weighting power quality evaluation based on cloud model and anti-entropy

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Abstract. There are subjectivity and uncertainty in the general comprehensive evaluation of power quality. And there are problems of randomness and ambiguity in the boundary of power quality classification. Firstly, the subjective weight is obtained based on the cloud model theory. Secondly, the objective weight is obtained based on the improved anti-entropy method. Thirdly, the subjective and objective combined weight is obtained through the moment estimation theory. And then the final score of each observation point is obtained and sorted by the improved TOPSIS. Finally, the effectiveness and feasibility of the method are verified by an example, which provides a new idea for the effective combination assessment of power quality.

1. Introduction

Nowadays, the country’s support for new energy power generation has increased, and distributed power sources such as photovoltaic and wind power have increased. The power quality problems that caused by distributed power sources are also more serious when they are connected to the grid. The application of large-capacity power electronic equipment and systems has further led to the deterioration of power quality. Comprehensive evaluation of power quality is of great significance to the establishment of a fair power market competition environment and power quality evaluation management system. It also can objectively and comprehensively reflect the overall performance of electric energy, and provide reference for power suppliers and users. Therefore, power quality assessment is the basis for comprehensive assessment of power quality and revision of electricity prices in the power market environment.

The power quality evaluation methods mainly include analytic hierarchy process[1-3], fuzzy comprehensive method[4-5], radar chart method[6-7], entropy weight method[8], combined weight method[9-11], Meta-analysis method[12] and various artificial intelligence algorithms[13-16]. The analytic hierarchy process is a subjective weighting method, so its subjective factors have a greater impact on the evaluation results. The entropy weight law ignores expert experience and only considers the actual situation of power indicators, and cannot reasonably evaluate the actual situation of power quality. Zhang et al. [17] proposed the shepard similar interpolation algorithm (PSO-SSI) based on the particle swarm optimization (PSO) algorithm and the ideal interval method (PSO-IIM) based on the PSO algorithm, although both methods can judge the quality of power, but the PSO-SSI algorithm is dependent on the sample, and the PSO-IIM method is more complicated to calculate. Tao et al. [18]
used the improved current physical component theory to evaluate the current quality on the power disturbance source branch or its lumped branch, and expands the power quality evaluation system. However, when there are distortion or asymmetry of the power supply and the load, the sharing effect of the dominant current component cannot be determined.

It can be seen that the above method has some shortcomings. Therefore, this paper introduces the cloud model theory that can overcome the uncertainty in the weighting and the ambiguity in the selection of the power quality interval to obtain the subjective weight. In order to avoid the situation that individual weights are too large or too small and cause important information to be overwhelmed when obtaining objective weights, this paper introduces an improved anti-entropy method to calculate objective weights. Then the moment estimation method is utilized to combine the subjective and objective weights to obtain the combined weights. On this basis, the technique for order preference by similarity to ideal solution (TOPSIS) is used for comprehensive evaluation. And a more objective, reliable and accurate comprehensive evaluation result can be obtained.

2. Building a power quality evaluation system

The increase of distributed generation (DG) raise the uncertainty in the process of grid connection. In the process of power generation, transmission, transformation and use of electricity, the diversity and complexity of power equipment and power load results in deterioration of power quality. In particular, it may damage precision instruments that require high power quality. Therefore, the power quality assessment for the supply of industrial load, residential life and commercial power is of great significance. The data basis of power quality evaluation is the selection of power indicators. Power quality indicators generally include: voltage deviation, frequency deviation, voltage three-phase unbalance, voltage fluctuation and flicker, and voltage harmonics. In order to improve the rationality of power quality evaluation, this paper adds frequency quality (frequency deviation), power supply reliability, and service-oriented indicators (demand-side services) to evaluate power quality more comprehensively. This article combines the national power quality standards of our country for index collection. Establish an electric energy index evaluation system, as shown in Figure 1.

![Fig 1. Power quality evaluation index](image-url)
3. Comprehensive variable weight calculation based on cloud model-anti-entropy

Since most power quality indicators are divided by intervals and there are multiple data extraction points, an evaluation model that can distinguish each data extraction point is needed. In this paper, the cloud model is used to evaluate the subjective weight of cloud computing by establishing the uncertainty interval, and the objective weight is obtained by the improved anti-entropy method. Finally, the combined weight is obtained by combining the subjective and objective weights through the moment estimation theory. The cloud model is a mathematical model that combines probability theory and fuzzy mathematical theory to transform the uncertain relationship between qualitative and quantitative. So far, cloud models have been applied to prediction, comprehensive evaluation, algorithm improvement, knowledge representation, reliability analysis, data mining, multi-criteria decision-making and other fields[18-19]. Using the cloud model can effectively overcome the uncertainty in conventional power quality assessment.

This paper proposes a combined weighted power quality evaluation model based on the cloud model and anti-entropy. The specific algorithm flow is shown in Figure 2.

Fig 2. Power quality assessment flowchart

3.1 Subjective weight calculation based on cloud model

The digital features of the cloud model can be represented by \((\text{Ex}, \text{En}, \text{He})\), that is, mathematical expectation \(\text{Ex}\), entropy \(\text{En}\), and hyper-entropy \(\text{He}\). \(\text{Ex}\) indicates that the corresponding fuzzy information is transformed into the central value of quantitative evaluation; \(\text{En}\) is a measure of the uncertainty of the attribute, reflecting the degree of dispersion of qualitative concept cloud drop and the value range of cloud drop in domain space; \(\text{He}\) is the entropy of the entropy \(\text{En}\), which represents the uncertainty of the entropy and reflects the thickness of the cloud and the degree of aggregation of the cloud drop[10].

In this paper, the subjective weight is calculated by the combination of the determination of the index interval, the cloud model and the expert judgment. When the criterion value is a random variable that obeys the normal distribution \(N(\mu, \sigma^2)\), and the decision maker cannot obtain more information, the criterion value can be approximately transformed into a random variable falling in the interval \([a, b]\), as shown in Equation (1):

\[
\begin{align*}
    a &= \mu - k\delta \\
    b &= \mu + k\delta
\end{align*}
\]

(1)
Where $\mu$ is the expected value. $\sigma$ is the standard deviation, the value of $k$ is 3 according to the Reference [20].

This article divides the uncertain language into 5 levels, namely {very low, low, average, high, very high}, and the corresponding 5 normal clouds are recorded as {excellent, good, attention, qualified, warning}. The corresponding uncertainty interval is $\{[0, 0.33], [0.17, 0.5], [0.33, 0.67], [0.5, 0.83], [0.67, 1]\}$. Therefore, according to the calculation method of Reference [20], the one-dimensional normal cloud corresponding to each evaluation language is shown in Table 1:

Tab 1. Semantic evaluation variables and corresponding cloud models

| Semantic variables | Cloud model parameters |
|--------------------|------------------------|
| excellent          | (0.165,0.055,0.0262)   |
| good               | (0.335,0.055,0.0162)   |
| note               | (0.5,0.0567,0.01)      |
| qualified          | (0.665,0.055,0.0162)   |
| caveat             | (0.835,0.055,0.0262)   |

Figure 3 shows the standard cloud of membership degrees corresponding to different evaluation index levels.

This article uses experts to define semantics for different observation points. It is necessary to synthesize and superimpose the evaluation clouds of different experts when multiple experts judge the same observation point, so as to obtain a comprehensive cloud judged by multiple experts. Suppose the two evaluation clouds are $C_1 = (E_{x1}, En_{1}, He_{1})$ and $C_2 = (E_{x2}, En_{2}, He_{2})$, $a$ and $b$ are two constants (the two parameters are defined according to the professional level of experts). According to the one-dimensional independent normal distribution algorithm, the synthesized comprehensive cloud is:

$$aC_1 + bC_2 = a(E_{x1}, E_{x1}, H_{x1}) + b(E_{x2}, E_{x2}, H_{x2}) = \left( aE_{x1}, aE_{x1}, aH_{x1} \right) + \left( bE_{x2}, bE_{x2}, bH_{x2} \right)$$

$$= \left( (aE_{x1} + bE_{x2}), \sqrt{(aE_{x1})^2 + (bE_{x2})^2}, \sqrt{(aH_{x1})^2 + (bH_{x2})^2} \right)$$

Through the semantic definition of the cloud model, the subjective weight can be calculated. The specific steps are as follows:

Step 1. Firstly, $S$ experts $F_k (k = 1, 2, 3, ..., s)$ are used to evaluate the importance of $C_i (i = 1, 2, 3, ..., m)$ evaluation indicators of $N_j (j = 1, 2, 3, ..., n)$ observation points.

Step 2. Through the evaluation sentences established in Table 1 and the corresponding cloud model parameters, the language evaluation of different observation points of each expert are converted into cloud model parameters.
Step 3. Synthesize different expert evaluation clouds \( Z_{ki} = (E_{kx}, E_{knzi}, H_{kezi}) \) of the same index through Equation (2), and then obtain the corresponding index evaluation comprehensive cloud according to Equation (3).

\[
Z_i = \frac{1}{s} \sum_{k=1}^{s} Z_{ik}^k
\]  
\hspace{10cm} (3)

Step 4. Take the corresponding evaluation cloud with excellent language as the reference cloud \( Z_0 \), and then calculate the similarity between the comprehensive evaluation cloud and the reference cloud \( \text{sim}(Z_i, Z_0) \) through Equation (4)\[20\] and the similarity method in the Reference \[22\], the greater the similarity, the higher the importance of this evaluation cloud, and the greater the weight, and vice versa.

\[
D(Z_i, Z_2) = \left( \frac{1}{2} \left[ |E_{x1} - E_{x2}|^2 + |E_{y1} - E_{y2}|^2 + |H_{e1} - H_{e2}|^2 \right] \right)^{1/2}
\]  
\hspace{10cm} (4)

Step 5. Normalize the similarity by Equation (5) to obtain the subjective weight of each indicator.

\[
\xi_i = \frac{\text{sim} (Z_i, Z_0)}{\sum_{i=1}^{s} \text{sim} (Z_i, Z_0)}
\]  
\hspace{10cm} (5)

3.2 Objective weight calculation based on improved anti-entropy method

Compared with the anti-entropy method, the sensitivity of the entropy method is too high. And the weight value will be too large or too small in the calculation process, which will cause the failure of some indicators. In order to better reflect the degree of index variation and overcome the disadvantages of partial index failure in extreme cases, this paper chooses the anti-entropy method to calculate objective weights. This can not only avoid the influence of human subjective factors, but also has higher authenticity and reliability. Compared with entropy method, it has obvious advantages. The calculation process is as follows:

Step 1. Calculate anti-entropy through the normalized evaluation matrix, as shown in Equation (6).

\[
h_i^* = -\sum_{j=1}^{n} y_{ij} \ln(1 - y_{ij})
\]  
\hspace{10cm} (6)

Where \( y_{ij} = \sum_{j=1}^{n} y_{ij} \), \( y_{ij} \) is the corresponding element of the dimensionless evaluation matrix, \( j=1, 2, ..., n \).

Step 2. With the aid of the anti-entropy formula, the objective weight of the index can be determined, as shown in Equation (7).

\[
\omega_i = h_i^* / \sum_{i=1}^{m} h_i^*
\]  
\hspace{10cm} (7)

When the index entropy \( h_i^* \) approaches 0 \( (i = 1, 2..., m) \), small differences between different indexes may cause huge differences between them. For example: a scheme has four indicators, the anti-entropy value vector is (0.001, 0.002, 0.003, 0.004), and through general anti-entropy weighting calculation, the anti-entropy weight vector is (0.1000, 0.2000, 0.3000, 0.4000). According to the definition and analysis of the anti-entropy method, when the anti-entropy value is not much different, its weight should be basically the same. In the case of extreme anti-entropy value, the result obtained by the general anti-entropy formula is not reasonable. Therefore, this paper optimizes the anti-entropy weight calculation formula\[22\], as shown in Equation (8).
\[
\omega_i = \frac{m + 2h_i^* - 1 - \sum_{k=1}^{m} h_k^*}{\sum_{s=1}^{m} (m + 2h_s^* - 1 - \sum_{k=1}^{m} h_k^*)}
\] (8)

Where \( k, s, i = 1, 2, ..., m \).

The rationality of Equation (8) is explained as follows: \( \sum_{i=1}^{m} \omega_i = 1, \ 0 \leq \omega_i \leq 1 \ (i=1, 2, ..., m) \).

When the anti-entropy value \( h_i^* \) is known, the corresponding \( \sum_{k=1}^{m} h_k^* \) and \( \sum_{s=1}^{m} (m + 2h_s^* - 1 - \sum_{k=1}^{m} h_k^*) \) is also certain, and \( h_i^* \leq 0, h_i^* \in [-1,0] \). It can be seen that \( \omega_i \) decreases with the decrease of \( h_i^* \), which conforms to the principle of anti-entropy calculation.

The improved advantages are as follows: For any two indexes \( x \) and \( y \) in the evaluation index set, the corresponding anti-entropy weights are \( \omega_x \) and \( \omega_y \), and the ratio of the two is calculated:

\[
\frac{\omega_x}{\omega_y} = \frac{m + 2h_x^* - 1 - \sum_{k=1}^{m} h_k^*}{m + 2h_y^* - 1 - \sum_{k=1}^{m} h_k^*}
\] (9)

Where \( x, y \in \{1,2,...,m\}, x \neq y \).

Suppose \( h_x^* - h_y^* = \epsilon \) (\( \epsilon \) is a small value), then Equation (9) can be converted to:

\[
\frac{\omega_x}{\omega_y} = 1 + \frac{2\epsilon}{m + 2h_y^* - 1 - \sum_{k=1}^{m} h_k^*}
\] (10)

When the change in the anti-entropy value \( h_i^* \) is small, Equation (11) is acquired.

\[
m + 2h_y^* - 1 - \sum_{k=1}^{m} h_k^* \approx m - 1 + (2 - m)h_y^* \in [1, m - 1]
\] (11)

Since \( \epsilon \) is a small value, relative to \( \epsilon \), the value of \( 2\epsilon / (m + 2h_y^* - 1 - \sum_{k=1}^{m} h_k^*) \) will be smaller, so it can be concluded that the change of \( \omega_x / \omega_y \) is relatively small. It can be seen from the above proof that when the anti-entropy value changes slightly, the calculation result of the improved anti-entropy formula will not appear in the extreme case where the weight changes exponentially.

Compare the calculation results of the anti-entropy method before and after the improvement, as shown in Table 2:

**Tab 2. Anti-entropy weight comparison before and after improvement**

| Anti-entropy | 0.001 | 0.002 | 0.003 | 0.004 |
|--------------|-------|-------|-------|-------|
| Anti-entropy weight before improvement | 0.1000 | 0.2000 | 0.3000 | 0.4000 |
| Improved anti-entropy weight | 0.2497 | 0.2499 | 0.2501 | 0.2503 |

Through comparison, it can be seen that in the case of extremely similar anti-entropy values, while the anti-entropy value changes slightly, the anti-entropy weight before the improvement has an obvious increase, it is obviously unreasonable. Through the improvement given in this article, the anti-entropy method solves the shortcomings.
3.3 Combination weight calculation based on moment estimation theory
Taking into account the different degrees of importance of each index, this paper calculates the combined weight based on the moment estimation theory. It effectively reduces the defect that important information is overwhelmed. The combined weight is shown as follows:

\[
\alpha_i = \frac{\xi_i}{\xi_i + \omega_i} \\
\beta_i = \frac{\omega_i}{\xi_i + \omega_i} \\
\omega_i' = \frac{\alpha_i \xi_i + \beta_i \omega_i}{\sum_{i=1}^{m} (\alpha_i \xi_i + \beta_i \omega_i)}
\]

(12)

(13)

Where \(\xi_i\) is the subjective weight, \(\omega_i\) is the objective weight, and \(\alpha_i\) and \(\beta_i\) are the important degree coefficients of the subjective and objective weights of each indicator.

4. Comprehensive evaluation based on improved TOPSIS
The traditional TOPSIS first determines a virtual optimal plan and a virtual worst plan according to the evaluation index system. Then it calculates the Euclidean distance between the two virtual schemes of the several schemes. Finally, according to the two principles of the best distance and the worst distance, the excellent plan among the plans to be evaluated is selected[24-26]. The TOPSIS method does not require a comprehensive evaluation value. It is simple, intuitive and accurate, and it is very convenient to calculate and process data, it can effectively evaluate power quality. This method overcomes the shortcomings of traditional decision-making methods to a certain extent, enriches and perfects the theoretical system of power quality evaluation, and can provide more comprehensive decision support for power quality evaluation.

4.1 Establishment of weighted evaluation matrix and positive and negative ideal solutions
The weighted evaluation matrix is established by combining the dimensionless evaluation matrix and the combination weight, and then the positive and negative ideal solutions are determined. The specific steps are as follows:

Step 1. Suppose that \(m\) indicators are selected, and \(n\) observation points are evaluated. Then \(X_j\) can be used to represent the value of the \(i\)-th \((i=1, 2, \ldots, m)\) index of the \(j\)-th \((j=1, 2, \ldots, n)\) observation point. Then, by summarizing the different index values of \(n\) observation points, the original evaluation moment \(X=(X_{ij})_{m \times n}\) can be constructed.

\[
X = \begin{bmatrix}
x_{11} & x_{12} & \cdots & x_{1n} \\
x_{21} & x_{22} & \cdots & x_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
x_{m1} & x_{m2} & \cdots & x_{mn}
\end{bmatrix}
\]

(14)

Step 2. Due to the relatively large differences in the data of various indicators of the original power quality, different indicators may not be completely the same in terms of dimension and order of magnitude during quantitative evaluation, and they lose their comparability. Therefore, it is necessary to perform dimensionless processing on the original evaluation matrix, so that the indicators are in the same order of magnitude, and construct the evaluation matrix \(Y=(Y_{ij})_{m \times n}\).

Cost-based index is calculated by Equation (15).

\[
Y_{ij} = \frac{\max_{j \in n} x_{ij} - x_{ij}}{\max_{j \in n} x_{ij} - \min_{j \in n} x_{ij}}
\]

(15)

Profit-based index is calculated by Equation (16).
Step 3. Multiply the dimensionless evaluation matrix and the comprehensive weight vector to obtain the weighted evaluation matrix as follows:

\[ Y_H \cdot \omega = \text{(17)} \]

The matrix can be denoted as \( H = (h_{ij})_{m \times n} \).

Step 4. The elements in the weighted evaluation matrix after data preprocessing are all positive indicators, and they are all in the range of 0 to 1. Therefore, the absolute positive and negative ideal samples \( H^+ \) and \( H^- \) can be set as:

\[ \{ H^+ = \max \{h_{ij} | i = 1,2, \ldots , m\} \} \]
\[ \{ H^- = \min \{h_{ij} | i = 1,2, \ldots , m\} \} \]

(18)

4.2 Solving closeness by using improved TOPSIS

This paper chooses the grey relational analysis method to improve TOPSIS. The gray correlation degree between each observation point and the positive and negative ideal solutions is calculated by the gray correlation analysis method, and then combined with TOPSIS for calculation, the steps are as follows:

Step 1. Use the grey relational analysis method to calculate the correlation coefficient between observation point \( j \) and ideal solution with respect to index \( i \) as follows:

\[ r_{ij}^+ = \frac{\min \min \{h_{ij}^+ - h_{ij}\} + \rho \max \max \{h_{ij}^+ - h_{ij}\}}{\max \max \{h_{ij}^+ - h_{ij}\}} \]
\[ r_{ij}^- = \frac{\min \min \{h_{ij}^- - h_{ij}\} + \rho \max \max \{h_{ij}^- - h_{ij}\}}{\max \max \{h_{ij}^- - h_{ij}\}} \]

(19)

Where \( \rho \) is the resolution coefficient and its value range is \([0,1]\), generally \( \rho = 0.5 \); \( |h_{ij}^\pm - h_{ij}| \) represents the absolute value of the difference between the observation point \( j \) and the corresponding index of the positive ideal (negative ideal).

Step 2. Combine the correlation coefficients to form a positive and negative gray correlation matrix \( R^+ = [r_{ij}]_{m \times n}, R^- = [r_{ij}]_{m \times n} \). The positive and negative grey relational degree \( r_{ij}^+ \) and \( r_{ij}^- \) are obtained by averaging the different indicators of each observation point in the positive and negative grey relational matrix.

Step 3. The formulas for the distance \( d_{ij}^+ \) from each observation point to the positive ideal solution and the distance \( d_{ij}^- \) to the negative ideal solution are as follows:

\[ d_{ij}^+ = \sqrt{\sum_{i=1}^{m} (h_{ij} - h_{ij}^+)^2} \]
\[ d_{ij}^- = \sqrt{\sum_{i=1}^{m} (h_{ij} - h_{ij}^-)^2} \]

(20)

Where \( h_{ij}^+ \) and \( h_{ij}^- \) are respectively the \( i \)-th distance in the positive ideal solution \( h^+ \) and the negative ideal solution \( h^- \).

Step 4. Standardize \( d_{ij}^+, d_{ij}^- \) with the positive and negative gray correlation degrees \( r_{ij}^+, r_{ij}^- \), the formula is as follows:
Step 5. Fitting and sorting. Relative closeness is a quantity that comprehensively characterizes the relationship between each observation point and the positive and negative ideal solutions. The greater the closeness, the better the plan, and the smaller the closeness, the worse the plan. The closeness calculation formula is shown in Equation (22) and (23):

\[
\begin{align*}
  G_j^+ &= \lambda D_j^+ + (1 - \lambda) R_j^- \\
  G_j^- &= \lambda D_j^- + (1 - \lambda) R_j^+ \\
  E_j &= \frac{G_j^-}{G_j^+ + G_j^-}
\end{align*}
\]

(22)  (23)

Where \( G_j^+ \) and \( G_j^- \) represent the proximity and distance of each observation point to the ideal point in terms of position and shape, \( \lambda \) reflects the preference of subjective decision-makers, and \( \lambda \in [0,1] \), in this paper \( \lambda = 0.5 \).

5. Example analysis

5.1 Analysis of power quality indicators

In this paper, the power quality index data in the Reference [27] is used for example analysis, and the 9 index data corresponding to the 5 observation points are shown in Table 3:

| Evaluation index | Observation point 1 | Observation point 2 | Observation point 3 | Observation point 4 | Observation point 5 |
|------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| \( X_1/Hz \)     | 0.0992              | 0.1562              | 0.1180              | 0.1787              | 0.1892              |
| \( X_2/\% \)     | 3.212               | 6.680               | 4.350               | 5.330               | 4.220               |
| \( X_3 \)        | 0.7963              | 0.1589              | 0.5156              | 0.5856              | 0.4863              |
| \( X_4/\% \)     | 0.830               | 1.360               | 1.350               | 1.740               | 1.830               |
| \( X_5/\% \)     | 1.330               | 1.530               | 1.950               | 1.370               | 1.580               |
| \( X_6/\% \)     | 0.473               | 0.847               | 0.634               | 0.826               | 0.828               |
| \( X_7/\% \)     | 1.720               | 4.280               | 2.670               | 3.360               | 4.570               |
| \( X_8 \)        | 0.833               | 0.762               | 0.796               | 0.740               | 0.764               |
| \( X_9 \)        | 0.832               | 0.713               | 0.864               | 0.684               | 0.783               |

5.2 Calculating the combination weight

Step 1. Calculate subjective weight. In this paper, 9 experts participate in the evaluation, and based on their own experience, the weight of each indicator is assigned linguistically. By using the data in Table 1, the cloud model and Equations (2)-(5), the subjective weight vector is calculated as follows:

\[
\xi = [0.1172 \ 0.1021 \ 0.1001 \ 0.1134 \ 0.1154 \ 0.1154 \ 0.1019 \ 0.1288 \ 0.1058]
\]

(24)

Step 2. Calculate the objective weight. The data in Table 2 is used to establish a dimensionless evaluation matrix through Equations (11) and (12), where power supply reliability and demand-side services are benefit-based indicators, and other indicators are cost-based indicators. The data obtained are as follows:
The objective weights of anti-entropy and improved anti-entropy can be calculated by Equations (6)-(8), and compared with the entropy method, the results are shown in Table 4:

Tab 4. Objective weight of each indicator

| index | Anti-entropy method | Improved anti-entropy method |
|-------|---------------------|------------------------------|
| X1    | 0.1133              | 0.1115                       |
| X2    | 0.0850              | 0.1067                       |
| X3    | 0.0984              | 0.1089                       |
| X4    | 0.1189              | 0.1124                       |
| X5    | 0.0796              | 0.1058                       |
| X6    | 0.1786              | 0.1226                       |
| X7    | 0.1126              | 0.1114                       |
| X8    | 0.1137              | 0.1116                       |
| X9    | 0.0999              | 0.1092                       |

As shown in Table 4, the overall trend of the objective weights obtained by the above two objective weighting methods is consistent. Comparing the results of the anti-entropy method with the improved anti-entropy method, the improved anti-entropy method can not only reflect the degree of difference between the indicators, but also avoid the failure of some indicators and the extreme conditions of excessive or too small weights. This effectively reduces the defect that important information is overwhelmed, and it can be seen that using improved anti-entropy method to obtain objective weights has obvious advantages.

Step 3. Calculate the comprehensive weight. Using Equations (12) and (13), the combined weights obtained through the moment estimation theory are:

$$
\omega' = [0.1150 \ 0.1050 \ 0.1052 \ 0.1133 \ 0.1112 \ 0.1193 \ 0.1073 \ 0.1190 \ 0.1046]
$$

The subjective and objective weights and comprehensive weights of the 9 evaluation indicators in power quality are plotted and analyzed as shown in Figure 4. Through the line graph, it can be seen that the comprehensive weight and the subjective and objective weights are in good agreement.

5.3 Comparison of program evaluation results.

The weighted evaluation matrix established by Equations (17) is:
According to Equations (18)-(23), the relative closeness is calculated and then sorted. The closeness before and after the improvement of the anti-entropy method is shown in Table 5.

Tab 5. Closeness value before and after the improvement of anti-entropy method

| Observation point | Observation point 1 | Observation point 2 | Observation point 3 | Observation point 4 | Observation point 5 |
|-------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Before improvement| 0.6748              | 0.3593              | 0.5148              | 0.3158              | 0.3258              |
| After improvement | 0.6743              | 0.3587              | 0.5077              | 0.3136              | 0.3248              |

Compare with Reference [27] and [28], as shown in Table 6:

Tab 6. Comparison of comprehensive evaluation results

| Observation point | Observation point 1 | Observation point 2 | Observation point 3 | Observation point 4 | Observation point 5 |
|-------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Reference [27]    | 1                   | 3                   | 2                   | 5                   | 4                   |
| Results           |                      |                     |                     |                     |                     |
| Reference [28]    | 1                   | 3                   | 2                   | 5                   | 4                   |
| Results           |                      |                     |                     |                     |                     |
| Results of this article | 1               | 3                   | 2                   | 5                   | 4                   |

From the evaluation results of the comparison of the various methods in Table 5, it can be seen that the ranking results obtained in this article are the same as those in the Reference [27] and [28]. It can be seen that the evaluation results obtained in this article are objective and reliable.

6. Conclusion

This paper proposes a combination of cloud model and anti-entropy variable weight method for power quality evaluation. Firstly, the cloud model and the improved anti-entropy method are used to obtain the subjective and objective weights, and the two are combined according to the moment estimation theory to obtain the combined weights. As a result, the evaluation effect of subjective and objective factors on the observation point are taken into consideration. Then the combined weights and the improved TOPSIS method based on the gray relational analysis method are integrated to obtain the relative closeness, and finally the power quality evaluation ranking is performed. According to the evaluation and ranking results of the case analysis, the following conclusions can be drawn:

1) The anti-entropy and cloud model group weighting power quality evaluation method combines the weight matrix and the decision matrix, and combines subjective and objective weights without preference through mathematical programming methods. The improved anti-entropy method not only overcomes the shortcomings of excessive sensitivity of the traditional entropy weight method, but also can better reflect the difference between the indicators. This method takes into account the
preference of the decision maker and the objectivity of the evaluation. Through the improvement of the conversion calculation formula of the existing anti-entropy method, the adaptability of the anti-entropy weight calculation is enhanced. It can be seen from the simulation results that the comprehensive evaluation method can more effectively identify the power quality level of each observation point, and it has certain practical value.

3) By comparing with the results of calculation examples in Reference [27] and [28], it can be seen that the power quality evaluation method that proposed in this paper has a certain guiding effect and expands new ideas for comprehensive power quality evaluation.

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