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A comprehensive evaluation method of electric power quality based on improved grey correlation analysis

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Abstract. Comprehensive evaluation of electric power quality is essential to the implementation of effective power quality control. In traditional evaluation methods, the weight of indicators is fixed and lacks flexibility. Aiming at this problem, this paper has proposed a power quality evaluation method based on improved grey correlation method. This method uses improved analytic hierarchy process (IAHP) to calculate subjective weights and introduces the improved entropy weight method (IEWM) that is modified using variable weight theory which calculates variable objective weights. The proposed method also uses intergrated weighting to combine the subjective and objective weights calculated above, obtaining multi-dimensional indicator weights. Finally, improved gray correlation analysis (IGCA), improved through employing ideal solution theory and logarithmic information aggregation method based on barrel theory, is implemented in this method to comprehensively evaluate electric power quality.

1 Introduction

With the development of electric power systems, especially the large increase in nonlinearity, and the capacity and quantity impact loads, power quality problems have become increasingly prominent [1]. The grid connection of distributed power sources has an impact on electric power quality, which may cause problems such as frequency deviation, voltage fluctuation, voltage flicker, voltage unbalance, harmonic distortion, and DC injection [2]. The seven existing electric power quality standards limited by electric power regulations are: voltage deviation, frequency deviation, voltage three-phase unbalance, voltage fluctuation and flicker, harmonics, interharmonics, temporary overvoltage and transient overvoltage [3]. How to achieve a more scientific and comprehensive evaluation of power quality is of great significance to the research on comprehensive assessment of electric power quality, and is crucial to the revision of power prices, power quality management and control in the power market environment [4].

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The current evaluation methods of electric power quality include fuzzy mathematics method based on indicator characteristics, set pair analysis method [5], probability statistics and vector algebra method [6]; subjective weighting method and objective weighting method based on weight characteristics [7], intergrated weighting method [8]; matter element analysis method based on model characteristics [9], radar chart method [10], gray correlation analysis method (GCA) [11]. Among them, Z. Cheng [5] proposed an evaluation method based on set pair analysis and variable fuzzy sets, and introduced the two-tuple linguistic method to conduct secondary evaluation within the evaluation level. Y. Xiong [6] improved the traditional analytic hierarchy process (AHP), which can quickly find the indicator items that affect the consistency to determine the reasonable weight. There are many power quality evaluation methods and weight determination methods, and each has its own advantages and disadvantages. It is necessary to select an appropriate method to evaluate electric power quality according to actual needs.

In this paper, the IGCA, modified through employing ideal solution theory and logarithmic information aggregation method based on barrel theory, has been proposed to evaluate the power quality of the distribution network, and combined with the intergrated weighting method to obtain the weights. Furthermore, the subjective and objective weights are obtained by IAHP and IEWM to obtain the evaluation results more scientifically and reasonably.

2 Evaluation process

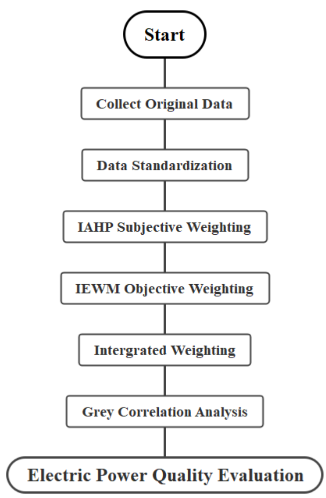

Fig. 1. Power quality assessment process.

This paper uses the IGCA combined with the intergrated weighting method, in which the subjective weight is obtained by using IAHP; the objective weight is obtained by using IEWM and the variable weight theory to form a variable objective weight; finally, intergrated weighting is used to calculate the combined weight and comprehensively evaluate the power quality. The specific process is shown in Figure 1.

3 Indicators

In this paper, seven indicators including voltage deviation X_1, voltage flicker X_2, voltage fluctuation X_3, harmonic distortion X_4, three-phase unbalance X_5, frequency deviation X_6 and power supply reliability X_7 are used as the first-level indicators of the power quality evaluation indicator set. The first-level indicator measurement value and the abnormal duration of the indicator are used as the 13 second-level indicators (there is only one second-level indicator under power supply reliability), the average voltage deviation x_1(%) and the deviation duration x_2(s) , flicker level x_3(%), flicker duration x_4(s), average fluctuation range x_5(%), fluctuation duration x_6(s), total harmonic distortion x_7(%), harmonic duration x_8(s), unbalance degree x_9(%), unbalance duration x_{10}(s), average deviation x_{11}(Hz), deviation duration x_{12}(s), voltage sag interruption time x_{13}(s). The judgment of indicator abnormality is based on the national standards of each first-level indicator. If the value exceeds the standard value, it is judged that the indicator is abnormal. The national standards for each indicator (take 10kV distribution network as an example) are as follows:

Table 1. 10kV power quality standards.

Indicators	Equation	Range
Voltage deviation	$\Delta U = \frac{U_{re} - U_N}{U_N}$	±7%
Voltage flicker	Short-term flicker P_{st} Long-term flicker P_{lt}	Short-term limit 0.35% Long-term limit 0.25%
Voltage fluctuation	$d = \frac{U_{\max} - U_{\min}}{U_N}$	When the fluctuation frequency r<100, the limit is 2%
Harmonic distortion	$THD_u = \frac{\sqrt{\sum_{h=1}^{\infty} U_h^2}}{U_1}$	Total harmonic limit 4% Odd harmonic limit 3.2% Even harmonic limit 1.6%
Three-phase unbalance	$\varepsilon_U = \frac{U_2}{U_1}$	Without distributed power, long-term 2%, short-term 4% With distributed power, 1.3% and 2.6%
Frequency deviation	$\Delta f = f_{re} - f_N$	Deviation limit±0.5Hz; Short-term impact limit ±0.2Hz

1) The voltage deviation range in the table is the range value of single-phase voltage. 2) In the table, the subscript re represents the measured value, and the subscript N represents the rated value.

4 Indicator weighting

4.1 IAHP calculates subjective weights

AHP is a simple subjective weighting method, but traditional AHP needs to check the consistency of the judgment matrix. In practical applications, the judgment matrix is mostly adjusted based on experience to meet the consistency test, which is blind and often fails to succeed at first try. IAHP is based on the general analytic hierarchy process, adding an optimal transfer matrix to make it easier to meet the consistency requirements. The calculation steps of IAHP are as follows:

(1) Determine the target and evaluate the set of factors

The research goal is the comprehensive evaluation of the electric power quality of the distribution network. The evaluation indicators are shown in Table 1.

(2) Construct a judgment matrix

A is the target, u_i is the evaluation factor, $u_i \in U$ (i=1, 2, 3, ..., n). u_{ij} represents the relative importance value of u_i to u_j (j=1, 2, 3, ..., n), and the judgment matrix W is obtained according to the meaning of the above symbols, which is called the A-U judgment matrix.

$$W=\left\{\begin{matrix} u_{11} & u_{12} & \dots & u_{1n} \\ u_{21} & u_{22} & \dots & u_{2n} \\ \dots & \dots & \dots & \dots \\ u_{n1} & u_{n2} & \dots & u_{nn} \end{matrix}\right\}\begin{matrix} u_1 \\ u_2 \\ \dots \\ u_n \end{matrix} \tag{1}$$

(3) Using the scale expansion method CE to improve the judgment matrix

The scale expansion method arranges n schemes in an sequence, in which their importance are undiminished, such as $X_1 \geq X_2 \geq ... \geq X_n$. Compare the importance of scheme X_i with X_{i+1} and determine its weight (i=1, 2, 3, ..., n-1). The value of other elements in the matrix can be passed through the transitivity of importance. The judgment matrix constructed by the CE algorithm is W^*, and its ranking vector is $(t_1t_2 \dots t_{n-1}, t_2t_3 \dots t_{n-1}, \dots, t_{n-1}, 1)^T$.

$$W^*=\begin{bmatrix} 1 & t_1 & t_1t_2 & t_1t_2t_3 & \dots & t_1t_2\dots t_{n-1} \\ 1/(t_1) & 1 & t_2 & t_2t_3 & \dots & t_2t_3\dots t_{n-1} \\ 1/(t_1t_2) & 1/(t_2) & 1 & t_3 & \dots & t_3t_4\dots t_{n-1} \\ 1/(t_1t_2t_3) & 1/(t_2t_3) & 1/(t_3) & 1 & \dots & t_4t_5\dots t_{n-1} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 1/(t_1t_2\dots t_{n-1}) & 1/(t_2t_3\dots t_{n-1}) & 1/(t_3t_4\dots t_{n-1}) & 1/(t_4t_5\dots t_{n-1}) & \dots & 1 \end{bmatrix} \tag{2}$$

Since the matrix W^* satisfies $w_{ij}=1/w_{ij}$, and any two rows of the matrix W^* are proportional, which means W^* is a positive and reciprocal matrix with complete consistency and automatically meets the consistency requirements. Therefore, the weight distribution can be obtained directly through the eigenvector of the maximum eigenvalue of W^*, without the need for consistency check.

(4) Calculate subjective weight

Calculate the eigenvector corresponding to the largest eigenvalue of W^* by matrix operation, and normalize it to the weight distribution of the target:

$$w_i = n\sqrt{\prod_{j=1}^{n} w_{ij}} \Big/ \sum_{i=1}^{n} n\sqrt{\prod_{j=1}^{n} w_{ij}} \tag{3}$$

Where w_i is the subjective weight value of each indicator of power quality calculated by the IAHP method.

4.2 IEWM calculates objective weights

The traditional EWM determines the indicator weight according to the degree of difference between the observed values of the indicators. The greater the degree of difference, the greater the indicator weight. This article combines variable weight theory and information entropy weighting method to construct variable objective weights. The specific calculation is as follows:

(1) Determine the constant entropy weight of the indicators

Define three variables $i\in[1, m]$, $j\in[1, n]$, $k\in[1, s]$, m, n, s are the number of monitoring points, the number of power quality indicators and the number of power quality levels, and i, j and k are all integers. In this paper, the power quality is divided into five levels: excellent, good, medium, poor, and inferior, so the value of s is 5; the constant entropy weight calculation needs to be performed on all secondary indicators, so the value of n is 13. The constant entropy weight is calculated according to Eq.4- Eq.6:

$$f_{jk} = r'_{jk} \Big/ \sum_{k=1}^{s} r'_{jk} \tag{4}$$

$$e_j = -\frac{1}{\ln s}\sum_{k=1}^{s} f_{jk} \cdot \ln f_{jk} \tag{5}$$

$$v_j = \left(1-e_j\right) / \sum_{j=1}^{n}\left(1-e_j\right) \tag{6}$$

Where $r_{jk}{}'$ is the fuzzy membership value of the evaluation indicator j to the power quality level k; f_{jk} is the fuzzy mapping between the power indicator set and the power evaluation set; e_j is the information entropy value; v_j is the constant entropy weight value, and it satisfies

$$\sum_{j=l}^{n} v_j = 1 \tag{7}$$

(2) Determine the indicators' variable entropy weight

If the indicator observation values of s monitoring points are evenly distributed, that is,

$$r_{jk}^{'} = \left(\sum_{k=1}^{S} r_{jk}^{'}\right) / s \tag{8}$$

According to Eq.4 to Eq.6 calculation, the constant entropy weight value v_j of the indicator j is very small. At this time, if the actual observation value of the indicator j deviates from the normal value seriously, it may cause the overall power quality to be judged as normal when the single power problem needs to be investigated, leading to a misjudgment phenomenon.

In actual engineering, when the observed value of a certain indicator j exceeds the value specified by the national standard, the weight of the indicator should be increased. Based on this, this paper introduces the variable weight theory to process the constant entropy weight, and realizes the information entropy variable weight to highlight the influence of bad indicators on the comprehensive evaluation results. Denote the power quality level "medium" as J, and the membership of the level "medium" and above as $r_j{}'$, introduce the relatively bad parameters shown in equation Eq.10, and realize the variable entropy weight according to equation Eq.11.

$$r_J^{'} = \max\left(r_{jk}^{'}, k < J\right) \tag{9}$$

$$x_j = r_J^{'} / \left(1 - r_J^{'}\right) \tag{10}$$

$$v_j^* = v_j x_j^{a-1} / \sum_{j=1}^{n} v_j x_j^{a-1} \tag{11}$$

In the equation, the smaller $r_j{}'$ means the worse the indicator, and the larger the variable weight coefficient x_j^{a-1}; a is the performance balance correction coefficient, which is taken as 0.2 in this paper. The fuzzy membership of indicator j to the five power quality levels from good to bad is recorded as $r_{j1}{}' \sim r_{j5}{}'$, and that $r_j{}'=\max(r_{j1}{}', r_{j2}{}', r_{j3}{}')$, suppose the observed value of indicator j changes from grade "medium" to grade" poor" and the observed values of other indicators remain unchanged, then $r_{j3}{}'$ decreases and $r_{j4}{}'$ increases, the denominator decreases in Eq.10, the numerator increases, x_j decreases, and x_j^{a-1} increases , v_j^* in Eq.9 is always less than 1 and the numerator and denominator increase by the same value, so v_j^*, the entropy weight value of the indicator j, increases.

4.3 Intergrated weighting method to calculate comprehensive weights

The subjective weighting method can be combined with the intention of the decision maker to determine the weight, but it will ignore the internal connection of the data itself, and the objectivity is poor, while the objective weighting method cannot reflect the importance of the decision maker to different indicators, and there is a possibility that the weight and actual indicators are opposite. Therefore, when assigning weights to indicators, an intergrated weighting method is adopted, which can not only take into account subjective human factors, but also does not ignore the inherent statistical laws between the indicator measurement data.

Intergrated weighting method aims at finding the balance point of subjective and objective weighting method, that is, the Nash equilibrium point, so as to obtain a more scientific and reasonable comprehensive weight of each indicator. The specific process is as follows:

The weights of the indicators obtained by IAHP and IEWM are recorded as w_1 and w_2 respectively, and then the combined weight vector is constructed by linear combination. The equation is as follows:

$$w = a_1 w_1^T + a_2 w_2^T \tag{12}$$

In the equation, a_1 and a_2 are the linear coefficients of the main and objective weights, respectively. According to the intergrated weighting theory, the Nash equilibrium point is where the deviation between the subjective and objective weights and the combined weight is the smallest. The equation is:

$$\min \left\| a_1 w_1^T + a_2 w_2^T - w_q^T \right\|_2, q = 1,2 \tag{13}$$

The optimal solution sought through the above equation is the optimal combination weight of subjective and objective weights intergrated. Under the optimal first derivative condition of the above equation:

$$a_1 w_q w_1^T + a_2 w_q w_2^T = w_q w_q^T \tag{14}$$

The weight coefficients a_1 and a_2 obtained by the above equation are normalized, and the equation is as follows:

$$a_q^* = \frac{a_q}{a_1 + a_2} \tag{15}$$

To determine the comprehensive intergrated weight, the equation is as follows:

$$w^* = a_1^* w_1 + a_2^* w_2 \tag{16}$$

5 Comprehensive evaluation based on IGCA

5.1 Principle of traditional GCA

The basic idea of traditional GCA is to judge whether the correlation between different data sequences is close according to the similarity of the curve geometry of the data sequence. In multi-indicator comprehensive evaluation problems, traditional GCA constructs the positive ideal sequence and calculates the correlation degree between each evaluation object and the positive ideal sequence. The greater the correlation degree, the more similar the positive ideal sequence and the better the evaluation result. In the multi-indicator comprehensive evaluation problem of electric power quality evaluation, the correlation coefficient is calculated by Eq.17 by the traditional GCA as $\gamma(r_i^+, r_{ij}^*)$. The larger the value, the more similar its is to the positive ideal sequence, and the better the evaluation result.

$$\gamma\left(r_j^+, r_{ij}^*\right) = \frac{\rho}{\left|r_j^+ - r_{ij}^*\right| / \left(\max_{i\in[1,m]j\in[1,n]}\left|r_j^+ - r_{ij}^*\right|\right) + \rho} \tag{17}$$

In Eq.17, m is the number of monitoring points in the system, n is the number of indicators, r_j^+represents the positive ideal solution of the indicator, r_{ij}^* is the number of indicator intervals after normalization, ρ is the introduced resolution coefficient and $\rho\in[0,1]$.

5.2 Improvement of the GCA

(1) Adjust the resolution coefficient

In traditional methods, the resolution coefficient is generally 0.5, which has limitations in practical applications. This paper adjusts the resolution coefficient based on the integrity of the indicator set and the anti-interference. First, rewrite Eq.17 into Eq.18 and Eq.19.

$$\Delta_{\max} = \left(\max_{i\in[1,m]j=[1,n]}\left|r_j^+ - r_{ij}^*\right|\right) \tag{18}$$

$$\gamma\left(r_j^+, r_{ij}^*\right) = \frac{\rho}{\left|r_j^+ - r_{ij}^*\right| / \Delta_{\max} + \rho} \tag{19}$$

For the monitoring value of the secondary indicator j at any monitoring point i, the number of solvable indicator intervals is r_{ij}^*. The integrity of the indicator set is reflected in the correlation coefficient $\gamma(r_i^+, r_{ij}^*)$. The larger the adjustment range, the better, and the anti-interference performance is reflected in the variation of the indicator interval number r_{ij}^* to the correlation coefficient $\gamma(r_i^+, r_{ij}^*)$ The smaller the impact, the better. In the denominator of Eq.19, $|r_i^+ - r_{ij}^*|/\Delta_{max}\in[0,1]$, therefore, the greater the value of ρ, the stronger the integrity of the indicator set but the resistance to interference is worse. On the contrary, the worse the integrity but the stronger the anti-interference. Accordingly, when the range of $|r_i^+ - r_{ij}^*|/\Delta_{max}$ is smaller, the value of ρ should be increased to improve the integrity of the indicator set, otherwise, the value ρ must be decreased. The actual value of resolution ρ is carried out according to Eq.20 and Eq.21.

$$\Delta_v = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left|r_j^+ - r_{ij}^*\right| \tag{20}$$

$$X_\Delta = \frac{\Delta_v}{\Delta_{\max}} \tag{21}$$

The value of ρ should satisfy: when $X_\Delta<1/3$, $X_\Delta\leq\rho\leq1.5\,X_\Delta$; when $X_\Delta\geq1/3$, $1.5\,X_\Delta\leq\rho\leq2\,X_\Delta$.

(2) Introduce the ideal solution to improve the correlation equation.

The traditional gray correlation method is used to calculate the gray correlation degree between the evaluation object and the positive ideal solution to make the ranking decision. It can only reflect the closeness of the overall trend of the data, and cannot directly reflect the distance between the indicators. It has shortcomings in comprehensive decision-making. The ideal solution method uses the Euclidean distance between the indicator and the ideal solution to make a decision sequence, which can make up for the deficiency of the gray correlation method.

Without considering the weighting of the indicator, the negative ideal solution r_j^- of indicator j is introduced, and the evaluation method based on the positive and negative gray correlation degree and the positive and negative Euclidean distance is shown in Eq.22 to Eq.25.

$$\varepsilon_i^+ = \sum_{j=1}^{n} \gamma\left(r_j^+, r_{ij}^*\right) / \sum_{i=1}^{m}\sum_{j=1}^{n} \gamma\left(r_j^+, r_{ij}^*\right) \tag{22}$$

$$\varepsilon_i^- = \sum_{j=1}^{n} \gamma\left(r_j^-, r_{ij}^*\right) / \sum_{i=1}^{m}\sum_{j=1}^{n} \gamma\left(r_j^-, r_{ij}^*\right) \tag{23}$$

$$\xi_i^+ = \sqrt{\sum_{j=1}^{n}\left(r_j^+ - r_{ij}^*\right)^2} / \sum_{i=1}^{m}\sqrt{\sum_{j=1}^{n}\left(r_j^+ - r_{ij}^*\right)^2} \tag{24}$$

$$\xi_i^- = \sqrt{\sum_{j=1}^{n}\left(r_j^- - r_{ij}^*\right)^2} / \sum_{i=1}^{m}\sqrt{\sum_{j=1}^{n}\left(r_j^- - r_{ij}^*\right)^2} \tag{25}$$

In the equation, $\gamma(r_j^-, r_{ij}^*)$ represents the correlation coefficient between the monitored value of indicator j at monitoring point i and the negative ideal solution of indicator j. The gray correlation between the indicator monitoring set of the monitoring point i (corresponding to the indicator interval number $r_{i1}^*\sim r_{in}^*$) and the positive ideal solution set $r_1^+\sim r_n^+$ and the negative ideal solution set $r_1^-\sim r_n^-$ The degree is recorded as $\varepsilon_i^+$and ε_i^-, and its Euclidean distance is recorded as $\zeta_i^+$and ζ_i^-. From the definition, the larger the value of ε_i^+ and ζ_i^-, the better the overall indicator set's evaluation result; similarly, the larger the value of ε_i^- and ζ_i^+, the worse the overall indicator se's evaluation result.

(3) Design information aggregation coefficient

In the traditional GCA, when the correlation degree equation is linearly aggregated in consideration of the indicator difference, the numerator of Eq.24 is adjusted to Eq.26.

$$\varepsilon_i^+ = \sum_{j=1}^{n} \omega_{js} \cdot \gamma\left(r_j^+, r_{ij}^*\right) \tag{26}$$

In the equation, ω_{js} is the comprehensive weight value calculated by Eq.16. Based on the exponential aggregation method, this article aims to implement the penalty for low indicators, and introduces the logarithmic method based on the barrel theory to aggregate indicators.

$$\varepsilon_i^+ = \sum_{j=1}^{n}\left(1 + \log_5\left(\gamma\left(r_j^+, r_{ij}^*\right) \cdot I_{jc} \cdot \omega_{js}\right)\right) \tag{27}$$

$$\varepsilon_i^+ = \sum_{j=1}^{n}\left(1 + \log_5\left(f\left(r_{ij}^*\right) \cdot \omega_{js}\right)\right) \tag{28}$$

In the equation, I_{jc} is the health score of indicator j and $I_{jc}\in[1,5]$. The logarithmic function amplifies the short-board effect when bad indicators collapse, and can reflect the "punishment" effect on short-board indicators.

5.3 The evaluation steps of IGCA

The improved evaluation method achieves effective correlation calculation by designing dynamic resolution coefficients; by calculating the correlation between each indicator in the sequence, it better characterizes the change trend and correlation of the two sequence curves, and can achieve better results. The specific implementation process of the excellent evaluation effect is as follows.

(1) Construct the original decision matrix

Assume that there are m monitoring points in the system, and a total of n evaluation indicators are monitored. The jth indicator of the monitoring point i is labeled r_{ij}, and $i\in[1,m]$, $j\in[1,n]$. $R_i=(r_{i1}, r_{i2},...,r_{in})^T$ constitutes an observation sequence, and the observation sequence of m monitoring points constitutes the original decision matrix $R=(r_{ij})_{m\times n}$.

(2) Construct a dimensionless decision matrix

In the original decision matrix, indicators with different meanings are not the same in dimension and order of magnitude. In order to ensure data comparability, the original decision matrix needs to be standardized, and two standardized methods are used according to the type of indicators. The original indicator data can generally be divided into two types: benefit-based and cost-based. The larger the value of the "benefit-based" indicator, the better, and the smaller the value of the "cost-based" indicator, the better. Respectively adopt normalized expressions:

$$r_{ij}^* = \left(r_{ij} - \min_j r_{ij} \right) / \left(\max_j r_{ij} - \min_j r_{ij} \right) \tag{29}$$

$$r_{ij}^* = \left(\max_j r_{ij} - r_{ij} \right) / \left(\max_j r_{ij} - \min_j r_{ij} \right) \tag{30}$$

The standardized calculation of r_{ij}^*, the larger the value, the better the indicator, and there is $r_{ij}^*\in[0,1]$, the new decision matrix is denoted as $R^*=(r_{ij}^*)_{m\times n}$.

(3) Determine the positive and negative ideal solution

The positive ideal solution is

$$r_j^+ = \left\{ \max_{i\in[1,m]} r_{ij}^* \right\} \tag{31}$$

and the negative ideal solution is

$$r_j^- = \left\{ \min_{i\in[1,m]} r_{ij}^* \right\} \tag{32}$$

the positive ideal solution sequence is $R^+=[r_1^+, r_2^+,\ldots, r_n^+]$, the negative ideal solution sequence is $R^-=[r_1^-, r_2^-,\ldots, r_n^-]$.

(4) Determine the resolution coefficient

Calculate the target resolution coefficient ρ according to Eq.20 and Eq.21.

(5) Calculate the comprehensive gray correlation degree

Calculate the positive and negative gray correlation degree ε_i^+ and ε_i^-, and the positive and negative ideal solution ζ_i^+ and ζ_i^- according to Eq.22-Eq.25.

(6) Forming decision criteria

Introduce the linear coefficients α_1 and α_2 to construct a comprehensive gray correlation degree:

$$D_i^+ = \alpha_1 \cdot \varepsilon_i^+ + \alpha_2 \cdot \xi_i^- \tag{33}$$

$$D_i^- = \alpha_1 \cdot \varepsilon_i^- + \alpha_2 \cdot \xi_i^+ \tag{34}$$

In the equation, α_1, $\alpha_2\in[0,1]$ and $\alpha_1+\alpha_2=1$. When $\alpha_1=1$, it is the traditional grey relational evaluation method; when $\alpha_1=0$, it is the traditional ideal solution evaluation method; when $\alpha_1\in(0,1)$ is the comprehensive evaluation method, this paper assumes $\alpha_1=0.5$ and $\alpha_2=0.5$. Based on the comprehensive correlation value, the decision criterion $S_i= D_i^+/(D_i^++ D_i^-)$ of the plan to be evaluated is further calculated, and the level boundary vector is compared with the S_i value of the evaluation indicator set to achieve the power quality level. Evaluation, the larger S_i, the better the power quality.

6 Example

Based on the data of 3 monitoring points in a 10kV power distribution system, the power quality assessment is carried out. A_1~ A_5 are five power quality grades from good to bad, and the indicator numbers and units are consistent with those in Table 1. Count the monitoring data collected in a certain week, and fill in Table 2 with the 95% probability as the original indicator data. Based on the above method, the comprehensive weight is calculated as Table 3.

In Table 3,ω_i is the subjective weight value, v_{i1} is the constant entropy weight objective weight value, v_{i2B1} , v_{i2B2} And v_{i2B3} are the objective weight values of the information entropy of the indicator set introduced with the variable weight theory, and a_i is the final comprehensive weight value. The variable weight objective weights of the three groups of indicators to be evaluated are shown in Figure 2.

Table 2. Original monitoring data.

Sample number	Indicator number												
	x_1/%	x_2/s	x_3/%	x_4/s	x_5/%	x_6/s	x_7/%	x_8/%	x_9/%	x_{10}/s	x_{11}/Hz	x_{12}/s	x_{13}/s
A1	1.8	0.1	0.25	0.1	4.0	0.5	1	1.2	0.5	1.2	0.1	1.2	0.1
A2	3.5	0.5	0.50	0.2	8.0	1.0	2	2.5	1.0	2.5	0.2	2.5	0.2
A3	5.3	2.0	0.75	0.5	12.0	2.0	3	5.0	1.5	5.0	0.4	5.0	0.5
A4	7.0	5.0	1.00	1.2	16.0	5.0	4	7.5	2	7.5	0.6	7.5	1.2
A5	14.0	10.0	2	2.5	20.0	10.0	8	10.0	4	10.0	0.8	10.0	2.5
B1	1.00	6.0	0.3	0.05	2.0	3.0	1.6	3.7	0.5	5.0	0.3	2.5	0
B2	6.00	10.0	0.8	0.11	11.0	8.0	3.3	10.0	1.3	8.0	0.2	2.2	0
B3	1.70	3.0	0.1	0.06	2.2	2.0	0.8	2.5	0.2	1.0	0.25	2.35	0

Table 3. The comprehensive weight of indicators.

Weight	Indicator number						
	x_1	x_2	x_3	x_4	x_5	x_6	x_7
ω_i	0.0605	0.0335	0.0725	0.0403	0.0725	0.0403	0.1233
v_{i1}	0.0724	0.0602	0.0636	0.1421	0.0653	0.0699	0.0741
v_{i2B1}	0.0614	0.1051	0.0589	0.1204	0.0553	0.0756	0.0690
v_{i2B2}	0.0059	0.4835	0.0051	0.0081	0.0063	0.0135	0.0058
v_{i2B3}	0.0712	0.0747	0.0599	0.1342	0.0620	0.0755	0.0698
a_i	0.0599	0.0276	0.0630	0.0783	0.0647	0.0385	0.1249
	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	
ω_i	0.0684	0.0503	0.0280	0.2219	0.1232	0.0653	
v_{i1}	0.0548	0.0681	0.0580	0.0577	0.0718	0.1421	
v_{i2B1}	0.0616	0.0616	0.0786	0.0640	0.0691	0.1204	
v_{i2B2}	0.0050	0.0050	0.0107	0.0036	0.0044	0.0079	
v_{i2B3}	0.0641	0.0641	0.0546	0.0659	0.0756	0.1338	
a_i	0.0468	0.0468	0.0222	0.1750	0.1209	0.1269	

Comparing the three curves of constant entropy weight, B_1 variable weight, and B_3 variable weight in Figure 2, it can be seen that the three curves have a better closeness, indicating that the information entropy weight considering the variable weight theory can still effectively reflect the characteristics of the indicator monitoring data. For monitoring point B3, the monitoring value of indicator x_2 is at the "poor" level and the quality of the indicator is poor, while the monitoring value of indicator x_5 is at the "excellent" level and the quality of the indicator is good. The deviation between the variable weight curve of the monitoring point B_2 and the constant entropy weight curve is relatively large. This is because the quality of the two indicators x_2 and x_5 in the monitoring value of B2 is poor and the quality of other indicators are good.

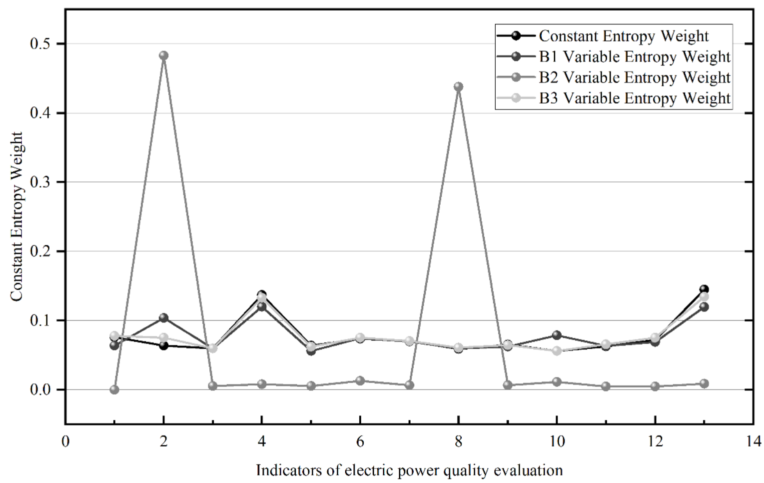

Fig. 2. The objective weights of variable weight theory.

According to Table 3, the comprehensive weight a_i is obtained, and the weighted decision matrix is obtained by normalization and weighting, and the positive and negative ideal solution is obtained as follows:

$$R^{+} = \begin{bmatrix} 0.0743 & 0.0629 & 0.0680 & 0.1269 & 0.0659 & 0.0717 & \\ 0.0761 & 0.0593 & 0.0718 & 0.0602 & 0.0630 & 0.0741 & 0.1259 \end{bmatrix} \tag{36}$$

$$R^{-} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{37}$$

According to Eq.18~ Eq.21, Δ_v=0.0254, X_Δ=0.2003<1/3, and the resolution is determined to be ρ=0.3.

Calculate the comprehensive correlation degree G_1 when ρ=0.3 under linear weighting and the comprehensive correlation degree G_2 when ρ=0.3 selected according to the method in this article, and calculate the respective data correlation The interval is equation (38) and equation (39).

$$\Delta G_1 = G_{1\max} - G_{1\min} = 0.7199 - 0.2634 = 0.4565 \tag{38}$$

$$\Delta G_2 = G_{2\max} - G_{2\min} = 0.7712 - 0.209 = 0.5622 \tag{39}$$

Comparing Eq.38 and Eq.39, it can be seen that $\Delta G_1 < \Delta G_2$, which shows that the correlation degree distribution interval obtained by selecting the ρ value according to the method in this paper is relatively large, and the interference of the bad values of the observation sequence on the evaluation results can be better suppressed.

Calculate the positive and negative gray correlation degree $\varepsilon_i^+$and ε_i^-, and the positive and negative ideal solution $\zeta_i^+$and ζ_i^-, according to Eq.22-Eq.25. Then, the comprehensive gray correlation degree is calculated by Eq.33 and Eq.34, and the final decision criterion S_i is calculated. Using the traditional GCA and the evaluation method proposed in this paper, respectively, the evaluation results of the calculation examples are shown in Table 4. The two evaluation schemes in Table 4 are: the traditional GCA and the IGCA proposed in this paper.

Table 3. Power quality evaluation results.

Monitor points	Traditional GCA		IGCA	
	S_i	Evaluation	S_i	Evaluation
A1 (excellent)	0.6787	[0.6355, 0.6787]	0.7253	[0.673 5,0.725 3]
A2 (good)	0.6355	[0.5657,0.6355)	0.6735	[0.588 1,0.673 5)
A3 (medium)	0.5657	[0.4738,0.5657)	0.5881	[0.470 9,0.588 1)
A4 (poor)	0.4738	[0.3085,0.4738)	0.4709	[0.257 8,0.470 9)
A5 (inferior)	0.3085	[0, 0.3085)	0.2578	[0, 0.257 8)
B1	0.6303	good	0.6038	good
B2	0.4286	poor	0.2566	inferior
B3	0.6638	excellent	0.7045	excellent

From the original monitoring data shown in Table 4, it can be seen that in the data of monitoring point B_2, indicator x_2 (voltage deviation duration) and indicator x_8 (harmonic duration) are at the level "bad", and the comprehensive evaluation result of power quality should tend to the level "bad" ". In the comprehensive evaluation results of monitoring point B_2, the result from traditional GCA is "poor", and the result from IGCA is "bad". The main reason for the difference between the results of the two methods is the linear information aggregation method adopted by the traditional GCA. Because the weights of indicator x_2 and indicator x_8 are low, their bad influence is concealed by other high-weight good indicatores, resulting in a better evaluation value. Using the same method in this article, the B2 indicator x_2 monitoring value is modified to 6.0, the influence of the bad indicators is weakened, and the final grade evaluation value becomes "poor", and the evaluation result is consistent with the traditional GCA. Comparing the evaluation results of monitoring point B2 under the two schemes, it can be seen that the method proposed in this paper can better reflect the punishment for a single bad indicator, and the final evaluation results obtained are more in line with the needs of engineering applications.

7 Conclusion

In the traditional comprehensive evaluation of power quality, insufficient attention is paid to low-weight indicators, which leads to inaccurate power quality evaluation under "bad" conditions. To address the above problems, this paper first introduces the intergrated weighting method, uses IAHP to determine subjective weights, uses IEWM to determine objective weights, and comprehensively considers subjective and objective weights to combine weights for various indicators, which is more scientific and reasonable. Among them, by adding the optimal transfer matrix as improvement for AHP, combined with the variable weight theory to improve the traditional EWM, giving higher objective weight to the bad indicators, and increasing the importance of the bad indicators in the decision-making plan. Next, the ideal solution method is introduced to improve the traditional gray correlation method and enhance the ability of the evaluation method to distinguish different sets of indicators to be evaluated. Finally, the logarithmic polymerization method based on the barrel theory was used to replace the traditional linear polymerization method, and the correlation calculation equation of the gray correlation method was adjusted to improve the ability to distinguish "bad" indicators and achieve an evaluation that is more in line with the power quality evaluation target result.

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