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EDITED BY
Rakibuzzaman Shah,
Federation University Australia, Australia

REVIEWED BY
B. M. Ruhul Amin,
Federation University Australia, Australia
Narottam Das,
Central Queensland University, Australia

*CORRESPONDENCE
Shuai Li,
bqdxsy2022@163.com

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Confidence relative off-targets distance-based multi-dimensional transparency evaluation of distribution station area

Jie Ren[1], Lisheng Li[2], Shuai Li[2]*, Minglin Liu[1], Mu Fang[1], Shidong Zhang[2], Wenbin Liu[2], Yang Liu[2] and Haidong Yu[2]

[1]State Grid Shandong Electric Power Company, Jinan, Shandong, China, [2]Distribution Technology Center, Shandong Smart Grid Technology Innovation Center, State Grid Shandong Electric Power Research Institute, Jinan, Shandong, China

With the large-scale integration of distributed renewable energy into low-voltage distribution station areas, rapidly growing services put forward new requirements on transparent monitoring. In order to accurately and objectively quantify the transparency of various distribution station areas and measure the impact of different dimensional indexes on the transparency evaluation of distribution station areas, this paper proposes a confidence relative off-target distance-based multi-dimensional transparency evaluation method. First, a multi-dimensional transparency evaluation index system with electrical and communication integration is constructed. Second, an improved gray target model combining both positive and negative target vectors is established to realize bi-directional quantitative analysis. Then, the relative off-target distance is calculated based on the endowment coefficient by leveraging both subjective and objective weights. Finally, the confidence of the relative off-target distance is calculated based on fuzzy entropy to improve the reliability of transparency evaluation. The simulation results show that this method can effectively distinguish the transparency gap between different distribution station areas, identify the single dimensional index with the greatest contribution or potential, and verify the effectiveness of the proposed method applied to the transparency evaluation of distribution station areas.

KEYWORDS

transparency evaluation, distribution station area, confidence relative off-target distance, multi-dimensional index, fuzzy entropy

1 Introduction

A low-voltage distribution station area is the "last mile" of a smart grid to connect users, which is also the core of reliable power supply guarantee (Noh et al., 2018; Wu et al., 2022). Transparent monitoring in the distribution station area can ensure the safe and stable operation of the power system, improve the operational efficiency of the power system, and reduce energy waste and operating costs (Hu et al., 2022; Liu et al., 2022). At the same time, transparent monitoring can also increase the reliability and sustainability of the power system, improve users' electricity experience, and ensure the electricity demand of all sectors of society. With the large-scale integration of distributed renewable energy into low-voltage distribution station areas, advanced services such as power quality analysis (Elphick et al., 2017; Harirchi and Simões, 2018; Lei et al., 2022), reactive power compensation monitoring (Kavousi-Fard et al., 2017; Liang and Zhu, 2018), distributed photovoltaic (PV) control (Haghdadi et al., 2018; León et al., 2022), and electric vehicle charging (Rezaei et al., 2018; Hu et al., 2021) have grown rapidly. These services require the collection of a large volume of data including voltage, current, active power, reactive power, temperature, sunlight intensity, and wind speed, which puts forward new requirements on transparent monitoring of distribution station areas (Liao et al., 2022). Therefore, how to accurately and objectively quantify the transparency of various distribution station areas to support the rational planning and deployment of monitoring devices has become an important research topic for smart grid construction (Vai et al., 2020; Zichang et al., 2021).

There exist some works investigating the performance evaluation of distribution station areas. Commonly used existing evaluation methods are the analytic hierarchy process (AHP), fuzzy analytic hierarchy process (FAHP), and entropy method. Bernardon et al. (2011) proposed an AHP-based evaluation method for a device configuration scheme to effectively support the operation planning of low-voltage distribution station areas. However, the AHP can hardly reflect the ambiguity of subjective judgment. It is difficult to guarantee the consistency of the judgment matrix of the AHP under a large number of evaluation indices. Dehghanian et al. (2012) proposed a FAHP-based performance evaluation method to assess various types of components of monitoring devices in low-voltage distribution station areas. Wang et al. (2018) proposed an electricity-user evaluation method in smart electricity utilization by integrating the entropy method and AHP. Liang et al. (2022) proposed a governance effect evaluation model of power quality in distribution station areas based on the fuzzy comprehensive evaluation method, which uses the comprehensive weighting method combined with the AHP and entropy weight coefficient method to determine the index weight. The above works are only applicable to the performance evaluation of a single station area because the calculation process is very complicated, and the confidence degree of the evaluation results is ignored. It is difficult to directly reflect the gap between the current evaluation scenario and the target scenario due to the bias for a certain evaluation index.

The gray target model can comprehensively integrate the multi-layer decision information to provide the low-complexity and accurate evaluation of numerous distribution station areas in complex decision-making (Zhengxin et al., 2009; Ma et al., 2020; Sun and Fang, 2021). It constructs a standard ideal vector by searching for the optimal value in the evaluation index vector. The off-target distance is calculated, and the transparency evaluation of various distribution station areas is achieved based on the comparison between the differentiated evaluation index vectors and the standard ideal vector. Although the gray target model has demonstrated great potential in transparency evaluation, there still exist some major technical challenges, which are introduced in the following paragraphs.

First, traditional gray target models only consider the unidirectional target distance, resulting in the severe loss of important evaluation information and poor evaluation accuracy. Moreover, the key factors affecting transparency evaluation cannot be effectively distinguished due to the lack of differentiated index treatment. Second, the traditional gray target model does not measure the confidence level of the off-target distance, which leads to poor authenticity of the evaluation results. The lack of confidence level measurement cannot reflect the gap between the evaluation scenario and the target scenario. Finally, existing transparency evaluation index systems do not contain integrated electrical and communication criteria. They mostly focus on electrical and electric energy quantities but ignore the quantities of the state, control, and event. The various indices related to new services such as PV monitoring, electric vehicle-charging pile monitoring (Zhou et al., 2023), and the failure rate of these mentoring devices have been largely neglected for the sake of simplicity.

The gray target model has been widely used for performance evaluation in distribution network. Zhang et al. (2012) used the gray target model to evaluate the economic performance of a 20-KV distribution network. Chen et al. (2020) proposed a gray target model-based evaluation framework to assess the performance of distribution network reconfiguration. However, a traditional gray target model only considers the positive target distance. The evaluation result can only reflect the unidirectional tendency between the evaluation candidate and the target, which causes the loss of key information on the bi-directional tendency for accurate transparency evaluation. The technique for order preference by similarity to an ideal solution (TOPSIS) can be used to improve the gray target model by adding a negative target distance to an existing positive target distance. Yin et al. (2021) proposed a two-way evaluation method based on the TOPSIS for an electric vehicle-charging station deployment scheme to maximize mutual benefits of electric vehicle aggregators and owners. Zhang et al. (2021) constructed a comprehensive evaluation model based on the AHP-TOPSIS for PV energy storage plants in AC–DC distribution networks. Zhang and Zhang (2022) proposed an index system for factors affecting the balance rate of distribution station areas based on the coefficient of variation and gray relational evaluation model. However, the above methods have not considered the measurement of confidence levels of a bi-directional off-target distance. A small confidence of transparency evaluation reflects that the probability of the true value falling within the confidence interval is low. In addition, these works have not considered the integration between the electrical and communication criteria in transparency evaluation. The key indices related to newly emerged services such as PV monitoring and electric vehicle-charging pile monitoring are not investigated, which makes them difficult to apply for distribution station areas with a high percentage of distributed PV and electric vehicle penetration.

Faced by these challenges, we propose a confidence relative off-targets distance-based multi-dimensional transparency evaluation method. First, we establish a multi-dimensional transparency evaluation index system, including the target layer, criterion layer, and index layer. Second, we propose an improved gray target model combining positive and negative target vectors to quantify the target distance between the transparency status vectors of different distribution station areas and the positive and negative target vectors. Then, the relative off-target distance is calculated based on the endowment coefficient by leveraging both subjective and objective weights. Finally, the confidence of the relative off-target distance is calculated based on the fuzzy entropy to improve the reliability of transparency evaluation. The key evaluation indices that affect the transparency of distribution station areas are analyzed based on a single-dimensional relative off-target distance. The contributions are summarized in the following paragraphs.

Improved gray target model considering positive and negative target vectors: Using the TOPSIS, we propose the improved gray target model considering positive and negative target vectors to realize the two-way quantitative analysis of distances between the transparency status vector and the two target vectors. The accuracy of transparency evaluation is also significantly improved by reducing the loss of key information on the unidirectional tendency.

Confidence relative off-target distance-based transparency evaluation: On the basis of the single-dimensional relative off-target distances, we utilize the fuzzy entropy to calculate the confidence level of transparency evaluation results to improve evaluation authenticity. The confidence and relative off-target distance are further combined based on the preferences of decision-making to improve the estimation accuracy.

Electrical and communication-integrated multi-dimensional transparency evaluation index system: We construct an electrical and communication-integrated multi-dimensional transparency evaluation index system. Electrical indices related to PV monitoring and electric vehicle monitoring are combined with communication indices such as delay, throughput, and link utilization to provide better adaptability with new services and guarantee the objectivity and accuracy of transparency evaluation.

The proposed method can measure the influence of different dimensional indices on the transparency evaluation of the distribution station area and accurately and reliably evaluate the transparency of each distribution station area. This enables the timely identification of potential problems in low-voltage distribution station areas with low transparency, thereby providing a reliable guarantee for the power services.

The rest of the paper is organized as follows: Section 2 introduces the multi-dimensional transparency index system. Section 3 elaborates the improved gray target model based on positive and negative targets. The proposed confidence relative off-target distance-based multi-dimensional transparency evaluation method is developed in Section 4. The simulation results are presented in Section 5. Section 6 concludes the paper.

2 Multi-dimensional transparency index system of the distribution station area

This paper considers the influence of multi-dimensional factors on the transparency evaluation of distribution station areas and constructs a multi-dimensional transparency evaluation index system, as shown in Figure 1. The index system consists of three layers, namely, the target layer, criterion layer, and index layer, which are elaborated in the following paragraphs.

2.1 Target layer

The purpose of constructing the index system is to evaluate the transparency of the distribution station area. The target layer of the index system is defined as the transparency evaluation of the distribution station area.

2.2 Criterion layer

The criterion layer is mainly considered from two dimensions: electrical criterion and communication criterion. The electrical criterion can be specifically divided into five sub-criteria, namely, the electrical quantity, electric energy quantity, state quantity, control quantity, and event quantity.

2.3 Index layer

The indices contained in the index layer support the criterion and sub-criterion of the criterion layer, which are elaborated in the following paragraphs.

2.3.1 Indices of the electrical quantity sub-criterion

The electrical quantity sub-criterion reflects the basic characteristics of the distribution station area, which includes two indices: bus voltage Z_1 and bus current Z_2.

1) Z_1 represents the voltage on the main power line in the power supply system, which usually refers to the voltage output by a transmission line of the substation.

2) Z_2 represents the current transmitted through the bus.

These indices can be measured directly and do not require further calculation.

2.3.2 Indices of the electric energy quantity sub-criterion

The electric energy quantity sub-criterion is used to describe the power quality of the distribution station area, which includes two indices: acquisition device power Z_3 and the capacity of the reactive power compensation device Z_4.

1) Z_3 represents the electric energy consumed using the acquisition device per unit time.

2) Z_4 indicates the total capacity of the reactive power compensation device. The reactive power compensation of the distribution station area is mainly based on the low-voltage centralized compensation, and the high-voltage compensation is utilized as an auxiliary.

These indices can be measured directly or prescribed by the system and do not require further calculation.

2.3.3 Indices of the state quantity sub-criterion

The state quantity sub-criterion is used to describe the state of the distribution station area, which includes four indices: equipment relay protection sensitivity Z_5, the failure rate of the intelligent circuit breaker Z_6, the failure rate of the distributed photovoltaic (PV) monitoring device Z_7, and the failure rate of the electric vehicle-charging pile monitoring device Z_8.

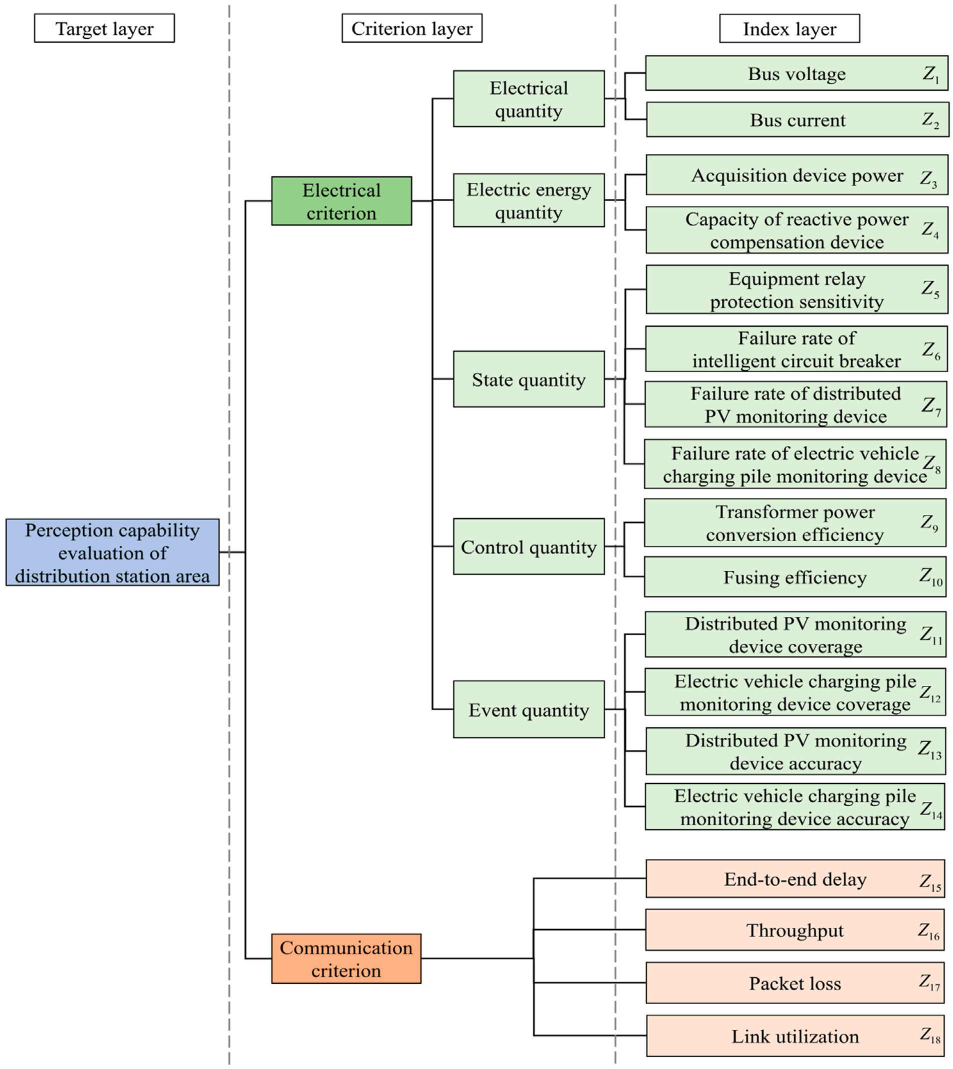

FIGURE 1
Multi-dimensional transparency evaluation index system.

1) Z_5 represents the capability of the relay protection device to detect and judge the fault signal. Higher sensitivity represents the faster detection of the fault signal of the relay protection device (Liao et al., 2021). Taking appropriate protective measures in time can effectively reduce the damage to the device. Z_5 can be calculated as

$$Z_5 = \frac{|I_1 + I_2|}{K\left(|I_1 - I_2| - I_g\right) + I_{\min}}, \tag{1}$$

where I_1 and I_2 are the currents of the high-voltage side and the low-voltage side, respectively. I_g is the inflection point current. $I_{\min}$ is the minimum operating current. K is the slope of the ratio restrain characteristic.

2) Z_6 depends on the specific product model and manufacturer. In general, a good quality intelligent circuit breaker has a low failure rate and can provide stable and reliable power protection. Different designs and manufactures lead to the difference in the failure rate of intelligent circuit breakers. Considering the distribution station area, Z_6 can be calculated as

$$Z_6 = \frac{\tilde{Z}_6}{e^{\tilde{H}A}} e^{AH}, \tag{2}$$

where A is the curvature coefficient. H is the health parameter. $\tilde{Z}_6$ is the historical average failure rate of intelligent circuit breakers. $\tilde{H}$ is the health parameter corresponding to $\tilde{Z}_6$.

The calculation of Z_7 and Z_8 is similar to Eq. 2.

2.3.4 Indices of the control quantity sub-criterion

The control quantity sub-criterion is used to describe the control efficiency of the distribution station area, which includes two indices: the transformer power conversion efficiency Z_9 and fusing efficiency Z_{10}.

1) Z_9 represents the power conversion efficiency achieved by the transformer when converting the electrical energy from one voltage level to another.

2) Z_{10} represents the capability of the fuse to quickly cut off the circuit and protect the electrical equipment in the event of overload or short-circuit.

These two indices can be obtained by simple measurement or inspection and do not require further calculation.

2.3.5 Indices of the event quantity sub-criterion

The event quantity sub-criterion is used to describe the coverage and accuracy of major operations, which includes four indices: the distributed PV monitoring device coverage Z_{11}, electric vehicle-charging pile monitoring device coverage Z_{12}, distributed PV monitoring device accuracy Z_{13}, and electric vehicle-charging pile monitoring device accuracy Z_{14}.

1) Z_{11} depends on the design and installation of the distributed PV monitoring device. In general, distributed PV monitoring devices can cover the entire power generation system of PV power stations. Considering the distribution station area, distributed PV monitoring device coverage Z_{11} can be calculated as

$$Z_{11} = \frac{A_{\text{cov}}}{A_{\text{act}}}, \tag{3}$$

where A_{ov} is the total area of the distributed PV actually monitored by the distributed PV monitoring device. A_{act} is the total area of distributed PV.

The calculation of Z_{12} is similar to Eq. 3.

2) Z_{13} is calculated by using the Weibull distribution to fit the accuracy curve of the distributed PV monitoring device, i.e.,

$$Z_{13} = e^{-\left(\frac{t}{\theta}\right)^{\alpha}}, \tag{4}$$

where t is the operating time of the distributed PV monitoring device. θ is the characteristic parameter, which magnifies and shrinks the function curve and reflects the average monitoring error time interval of the monitoring device. α is the shape parameter, reflecting the basic shape of the accuracy distribution function.

The calculation of Z_{14} is similar to Eq. 4.

2.4 Indices of the communication criterion

Communication indices assist in the transparency evaluation of distribution station areas from the perspective of communication performance, which consist of end-to-end delay Z_{15}, throughput Z_{16}, packet loss Z_{17}, and link utilization Z_{18}.

1) Z_{15} indicates the total time it takes for data to be sent from the source node to the destination node.

2) Z_{16} indicates the amount of data successfully transmitted per unit time.

3) Z_{17} indicates the proportion of packets that are lost during data transmission.

4) Z_{18} indicates the ratio of the time a network link is actually used to the total time.

These communication indices can be easily obtained using communication monitoring tools and do not require further calculation.

3 Improved gray target model based on positive and negative targets

The transparency evaluation of the distribution station area is a complex system decision problem that encompasses multiple dimensions and indices. First, we construct a vector space based on the multi-dimensional transparency index system. The index system that is composed of N indices constitutes the N-dimensional evaluation space $\boldsymbol{Z} = [Z_1, \ldots, Z_n, \ldots, Z_N]$.

There are M distribution station areas with varying resource endowments to be evaluated, and the evaluation vector representing different distribution station areas is denoted as $\boldsymbol{S} = [S_1, \ldots, S_m, \ldots, S_M]$. The transparency evaluation space matrix $\boldsymbol{A^S}$, which includes all the distribution station areas requiring evaluation, can be defined as

$$\boldsymbol{A^S} = \begin{array}{c} \\ S_1 \\ \vdots \\ S_M \end{array} \begin{array}{c} \begin{array}{ccc} Z_1 & \cdots & Z_N \end{array} \\ \begin{pmatrix} a_{11} & \cdots & a_{1N} \\ \vdots & \ddots & \vdots \\ a_{M1} & \cdots & a_{MN} \end{pmatrix} \end{array} \tag{5}$$

where a_{mn} is the index value of the distribution station area S_m on the dimension Z_n. The mth row represents the state vector of the distribution station area S_m in the evaluation space, denoted as $\boldsymbol{a}_m = [a_{m1}, \ldots, a_{mn}, \ldots, a_{mN}]$.

The gray target model can synthesize multi-level decision-making information and evaluate the level of each scheme in complex decision-making problems. Therefore, we use the gray target model to evaluate and analyze the transparency evaluation of the distribution station area. The gray target model takes the ideal scenario as the target, compares different evaluation objects with the target, and quantifies the deviation between the evaluation object and the target. We define the positive target vector as $\boldsymbol{a}^+$, which is formed by the target values of each dimension index. The distribution station areas gradually evolve from their current state vector $\boldsymbol{a}_i$ toward the positive target vector $\boldsymbol{a}^+$, indicating a unidirectional positive trend.

The traditional gray target model only considers the unidirectional target distance, which leads to the loss of evaluation information and inaccurate evaluation. The TOPSIS takes the negative target distance into account on the basis of the positive evaluation. By incorporating the TOPSIS into the gray target model, we can enhance its performance (Madavan, 2020; Zhang, 2021). In addition to setting the positive target vector, we can introduce a negative target vector for comparative analysis and create a reverse reference scenario for the distribution station area S_m. In the process of transparency evaluation of the distribution station area, the current state vector of the distribution station area will deviate from the negative target vector $\boldsymbol{a}^-$. Therefore, by considering the negative target vector, we can assess the reversed trend of the distribution station area toward the reverse reference scenario.

The improved gray target model including positive and negative target vectors and transparency state vectors of all distribution station areas is constructed. The positive target vector $\boldsymbol{a}^+$ and negative target vector $\boldsymbol{a}^-$ can be represented as

$$\begin{cases} \boldsymbol{a}^+ = [a_1^+, a_2^+, \ldots, a_N^+] \\ \boldsymbol{a}^- = [a_1^-, a_2^-, \ldots, a_N^-]. \end{cases} \tag{6}$$

In the process of the transparency evaluation of the distribution station area, in order to avoid the decrease in the evaluation accuracy caused by different dimensions of each index, it is necessary to perform gray target transformation on the spatial axis, i.e., $T(a_{mn}) = b_{mn}$, which is formulated as

$$\begin{cases} T(a_{mn}) = (a_n^- - a_{mn}) / (a_n^- - a_n^+) = b_{mn}, & a_{mn} \in \Psi_J \\ T(a_{mn}) = (a_{mn} - a_n^-) / (a_n^+ - a_n^-) = b_{mn}, & a_{mn} \in \Psi_E \\ T(a_{mn}) = 1 - |a_{mn} - a_n^+| / G = b_{mn}, & a_{mn} \in \Psi_F, \end{cases} \tag{7}$$

where $G = \max|a_n^+ - a_n^-|$, and Ψ_J, Ψ_E, and Ψ_F are cost-based index sets, revenue-based index sets, and fixed index sets, respectively. After applying the gray target transformation to $\boldsymbol{A}^S$, a multi-dimensional gray target model $\boldsymbol{B}^S = [b_{mn}]_{M\times N}$ can be established. Simultaneously, by performing transformation on $\boldsymbol{a}^+$ and $\boldsymbol{a}^-$, we obtain the standard positive target vector $\boldsymbol{b}^+ = [1, 1, \ldots, 1]$ and the standard negative target vector $\boldsymbol{b}^- = [0, 0, \ldots, 0]$.

In summary, the gray target model is improved by considering both positive and negative target vectors. The model can precisely reflect the tendency of the current state vector of the distribution station area. Based on the positive and negative target vectors, we can establish an improved gray target model $\boldsymbol{B}$, which is formulated as

$$\boldsymbol{B} = \begin{pmatrix} \boldsymbol{B}^S \\ \boldsymbol{b}^+ \\ \boldsymbol{b}^- \end{pmatrix} = \left(\begin{array}{ccc} b_{11} & \cdots & b_{1N} \\ \vdots & \ddots & \vdots \\ b_{M1} & \cdots & b_{MN} \\ \hdashline 1 & \cdots & 1 \\ 0 & \cdots & 0 \end{array}\right) \tag{8}$$

The positive target distance d_i^+ between $\boldsymbol{b}_i$ and $\boldsymbol{b}^+$, as well as the negative target distance d_i^- between $\boldsymbol{b}_i$ and $\boldsymbol{b}^-$, can be calculated as

$$\begin{cases} {d_m^+}^2 = \sum_{n=1}^{N} (b_{mn} - b_n^+)^2 \\ {d_m^-}^2 = \sum_{n=1}^{N} (b_{mn} - b_n^-)^2. \end{cases} \tag{9}$$

The positive and negative target distances, d_m^+ and d_m^-, respectively, reflect the bidirectional tendencies of $\boldsymbol{b}_{mn}$ toward the positive and negative target vectors, $\boldsymbol{b}^+$ and $\boldsymbol{b}^-$, respectively. They also indicate the deviations of $\boldsymbol{b}_{mn}$ from the positive and negative target vectors, thus providing a quantitative analysis of transparency evaluation.

4 Confidence relative off-targets distance-based transparency evaluation

As shown in Figure 2, we propose a confidence relative off-target distance-based multi-dimensional transparency evaluation method. First, the endowment coefficient of each distribution station area is calculated based on the subjective weight and objective weight. Second, the relative off-target distance is calculated by combining the endowment coefficient. Then, the confidence of transparency evaluation can be measured based on the fuzzy entropy, and the confidence relative off-target distance can be calculated. Finally, a transparency evaluation mapping criterion is constructed to realize the transparency evaluation of the distribution station area combined with the confidence relative off-target distance. The specific transparency evaluation process is described in the following paragraphs.

4.1 Assignment of the endowment coefficient

The entropy weight method (EWM) identifies objective information in data through the calculation of entropy (Jiayi et al., 2022), while the FAHP considers decision-making experience to establish judgment matrices (Mansouri, 2019; Ramanayaka, 2019). We combine the advantages of both methods to integrate subjective and objective information. Based on the integration of subjective information and objective information, we can calculate the endowment coefficients of various dimension indicators, quantifying the resource endowment disparities in the distribution station areas requiring evaluation.

First, based on the improved EWM, the entropy H_n that represents the importance of the evaluation indices can be calculated as

$$1 - H_n = 1 + \frac{1}{\ln M} \sum_{m=1}^{M} \left(\frac{1 + b_{mn}}{\sum_{m=1}^{M} (1 + b_{mn})} \ln \frac{1 + b_{mn}}{\sum_{m=1}^{M} (1 + b_{mn})} \right), \tag{10}$$

where $1 + b_{mn}$ is used to prevent the entropy value of the indicator from becoming excessively large and losing its value.

The objective weights are defined as $\boldsymbol{L} = [\lambda_n]^{\mathrm{T}}$. The calculation of λ_n is given by

$$\lambda_n = \frac{\left| 1 + \frac{1}{\ln M} \sum_{m=1}^{M} \left(\frac{1+b_{mn}}{\sum_{m=1}^{M}(1+b_{mn})} \ln \frac{1+b_{mn}}{\sum_{m=1}^{M}(1+b_{mn})} \right) \right|}{\sum_{n=1}^{N} \left| 1 + \frac{1}{\ln M} \sum_{m=1}^{M} \left(\frac{1+b_{mn}}{\sum_{m=1}^{M}(1+b_{mn})} \ln \frac{1+b_{mn}}{\sum_{m=1}^{M}(1+b_{mn})} \right) \right|}. \tag{11}$$

The subjective weights are defined as $\boldsymbol{U} = [\mu_n]^{\mathrm{T}}$, which can be obtained based on the FAHP. Then, we use a linear weighted combination method to consider both the subjective and objective weights and obtain the endowment coefficient $\boldsymbol{W} = [\omega_n]^{\mathrm{T}}$, where ω_n is

$$\omega_n = \frac{\sqrt{\mu_n \lambda_n}}{\sum_{n=1}^{N} \sqrt{\mu_n \lambda_n}}. \tag{12}$$

The range of ω_n is [0,1], and a larger value of ω_n represents a greater impact on the transparency evaluation of the distribution station area S_n.

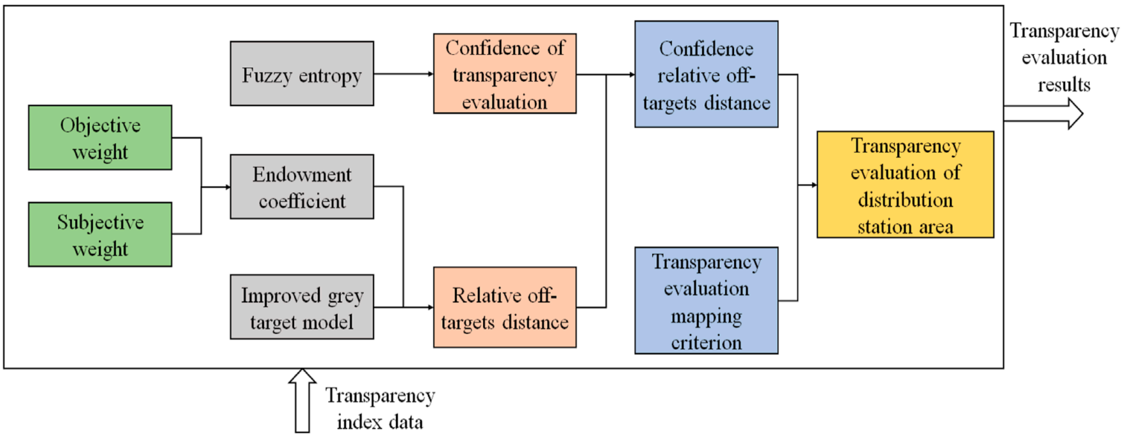

FIGURE 2
Diagram of the confidence relative off-target distance-based transparency evaluation method.

TABLE 1 Mapping between Q_m and the transparency level.

Range	$[\kappa_1, \kappa_2]$	$[\kappa_2, \kappa_3]$	$[\kappa_3, \kappa_4]$	$[\kappa_4, \kappa_5]$	$[\kappa_5, \kappa_6]$
Transparency level	Poor	Relatively poor	Moderate	Good	Excellent

4.2 Calculation of the confidence relative off-targets distance

Each dimension index has different influences on the transparency evaluation of the distribution station area (Zhang et al., 2023). If index Z_n has a higher weight value, the change in this index will result in a larger change in the positive target distance d_m^+. To account for this, we can use the endowment coefficients to adjust the positive and negative target distances, obtaining the weighted positive target distance D_m^+ and weighted negative target distance D_m^-. The expression is given by

$$\begin{cases} {D_m^+}^2 = \sum_{n=1}^{N} \omega_n^2 (b_{mn} - b_n^+)^2 \\ {D_m^-}^2 = \sum_{n=1}^{N} \omega_n^2 (b_{mn} - b_n^-)^2. \end{cases} \tag{13}$$

To comprehensively assess the transparency evaluation of the distribution station area, it is necessary to consider both D_m^+ and D_m^-. The relative off-target distance of the distribution station area can be defined as

$$C_m = \frac{D_m^-}{D_m^+ + D_m^-}. \tag{14}$$

The range of values for the relative off-target distance C_m is [0,1]. A value closer to 0 indicates that $\boldsymbol{Wb}_m$ is closer to $\boldsymbol{Wb}^-$ and farther from $\boldsymbol{Wb}^+$, implying a lower transparency performance of the distribution station area.

To effectively measure the impact of a single-dimension index on the transparency evaluation of the distribution station area, we introduce the concept of the relative off-target distance for a single dimension index. First, the weighted positive target distance D_{mn}^+ and the weighted negative target distance D_{mn}^- for the distribution station area with respect to a specific dimension index can be calculated as

$$\begin{cases} D_{mn}^+ = \omega_n |b_{mn} - b_n^+| \\ D_{mn}^- = \omega_n |b_{mn} - b_n^-| \end{cases}. \tag{15}$$

The relative off-target distance for a single dimension index can be represented as

$$C_{mn} = \frac{D_{mn}^-}{D_{mn}^+ + D_{mn}^-}. \tag{16}$$

Based on the relative off-target distance for each dimension of the distribution station area, further analysis can be conducted to evaluate the transparency and identify key indices that influence the transparency evaluation of the distribution station area.

Entropy is a measure of uncertainty in information theory. With the development of the fuzzy theory, the application of entropy in fuzzy sets is called fuzzy entropy, which reflects the degree of fuzziness of a fuzzy set (Liu et al., 2020; Zheng et al., 2021). When the multi-dimensional transparency index system is used to evaluate the transparency of the distribution station area, if there is a large difference between the relative off-target distance of each transparency evaluation index, the transparency status of the distribution station area is difficult to be reflected by the relative off-target distance, and the transparency evaluation result has a small confidence. Therefore, we utilize the fuzzy entropy to measure the confidence of the transparency evaluation of the distribution station area. The confidence φ_m of the transparency evaluation of the distribution station area S_m is defined as

$$\varphi_m = \frac{1}{5}\left\{1 - \eta \sum_{n=1}^{N} \left[C_{mn} \ln(C_{mn}) + (1 - C_{mn}) \ln(1 - C_{mn})\right]\right\}, \tag{17}$$

where η is the standardized coefficient and is given by

$$\eta = \frac{-1}{\delta \ln(\delta) + (1-\delta)\ln(\delta - 1)}. \tag{18}$$

δ is the number of distribution station area transparency evaluation levels.

The range of the confidence φ_m is [0,1]. When φ_m approaches 0, it indicates the lower confidence of the transparency evaluation result, which means that the probability of the true transparency evaluation value falling within the confidence interval is low. Conversely, when φ_m approaches 1, it indicates higher confidence of the transparency evaluation result, which means that the probability of the true transparency evaluation value falling within the confidence interval is high.

After the calculation of the relative off-target distance C_m and confidence φ_m, we combine them to calculate the confidence relative off-target distance, which can be represented as

$$Q_m = \varpi C_m + (1-\varpi)\varphi_m. \tag{19}$$

The value of ϖ is based on the preferences of the ultimate decision-maker regarding the overall evaluation results of the distribution station area and the influence of individual dimension indices.

4.3 Transparency evaluation of the distribution station area

Based on the confidence relative off-target distance $Q_m \in [0,1]$, we can realize the transparency evaluation of the distribution station area. When Q_m approaches 0, it indicates a poor transparency level of the distribution station area. Conversely, when Q_m approaches 1, it indicates a higher transparency level of the distribution station area. To achieve an accurate transparency evaluation of the distribution station area, we divide the transparency level of the distribution station area into five levels: poor, relatively poor, moderate, good, and excellent. The values of Q_m corresponding to different transparency levels are shown in Table 1. The values of κ_1, κ_2, κ_3, κ_4, κ_5, and κ_6 can be flexibly set, according to the actual situation of the distribution station area. Based on Table 1, we can map the confidence relative off-target distance Q_m of the distribution station area to the above five transparency levels to realize transparency evaluation.

The implementation procedures of the proposed confidence relative off-target distance-based transparency evaluation algorithm are summarized in Algorithm 1.

Improved gray target model:
The evaluation space is constructed based on the multi-dimensional transparency index system.
The positive target vector $\boldsymbol{a}^+$ and the negative target vector $\boldsymbol{a}^-$ are set based on (6).
A multi-dimensional gray target model $\boldsymbol{B}^S$ is established based on (7).
An improved gray target model $\boldsymbol{B}$ is established based on (8).
The positive target distance d_i^+ and negative target distance d_i^- are calculated based on (9).
Assignment of the endowment coefficient:
$1-H_n$ is calculated based on (10).
The objective weight λ_n is calculated based on (11), and the subjective weight μ_n is calculated based on the FAHP.
The endowment coefficient ω_n is calculated based on (12).
Calculation of the confidence relative off-target distance:
The weighted positive target distance D_m^+ and weighted negative target distance D_m^- are calculated based on (13).
The relative off-target distance C_m is calculated based on (14).
The weighted positive target distance D_{mn}^+ and the weighted negative target distance D_{mn}^- are calculated for a single-dimension index based on (15).
The relative off-target distance for a single-dimension index is calculated based on (16).
The confidence φ_m is calculated based on (17) and 18.
The confidence relative off-target distance Q_m is calculated based on (19).
Transparency evaluation of the distribution station area:
The transparency evaluation of the distribution station area is realized based on Table 1.

Algorithm 1. The proposed confidence relative off-target distance-based multi-dimensional transparency evaluation algorithm.

5 Example of the transparency evaluation of the distribution station area

We select six distribution station areas, S_1–S_6, in Shandong Province, China, for the transparency evaluation of distribution station areas to verify the proposed method. The distribution station areas S_1–S_2 are located in the commercial districts, the distribution station areas S_3–S_4 are located in the residential districts, and the distribution station areas S_5–S_6 are located in the industrial districts. Compared with the distribution station area in the industrial districts, the loads of distribution station areas located in the commercial and residential districts are relatively smaller. The power supply radius of S_1–S_2 is approximately 200 m. The coverage rates of distributed PV monitoring devices are 97.30% and 99.07%, respectively, and the coverage rates of electric vehicle-charging pile monitoring devices are approximately 96.41% and 97.25%, respectively. The power supply radius of S_3–S_4 is approximately

TABLE 2 Transparency evaluation space.

	S_1	S_2	S_3	S_4	S_5	S_6
Z_1 (kV)	9.90	10.10	10.05	10.05	10.05	10.10
Z_2 (A)	20.50	19.80	20.30	19.80	20.20	20.10
Z_3 (kW)	27.00	26.00	24.00	24.50	29.00	28.00
Z_4 (kvar)	135.00	129.00	130.50	132.00	133.50	130.50
Z_5 (%)	99.99	99.90	99.00	99.90	99.90	99.90
Z_6 (%)	3.00	4.00	7.00	5.00	2.00	2.00
Z_7 (%)	5.00	7.00	7.30	8.50	2.10	1.50
Z_8 (%)	6.00	5.00	5.20	6.80	1.00	1.00
Z_9 (%)	98.90	99.20	98.90	99.10	99.40	99.70
Z_{10} (%)	95.00	96.00	95.00	95.50	98.00	99.00
Z_{11} (%)	97.30	99.07	97.35	98.82	99.72	98.08
Z_{12} (%)	96.41	97.25	93.07	95.66	99.30	99.29
Z_{13} (%)	94.10	90.40	95.13	88.36	99.27	99.97
Z_{14} (%)	95.30	92.01	91.06	93.10	95.50	95.30
Z_{15} (s)	0.50	3.00	0.80	1.00	0.20	0.50
Z_{16} (kbs)	2.85	1.05	2.50	2.05	3.00	4.50
Z_{17} (%)	11.20	9.51	13.55	11.42	4.32	5.48
Z_{18} (%)	96.30	95.00	96.00	94.20	96.20	97.00

150 m. The coverage rates of distributed PV monitoring devices are 91.52% and 90.24%, respectively, and the coverage rates of electric vehicle-charging pile monitoring devices are approximately 93.61% and 96.21%, respectively. The power supply radius of S_5–S_6 is approximately 500 m. The coverage rates of distributed PV monitoring devices are 99.72% and 98.08%, respectively, and the coverage rates of electric vehicle-charging pile monitoring devices are approximately 99.30% and 99.29%, respectively. In addition, the distribution station areas S_5–S_6 are upgraded, and their levels of informatization and automation are relatively high.

To achieve the transparency evaluation of the distribution station area, the evaluation index $\boldsymbol{Z} = [Z_1, Z_2, \ldots, Z_{18}]$ based on statistical data collected from the distribution station area has been established. Table 2 shows the transparency evaluation space for distribution station areas S_1–S_6.

To describe the differences in the transparency evaluation of different distribution station areas based on various dimensional indices, the endowment coefficient matrix $\boldsymbol{W}$ needs to be calculated. First, we consider the rationality of concrete data, and the positive target vector $\boldsymbol{a}^+$ and negative target vector $\boldsymbol{a}^-$ can be set as shown in (20). Then, based on (7), by applying the gray target transformation to transparency evaluation space $\boldsymbol{A}^S$, as shown in Table 2, a multi-dimensional gray target model $\boldsymbol{B}^S = [b_{mn}]_{M\times N}$ can be established. Take Z_1 in S_1 as an example. In this case, $m = 1$ and $n = 1$. Based on (7), Z_1 conforms to a fixed index set, which means that $a_{mn} \in \Psi_F$, and set $G = \max|a_n^+ - a_n^-| = 1$. Thus, b_{11} is calculated as

$$\begin{cases} \boldsymbol{a}^+ = [10, 20, 30, 133, 100\%, 0, 0, 0, 100\%, 100\%, 100\%, 100\%, 100\%, 100\%, 0, 5, 0, 100\%] \\ \boldsymbol{a}^- = [0, 0, 5, 0, 95\%, 15\%, 15\%, 15\%, 90\%, 85\%, 95\%, 90\%, 75\%, 85\%, 10, 1, 20\%, 90\%], \end{cases} \tag{20}$$

$$\boldsymbol{B} = \left(\begin{array}{cccccccccccccccccc} 0.90 & 0.75 & 0.88 & 0.90 & 1.00 & 0.80 & 0.67 & 0.60 & 0.89 & 0.67 & 0.40 & 0.60 & 0.76 & 0.67 & 0.95 & 0.46 & 0.44 & 0.63 \\ 0.90 & 0.90 & 0.84 & 0.80 & 0.98 & 0.73 & 0.53 & 0.67 & 0.92 & 0.73 & 0.80 & 0.70 & 0.60 & 0.47 & 0.70 & 0.01 & 0.52 & 0.50 \\ 0.95 & 0.85 & 0.76 & 0.88 & 0.80 & 0.53 & 0.51 & 0.65 & 0.89 & 0.67 & 0.47 & 0.31 & 0.81 & 0.40 & 0.92 & 0.38 & 0.32 & 0.60 \\ 0.95 & 0.90 & 0.78 & 0.95 & 0.98 & 0.67 & 0.43 & 0.55 & 0.91 & 0.70 & 0.76 & 0.57 & 0.53 & 0.54 & 0.90 & 0.26 & 0.43 & 0.42 \\ 0.95 & 0.90 & 0.96 & 0.98 & 0.98 & 0.87 & 0.86 & 0.93 & 0.94 & 0.87 & 0.98 & 0.90 & 0.96 & 0.70 & 0.98 & 0.50 & 0.78 & 0.62 \\ 0.90 & 0.95 & 0.92 & 0.88 & 0.98 & 0.87 & 0.90 & 0.93 & 0.97 & 0.93 & 0.80 & 0.90 & 0.96 & 0.67 & 0.95 & 0.88 & 0.73 & 0.70 \\ \hdashline 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{array}\right) \tag{21}$$

$$b_{11} = 1 - \frac{|a_{11} - a_1^+|}{G} = 1 - \frac{|9.9 - 10|}{1} = 0.9. \tag{22}$$

Simultaneously, by performing a transformation on $\boldsymbol{a}^+$ and $\boldsymbol{a}^-$, we obtain the standard vectors $\boldsymbol{b}^+ = [1, 1, \ldots, 1]$ and $\boldsymbol{b}^- = [0, 0, \ldots, 0]$. To sum up, the improved gray target model $\boldsymbol{B}$ is constructed as (21).

The subjective weight $\boldsymbol{U}$ is obtained using the FAHP. Taking Z_1 as an example, the subjective weight μ_1 is defined as 0.0956. The objective weight $\boldsymbol{L}$ is obtained by using the EWM through (11). The objective weight λ_1 is calculated, and the result is 0.0049. By comprehensively considering the subjective weight and objective weight, the endowment coefficient $\boldsymbol{W}$ is calculated based on (12). The endowment coefficient $\boldsymbol{W}$ for Z_1 is calculated, and the result is 0.0321. Finally, the subjective weight, objective weight, and endowment coefficient of each evaluation index are obtained, as shown in Table 3.

Then, based on the obtained endowment coefficients, the weighted positive and negative target distances of each distribution station area, as well as the relative off-targets distance, can be calculated based on Eqs 13, 14.

Taking S_1 as an example, in this case, parameter m is 1. Based on Eq. 13, the weighted positive target distance of S_1 is calculated as

$$D_1^+ = \sqrt{\sum_{n=1}^{18} \omega_n^2 (b_{1n} - b_n^+)^2} = 0.1287. \tag{23}$$

Similarly, the weighted negative target distance of S_1 is calculated as

$$D_1^- = \sqrt{\sum_{n=1}^{18} \omega_n^2 (b_{1n} - b_n^-)^2} = 0.1819. \tag{24}$$

Afterward, D_1^+ and D_1^- are integrated into (14). The relative off-target distance C_1 is calculated as

$$C_1 = \frac{D_1^-}{D_1^+ + D_1^-} = 0.5857. \tag{25}$$

The full results are shown in Table 4.

Then, the confidence level φ_m of the relative off-target distance can be calculated based on (15), (16), and (Eqs 17, 18).

According to Table 1, this paper divides the transparency evaluation results into five levels, i.e., $\delta = 5$. Eq. 18 becomes

$$\eta = \frac{-1}{5\ln(5) + (1-5)\ln(5-1)}. \tag{26}$$

Based on Eq. 17, the confidence level is obtained as

$$\begin{aligned} \varphi_1 &= \frac{1}{5}\left\{1 - \eta \sum_{n=1}^{18} \left[C_{1n}\ln(C_{1n}) + (1 - C_{1n})\ln(1 - C_{1n})\right]\right\} \\ &= 0.7317, \end{aligned} \tag{27}$$

TABLE 3 Subjective and objective weights and endowment coefficients.

	μ	λ	W
Z_1	0.0956	0.0049	0.0321
Z_2	0.0856	0.0074	0.0308
Z_3	0.0956	0.0059	0.0328
Z_4	0.0456	0.0047	0.0169
Z_5	0.0526	0.0066	0.0204
Z_6	0.0056	0.0398	0.0295
Z_7	0.0636	0.1528	0.1260
Z_8	0.0606	0.0574	0.0584
Z_9	0.0256	0.0012	0.0085
Z_{10}	0.0256	0.1452	0.1093
Z_{11}	0.0656	0.0736	0.0712
Z_{12}	0.0576	0.0218	0.0325
Z_{13}	0.0566	0.1118	0.0953
Z_{14}	0.0456	0.0354	0.0384
Z_{15}	0.1056	0.0144	0.0417
Z_{16}	0.0556	0.2230	0.1728
Z_{17}	0.0456	0.0778	0.0681
Z_{18}	0.0126	0.0164	0.0152

TABLE 4 Weighted positive and negative target distances and relative off-target distances.

	D_m^+	D_m^-	C_m
S_1	0.1287	0.1819	0.5857
S_2	0.1933	0.1596	0.4523
S_3	0.1731	0.1458	0.4572
S_4	0.1775	0.1510	0.4597
S_5	0.0919	0.2338	0.7179
S_6	0.0387	0.2651	0.8726

where C_{1n} can be obtained from Eq. 15 and Eq. 16. For the convenience of subsequent calculation, the values of C_m and φ_m are also shown in Table 5.

Based on the obtained C_m and φ_m, the confidence relative off-target distance Q_m can be calculated based on Eq. 19. In this paper, the parameter ϖ in Eq. 19 is set as 0.8. Q_1 is calculated as

$$Q_1 = \varpi C_1 + (1 - \varpi)\varphi_1 = 0.6149. \tag{28}$$

TABLE 5 Transparency evaluation results.

	S_1	S_2	S_3	S_4	S_5	S_6
C_m	0.5857	0.4523	0.4572	0.4597	0.7179	0.8726
φ_m	0.7317	0.7188	0.7817	0.7311	0.4594	0.4814
Q_m	0.6149	0.5056	0.5221	0.5140	0.6662	0.7944
Result	Good	Moderate	Moderate	Moderate	Good	Good

The full results of the confidence relative off-target distance are shown in Table 5.

Finally, the transparency evaluation of the distribution station area can be realized based on Table 1. In this paper, $\kappa_1 = 0.00$, $\kappa_2 = 0.20$, $\kappa_3 = 0.40$, $\kappa_4 = 0.60$, $\kappa_5 = 0.80$, and $\kappa_6 = 1.00$. Combined with Table 1, the transparency evaluation results are shown in Table 5.

As shown in Figure 3, the transparency evaluation results of the six distribution station areas are given according to Table 5. The y-axis shown in Figure 3 represents the positive target distance, the x-axis represents the negative distance, and the z-axis represents the confidence relative off-target distance. In order to enhance the readability of the graph, we set breaks in the 0.3–1.0 part of the x-axis and y-axis. The red sphere represents the standard positive target vector, the black sphere represents the standard negative target vector, and the blue sphere represents the transparency evaluation status vector (D_m^+, D_m^-, and Q_m) of the distribution station area S_m. Figure 3 shows that the confidence relative off-target distance of the distribution station area S_3 is the smallest, indicating that its transparency level is the worst compared to other distribution station areas. The confidence relative off-target distance of the distribution station area S_4 is the largest, indicating that its transparency level is the best compared to other distribution station areas. In addition, from Figure 3, it can be concluded that the transparency levels of the distribution station areas S_1–S_3 are lower than those of S_4–S_6. This is consistent with Table 2, where the distributed PV monitoring device coverage, throughput, and electric vehicle-charging pile monitoring device coverage of distribution station areas S_1–S_3 are lower than those of S_4–S_6. At the same time, the end-to-end delay and packet loss rate of S_1–S_3 are higher than those of S_4–S_6. The communication performance and information intelligence level of S_1–S_3 in the commercial area are lower than those of S_4–S_6 in the industrial park. Therefore, based on the confidence relative off-target distance-based multi-dimensional transparency evaluation method, the conclusion that the transparency levels of S_1–S_3 are lower than those of S_4–S_6 is consistent with the simulation setting.

As shown in Figure 4, the analysis of the single-dimension relative off-target distance of distribution station areas S_5 and S_6 in 18 indices is given. The vertices of the red polygon and the yellow polygon represent the positive and negative target vectors of the single dimension of each index, respectively. In addition, the vertices of the blue polygon and the orange polygon represent the

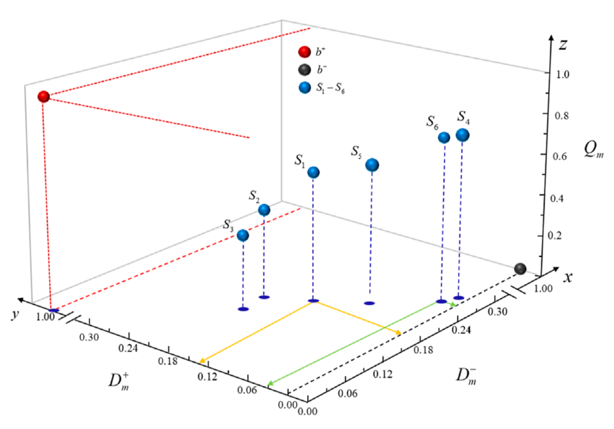

FIGURE 3
Transparency evaluation results of the six distribution station areas.

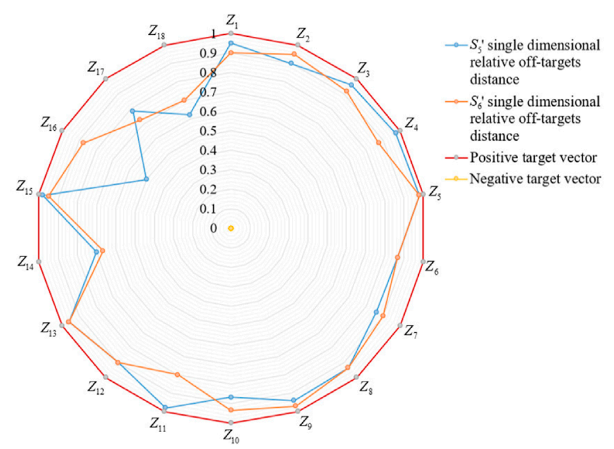

FIGURE 4
Single-dimension relative off-target distance of distribution station areas S_5 and S_6.

single-dimension relative off-target distance of each index of the distribution station areas S_5 and S_6, respectively.

For the distribution station area S_5, the single-dimension vector of equipment relay protection sensitivity, distributed PV monitoring device coverage, and end-to-end delay is closest to the positive target vector, and the deviation from the negative target vector is the largest, indicating that these three indices have the greatest contribution to the transparency of the distribution station area S_5. The single dimension of throughput is smaller than other indices, indicating that it has the greatest potential for transparency improvement in this dimension. In addition, for the distribution station area S_6, the relative off-target distance of the single dimension of equipment relay protection sensitivity is the largest, indicating that the equipment relay protection sensitivity has the greatest contribution to the transparency. The single-dimension relative off-target distance of the electric vehicle-charging pile monitoring device accuracy of the distribution station area S_6 is the smallest, indicating that the electric vehicle-charging pile monitoring device accuracy has the greatest potential for the improvement of the transparency of the distribution station area S_6.

6 Conclusion

In this paper, a multi-dimensional transparency evaluation method based on the confidence relative off-target distance is proposed to analyze and evaluate the transparency of distribution station areas. First, the proposed method constructs a multi-dimensional transparency evaluation index system with electrical and communication integration, ensuring the objectivity of transparency evaluation. Second, by combining positive and negative target vectors, the proposed method overcomes the unidirectional tendency problem of the conventional gray target model, reducing the loss of key information and significantly improving the accuracy of transparency evaluation. Finally, the reliability and accuracy of transparency evaluation are further improved based on the different endowment coefficients and confidence calculation. The simulation results show that the proposed method can effectively distinguish the transparency gap and identify the single dimension of the index with the greatest contribution or potential. This enables the timely identification of potential problems in low-voltage distribution station areas with low transparency, thereby providing a reliable guarantee for power services. In the future, we will carry out further study on transparency evaluation from the perspective of integration of the information flow, energy flow, service flow, and value flow.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

JR: writing–original draft and writing–review and editing. LL: writing–original draft and writing–review and editing. SL: writing–original draft and writing–review and editing. ML: writing–original draft. MF: writing–original draft and writing–review and editing. SZ: writing–review and editing. WL: writing–review and editing. YL: writing–review and editing. HY: writing–review and editing.

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Conflict of interest

Authors JR, ML, and MF were employed by State Grid Shandong Electric Power Company.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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