the intrinsic importance of individual indicators, resulting in significant deviations from expectations. The weights derived from the proposed GTCW method fall between the values obtained from the three individual methods, effectively combining the strengths of both subjective and objective weighting methods. This approach places emphasis on objective features while also considering subjective preferences, thereby enhancing the accuracy of the evaluation.

4.2 | Indicator weighting results for the EV battery swapping stations

The statistical values for various indicators at each EV battery swapping station are shown in Table 3. There are two types of EV battery swapping stations: one type involves swapped batteries being delivered from outside for replacement, while the other type charges the swapped batteries on-site at the stations.

By employing the proposed service evaluation method, it is possible to allocate weights to each indicator, thereby

TABLE 2 Normalised values of various evaluation indicators for the EV charging stations.

Charging station nodes	1	2	3	4	5	6	7	8	9
Average utilisation rate of charging piles (%)	0.002	0.510	0.607	0.514	0.154	1.000	0.731	0.275	0.470
Percentage of peak utilisation periods (%)	0.056	0.524	0.578	0.416	0.002	1.000	0.768	0.131	0.342
Vacancy rate of charging piles (%)	0.021	0.466	0.564	0.376	0.002	1.000	0.670	0.280	0.359
Charging incomes (¥)	0.002	0.728	0.783	0.627	0.037	1.000	0.878	0.272	0.492
Average waiting time per EV in the queue (min)	0.748	0.308	0.169	0.002	0.473	1.000	0.805	0.845	0.828
Percentage of peak queue periods (%)	1.000	0.730	0.564	0.002	0.751	0.646	0.730	0.793	0.772
Maximum queue waiting time (min)	1.000	0.826	0.696	0.045	0.219	0.045	0.609	0.436	0.002
Daily average traffic congestion duration at the station entrance (h)	1.000	1.000	1.000	1.000	0.815	0.902	0.002	1.000	1.000
Maximum node voltage deviation (%)	0.128	0.499	0.994	1.000	0.002	0.854	0.753	0.599	0.280
Node overload ratio (%)	0.230	0.731	1.000	1.000	0.002	1.000	1.000	0.450	1.000

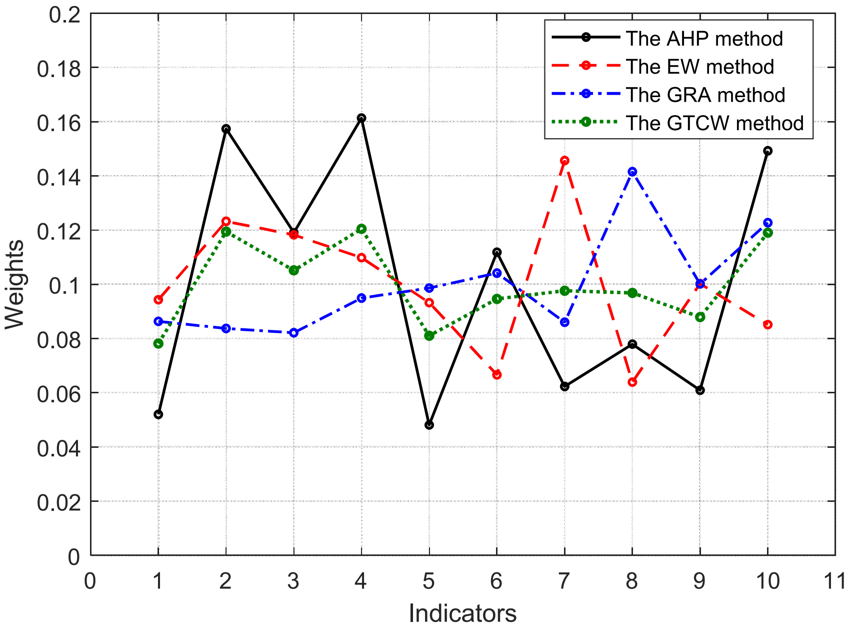

FIGURE 2 Comparison of indicator weights for electric vehicle charging stations.

TABLE 3 Statistical values of various evaluation indicators for the EV battery swapping stations.

Battey swapping station nodes	10 (Battery delivery)	11 (Battery delivery)	10 (On-site charging)	11 (On-site charging)
Battery swapping satisfaction rate (%)	47.99	42.07	92.27	89.29
Swapping fees (¥)	1030.30	1007.10	1776.82	1865.03
Average waiting time per vehicle in the queue (min)	9.05	9.03	12.30	11.41
Percentage of peak queue periods (%)	8.36	8.28	8.62	8.55
Maximum queue waiting time (min)	34	35	54	50
Daily average traffic congestion duration at the station entrance (h)	1.80	18.17	1.87	17.47

evaluating the service capabilities of each EV battery swapping station. Utilising individual evaluation methods to assign weights to each indicator in the service evaluation of EV battery swapping stations, and employing the proposed GTCW method to combine the weights obtained from the three methods, resulting in composite weights.

4.2.1 | Results of the AHP method

First, the importance of each primary indicator is ranked using the '1–9 scale', resulting in an interval judgement matrix.

$$\boldsymbol{K}_{A,hd} = \begin{bmatrix} [1,1] & [2,3] & [2,3] \\ [1/3,1/2] & [1,1] & [1/2,1] \\ [1/3,1/2] & [1,2] & [1,1] \end{bmatrix} \quad (39)$$

The weight vector for each primary indicator, based on the AHP method with uncertainty, can then be determined.

$$\omega_{1,hd}{}^{(1)} = [0.6536, 0.1435, 0.2029] \quad (40)$$

Next, the importance of each secondary indicator is ranked, yielding individual interval judgement matrices. Since the efficiency and economic indicators only selected the single secondary indicators of the swapping satisfaction rate and swapping cost, respectively, there is no need to construct judgement matrices for them. The interval judgement matrix for the secondary indicators under the convenience index is obtained.

$$\boldsymbol{K}_{A3,hd} = \begin{bmatrix} [1,1] & [1/3,1/2] & [1/2,1] & [1/2,1] \\ [2,3] & [1,1] & [1,3] & [1,2] \\ [1,2] & [1/3,1] & [1,1] & [1/2,1] \\ [1,2] & [1/2,1] & [1,2] & [1,1] \end{bmatrix} \quad (41)$$

The corresponding weight vector is calculated.

$$\omega_{13,hd}{}^{(1)} = [0.1602, 0.3726, 0.2077, 0.2596] \quad (42)$$

Combining the weight calculations for primary and secondary indicators, the weight vectors for each indicator, based on the AHP method with uncertainty, are determined.

$$\omega_{hd}{}^{(1)} = [0.6536, 0.1435, 0.0325, 0.0756, 0.0421, 0.0527] \quad (43)$$

4.2.2 | Results of the EW method

The normalised values for each statistical indicator are shown in Table 4.

By calculating the feature weights, the feature weight matrix is obtained as follows:

$$\boldsymbol{P}_{hd} = \begin{bmatrix} 0.0582 & 0.0010 & 0.4847 & 0.4561 \\ 0.0150 & 0.0010 & 0.4652 & 0.5187 \\ 0.4379 & 0.4405 & 0.0009 & 0.1207 \\ 0.3875 & 0.5066 & 0.0010 & 0.1049 \\ 0.4643 & 0.4410 & 0.0009 & 0.0938 \\ 0.4897 & 0.0010 & 0.4878 & 0.0215 \end{bmatrix} \quad (44)$$

The weight vectors for each indicator based on the entropy method are obtained as follows:

$$\omega_{hd}{}^{(2)} = [0.1677, 0.1888, 0.1488, 0.1541, 0.1559, 0.1847] \quad (45)$$

4.2.3 | Results of the GRA method

The grey correlation coefficient matrix is denoted as follows:

$$\boldsymbol{R}_{hd} = \begin{bmatrix} 0.3619 & 0.3333 & 1.0000 & 0.8943 \\ 0.3395 & 0.3333 & 0.8289 & 1.0000 \\ 0.9881 & 1.0000 & 0.3333 & 0.4073 \\ 0.6798 & 1.0000 & 0.3333 & 0.3862 \\ 1.0000 & 0.9089 & 0.3333 & 0.3847 \\ 1.0000 & 0.3333 & 0.9920 & 0.3430 \end{bmatrix} \quad (46)$$

The weight vectors for each indicator based on the GRA method are calculated and represented as follows:

$$\omega_{hd}{}^{(3)} = [0.1669, 0.1612, 0.1759, 0.1547, 0.1693, 0.1720] \quad (47)$$

TABLE 4 Normalisation values of various evaluation indicators for the EV battery swapping stations.

Battery swapping station nodes	10 (Battery delivery)	11 (Battery delivery)	10 (On-site charging)	11 (On-site charging)
Battery swapping satisfaction rate (%)	0.120	0.002	1.000	0.941
Swapping fees (¥)	0.029	0.002	0.897	1.000
Average waiting time per vehicle in the queue (min)	0.994	1.000	0.002	0.274
Percentage of peak queue periods (%)	0.765	1.000	0.002	0.207
Maximum queue waiting time (min)	1.000	0.950	0.002	0.202
Daily average traffic congestion duration at the station entrance (h)	1.000	0.002	0.996	0.044

4.2.4 | Results of the proposed GTCW method

By calculating and normalising the consistency correlation coefficients, the weights obtained from the proposed GTCW method for the three individual evaluation methods are represented as follows:

$$\omega_{hd} = [0.3260, 0.1648, 0.1199, 0.1287, 0.1233, 0.1374] \quad (48)$$

A comparison of the weights obtained from the three individual weighting methods and the combination weighting method is shown in Figure 3. Similarly, from Figure 3, it can be observed that the weights of various indicators obtained using the proposed GTCW method fall between those obtained from the three individual methods, which to some extent can enhance the accuracy of the evaluation.

4.3 | Result analysis

The service capability evaluation results for each EV charging station and EV battery swapping station are obtained by weighting and calculating various evaluation indicators.

From Table 5, it can be observed that the EV charging station service capability assessment values at traffic network nodes 2, 3, 6, and 7 are relatively high. The main reason for this is that these stations exhibit high utilisation rates and charging incomes, indicating good efficiency and economic performance. Additionally, the voltage deviation at these nodes is small, resulting in minimal impact on the power grid and higher reliability in grid operation. In contrast, the service capability assessment values at nodes 1 and 5 are relatively low. This is due to their lower utilisation rates and charging incomes, significant voltage deviation, and the concentration of charging during peak load periods. During other periods, there is less appeal for EV charging, resulting in higher charging station vacancy rates. As a result, their overall efficiency, economic performance, and reliability are relatively poor across the four primary indicators. Therefore, it is suggested to consider a reevaluation and planning for these stations in the future.

From Table 6, it can be observed that the service capability of the EV battery swapping station at Node 10, under various operational modes, is higher than that of the EV battery swapping station at Node 11 within the same mode. This is attributed to the higher swapping satisfaction rate at Node 10, which is assigned a higher weight.

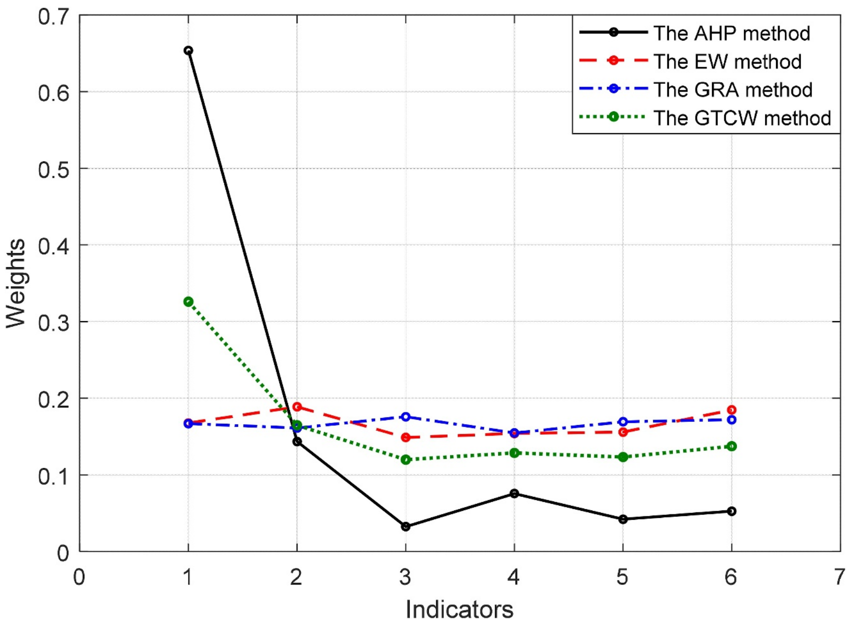

FIGURE 3 Comparison of indicator weights for electric vehicle battery swapping stations.

TABLE 5 Service capacity evaluation of the EV charging station.

Nodes	1	2	3	4	5	6	7	8	9
Service capacity evaluation	0.3975	0.6414	0.7082	0.5133	0.2270	0.8510	0.7041	0.4884	0.5553

TABLE 6 Service capacity evaluation of EV battery swapping stations.

Nodes	10 (Battery delivery)	11 (Battery delivery)	10 (On-site charging)	11 (On-site charging)
Service capacity evaluation	0.5222	0.3670	0.6114	0.5620

Additionally, Node 10 has fewer direct road connections and less traffic flow compared to Node 11, resulting in significantly lower traffic congestion duration. Furthermore, EV battery swapping stations under the on-site charging mode generally exhibit stronger service capabilities than those under the battery delivery mode. This is because there is a higher demand for swapping vehicles in this area. Under the battery delivery mode, EV battery swapping stations are constrained by the limited number of batteries available for distribution each day. Compared to EV battery swapping stations that can flexibly charge batteries on-site, those under the delivery mode can provide fewer batteries, making it challenging to meet the swapping demand in the area. Moreover, due to the lower number of swapping EVs per day, the swapping income is also lower. Therefore, despite having shorter queue times, EV battery swapping stations under the delivery mode have lower overall service capabilities than those with on-site charging. Therefore, future planning of EV battery swapping stations should consider the potential number of swapping EVs in the area, along with their construction cost.

5 | CONCLUSION

This paper explores the evaluation method for the service capability of EV-CBSSs. Firstly, it establishes a comprehensive evaluation indicator system for evaluating the service capability of EV-CBSSs, including primary indicators such as efficiency, economy, convenience, reliability, and multiple secondary indicators. Three evaluation methods, including the AHP method, the EW method, and the GRA method, are analysed and used to calculate the weights for each indicator. Subsequently, by using the proposed GTCW method in this paper, the weights of indicators obtained from these three methods are integrated to evaluate the service capability of EV-CBSSs, and the service capability levels of EV-CBSSs are then classified. The evaluation results provide a more reasonable basis for adjusting the construction plans of EV-CBSSs and also offer comprehensive recommendations for the site selection and capacity determination of EV-CBSSs.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available within the article and also in appropriate references.

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