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Comprehensive Evaluation of Power Quality Based on an Improved TOPSIS Method Considering the Correlation between Indices

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Abstract: In order to improve the scientific and rationality of power quality (PQ) comprehensive evaluation, an improved Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) strategy in consideration of the correlation between indices is proposed to evaluate PQ. The strategy overcomes the shortcomings of the traditional methods that ignore the correlation between PQ performance parameters. Firstly, the AHP-entropy weight (EW) method is obtained by combining the improved analytic hierarchy process (AHP) and the EW method, and the combined weights of the PQ indices are calculated. Secondly, the Mahalanobis distance is used to replace the Euclidean distance in the traditional TOPSIS method, and the PQ samples that need to be evaluated are sorted. The Mahalanobis distance nonlinearly correlates the components inside the evaluation matrix through its own covariance matrix, which solves the problem that the dimensions of each index are not uniform and eliminates the correlation interference between the indices. The example shows that the improved TOPSIS method effectively avoids the misjudgment caused by the correlation between the indices, and the evaluation results are more reasonable and scientific, with greater superiority and effectiveness.

Keywords: power quality; comprehensive evaluation; correlation between indices; improved TOPSIS method; entropy weight method; improved analytic hierarchy process; Mahalanobis distance

1. Introduction

The gradual depletion of fossil fuels has not only led to tight energy supplies, but has also caused serious environmental problems [1,2]. This has driven the global dependence on renewable energy. In addition, due to the fragility of the large power grid, a series of large power outages have occurred, and the distributed power generation system can improve the stability of the system to some extent. Therefore, these factors together lead to an increasing penetration of distributed generation in the power system. However, the distributed generation (DG) grid-connecting process generally requires a large number of power electronic interface devices for energy conversion [3], so the grid connection will have a potential impact on power quality (PQ). It may cause problems such as frequency deviation, voltage fluctuation, voltage flicker, voltage unbalance, harmonic distortion, and DC injection [4,5]. As DG systems account for a larger proportion of power system capacity, DG has an increasingly greater impact on the PQ of distribution networks. Therefore, establishing a comprehensive PQ comprehensive evaluation model can not only accurately know the operation level of each DG system, but also provide a basis for DG grid-connected pricing, which is of great significance.

Comprehensive evaluation of PQ is an important approach to quantify the overall PQ performance, and its results can be used as an important reference to distinguish PQ. The overall performance of PQ is usually derived from a comprehensive description of multiple indices [6]. In order to obtain more comprehensive and perfect power performance, it is necessary to comprehensively evaluate and analyze the PQ data, and its core task is to obtain a single quantitative index by means of weighting and merging of multiple PQ indices [7,8]—that is, to sort the PQ samples that contain multiple power quality evaluation indices.

However, the current PQ evaluation methods have not considered the correlation between the PQ indices, or there are some shortcomings such as the weighting methods being simple, a large amount of calculation, and a lack of practical engineering guidance [9–11]. The artificial neural network method proposed in [12] requires a large amount of sample data to train the network. The fuzzy comprehensive evaluation method proposed in [13–15] relies too much on experience and is too subjective in the process of determining membership function and obtaining weights. The traditional analytic hierarchy process (AHP) proposed in [16,17] needs to construct a judgment matrix, and the calculation amount is too large. The entropy weight (EW) method and its combination method proposed in [18,19] do not take subjective weights into account, which may result in inaccurate weights. In [20], a TOPSIS method based on entropy weight is proposed. The algorithm sorts the PQ samples by calculating the proximity to the ideal solution, where the proximity is calculated by the Euclidean distance between power performance of PQ sampling points and positive and negative ideal solutions. This method of adopting double reference values avoids the situation of juxtaposed evaluation results.

However, after the correlation analysis of the measured data of PQ, it is found that each batch of indices participating in the evaluation shows a high correlation, which has not received attention in the previous PQ evaluation methods. If the Euclidean distance in the traditional TOPSIS method is replaced by the Mahalanobis distance, the correlation between the PQ indices can be considered, and the juxtaposition of the evaluation results can be avoided, making the evaluation results more scientific.

Therefore, this paper proposes an improved TOPSIS method for comprehensive evaluation of power quality considering the correlation of indices. The distance algorithm in the traditional TOPSIS method is improved, and Mahalanobis distance is adopted to replace Euclidean distance, which can avoid the juxtaposition of evaluation results and effectively overcome the misjudgment caused by the correlation between PQ indices. Due to the weighting being the precondition of PQ evaluation, this paper also proposes a new AHP-EW weighting method based on the combination of improved analytic hierarchy process (AHP) and entropy weight (EW) method to calculate the subjective and objective weights of indices. Compared with the traditional subjective and objective weighting methods, this method can consider the subjective and objective factors at the same time, and greatly reduce the amount of calculation, with strong operability. Finally, the statistical values of PQ monitoring data are evaluated by an example, and the results are compared with the traditional methods to verify the validity and correctness of the proposed algorithm.

Figure 1 shows the improved process of the TOPSIS method. It can be seen that the EW-AHP is used to replace the existing single weighting method, and the objective weight of the original data is obtained by EW. The subjective weight can be obtained by AHP. The combination of the two can take into account the subjective and objective weights at the same time. The Mahalanobis distance replaces the Euclidean distance and eliminates the impact of the correlation between the evaluation indices on the evaluation results.

Figure 1. Improved process of the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method.

It should be noted that the evaluation method proposed in this paper is universal. It can be widely used in the evaluation of multiple targets with multiple indices, as shown in Figure 2, including energy efficiency evaluation, service satisfaction evaluation, risk evaluation and so on. Next, the paper will apply the proposed method to PQ evaluation to verify its effectiveness.

Figure 2. Evaluation system diagram.

2. Improved TOPSIS Method

As a common multi-objective decision analysis method [21,22], TOPSIS sorts the evaluation samples based on their proximity to the ideal effect. The algorithm constructs the virtual best solution and the worst solution, namely the positive ideal solution and the negative ideal solution, and calculates the relative Euclidean distance of the evaluation sample and the positive and negative ideal solutions, which is close to the positive ideal solution and far from the negative ideal solution as the optimal solution, and then sorts the evaluation samples in order.

The positive ideal solution and the negative ideal solution are the ideal values of the hypothesis, that is, the positive ideal solution is the virtual best feasible solution, and the negative ideal solution is the virtual worst feasible solution. Figure 3 is a schematic diagram of the decision of the TOPSIS method for two objectives. In the figure, A^+ and A^- are positive ideal solutions and negative ideal solutions, respectively, which are virtual optimal solutions and worst solutions. Although A_1 is closer to the positive ideal solution than A_2 , it is not far from the negative ideal solution. It can be seen that A_2 is farther away from the negative ideal solution. Therefore, the advantage of TOPSIS method is that, among the solutions with the same distance from the positive ideal solution, the one with a longer distance from the negative ideal solution is selected as the satisfactory solution, which avoids the situation where a single ideal solution results in the same evaluation result.

Figure 3. Decision diagram of the TOPSIS method.

Some researchers have improved the TOPSIS method by adding weights again in the calculation process of Euclidean distance. However, the above improvements are only supplemented by the weight issue, and the correlation between PQ indices is still not considered. If the correlation between the indices is neglected, the evaluation results obtained by traditional PQ evaluation methods will inevitably have deviations. In this paper, the Euclidean distance in the traditional TOPSIS method is replaced by the Mahalanobis distance. The Mahalanobis distance nonlinearly correlates the internal components of the evaluation matrix by its own covariance matrix. It can not only solve the problem of different dimensions of indices, but also eliminate the correlation interference between indices. It should be one of the preferred solutions for multi-objective evaluation.

3. Determine the Weights of PQ Indices

The weighting method combining subjectivity and objectivity, which can not only consider experts' opinions, but also take into account the impact of indices' data changes on evaluation results, has been applied in the fields of environment, medicine, computer, machinery, etc. [23–26]. In this paper, the improved AHP and EW method are combined to form a new combined weight calculation method called AHP-EW. The improved AHP eliminates the need to construct the judgment matrix, avoids the consistency test, and greatly reduces the computation.

3.1. Determination of Subjective Weight Based on Improved AHP

AHP is a multi-objective decision-making method founded by American operations researcher T. L. Satty. Its core idea is to rank the evaluation indices according to the experience of experts [27,28]. However, the traditional AHP usually constructs a judgment matrix and needs to pass the consistency test. In the actual calculation process, the test is often difficult to pass. As shown in Figure 4a, the portion of the red dashed box is uncontrollable. Therefore, the amount of calculation of the conventional AHP is large. Moreover, when the order of the judgment matrix is high, the amount of calculation will be larger. Therefore, experts [29] proposed using the scale method to construct the judgment matrix, as shown in Figure 4b. The improved AHP avoids the consistent test by constructing a judgment matrix, making the calculation process more straightforward and reducing the workload greatly.

Figure 4. Comparison between traditional AHP and improved AHP: (a) flow chart of traditional AHP; (b) flow chart of improved AHP.

Therefore, this paper uses the comparison scale to construct the judgment matrix. It is assumed that an evaluation sample has n indices, according to the expert opinion, the n indices are sorted in descending order of importance, such as: index 1 > index 2 > ... > index n . By comparing the index j and the index $j + 1$ in pairs, the corresponding scale is recorded as b_j . The specific definition of the scale is shown in Table 1.

Table 1. The meanings of scale values.

Scale Values b_j	Scale Definition
1	A and B are equally important
1.2	A is slightly more important than B
1.4	A is obviously more important than B
1.6	A is strongly more important than B
1.8	A is extremely more important than B
1.1, 1.3, 1.5, 1.7	Intermediate values of the above-mentioned judgment.

According to the scale assignment method described above, the judgment matrix $R = [r_{jk}]$ is constructed, and the matrix is defined as follows:

r_{jk} is the scale value after comparing the j th index with the k th index, where $j, k = 1, 2, \dots, n$;
 $r_{kj} = 1/r_{jk}$, where $j, k = 1, 2, \dots, n$;
 $r_{jj} = 1$, where $j = 1, 2, \dots, n$.

Based on the above definition, the judgment matrix $R = [r_{jk}]$ can be obtained as follows:

$$R = \begin{bmatrix} 1 & b_1 & b_1 b_2 & b_1 b_2 b_3 & b_1 b_2 b_3 b_4 & b_1 b_2 b_3 b_4 b_5 & \dots & b_1 b_2 \dots b_{n-1} \\ 1/(b_1) & 1 & b_2 & b_2 b_3 & b_2 b_3 b_4 & b_2 b_3 b_4 b_5 & \dots & b_2 b_3 \dots b_{n-1} \\ 1/(b_1 b_2) & 1/(b_2) & 1 & b_3 & b_3 b_4 & b_3 b_4 b_5 & \dots & b_3 b_4 \dots b_{n-1} \\ 1/(b_1 b_2 b_3) & 1/(b_2 b_3) & 1/(b_3) & 1 & b_4 & b_4 b_5 & \dots & b_4 b_5 \dots b_{n-1} \\ 1/(b_1 b_2 b_3 b_4) & 1/(b_2 b_3 b_4) & 1/(b_3 b_4) & 1/(b_4) & 1 & b_5 & \dots & b_5 b_6 \dots b_{n-1} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 1/(b_1 b_2 \dots b_{n-2}) & 1/(b_2 b_3 \dots b_{n-2}) & 1/(b_3 b_4 \dots b_{n-2}) & 1/(b_4 b_5 \dots b_{n-2}) & 1/(b_5 b_6 \dots b_{n-2}) & 1 & \dots & b_{n-1} \\ 1/(b_1 b_2 \dots b_{n-1}) & 1/(b_2 b_3 \dots b_{n-1}) & 1/(b_3 b_4 \dots b_{n-1}) & 1/(b_4 b_5 \dots b_{n-1}) & 1/(b_5 b_6 \dots b_{n-1}) & 1/(b_6 \dots b_{n-1}) & \dots & 1 \end{bmatrix} \quad (1)$$

According to the matrix R , the subjective weights of each index can be calculated, as shown in Equation (2):

$$\alpha_j = \sqrt[n]{\prod_{k=1}^n r_{jk}} / \sum_{j=1}^n \sqrt[n]{\prod_{k=1}^n r_{jk}}, \quad (2)$$

where α_j is the subjective weight of each index, $j, k = 1, 2, \dots, n$.

3.2. Determination of Objective Weight Based on the EW Method

C. E. Shannon, the founder of information theory, introduced entropy theory into information theory as a measure of information disorder [30,31]. In this paper, the EW method is used to determine the objective weight of each index of PQ. As an objective method of weighting, the entropy method can obtain objective weights independently of subjective factors. The smaller the entropy value, the lower the information disorder, and the higher the available value, so the corresponding index weight should be larger. On the contrary, the larger the entropy value, the higher the information disorder, and the lower the available value, so the corresponding index weight should be smaller. The detailed relationship is shown in Table 2.

Table 2. Relationship between entropy weight and entropy value.

	Disorder of Information	Value of Information	Weight to Be Given
Large entropy value	High	Low	Small
Small entropy value	Low	High	Large

Let the evaluation matrix be $A = (a_{ij})_{m \times n}$, and the objective weights calculation procedure of the indices is as follows [32]:

Standardization processing of evaluation data using standard 0–1 transformation:

When the index is a benefit attribute index, that is, the larger the index value, the better. The standardization equation is as follows:

$$a_{ij}^* = \frac{a_{ij} - \min_j a_{ij}}{\max_j a_{ij} - \min_j a_{ij}}, \quad i = 1, 2, \dots, m; \quad j = 1, 2, \dots, n. \quad (3)$$

When the index is a cost-based attribute index, that is, the smaller the index value, the better. The standardization equation is as follows:

$$a_{ij}^* = \frac{\max_j a_{ij} - a_{ij}}{\max_j a_{ij} - \min_j a_{ij}}, \quad i = 1, 2, \dots, m; \quad j = 1, 2, \dots, n, \quad (4)$$

where b_{ij} is the standardized value of the j th index of the i th evaluation sample.

- 1 According to the standardized decision matrix, the characteristic proportion of the j th index of the i th evaluation sample:

$$p_{ij} = a_{ij}^* / \sum_{i=1}^m a_{ij}^*, \quad j = 1, 2, \dots, n, \quad (5)$$

where, $0 < p_{ij} < 1$.

- 2 The entropy value of the j th index is:

$$e_j = -\frac{1}{\ln(m)} \sum_{i=1}^m p_{ij} \ln(p_{ij}), \quad j = 1, 2, \dots, n, \quad (6)$$

where $p_{ij} \ln(p_{ij}) \rightarrow 0$ for $p_{ij} \rightarrow 0$.

- 3 Difference coefficient of the j th index can be obtained as follows:

$$g_j = 1 - e_j, \quad j = 1, 2, \dots, n. \quad (7)$$

- 4 The entropy weight β_j of the j th index can be obtained as follows:

$$\beta_j = g_j / \sum_{j=1}^n g_j, \quad j = 1, 2, \dots, n. \quad (8)$$

According to Figure 5, we can understand the relationship between entropy value and entropy weight intuitively, and how the objective weight is obtained from the original data.

Figure 5. Schematic diagram of obtaining objective weight based on an entropy weight (EW) method.

3.3. Determination of Combination Weight

Equation (2) obtains the subjective weights of PQ indices, and Equation (8) obtains the objective weights of PQ indices. The subjective and objective weights of each index are multiplied and normalized, and the combined weight can be obtained as follows:

$$w_j = (\alpha_j \beta_j) / \sum_{k=1}^n \alpha_k \beta_k, \quad j = 1, 2, \dots, n. \quad (9)$$

It can be seen from the combination weight Equation (9) that it not only considers expert opinions to scale the importance of indices, but also distinguishes the quality of the index data, overcomes the shortcomings of the single weighting method, and meets the engineering practice of PQ evaluation.

4. Realization of PQ Comprehensive Evaluation

1. Solve the weighted normalized decision matrix:

Let $\omega_j = [w_1, w_2, \dots, w_n]^T$ be the combined weight vector of each PQ index, then the weighted normalized decision matrix $C = (c_{ij})_{m \times n}$ can be obtained as follows:

$$c_{ij} = w_j a_{ij}, \quad i = 1, 2, \dots, m; \quad j = 1, 2, \dots, n. \quad (10)$$

2. Determine the absolute ideal solution of the evaluation system:

According to Equation (10), the weighted normalized matrix $C = (c_{ij})_{m \times n}$ is obtained, and, according to the basic principle of the TOPSIS method, two vectors of positive ideal solution A_j^+ and negative ideal solution A_j^- are constructed:

$$A_j^+ = \begin{cases} 1, & j \in T1 \\ 0, & j \in T2 \end{cases}, \quad (11)$$

$$A_j^- = \begin{cases} 0, & j \in T1 \\ 1, & j \in T2 \end{cases}, \quad (12)$$

where, 1 and 0 respectively represent the maximum and minimum values of the corresponding indices. T1 means the benefit attribute index, that is, the positive index; T2 means the cost-based attribute index, that is, the inverse index.

3. Calculate the Mahalanobis distance:

Let the multi-index vector $x = (x_1, x_2, \dots, x_p)$ whose mean vector is $\mu = (\mu_1, \mu_2, \dots, \mu_p)$, and s^{-1} be the co-inverse matrix of x , then define the Mahalanobis distance equation for x as follows:

$$M(x) = \sqrt{(x - \mu)^T s^{-1} (x - \mu)}. \quad (13)$$

Combined with Equation (13), the Mahalanobis distance of the i th PQ evaluation sample to the positive and negative ideal solutions can be respectively defined as follows:

$$\tilde{M}(A_i, A^+) = \sqrt{(A_i - A^+)^T s^{-1} (A_i - A^+)}, \quad (14)$$

$$\tilde{M}(A_i, A^-) = \sqrt{(A_i - A^-)^T s^{-1} (A_i - A^-)}. \quad (15)$$

4. Calculate the proximity of the i th evaluation sample:

Let c_i be the relative proximity of the i th evaluation index to the ideal solution, and sort the evaluation sample according to the values of proximity c_i . The larger the c_i , the better the evaluation sample. Conversely, the smaller the c_i , the worse the evaluation sample. The c_i can be obtained as follows:

$$c_i = \frac{\tilde{M}(A_i, A^-)}{\tilde{M}(A_i, A^-) + \tilde{M}(A_i, A^+)}, \quad i = 1, 2, \dots, m. \quad (16)$$

5. An improved TOPSIS method for comprehensive evaluation of PQ considering the correlation between indices is shown in Figure 6:

Figure 6. The flowchart of power quality (PQ) comprehensive evaluation based on the improved TOPSIS method.

5. Experimental Results

The PQ performance is usually determined in terms of six indices, namely frequency deviation, voltage total harmonic distortion, voltage fluctuation, voltage flicker, voltage deviation and three-phase voltage unbalance. Table 3 shows the measured PQ data of the five major substation busbar nodes of a large wind farm in China, and obtained five sets of PQ indices data sets. The five substation nodes are: 10 kV busbar of substation 1, recorded as sample 1; 110 kV busbar of substation 2, recorded as sample 2; 10 kV busbar of substation 3, recorded as sample 3; 35 kV busbar of substation 4, recorded as sample 4; 10 kV busbar of substation 5, recorded as sample 5.

Take the PQ data of the above five evaluation samples as an example. Since the PQ is fluctuating, the PQ data obtained only once is not sufficient to explain the overall performance of the power. Therefore, in order to obtain reasonable PQ data, long-term monitoring of observation points is required. In the PQ monitoring system, when the PQ data are collected and summarized daily, weekly, monthly, seasonally, and annually, the 95% probability value is often used as the quantitative statistical index. The data in Table 3 is the statistical value measured in days, which can represent a dynamic PQ level.

Table 3. Measured PQ data.

Samples/Indices ¹	x_1/Hz	$x_2/\%$	$x_3/\%$	$x_4/\%$	$x_5/\%$	$x_6/\%$
1	0.09	1.12	0.96	0.22	2.53	0.88
2	0.04	1.26	1.05	0.34	1.66	1.07
3	0.19	1.18	1.41	0.47	3.85	0.83
4	0.11	0.82	0.85	0.38	2.01	0.58
5	0.07	1.35	1.27	0.53	3.18	1.23

¹ x_1 —frequency deviation, x_2 —voltage total harmonic distortion, x_3 —voltage fluctuation, x_4 —voltage flicker, x_5 —voltage deviation, x_6 —three-phase voltage unbalance.

The original data in Table 3 was imported into the software SPSS (version, Manufacturer, City, US State abbrev. if applicable, Country) for correlation analysis, and the Pearson correlation coefficient (Pcc) was obtained, as shown in Table 4. It can be seen from Table 4 that, under the two-sided test of the significance level of 0.01, the correlation coefficient between the voltage deviation and the three-phase voltage unbalance is 1, and the probability value of the two-sided test is 0, less than 0.01, which means the correlation degree is significant and completely positive. Under the two-sided test of

the significance level of 0.05, the correlation coefficient between the voltage deviation and the voltage total harmonic distortion is 0.95, and the probability of the two-sided test is 0.013, less than 0.05, which means that the correlation degree is significant and highly positive. The correlation coefficient between voltage total harmonic distortion and three-phase voltage unbalance is 0.95, and the probability of two-sided test is 0.013, less than 0.05, which means that the correlation degree is significant and highly positive. Therefore, there is a clear correlation between some indices. In this case, if traditional evaluation methods are still adopted, certain errors will be caused.

Table 4. Pearson correlation analysis of measured data.

		x_1	x_2	x_3	x_4	x_5	x_6
x_1	Pcc	1	−0.526	0.477	0.280	−0.283	−0.526
	significance level	—	0.362	0.416	0.648	0.645	0.362
x_2	Pcc	−0.526	1	0.478	0.328	0.950 ¹	1.000 ²
	significance level	0.362	—	0.415	0.590	0.013	0.000
x_3	Pcc	0.477	0.478	1	0.706	0.676	0.478
	significance level	0.416	0.415	—	0.182	0.211	0.415
x_4	Pcc	0.280	0.328	0.706	1	0.344	0.328
	significance level	0.648	0.590	0.182	—	0.571	0.590
x_5	Pcc	−0.283	0.950 ¹	0.676	0.344	1	0.950 ¹
	significance level	0.645	0.013	0.211	0.571	—	0.013
x_6	Pcc	−0.526	1.000 ²	0.478	0.328	0.950 ¹	1
	significance level	0.362	0.000	0.415	0.590	0.013	—

¹ Correlation is significant on the 0.05 layer (two sides), ² Correlation is significant on the 0.01 layer (two sides).

The PQ measured data of Table 3 will be comprehensively evaluated according to the method proposed in this paper. The first step is to determine the combined weights of the six PQ indices.

The AHP is used to calculate the subjective weights of the indices. According to the experts' opinions, the six indices can be arranged in descending order of importance as follows: frequency deviation > voltage total harmonic distortion > voltage fluctuation ≥ voltage flicker > voltage deviation > three-phase voltage unbalance. The scale values can be determined according to the experts' opinions when it is actually applied. Here, it is assumed that $r_{12} = 1.8$, $r_{23} = 1.7$, $r_{34} = 1$, $r_{45} = 1.4$, $r_{56} = 1.2$. According to the Equation (1), the judgment matrix R can be calculated as follows:

$$R = \begin{bmatrix} 1 & 1.8 & 3.06 & 3.06 & 4.284 & 5.1408 \\ 1/1.8 & 1 & 1.7 & 1.7 & 2.38 & 2.856 \\ 1/3.06 & 1/1.7 & 1 & 1 & 1.4 & 1.68 \\ 1/3.06 & 1/1.7 & 1 & 1 & 1.4 & 1.68 \\ 1/4.284 & 1/2.38 & 1/1.4 & 1/1.4 & 1 & 1.2 \\ 1/5.1408 & 1/2.856 & 1/1.68 & 1/1.68 & 1/1.2 & 1 \end{bmatrix}.$$

According to Equation (2), the subjective weights of six indices such as frequency deviation, voltage total harmonic distortion, voltage fluctuation, voltage flicker, voltage deviation and three-phase voltage unbalance are calculated in order:

$$\alpha_j = (0.379205, 0.210669, 0.123923, 0.123923, 0.088516, 0.073764).$$

The EW method is used to calculate the objective weights of the indices. The data can be normalized according to Equations (4) and (5) to obtain the characteristic proportion matrix P_{ij} . The objective weights of each index can be calculated according to Equations (6)–(8):

$$\beta_j = (0.126304, 0.212929, 0.161242, 0.18105, 0.153006, 0.165469).$$

According to Equation (9), the combined weights of PQ indices can be calculated as follows:

$$w_j = (0.297634, 0.278758, 0.124171, 0.139425, 0.084163, 0.075849).$$

According to Equation (10), the measured data of Table 3 is weighted to obtain a weighted normalized matrix C_{ij} , as shown in Table 5. In addition, the positive and negative ideal solutions are determined by Table 5, which are:

$$A^+ = (0.011905, 0.228581, 0.105545, 0.030674, 0.139711, 0.043992),$$

$$A^- = (0.056550, 0.376323, 0.175081, 0.073895, 0.324028, 0.093294).$$

Table 5. Weighted normalized matrix.

Samples/Indices	x_1	x_2	x_3	x_4	x_5	x_6
1	0.026787	0.312209	0.119204	0.030674	0.212933	0.066747
2	0.011905	0.351235	0.130379	0.047405	0.139711	0.081158
3	0.056550	0.328934	0.175081	0.065530	0.324028	0.062955
4	0.032740	0.228581	0.105545	0.052982	0.169168	0.043992
5	0.020834	0.376323	0.157697	0.073895	0.267639	0.093294

According to Equations (14) and (15), the Mahalanobis distance of each evaluation sample to positive and negative ideal solutions can be obtained by Matlab (version, Manufacturer, City, US State abbrev. if applicable, Country):

$$M_i^+ = (2.1176, 2.5083, 2.9249, 1.0889, 3.1036),$$

$$M_i^- = (2.6738, 2.6294, 1.2683, 2.9900, 1.7596).$$

According to Equation (16), the proximity of each evaluation sample can be obtained, which are: $c_1 = 0.558041$, $c_2 = 0.511785$, $c_3 = 0.302466$, $c_4 = 0.733041$, $c_5 = 0.361819$. Then, the proximity of each evaluation sample is sorted as: $c_4 > c_1 > c_2 > c_5 > c_3$.

In order to test the superiority and rationality of the proposed algorithm, the calculation results of the traditional TOPSIS method in [15] are compared with the results in this paper, as shown in Table 6. It can be seen that the proximity values calculated by the traditional TOPSIS method in [15] are: $c_4 > c_1 > c_2 > c_3 > c_5$, that is, sample 4 > sample 1 > sample 2 > sample 3 > sample 5, where, ">" means "better than". The proximity values calculated by the method in this paper are sorted as: $c_4 > c_1 > c_2 > c_5 > c_3$, that is, sample 4 > sample 1 > sample 2 > sample 5 > sample 3. Obviously, the improved TOPSIS method proposed in this paper differs from the traditional TOPSIS method in the ranking of samples 3 and 5.

Table 6. Comparison of evaluation results.

	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
Traditional TOPSIS method	0.492999	0.395786	0.271828	0.858968	0.213107
Proposed method	0.558041	0.511785	0.302466	0.733041	0.361819

According to the experience given by experts, the importance of the six PQ indices in descending order is as follows: frequency deviation > voltage total harmonic distortion > voltage fluctuation > voltage flicker > voltage deviation > three-phase voltage unbalance. According to the above order, the PQ of the samples 3 and 5 are compared in detail, as shown in Table 7. It can be seen that the sample 5 is better than the sample 3, and this result is consistent with the evaluation result of this paper.

Table 7. Comparison of samples 3 and 5.

	Sample 3	Sample 5	Importance	Contrast
x_1/Hz	0.19	0.07	1	Sample 5 better
$x_2/\%$	1.18	1.35	2	Sample 3 better
$x_3/\%$	1.41	1.27	3	Sample 5 better
$x_4/\%$	0.47	0.53	4	Sample 3 better
$x_5/\%$	3.85	3.18	5	Sample 5 better
$x_6/\%$	0.83	1.23	6	Sample 3 better

In order to further verify the effectiveness of the improved TOPSIS method for comprehensive evaluation of PQ in consideration of the correlation of indices proposed in this paper, the evaluation results of existing evaluation methods, including AHP, fuzzy theory method, combined weighting method, traditional TOPSIS method, and the results of this paper are compared, as shown in Table 8. In the process of calculation, the traditional AHP needs to construct the judgment matrix, and the consistency test is performed many times, that is, the calculation amount is huge. The fuzzy theory method is too subjective because it relies too much on experience in determining the membership function and obtaining weights, and does not consider the information of the data itself. The combined weighting method only aggregates the PQ data through the combination weights of the indices, and lacks the rigor of engineering mathematics. None of the above methods took measures to resolve the correlation between PQ indices. It can be seen from Table 8 that the evaluation results of this paper are consistent with the evaluation results of other methods, which is consistent with the fitting trend of each evaluation result, which confirms the effectiveness and superiority of the proposed method.

Table 8. Comparison of results of each evaluation method.

Evaluation Methods	Power Quality Evaluation Results
Analytic hierarchy process	Point 4 > Point 1 > Point 2 > Point 5 > Point 3
Fuzzy theory method	Point 4 > Point 2 > Point 1 > Point 5 > Point 3
Combined weight method	Point 1 > Point 4 > Point 2 > Point 5 > Point 3
Traditional TOPSIS method	Point 4 > Point 1 > Point 2 > Point 3 > Point 5
Method of this paper	Point 4 > Point 1 > Point 2 > Point 5 > Point 3

6. Conclusions

Aiming at the influence of the correlation between the power quality performance parameters (that is, the PQ indices in this paper) on the comprehensive evaluation results of PQ, this paper proposes to establish a comprehensive evaluation model by combining the improved TOPSIS method and the AHP-EW combination weighting method. This method is suitable for a variety of evaluation scenarios, mainly for targets with multiple indices. In these scenarios, you only need to select the required indicators. This paper applies this method to PQ evaluation, through the analysis of actual case data, the following conclusions are drawn:

1. There is a high correlation between some steady state indices of PQ, and it has not received attention and treatment in the previous comprehensive evaluation of PQ.
2. The Mahalanobis distance nonlinearly correlates the internal components of the evaluation matrix by its own covariance matrix. It can not only solve the problem of different dimensions of indices, but also eliminate the correlation interference between indices.
3. The new AHP-EW combination weighting method has the advantages of less calculation and strong operability compared with the traditional subjective and objective weighting method;
4. The evaluation results of the proposed method are in line with the fitting trend of other evaluation results, and the evaluation errors of other methods are corrected. The validity and superiority of the proposed TOPSIS method for comprehensive evaluation of PQ can be confirmed.

5. The correlation between the steady state indices of PQ has been the first concern for the comprehensive evaluation results of PQ, which provides a new reference and consideration for the following work of PQ evaluation.

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