Combination Weighting Method and Its Application in the Comprehensive Evaluation of the Power Quality Attributes

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Abstract. To evaluate the power quality scientifically and reasonably is of important practical significance. This paper applies attribute mathematics to the power quality evaluation, and puts forward a combination weighting method which is based on similarity weight method and AHM weighting method. At last, the attribute comprehensive evaluation method put forward in the paper is tested by using the measured data of a power station as an example, and the results are compared with multiple fuzzy comprehensive evaluation methods. The results show that, the attribute comprehensive evaluation method put forward in the paper has effectively overcome the issue of inaccuracy in determining membership functions by the fuzzy comprehensive evaluation method, the presented approach to determine weight can indicate the importance level of each index reasonably, so that the power quality grade can be identified more scientifically.

Keywords: Attribute synthetic assessment, Combination weighting method, AHM weighting method, Power quality evaluation.

1. Introduction

Power quality issues have an important impact on many aspects of the national economy. Along with the use of many computer- and micro processing controller-based precision equipment and the incorporation of disturbed loads into power system, demands of users for the power quality are growing higher. Especially with the development of power market, power plants are separated from power grids, the power as a commodity is involved in market competition and subject to price bidding like other commodities [1]. To establish a fair electricity market, one of the prerequisites is evaluate the power quality scientifically and reasonably so as to fix a price based on quality with high price for high quality [2, 3]. Therefore, the research on the power quality comprehensive evaluation has profound theoretical and practical significance.

Reflected by a variety of indexes, power quality is an organic combination of multiple indexes. At present, the national standard of power quality in China covers six aspects including deviation of supply voltage, harmonics, frequency deviation for power system, unbalance of three-phase voltage, temporary overvoltage & transient overvoltage, and voltage fluctuation & flicker, providing clear assessment indexes and methods for the problems of power quality [4,5]. But on the whole there is a lack of a recognized method for the comprehensive evaluation of the power quality. Most of the available literatures use the method of fuzzy mathematics and probability statistics to evaluate the power quality comprehensively [6]. This paper presents an attribute recognition theory-based power quality comprehensive evaluation method and uses the combination weighting method of comprehensive AHM weighting method and similarity weight method to determine the weight of each index. As a new method, it can make up the shortcoming of fuzzy comprehensive evaluation method and solve the problem in comprehensive evaluation of power quality that has multiple fuzzy attributes.

2. Attribute comprehensive evaluation system

This system consists of three subsystems: single index performance function analysis subsystem, multiple index performance function analysis subsystem and recognition analysis subsystem. The single index performance function analysis determines the performance function based on the index values and the evaluation class relationships, and calculate the performance function values with measured values. The multiple index performance function analysis integrates all the single-index performance function analyses into one performance function analysis. While the recognition analysis provides recognition criteria according to the output results of the multiple index performance function analysis to tell which class the sample is in [7,8].

2.1. Attribute pattern recognition of the known index classification criteria and recognition criteria

Take n samples of $x_1, x_2, \cdots x_n$ from the research object space X , and measure k indexes of $I_1, I_2, \cdots I_k$ for each sample. The measured value of the Index j of the Sample i , i.e. x_i , is x_{ij} . Provided $(C_1, C_2 \cdots C_m)$ is an ordinal classification in the attribute space F with the condition of $C_1 > C_2 > C_3 \cdots > C_m$. In addition, the classification standards of each index are given, then the classification matrix can be written as:

$$\begin{array}{c} \\ I_1 \\ I_2 \\ \vdots \\ I_k \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_m \end{array} \\ \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ a_{k1} & a_{k2} & \cdots & a_{km} \end{bmatrix} \end{array} \quad (1)$$

Where, a_{jm} meets $a_{j1} < a_{j2} < \cdots < a_{jm}$ or $a_{j1} > a_{j2} > \cdots > a_{jm}$.

Criteria of confidence recognition:

Provided $(C_1, C_2 \cdots C_m)$ is an ordinal classification in the attribute space F . λ is a confidence with a value between 0.6 and 0.7 in general though the common range is $0.5 < \lambda < 1$.

When $C_1 > C_2 > C_3 \cdots > C_m$, $k_0 = \min\{k : \sum_{i=1}^{n} \mu_x(C_i) \geq \lambda, 1 \leq n \leq m\}$

When $C_1 < C_2 < C_3 \cdots < C_m$, $k_0 = \max\{k : \sum_{i=1}^{n} \mu_x(C_i) \geq \lambda, 1 \leq n \leq m\}$;

Then, x is considered to be in Class C_{j0} .

2.2. Single index attribute measure analysis subsystem

Provided x_{ij} is in C_l in Class l , its attribute measure is $\mu_{ijl} = \mu(x_{ij} \in C_l)$. According to the attribute measure's properties, μ_{ijl} must satisfy: $\sum_{l=1}^{m} \mu_{ijl} = 1, 1 \leq i \leq n, 1 \leq j \leq k$ (2)

For the Index I_j , the attribute measure must be determined according to the specific problems, experimental data and some mathematical methods.

The matrix for single index measure evaluation is

$$\mu_{ijk} = \begin{bmatrix} \mu_{i11} & \mu_{i12} & \cdots & \mu_{1m} \\ \mu_{i21} & \mu_{i22} & \cdots & \mu_{i2m} \\ \vdots & \vdots & \vdots & \vdots \\ \mu_{ik1} & \mu_{ik2} & \cdots & \mu_{ikm} \end{bmatrix} \quad (3)$$

Table 1 List of the single index classification

	C_1	C_2	…	C_m
I_1	$a_{10} - a_{11}$	$a_{11} - a_{12}$	…	$a_{1m-1} - a_{1m}$
I_2	$a_{20} - a_{21}$	$a_{21} - a_{22}$	…	$a_{2m-1} - a_{2m}$
⋮	⋮	⋮	⋮	⋮
I_k	$a_{k0} - a_{k1}$	$a_{k1} - a_{k2}$	…	$a_{km-1} - a_{km}$

Provided $a_{j0} < a_{j1} < a_{j2} < \cdots < a_{jm}$, set

$$b_{jl} = \frac{a_{jl-1} + a_{jl}}{2}, l = 1, 2, \cdots, m \quad (4)$$

$$d_{jl} = \min(|b_{jl} - a_{jl}|, |b_{jl+1} - a_{jl}|), l = 1, 2, \cdots, m-1 \quad (5)$$

Single index attribute measure function $\mu_{ijt}(x_{ij})$ is determined as follows

$$\mu_{ij1}(x_{ij}) = \begin{cases} 1, x_{ij} < a_{j1} - d_{j1}; \\ \dfrac{|x_{ij} - a_{j1} - d_{j1}|}{2d_{j1}}, a_{j1} - d_{j1} \le x_{ij} \le a_{j1} + d_{j1}; \\ 0, a_{j1} + d_{j1} < x_{ij;} \end{cases} \tag{6}$$

$$\mu_{ijm}(x_{ij}) = \begin{cases} 1, a_{jm-1} + d_{jm-1} < x_{ij}; \\ \dfrac{|x_{ij} - a_{jm-1} + d_{jm-1}|}{2d_{jk-1}}, a_{jm-1} - d_{jm-1} \le x_{ij} \le a_{jm-1} + d_{jm-1}; \\ 0, x_{ij} < a_{jm-1} - d_{jm-1}; \end{cases} \tag{7}$$

$$\mu_{xjl}(x_{ij}) = \begin{cases} 0, x_{ij} < a_{jl-1} - d_{jl-1}; \\ \dfrac{|x_{ij} - a_{jl-1} + d_{jl-1}|}{2d_{jl-1}}, a_{jl-1} - d_{jl-1} \le x_{ij} \le a_{jl-1} + d_{jl-1}; \\ 1, a_{jl-1} + d_{jl-1} < x_{ij} < a_{jl} - d_{jl}; \\ \dfrac{|x_{ij} - a_{jl} - d_{il}|}{2d_{jl}}, a_{jl} - d_{jl} \le x_{ij} \le a_{jl} + d_{jl}; \\ 0, a_{jl} + d_{jl} < x_{ij;} \end{cases} \tag{8}$$

2.3. Multiple index synthetic attribute measure analysis subsystem

After the attribute measure $\mu_{ijl} = \mu$ of each sample x_i to each single index $I_j, 1 \le j \le k$ is obtained, integrate μ_{ijl} into the attribute measure $\mu_{il} = \mu$ of x_i by weighted sum, that is, to obtain the comprehensive attribute measure after the single index attribute measure is weighted before summation

$$\mu_{il} = \mu(x_i \in C_m) = \sum_{j=1}^{k} A_j \mu(x_{ij} \in C_l), 1 \le l \le m \tag{9}$$

Where, A_j the weight is the index No. j, $A_j \ge 0, \sum_{j=1}^{k} A_j = 1$. The weight ω_j shows the importance of the index No. j, which can be determined by a lot of methods. This paper presents a combination weighting method based on the similarity weight method and AHM weighting method to solve the problem of the attribute comprehensive evaluation.

3. To determine the index weight in the attribute comprehensive evaluation

3.1. AHM-based subjective weighting method.

AHM is a method of unstructured decision making is presented based on the conception of related attribute measure and attribute judgment matrix [9].

To get the attribute judgment matrix. Provided there are k indexes of $I_1, I_2, \cdots I_k$. Compare two different indexes of I_i and I_j $(i \ne j)$ for Criterion C, and the values of importance of I_i and I_j to Criterion C are μ_{ij} and μ_{ji} respectively, in addition, μ_{ij} and μ_{ji} must meet: $\mu_{ij} \ge 0, \mu_{ji} \ge 0, \mu_{ij} + \mu_{ji} = 1$.

Because it is meaningless to compare Index I_i with itself, there is a rule: $\mu_{ii} = 0, 1 \le i \le k$.

According to the reference [10, 11], define the relative attribute measure μ_{ij} to be

$$\mu_{ij} = \frac{k}{k+1}, b_{ij} = k, i \ne j \tag{10}$$

The obtained relative attribute measure matrix is

$$\begin{array}{cccccc} C & I_1 & I_2 & \cdots & I_k & v_c \\ I_1 & \mu_{11} & \mu_{12} & \cdots & \mu_{1k} & v_c(1) \\ I_2 & \mu_{21} & \mu_{22} & \cdots & \mu_{2k} & v_c(2) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ I_k & \mu_{k1} & \mu_{k2} & \cdots & \mu_{kk} & v_c(k) \end{array} \tag{11}$$

To get the relative attribute weight. Based on Criterion C, call $v_c = [v_c(1), v_c(2), \cdots, v_c(k)]^T$ the relative attribute weight of $I_1, I_2, \cdots I_k$, the expression is:

$$v_c(i) = \frac{2}{k(k-2)} \sum_{j=1}^{k} \mu_{ij} \tag{12}$$

3.2. Similarity weight-based objective weighting method.

When the evaluation index is an objective index, preliminary assume that each index has the same weight, meaning each index has an mean important value: $\omega_j = \frac{1}{m}(j = 1, 2, \cdots m)$. Under this hypothesis, the following formula can be used:

$$\mu_{il} = \frac{1}{m} \sum_{j=1}^{m} \mu_{ijl} \tag{13}$$

To get the comprehensive attribute measure vector $(\mu_{i1}, \mu_{i2}, \cdots \mu_{ik})$ of x_i. $(\mu_{i1}, \mu_{i2}, \cdots \mu_{ik})$ in line i in the comprehensive measure matrix obtained by compressing m vector lines in the single index evaluation matrix into one line. That is to say, μ_{ik} is m measured values of Sample x_i, and each of these values is the separate arithmetic mean value of Class C_k, i.e.

$$\mu_{ik} = \frac{1}{m}(\mu_{i1k} + \mu_{i2k} + \cdots + \mu_{imk}) \tag{14}$$

Put it another way, $(\mu_{i1}, \mu_{i2}, \cdots \mu_{ik})$ reflects the overall evaluation of x_i in the average sense. Thus, the similarity of the vector $(\mu_{ij1}, \mu_{ij2}, \cdots \mu_{ijk})$ of the single index attribute measure evaluation with the vector $(\mu_{i1}, \mu_{i2}, \cdots \mu_{ik})$ of the comprehensive attribute measure evaluation embodies the ability Index I_j to reflect the overall conditions. Higher similarity of the two indicates that I_j can reflect the overall conditions better, and the weight should be greater. Providing ω_j is a similarity weight, γ_j is a similarity coefficient.

$$\gamma_j = \frac{1}{n} \sum_{i=1}^{n} (\mu_{ij1}, \mu_{ij2}, \cdots, \mu_{ijk}) \cdot (\mu_{i1}, \mu_{i2}, \cdots, \mu_{ik})^T$$

$$= \frac{1}{n} \sum_{i=1}^{n} \sum_{l=1}^{k} \mu_{ijl} \cdot \mu_{il} \tag{15}$$

$$\omega_j = \frac{\gamma_j}{\sum_{j=1}^{m} \gamma_j} \tag{16}$$

3.3. Combination weighting method.

This method is used to determine the comprehensive weight of an index by combining the subjective weighting method with the objective weighting method. The method can take the subjective experience of analysts on the index importance into account besides making full use of the objective information on the index importance provided by the results, so that the subjectivity and objectivity are unified for index weighting, bringing about objective, real and effective evaluations.

Evaluation matrix and its standardization. In order to unify the index trend requirements and eliminate the incommensurability between indexes, the evaluation matrix must be standardized.

To unify the index trend requirements. Set $I_1 =$ {indexes with minimum requirements}, $I_2 =$ {indexes with maximum requirements}, $I_3 =$ {indexes with requirements stable at ideal values}; plus $I_1 \cup I_2 \cup I_3 = I$, $I_i \cap I_j = \varnothing (i \neq j, i, j = 1, 2, 3)$.

When subject to the criterion of the-smaller-the-better, set

$$y_{ij} = \begin{cases} x_{ij}, j \in I_1 \\ -x_{ij}, j \in I_2 \\ \left| x_{ij} - x^*_j \right|, j \in I_3 \end{cases} \tag{17}$$

Where, x^*_j is the ideal value of Index j.

When subject to the criterion of the-larger-the-better, set

$$y_{ij} = \begin{cases} -x_{ij}, j \in I_1 \\ x_{ij}, j \in I_2 \\ -\left|x_{ij} - x^*{}_j\right|, j \in I_3 \end{cases} \quad (18)$$

To unify the magnitude orders of indexes and eliminate dimensions.

Set $Z_{ij} = 100 \times \frac{y_{ij} - y_{j\min}}{y_{j\max} - y_{j\min}}, i = 1, 2, \cdots, n; j = 1, 2, \cdots, m$ (19)

Where, $y_{j\min} = \min\{y_{ij} \left| i = 1, 2, \cdots, n\right.\}$, $y_{j\max} = \max\{y_{ij} \left| i = 1, 2, \cdots, n\right.\}$.

Determination of weights. To determine the subjective weights. This paper choose to use the AHM-based subjective weighting method to determine the subjective weight as follows:

$v = (v_1, v_2, \cdots, v_m)^T$ where: $\sum_{j=1}^{m} v_j = 1, v_j \geq 0 (j = 1, 2, \cdots, m)$.

To determine the objective weights. This paper choose to use similarity weight-based objective weighting method to determine the objective weight as follows: $\omega = (\omega_1, \omega_2, \cdots, \omega_m)^T$ where: $\sum_{j=1}^{m} \omega_j = 1, \omega_j \geq 0 (j = 1, 2, \cdots, m)$.

To determine the comprehensive weights. Set the comprehensive weight of each index as $A = (A_1, A_2, \cdots, A_m)^T$ where: $\sum_{j=1}^{m} A_j = 1, A_j \geq 0 (j = 1, 2, \cdots, m)$.

In order to take the subjective preferences for the subjective and objective weighting methods into account, in addition that the objective weighting method is integrated, the following optimization decision model is established:

$$\min F(A) = \sum_{i=1}^{n} \sum_{j=1}^{m} \{\rho[A_j - a_j) z_{ij}]^2 + (1-\rho)[(A_j - b_j) z_{ij}]^2\} \quad (20)$$

Where, ρ is the preference coefficient, which reflects the preference of decision-makers for the subjective and objective weighs? When $0 < \rho < 0.5$, it indicates that the decision-makers want the objective weight to be closer to the comprehensive weight; when $0.5 < \rho < 1$, it indicate that the decision-makers want the subjective weight to be closer to the comprehensive weight; when $\rho = 0.5$, it indicates that the decision-makers think that the subjective and objective weights are equally important.

If $\sum_{i=1}^{n} z_{ij}{}^2 > 0 (j = 1, 2, \cdots, m)$, the model has a unique solution, which is

$$A = (\rho v_1 + (1-\rho)\omega_1, \rho v_2 + (1-\rho)\omega_j, \cdots, \rho v_m + (1-\rho)\omega_j)^T \quad (21)$$

4. Analysis on application examples

Use power quality data measured at 5 observation points in a certain station to calculate and analyze, and grade all the indexes according to the national standard. For there is no national standards on voltage sags, they are graded subject to IEEE.

Table 2 Monitoring points measured data

Monitoring points	1	2	3	4	5
Voltage deviation(%)	3.212	6.68	4.35	5.33	4.22
Voltage dips(%)	0.7963	0.1589	0.5156	0.5856	0.4863
Unbalanced	0.83	1.36	1.35	1.74	1.83
Voltage fluctuation(%)	1.33	1.53	1.95	1.37	1.58
Voltage flicker(%)	0.473	0.847	0.634	0.826	0.828
Total harmonic	1.72	4.28	2.67	3.36	4.57
Frequency deviation(%)	0.0922	0.1562	0.118	0.1787	0.1894
Power distribution	0.833	0.762	0.796	0.74	0.764
Services index	0.832	0.713	0.864	0.684	0.783

4.1. Using principal component analysis to get the main indexes that affect power quality.

First of all, use zscore function in MATLAB statistics toolbox to standardize data; then, use princomp function, one of four analysis functions in MATLAB, to analyze the standardized data. According to the contribution rate of each eigenvalue and the cumulative obtained by calculation, among all the indexes that reflect the power quality, voltage flicker, voltage fluctuation and three-phase imbalance are the main indexes that affect the power quality.

4.2. Attribute recognition model for the comprehensive evaluation of power quality.

The research object space X is the measured data of five observation points, the attribute space $F=$ {power quality conditions}, an ordinal classification in F is $(C_1, C_2 \cdots C_4)$ subject to $C_1 > C_2 > C_3 > C_4$, where $C_1=$ {excellent}, $C_2=$ {good}, $C_3=$ {fair} and $C_4=$ {qualified}. There are 3 indexes for each measuring point in X, which are $I_1=$ {voltage flicker}, $I_2=$ {voltage fluctuation} and $I_3=$ {three-phase imbalance}.

4.3. To establish a single index attribute measure subsystem.

Single index measure function.

Voltage flicker

$$\mu_{12}=\begin{cases}0; x_{12}\le 0.2, x_{12}\ge 0.8\\ 3.33x_{12}-0.67; 0.2<x_{12}<0.5\\ -3.33x_{12}+2.67; 0.5\le x_{12}<0.8\end{cases}\qquad \mu_{13}=\begin{cases}0; x_{13}\le 0.5, x_{13}\ge 1.0\\ 3.33x_{13}-1.67; 0.5<x_{13}<0.8\\ -5x_{13}+5; 0.8\le x_{13}<1.0\end{cases}$$

$$\mu_{14}=\begin{cases}0; x_{14}\le 0.8\\ 5x_{14}-4; 0.8<x_{14}<1.0\\ 1; x_{14}\ge 1.0\end{cases}$$

Voltage fluctuation

$$\mu_{21}=\begin{cases}0; x_{21}\ge 1.0\\ -2x_{21}+2; 0.5<x_{21}<1.0\\ 1; x_{21}\le 0.5\end{cases}\qquad \mu_{22}=\begin{cases}0; x_{22}\le 0.5, x_{22}\ge 1.5\\ 2x_{22}-1; 0.5<x_{22}\le 1.0\\ -2x_{22}+3; 1.0<x_{22}<1.5\end{cases}$$

$$\mu_{23}=\begin{cases}0; x_{23}\le 1.0, x_{23}\ge 2.0\\ 2x_{23}-2; 1.0<x_{23}<1.5\\ -2x_{23}+4; 1.5<x_{23}<2.0\end{cases}\qquad \mu_{24}=\begin{cases}0; x_{24}\le 1.5\\ 2x_{24}-3; 1.5<x_{24}<2.0\\ 1; x_{24}\ge 2.0\end{cases}$$

Three-phase imbalance

$$\mu_{31}=\begin{cases}0; x_{31}\ge 1.0\\ -2x_{31}+2; 0.5<x_{31}<1.0\\ 1; x_{31}\le 0.5\end{cases}\qquad \mu_{32}=\begin{cases}0; x_{32}\le 0.5, x_{32}\ge 1.5\\ 2x_{32}-1; 0.5<x_{32}\le 1.0\\ -2x_{32}+3; 1.0<x_{32}<1.5\end{cases}$$

$$\mu_{33}=\begin{cases}0; x_{33}\le 1.0, x_{33}\ge 2.0\\ 2x_{33}-2; 1.0<x_{33}<1.5\\ -2x_{33}+4; 1.5<x_{33}<2.0\end{cases}\qquad \mu_{34}=\begin{cases}0; x_{34}\le 1.5\\ 2x_{34}-3; 1.5<x_{34}<2.0\\ 1; x_{34}\ge 2.0\end{cases}$$

Single index measure matrix

$$x_1=\begin{bmatrix}0.0949 & 0.9051 & 0 & 0\\ 0 & 0.3400 & 0.6600 & 0\\ 0.3400 & 0.6600 & 0 & 0\end{bmatrix}\qquad x_2=\begin{bmatrix}0 & 0 & 0.7650 & 0.2150\\ 0 & 0 & 0.9400 & 0.0600\\ 0 & 0.2800 & 0.7200 & 0\end{bmatrix}$$

$$x_3=\begin{bmatrix}0 & 0.5590 & 0.4410 & 0\\ 0 & 0 & 0.1000 & 0.9000\\ 0 & 0.3000 & 0.7000 & 0\end{bmatrix}\qquad x_4=\begin{bmatrix}0 & 0 & 0.8700 & 0.1300\\ 0 & 0.2600 & 0.7400 & 0\\ 0 & 0 & 0.5200 & 0.4800\end{bmatrix}$$

4.4. Determination of weights.

To get the subjective weight by AHM method. Firstly, provide the importance levels according to expert opinions and user needs: voltage fluctuation > voltage flicker > three-phase imbalance, with the relative scales $b_{12}=1, b_{23}=5, b_{13}=5$. Then, the relative attribute measure matrix can be obtained as follows:

$$\mu_{ij}=\begin{bmatrix}0 & 0.5 & 0.833\\ 0.5 & 0 & 0.833\\ 0.167 & 0.167 & 0\end{bmatrix}$$

At last, the subjective weight is get subject to the formula $v(i) = (0.4443, 0.4443, 0.1114)$

To get the objective weight by similarity weight method. First of all, set $\omega_j = \frac{1}{m}(j = 1, 2, \cdots m), m = 3$, according to the formula $\mu_{it} = \frac{1}{m}\sum_{j=1}^{m}\mu_{ijt}$ to get the comprehensive measure evaluation matrix

$$\mu_{ik} = \begin{bmatrix} 0.1445 & 0.635 & 0.220 & 0 \\ 0 & 0.093 & 0.808 & 0.0917 \\ 0 & 0.268 & 0.414 & 0.30 \\ 0 & 0.087 & 0.710 & 0.203 \\ 0 & 0 & 0.680 & 0.320 \end{bmatrix}$$

Then, according to the formula $\gamma_j = \frac{1}{n}\sum_{i=1}^{n}(\mu_{ij1}, \mu_{ij2}, \cdots, \mu_{ijk}) \cdot (\mu_{i1}, \mu_{i2}, \cdots, \mu_{ik})^T$ to calculate the similarity coefficients

$\gamma_1 = 0.56844$

$\gamma_2 = 0.52164$

$\gamma_3 = 0.47220$

At last, according to the formula $\omega_j = \frac{\gamma_j}{\sum_{j=1}^{m}\gamma_j}$ to calculate the objective weight $\omega_j = (0.3639, 0.3339, 0.3022)$.

To determine the comprehensive weight. Because the subjective and objective weights are considered to share the same important degree, set $\rho = 0.5$, and get the comprehensive weight $A_i = (0.4041, 0.3891, 0.2068)$.

4.5. To re-determine comprehensive measure matrix according to the comprehensive weight.

By weighted summation of the single index attribute measure, the comprehensive attribute measure can be obtained with the formula:

$$\mu_{it} = \mu(x_i \in C_m) = \sum_{j=1}^{k} A_j \mu(x_{ij} \in C_t), 1 \le t \le m$$

The comprehensive measure matrix is:

$$\mu_{it} = \begin{bmatrix} 0.1087 & 0.6345 & 0.2568 & 0 \\ 0 & 0.0579 & 0.8238 & 0.1102 \\ 0 & 0.2879 & 0.3619 & 0.3502 \\ 0 & 0.1012 & 0.7470 & 0.1518 \\ 0 & 0 & 0.7447 & 0.2553 \end{bmatrix}$$

4.6. To recognize by applying the confidence criterion.

Take $\lambda = 0.7$, the level of each measuring point can be obtained, as shown in Table 3.

Table 3 Measuring point level

Measuring point	1	2	3	4	5
Level	2	3	4	3	3

5. Conclusion

The examples above have verified the rationality of the power quality comprehensive evaluation method present in this paper, this method based on the similarity weight method and AHM weighting method is effective in evaluating the power quality comprehensively. By comparing with other fuzzy comprehensive evaluation methods, it proves that this method can effectively overcome the issue of inaccuracy in determining membership functions by the fuzzy comprehensive evaluation method. The presented method for determining weights can provide proper importance levels of the indexes, so that the power quality levels can be evaluated more scientifically.

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