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Comprehensive evaluation of voltage stability based on EW-AHP and Fuzzy-TOPSIS

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ABSTRACT

Large-scale voltage collapse incidences, which result in power outages over large regions and extensive economic losses, are presently common occurrences worldwide. Therefore, the voltage stability analysis of power systems has become a topic of increasing interest. This paper firstly presents a comprehensive evaluation method for conducting static and transient voltage stability analysis in electric power systems. To overcome the limitations associated with single-index systems in the evaluation of voltage stability, the analysis approach employs a multi-index system with four primary criteria based on separate analysis methods with ten sub-criteria based on individual indices. In addition, this paper proposes a comprehensive method for establishing index weights, which combines the subjective analytic hierarchy process weighting method and the objective entropy weighting method. An innovative index-weight optimization method based on the Lagrange conditioned extreme value is presented and sensitivity analysis is applied to test the robust of the proposed method. Finally, Fuzzy-TOPSIS is employed to rank the voltage buses of a power system as the final results, considering system functionality and proportionality. The results obtained for an actual power grid in Hami City, China demonstrate that the proposed method represents an effective approach for determining the weakest bus in power systems.

1. Introduction

Continuous economic development worldwide has fostered an increasingly large construction scale of power grids, resulting in the construction of extensive power networks of increasing complexity. As a result, large-scale voltage collapse incidences, which result in power outages over large regions and extensive economic losses, are presently common occurrences all over the world. Moreover, the frequency of these occurrences increases as renewable energy sources are increasingly integrated into power systems owing to the more complex operating conditions associated with their inherently uncertain power generation [1, 2]. The ability of power systems to maintain uniform voltages on all buses after disturbances, which depends on maintaining an appropriate balance between demand and generation, is denoted as voltage stability [3, 4]. Voltage stability has been the key topic of numerous power system studies for decades. In a seminal study [5], voltage stability was divided into two categories, i.e., transient voltage stability and static voltage stability. The calculation of the static voltage stability margin and transient fault analysis has become a basis for evaluating the voltage stability of power systems. Here, a loss of voltage stability can emerge as a progressive decrease or increase in the voltage of some or all buses in the system. This process usually begins with weak buses, and then expands to other buses, which finally results in the voltage collapse of the entire power system. Therefore, voltage stability has become one of the vital issues in both the planning and operation of power systems.

Voltage analysis tools are often effective means of evaluating stability margins, identifying the weakest buses, and accounting for a wide range of system conditions. Among the standard static analysis techniques available, methods based on singular values [6] and the eigenvalues of the power system load flow Jacobian [7] have been well explored for identifying the static voltage stability margin and identifying the weakest buses. Meanwhile, the existing methods of assessing the transient voltage stability are direct method of Lyapunov, transient energy function (TEF), extended equal area criterion (EEAC), and time-domain simulation methods, etc. Other mature voltage stability

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analysis methods, such as voltage stability indices based on the power flow solution or transient fault analysis, can be employed to either quantitatively explore power systems for identifying the weakest buses or calculate the stability margins of the system (W or Var) [8]. For instance, static voltage stability indices based on active power-voltage (P-V) and reactive power-voltage (Q-V) curves have been employed to analyze the voltage stability and reliability in wind power systems [9]. Transient voltage stability indices based on time-domain simulation, such as critical clearing time and maximum voltage drop amplitude can be used in reflecting transient voltage stability in power system's cascading failures evaluation. In addition, voltage sensitivity indices have been utilized to identify weak buses by performing load flow analyses for various amounts of active wind power injected [10]. Voltage stability analysis of an IEEE 14 bus system is done by calculating L-index of the buses in [11]. The calculated L-index values can find out vulnerable buses. Moreover, a Q-V sensitivity index has been employed to determine the most effective location for dynamic reactive power compensation sources such as static synchronous compensators (STATCOMs), static VAR compensators (SVCs), and capacitor banks [12].

As indicated by the above discussion, these single indicators are based on specific power grid factors such as voltage, active power, reactive power, and load condition. As a result, the analysis of power grids by means of single indicators, e.g., margin index, a representative sensitivity index, L-index, or other indicators [13], can be expected to yield different results. In fact, these indices can provide different results even for the same operation on the same timeline. Considering that each of the above voltage indicators fails to evaluate all aspects of a power grid, the voltage stability analysis of a power system would be more accurate if it employed a comprehensive multi-level index system.

The development of a multi-level index system by combining different types of voltage stability indices can be conducted by multi-criteria decision making (MCDM) problem. MCDM is a simple, intuitive, and effective multi-disciplinary technology that has been applied extensively in power system analysis for some time. Its application has been well-demonstrated in power system analysis, such as in a UHVDC system and a distribution system [14, 15]. Here, a comprehensive evaluation index system was proposed [14], and employed in an integrated distributed photovoltaic and energy storage (PV-ES) system to analyze its grid-connected performance. In addition, the impacts of distributed generation (DG) on both voltage and line loss in a distribution system were analyzed by a comprehensive evaluation [15].

The primary Step in MCDM analysis is the calculation of weights for the various indicators [16]. This includes two main approaches. The first involves subjective weighting methods such as the analytic hierarchy process (AHP), Delphi analysis, and the fuzzy comprehensive evaluation method (FCEM). The second approach involves objective weighting methods such as the grey comprehensive evaluation method (GCEM) and entropy method. The characteristic of objective weighting methods is that they emphasize the differences between indices, while subjective weighting methods has obvious advantage for weight calculation procedures based on a pair-wise comparison. It is noted however that most studies have employed only either subjective or objective methods to determine weights. For example, a comprehensive assessment method that considers voltage and power losses was presented, where the weights were determined only by objective judgment [17]. In another case [18], only a subjective methodology that combined the AHP method and expert feedback was employed to evaluate different renewable energy options. Moreover, the proportions of subjective and objective evaluation methods in these studies are usually defined as fifty-fifty [19, 20, 21, 22]. However, a fifty-fifty proportion cannot always provide an accurate result. In response to the limitations of subjective and objective weighting methods, both methods would ideally be employed in proportion to

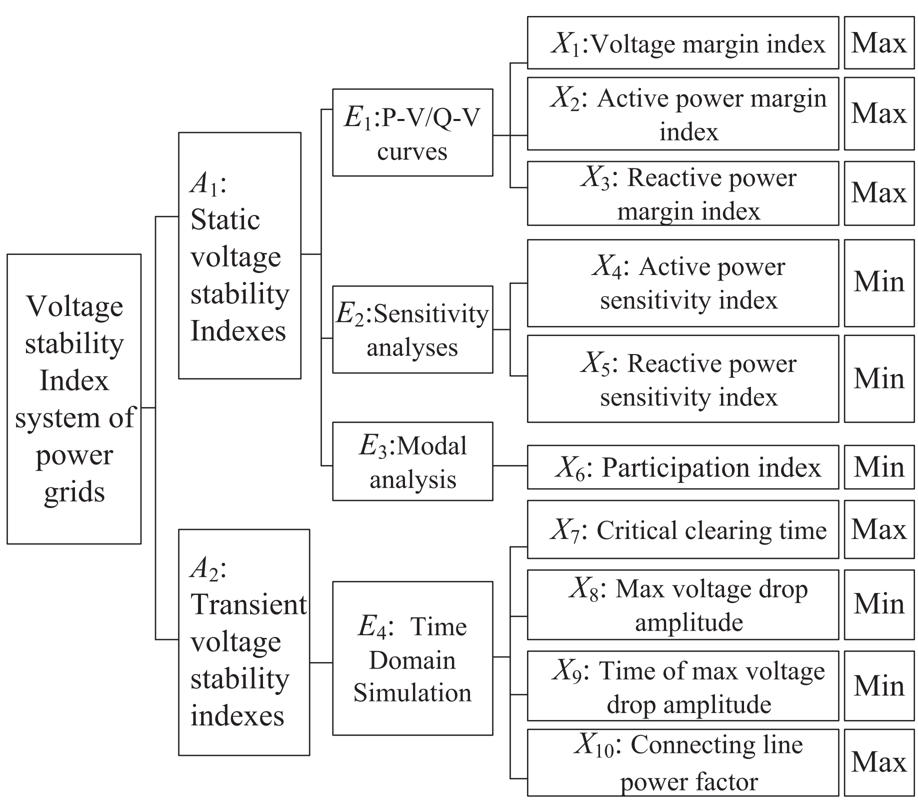


Fig. 1. Hierarchy of proposed assessment indexes.

their designated importance.

To address the issues associated with the use of single indices for voltage analysis (which included transient and static voltage stability analysis), the proposed analysis approach employs a multi-index system with four primary criteria based on separate analysis methods with ten sub-criteria based on individual indices. MCDM is used to integrate different indices in a multi-index system. To address the limitations of subjective and objective weighting methods, this paper presents an index weighting optimization method that combines both subjective weighting and objective weighting methods in proportion to their designated importance. Here, the entropy weighting (EW) method is employed as an objective weighting method to obtain an objective evaluation of differences between indices, and the AHP method based on expert opinion is employed to revise the objective weighting of indices. Finally, the Lagrange conditioned extreme value (LCEV) is employed to optimize the proportion of each index weight assigned by the objective and subjective methods. Lastly, the technique for fuzzy order preference by similarity to ideal solution (Fuzzy-TOPSIS) method [23, 24] is employed in this paper to provide a reasonable ranking of the voltage buses of a power system, considering system functionality and proportionality. This method can make full use of existing information and model problems like uncertainty in human preferences, and can therefore enhance the objectivity of the ranking result. The results obtained for an actual power grid in Hami City, China demonstrate that the proposed method represents an innovative approach for determining the weakest bus in power systems.

2. Theory

2.1. Establish voltage stability index system

MCDM can provide a comprehensive and reasonable evaluation of the voltage stability of a power system based on multiple parameters that have a variety of attributes or their overall characteristics are influenced by many factors. The first Step of MCDM is to establish the index system. The indices employed in the present work for analyzing the voltage stability of power systems are presented in Fig. 1. We note that the proposed stability analysis consists of four primary criteria denoted as E_1, E_2, E_3, and E_4, and ten sub-criteria denoted as X_1, X_2, X_3, … and X_{10}, where $E_1 = \{X_1, X_2, X_3\}$, $E_2 = \{X_4, X_5\}$, $E_3 = \{X_6\}$, and $E_4 = \{X_7, X_8, X_9, X_{10}\}$. Thereafter, the model was applied on a case study with real wind farms to allow experts to provide their opinions on the pair-wise comparison of every index and calculate the scores of their weights.

2.2. Comprehensive weight calculation

As discussed, the core Step of MCDM analysis is the appropriate calculation of weights for the selected indicators. Therefore, the present study combines AHP for the calculation of subjective weights and the EW method for the calculation of objective weights. Firstly, the EW method is applied to render an objective weighting for each index. Secondly, AHP is employed to revise the objective weighting and render a comprehensive evaluation of weighting. We note that AHP has been widely used in power systems as a technique for assessing and selecting critical power system components against a set of selected criteria. The application of AHP can mitigate the interference caused by objective factors in the assessment process. Then, an index weight optimization method based on the LCEV is proposed for calculating the reasonable proportions of the weighting provided by AHP and EW, which then provides a comprehensive weighting for each index. The proposed comprehensive weight calculation approach includes the following eight primary steps.

Step one: Calculate probability of indices for the preparation of EW method

Define a sequence $x_{ij} = \{x_{1j}, x_{2j}, x_{3j}, \dots x_{nj}\}, x_{ij} \geq 0$, which means the observed value of the j^{th} alternative for the i^{th} index, the proportion of x_{ij} is defined as

$$\mathrm{Pro}(x_{ij}) = x_{ij} \Big/ \sum_{i=1}^{n} x_{ij} \tag{1}$$

where $i = 1, 2, 3, \dots, n$, and $j = 1, 2, 3, \dots, m$.

Step two: Entropy value calculation

Based on the first Step, the entropy value (e_{ij}) of index x_{ij} defined as

$$e_{ij} = -\frac{1}{\ln n} \sum_{i=1}^{n} \mathrm{Pro}(x_{ij}) \ln \mathrm{Pro}(x_{ij}) \tag{2}$$

Step three: Calculate the discrimination factor

The discrimination factor (g_{ij}) is defined as

$$g_{ij} = 1 - e_{ij} \tag{3}$$

Step four: Calculate the objective weight based on EW method

The objective weight matrix of $\boldsymbol{q}_{objective}$ is defined as

$$\boldsymbol{q}_{objective} = [q_{ij}]_{n \times m} = \left[g_{ij} \Big/ \sum_{j=1}^{m} g_{ij} \right]_{n \times m} \tag{4}$$

Here, we note that the amount of information that can be provided by an index increases with decreasing entropy; thus, the index has greater importance, and a corresponding greater objective weight.

Step five: Construct an evaluation matrix by AHP:

For the subjective weighting operation, the power grid experts selected options from the fundamental ranking criteria, which is employed to simplify the representation of the degree of expert-chosen preferences to rank the indices. In order to obtain the subjective weight indexes, we need to establish the comparison matrix $\boldsymbol{A}$ first:

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} \tag{5}$$

in which every element a_{ij} represents the individual preference of experts according to the relative importance of the two indices based on [16]. Here, $a_{ij} > 0$, $a_{ii} = 1$, and $a_{ji} = 1/a_{ij}$.

Step six: Derive subjective weights

This Step aims to transform the pair-wise matrix $\boldsymbol{A}$ into a vector of subjective weights that can be attached to multiple outcomes. The subjective weight matrix $\boldsymbol{p}_{objective}$ can be obtained from $\boldsymbol{A}$ by the eigenvector method.

$$\begin{cases} \mathbf{p}_{subjective} = [p_{ij}]_{n \times m} \\ \mathbf{A}\mathbf{p}_{subjective} = \lambda_{\max} \mathbf{p}_{subjective} \end{cases} \tag{6}$$

where $\boldsymbol{p}_{objective}$ is the eigenvector corresponding to the maximal eigenvalue λ_{max} of $\boldsymbol{A}$.

Step seven: Check the consistency

The final consistency ratio C_R is defined as

$$C_R = \frac{\lambda_{\max} - k}{\gamma_m (m-1)} \tag{7}$$

The consistency is defined by the relation among the entries of $\boldsymbol{A}$: $a_{ij} \times a_{jk} = a_{ik}$. And γ_m is the random consistency index. The values of γ_m are obtained based on different values of k. If $C_R < 0.1$, $\boldsymbol{A}$ is deemed acceptable. Otherwise, $\boldsymbol{A}$ is considered inconsistent, and matrix $\boldsymbol{A}$ should be reviewed and improved until $C_R < 0.1$.

Step eight: Calculate comprehensive weights

Although a combination of subjective and objective evaluation methods can be expected to provide more accurate results, the relative importance that should be placed on the subjectively and objectively determined weights of the indices remains uncertain. As a result, the present study proposed a Lagrange conditioned extreme value (LCEV). As noted before, p_{ij} and q_{ij} are the subjective and objective weights values of $\boldsymbol{p}_{\ subjective}$ and $\boldsymbol{q}_{\ objective}$ matrixes, respectively, thereby defining the comprehensive weight matrix $\boldsymbol{\omega}_{com}$ as:

$$\boldsymbol{\omega}_{com} = [\omega_{ij}]_{n\times m} = \left[k_i^{(1)}p_{ij} + k_i^{(2)}q_{ij}\right]_{n\times m} \tag{8}$$

where $k_i^{(1)}$ and $k_i^{(2)}$ are constants that satisfy the conditions $k_i^{(1)} > 0, k_i^{(2)} > 0$, and $(k_i^{(1)})^2 + (k_i^{(2)})^2 = 1$. The comprehensive values y_j in Eq. (9) are defined by applying additive method:

$$y_i = \sum_{j=1}^{m} \omega_{ij}x_{ij} = \sum_{j=1}^{m}\left(k_i^{(1)}p_{ij} + k_i^{(2)}q_{ij}\right)x_{ij} \tag{9}$$

where the evaluated project will become more advantageous with increasing values of y_i. Meanwhile, the weights of indexes actually belong to random variable, which can be described as the sum of the mean value and the random error. The deviation ε_i of y_i based on minimum deviation is defined as:

$$\varepsilon_i = \sum_{j=1}^{m}\left[(\omega_{ij} - \omega_{ij}^{j})x_{ij}\right]^2 \tag{10}$$

Here, when the sum of the comprehensive values, $\sum_{i=1}^{n} y_i$, is at its maximum while the sum of the deviation values, $\sum_{i=1}^{n}\varepsilon_i$ is at its minimum, then $k_i^{(1)}$ and $k_i^{(2)}$ can be determined. Simultaneous Eqs. (9) and (10), then can obtain Eq. (11):

$$\begin{cases} \max\sum_{i=1}^{n} y_i = \max\sum_{i=1}^{n}\sum_{j=1}^{m}\omega_{ij}x_{ij} \\ \min\sum_{i=1}^{n}\varepsilon_i = \min\left[\sum_{i=1}^{n}\sum_{j=1}^{m}(\omega_{ij} - \omega_{ij}^{j})x_{ij}\right]^2 \\ 1 \geq \omega_{ij} \geq 0 \end{cases} \tag{11}$$

Then transfer the multi-objective optimization problem into single objective optimization problem by Eq. (12):

$$\begin{cases} \min\lambda\sum_{i=1}^{n}\sum_{j=1}^{m}\left[(\omega_{ij} - \omega_{ij}^{j})x_{ij}\right]^2 + \\ (1-\lambda)\max\sum_{i=1}^{n}\sum_{j=1}^{m}\omega_{ij}x_{ij} \\ 1 \geq \omega_{ij} \geq 0 \end{cases} \tag{12}$$

where, λ is the balance coefficient. The function of λ is to balance the sum of the comprehensive values (y_i) and deviation values (ε_i). These two parts are making identical contribution to Eq. (12). Thus, the value of λ is usually defined as 0.5 [25]. According to the above stated conditions for $k_i^{(1)}$ and $k_i^{(2)}$, the LCEV is defined as follows.

$$\begin{aligned} L\left(k_i^{(1)}, k_i^{(2)}, \mu\right) = \lambda\sum_{i=1}^{n}\sum_{j=1}^{m}\Big\{\Big[\left(k_i^{(1)}p_{ij} + k_i^{(2)}q_{ij}\right) \\ -\left(k_i^{(1)}p_{ij}^{j} + k_i^{(2)}q_{ij}^{j}\right)\Big]x_{ij}\Big\}^2 \\ +(1-\lambda)\sum_{i=1}^{n}\sum_{j=1}^{m}\left(k_i^{(1)}p_{ij} + k_i^{(2)}q_{ij}\right)x_{ij} \\ -\mu\left(\left(k_i^{(1)}\right)^2 + \left(k_i^{(2)}\right)^2 - 1\right) \end{aligned} \tag{13}$$

If the partial derivatives of the LCEV with respect to $k_i^{(1)}, k_i^{(2)}$, and μ are set to zero, as in Eq. (13).

Eq. (14) consists of $3n$+1 sub-equation with a total number of $3n$+1 variables which can be solved by MATLAB, then we can obtain the values of $k_i^{(1)}$ and $k_i^{(2)}$. Substitute $k_i^{(1)}$ and $k_i^{(2)}$ into Eq. (8), then can obtain comprehensive weight $\boldsymbol{\omega}_{com}$.

$$\begin{cases} \frac{\partial L}{\partial k_i^{(1)}} = 2\lambda\sum_{i=1}^{n}\sum_{j=1}^{m}\Big\{\Big[\left(k_i^{(1)}p_{ij} + k_i^{(2)}q_{ij}\right) \\ \quad -\left(k_i^{(1)}p_{ij}^{j} + k_i^{(2)}q_{ij}^{j}\right)\Big]x_{ij}\Big\} \\ \quad \times(p_{ij} - p_{ij}^{j})x_{ij} \\ \quad +(1-\lambda)\sum_{i=1}^{n}\sum_{j=1}^{m}p_{ij}x_{ij} - 2\mu k_i^{(1)} = 0 \\ \frac{\partial L}{\partial k_i^{(2)}} = 2\lambda\sum_{i=1}^{n}\sum_{j=1}^{m}\Big\{\Big[\left(k_i^{(1)}p_{ij} + k_i^{(2)}q_{ij}\right) \\ \quad -\left(k_i^{(1)}p_{ij}^{j} + k_i^{(2)}q_{ij}^{j}\right)\Big]x_{ij}\Big\} \\ \quad \times(q_{ij} - q_{ij}^{j})x_{ij} \\ \quad +(1-\lambda)\sum_{i=1}^{n}\sum_{j=1}^{m}q_{ij}x_{ij} - 2\mu k_i^{(2)} = 0 \\ \frac{\partial L}{\partial \mu} = 1 - \left(\left(k_i^{(1)}\right)^2 + \left(k_i^{(2)}\right)^2\right) = 0 \end{cases} \tag{14}$$

3. Methods

Many real world decisions are taken with uncertain and imprecise evaluation data. In order to solve complex problems involving uncertainty, fuzzy set theory can be used. Thus this paper applied fuzzy logic to enhance the performance of the conventional TOPSIS method and to obtain final ranking of the voltage stability of power system. The main idea of Fuzzy-TOPSIS is based on the optimal solution should have the distance farthest from the negative ideal solution and the shortest from the positive ideal solution. The solution in this paper is determining as a positive ideal solution if it minimizes the cost or maximizes the benefit. The specific steps of Fuzzy-TOPSIS are presented as follows.

Step one: Normalize the initial index system

The attributes of different indices may be substantially different. Some indices, such as the active power margin and reactive power margin, represent a benefit-type index, where increasing index values indicate increasing voltage stability, while some indices, such as the sensitivity indices and participation index represent a cost-type index, where increasing index values indicate decreasing voltage stability. Moreover, the unit of X_1 is V while the unit of X_2 is kW. And the order of magnitudes of X_1 and X_2 also differ. It is thus not fair to compare different kinds of order of magnitudes of indexes, because those with the largest values would determine the final results. Thus, the vector norm method was employed to make the indexes dimensionless and to assign each index a comprehensive weight, ultimately allowing each index to determine the final results. The data matrix was configured as $\boldsymbol{X} = [x_{ij}]_{n*m}$ where x_{ij} is the observed value of the j^{th} alternative for the i^{th} index assuming there are n samples and m indexes in each sample.

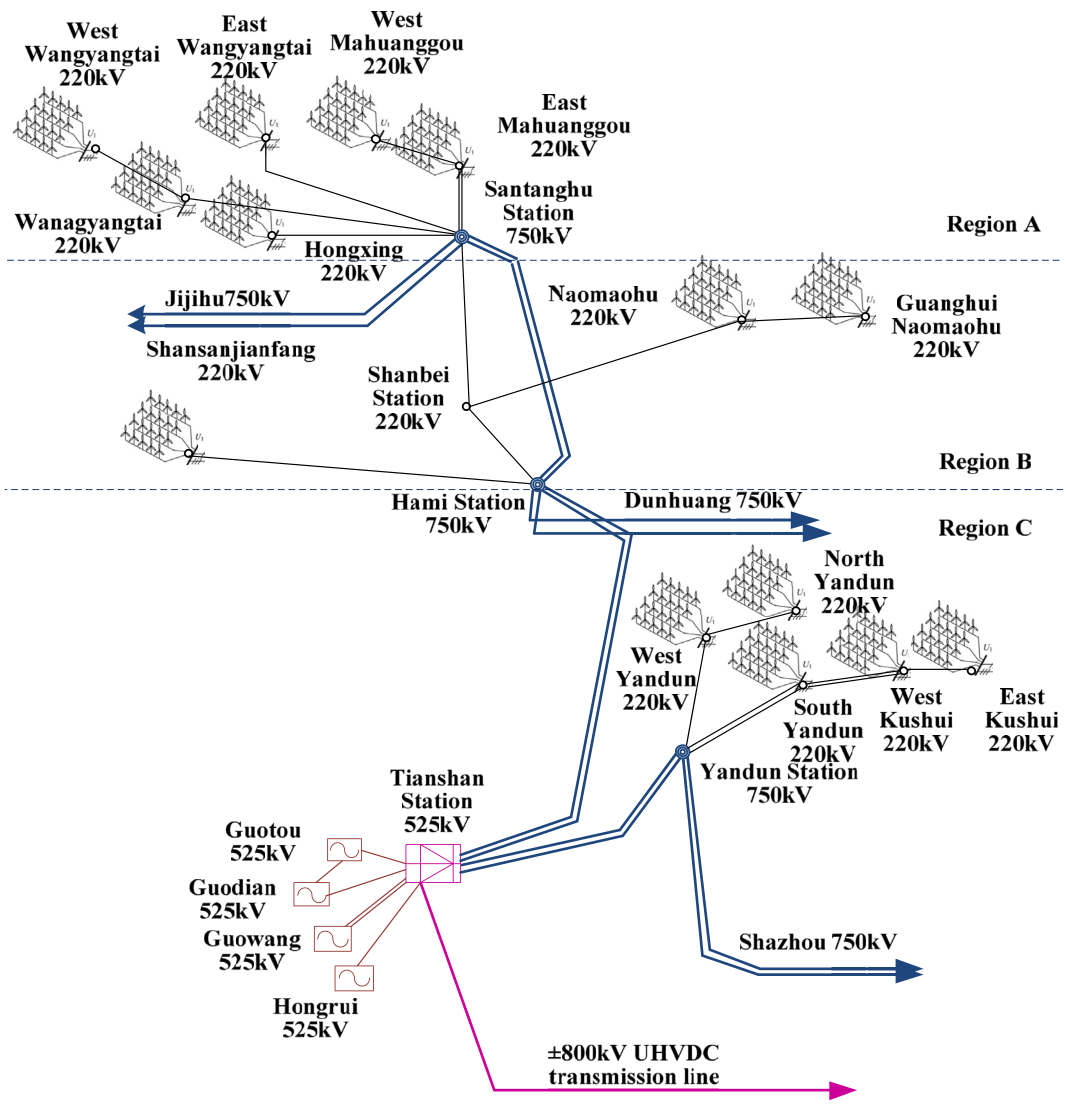


Fig. 2. Primary structure of the Hami grid employed in this study to demonstrate the proposed approach.

$$x_{ij}^{*}=\begin{cases} x_{ij}\Big/\sqrt{\sum_{i=1}^{n}x_{ij}^{2}} & (a)\\ \sqrt{\sum_{i=1}^{n}x_{ij}^{2}}\Big/x_{ij} & (b)\end{cases} \tag{15}$$

where $i = 1, 2, 3, \ldots, n$, $j = 1, 2, 3, \ldots, m$, $x_{ij} \geq 0$, $x_{ij} \in (0, 1)$, and $\sum_i^n (x_{ij}^*)^2 = 1$.

For the benefit-type index, we use Eq. (15a) to normalize the initial index while use Eq. (15b) to normalize the cost-type index. All the indexes are changed into benefit-type in this paper, which means increasing index values indicate increasing voltage stability.

Step two: Aggregate the fuzzy sets for the indices of all system components

Because of its simple computation process, a fuzzy linguistic value is always represented by a triangular fuzzy number (TFN), defined by the triplet $V = \{V_L, V_M, V_H\}$. The membership function $r_{ij}(\tilde{x}_{ij})$ of a TFN is expressed as follows.

$$r_{ij}(\tilde{x}_{ij})=\begin{cases} 0, \tilde{x}_{ij} > V^L \\ \dfrac{\tilde{x}_{ij}-V^L}{V^M-V^L}, V^L \leq \tilde{x}_{ij} < V^M \\ \dfrac{V^H-\tilde{x}_{ij}}{V^H-V^M}, V^M \leq \tilde{x}_{ij} < V^H \\ 0, \tilde{x}_{ij} > V^H \end{cases} \tag{16}$$

Here, V_L, V_M, V_H are precise numbers, where $V_L < V_M < V_H$, and V_L and V_H are the available bounds for evaluation the uncertainty of the criteria. The criteria performance is determined with linguistic terms that are obtained from decision makers. Then, aggregate the fuzzy decision matrix $\boldsymbol{R}$ for index i as follows.

$$\boldsymbol{R} = \left[r_{ij}^{L,M,H}\right]_{n\times n} \tag{17}$$

Step three: Structure the weighted normalized fuzzy decision matrix

The normalized weighted fuzzy decision matrix $\boldsymbol{Y}$ is constructed by multiplying $\boldsymbol{R}$ with the comprehensive weights of criteria (which is Eq. (8)), as follows:

$$\mathbf{Y} = \mathbf{R} \times \boldsymbol{\omega}_{\text{com}} = \left[y_{ij}\right]_{nm} \tag{18}$$

Step four: Determine the two types of ideal solutions

Indices are divided into sets J and J' according to whether they are benefit-type or cost-type indices, respectively, and ideal solutions denoted as a benefit-type ideal solution Y^+ and a cost-type ideal solution Y^- can be accordingly obtained from $\boldsymbol{Y}$ using Eqs. (19) and (20), respectively.

$$\begin{aligned} Y^+ &= \left\{ \left(y_{ij}^{\max} | j \in J \right), \left(y_{ij}^{\min} | j \in J' \right) i = 1, 2, \cdots m \right\} \\ &= \left\{ y_1^+, y_2^+ \cdots y_j^+ \cdots y_n^+ \right\} \end{aligned} \tag{19}$$

$$\begin{aligned} Y^- &= \left\{ \left(y_{ij}^{\min} | j \in J \right), \left(y_{ij}^{\max} | j \in J' \right) i = 1, 2, \cdots m \right\} \\ &= \left\{ y_1^-, y_2^- \cdots y_j^- \cdots y_n^- \right\} \end{aligned} \tag{20}$$

Step five: Calculate the distance of each system component from the two types of ideal solutions

Geometrical distance is a common means of calculating the distance between two values. Recently, the Euclid distance has demonstrated distinct advantages in terms of discrimination and evaluation. Therefore, the distance D_i^+ and D_i^- of each system component from Y^+ and Y^- is defined by Eqs. (21) and (22), respectively.

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(y_j^+ - y_{ij} \right)^2} \tag{21}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(y_j^- - y_{ij} \right)^2} \tag{22}$$

Step six: Calculate the closeness coefficients for all system components

As noted before, the solution in this paper is determining as a positive ideal solution. Thus, the closeness coefficient C_i which reflects the distance closest to D_i^+ and can be computed as

$$C_i = \frac{D_i^+}{D_i^- + D_i^+} \tag{23}$$

The value of C_i is between 0 and 1. Usually, the bigger the C_i value, the better the performance of a design. Which is also meaning that ranking according to C_i then can identify weak buses.

4. Results & discussion

4.1. Experimental setup and data collection

The proposed method was demonstrated based on an actual power grid in Hami City, China, which is a mainland city with a wealth of wind and coal energy resources. Moreover, the Hami grid has the characteristics of a multi-level voltage and complex power grid construction, making it ideal for demonstrating the proposed method. The built power system structure included the main AC grid structure with voltage levels from 0.69 kV to 750 kV, wind farms, thermal power plants, and a UHVDC transmission line.

As shown in Fig. 2, the Hami grid was divided into region A, region B, and region C according to the geographical locations of wind farm groups. Region A is comprised of six wind farms, and employed 220 kV lines for connection to the 750 kV STH station, while region B contains three main wind farms connected to the 750 kV HM station. Lastly, region C consists of five main wind farms connected to the 750 kV YD station. We note that wind energy resources are considerably more unstable than thermal power. As such, voltage collapse incidences are far more likely to occur with respect to wind farms than with respect to thermal power plants. Thus, only the voltage stability of the 220 kV bus bar systems associated with the wind farms in the Hami grid will be discussed here. The original indices data thereby obtained by load flow calculation and fault calculation (calculated by DIgSILENT Powerfactory software) are reprocessed based on Eq. (15), we obtain the following normalized data in Eq. (24).

$$\mathbf{X} = \begin{bmatrix}
0.1579 & 0.0464 & 0.2278 & 0.125 & 0.0031 & 0.0854 & 0.2234 & 0.0822 & 0.0400 & 0.0051 \\
0.1816 & 0.5452 & 0.1678 & 0.1379 & 0.0031 & 0.0642 & 0.2503 & 0.0962 & 0.0313 & 0.0029 \\
0.0738 & 0.0503 & 0.4543 & 0.1516 & 0.0032 & 0.0725 & 0.3037 & 0.1485 & 0.0639 & 0.0037 \\
0.3170 & 0.5496 & 0.6562 & 0.1073 & 0.0192 & 0.2066 & 0.1652 & 0.0209 & 0.0107 & 0.0068 \\
0.5097 & 0.5517 & 0.3389 & 0.6725 & 0.0529 & 0.8224 & 0.2084 & 0.0688 & 0.0157 & 0.0087 \\
0.4769 & 0.1504 & 0.0671 & 0.2264 & 0.3616 & 0.2206 & 0.2881 & 0.0532 & 0.0110 & 0.0067 \\
0.0349 & 0.0262 & 0.1485 & 0.0141 & 0.0009 & 0.2882 & 0.3454 & 0.2906 & 0.0522 & 0.0097 \\
0.4186 & 0.0696 & 0.0500 & 0.5505 & 0.0011 & 0.2268 & 0.3590 & 0.2258 & 0.0917 & 0.0358 \\
0.2868 & 0.086 & 0.3206 & 0.0925 & 0.0017 & 0.1420 & 0.3379 & 0.1931 & 0.0687 & 0.0141 \\
0.1368 & 0.1955 & 0.1490 & 0.1283 & 0.0011 & 0.0875 & 0.2076 & 0.0919 & 0.0892 & 0.0053 \\
0.1462 & 0.0327 & 0.0026 & 0.1965 & 0.0014 & 0.1259 & 0.2124 & 0.1106 & 0.0130 & 0.0110 \\
0.1576 & 0.0978 & 0.0360 & 0.1537 & 0.0014 & 0.0964 & 0.2491 & 0.1522 & 0.0070 & 0.0065 \\
0.1259 & 0.0812 & 0.0803 & 0.1423 & 0.0011 & 0.1008 & 0.2885 & 0.2000 & 0.0077 & 0.0071 \\
0.0971 & 0.0265 & 0.0803 & 0.1291 & 0.9306 & 0.1344 & 0.2874 & 0.2079 & 0.0070 & 0.0126
\end{bmatrix}_{14 \times 10} \tag{24}$$

4.2. Comprehensive weight calculation

The objective weights calculated by the EW method, i.e. by Eqs. (1), (2), (3), and (4), are listed in Eq. (25).

$$\mathbf{q}_{objective} = \begin{bmatrix} 0.0544 & 0.0711 & 0.0233 & 0.0982 & 0.0750 & 0.0751 & 0.0573 & 0.0448 & 0.0376 & 0.0317 \\ 0.1124 & 0.0690 & 0.1054 & 0.0448 & 0.0771 & 0.1117 & 0.0707 & 0.0588 & 0.0517 & 0.0234 \\ 0.1199 & 0.0690 & 0.0873 & 0.0715 & 0.0771 & 0.1112 & 0.0104 & 0.0092 & 0.0043 & 0.0025 \\ 0.1048 & 0.0691 & 0.0771 & 0.0855 & 0.0760 & 0.1036 & 0.0994 & 0.0403 & 0.0762 & 0.1124 \\ 0.0195 & 0.0835 & 0.0226 & 0.0774 & 0.0604 & 0.0066 & 0.0916 & 0.0724 & 0.0767 & 0.1000 \\ 0.0561 & 0.0698 & 0.1002 & 0.0396 & 0.0396 & 0.0804 & 0.1200 & 0.0720 & 0.1133 & 0.0998 \\ 0.0901 & 0.0754 & 0.0214 & 0.0818 & 0.0583 & 0.0121 & 0.0143 & 0.0199 & 0.0080 & 0.0075 \\ 0.0298 & 0.0718 & 0.0920 & 0.0996 & 0.0767 & 0.0569 & 0.0110 & 0.0120 & 0.0053 & 0.0169 \\ 0.0547 & 0.0705 & 0.0346 & 0.0984 & 0.0766 & 0.0777 & 0.0112 & 0.0112 & 0.0051 & 0.0080 \\ 0.1013 & 0.0691 & 0.0892 & 0.0736 & 0.0771 & 0.1017 & 0.0319 & 0.0273 & 0.0176 & 0.0172 \\ 0.0423 & 0.0710 & 0.1166 & 0.0109 & 0.0757 & 0.0498 & 0.0990 & 0.1081 & 0.0987 & 0.1348 \\ 0.0806 & 0.0692 & 0.1030 & 0.0470 & 0.0768 & 0.0892 & 0.1251 & 0.1614 & 0.1569 & 0.1195 \\ 0.0818 & 0.0693 & 0.0826 & 0.0769 & 0.0768 & 0.0842 & 0.1258 & 0.1728 & 0.1639 & 0.1155 \\ 0.0516 & 0.0715 & 0.0444 & 0.0940 & 0.0761 & 0.0391 & 0.1323 & 0.1899 & 0.1848 & 0.2109 \end{bmatrix}_{14\times10} \quad (25)$$

For subjective weighting, experts were invited to provide scores on the basis of the pairwise comparison of indices to represent the relative importance of the various indicators. Here, it is assumed that the subjective weighting of each index is equivalent in all wind farms. The comparison matrix and the weight of each index are obtained using Eqs. (5), (6), and (7). The first pairwise comparison matrix from voltage stability of view ($\boldsymbol{A}_1\boldsymbol{E}$) is $\mathbf{A_1E} = \begin{bmatrix} 1 & 2 & 2 \\ 1/2 & 1 & 2 \\ 1/2 & 1/2 & 1 \end{bmatrix}$, and transient voltage stability of view ($\boldsymbol{A}_2\boldsymbol{E}$) is $\mathbf{A_2E} = \begin{bmatrix} 1 & 1/3 & 1/3 & 1/2 \\ 3 & 1 & 1/2 & 1/2 \\ 3 & 2 & 1 & 1/2 \\ 2 & 2 & 2 & 1 \end{bmatrix}$. Second pairwise comparison matrix from PV and QV curves of view ($\boldsymbol{E}_1\boldsymbol{X}$) is $\mathbf{E_1X} = \begin{bmatrix} 1 & 1/3 & 1/3 \\ 3 & 1 & 1/2 \\ 3 & 2 & 1 \end{bmatrix}$, while the third pairwise comparison matrix from sensitivity analysis of view ($\boldsymbol{E}_2\boldsymbol{X}$) is $\mathbf{E_2X} = \begin{bmatrix} 1 & 3 \\ 1/3 & 1 \end{bmatrix}$. The weight of each pairwise comparison matrix was obtained using Eq. (7), which are $\boldsymbol{p}_{\text{subjective}}(\boldsymbol{A}_1\boldsymbol{E}) = [0.4930, 0.3111, 0.1969]^T$, $\boldsymbol{p}_{\text{subjective}}(\boldsymbol{A}_2\boldsymbol{E}) = [0.1119, 0.2099, 0.2946, 0.3834]^T$, $\boldsymbol{p}_{\text{subjective}}(\boldsymbol{E}_1\boldsymbol{X}) = [0.1189, 0.4406, 0.4406]^T$, and $\boldsymbol{p}_{\text{subjective}}(\boldsymbol{E}_2\boldsymbol{X}) = [0.75, 0.25]^T$. Then can get the final subjective weights: $\boldsymbol{p}_{\text{subjective}} = [0.5686, 0.2172, 0.2172. 0.2333, 0.0778, 0.1960, 0.1119, 0.2099, 0.2946, 0.3834]^T$.

Moreover, the proportions of importance attached to the objective and subjective weights were calculated for the wind farms by Eqs. (8), (9), (10), (11), (12), (13), and (14), and the results are shown in Fig. 3. The results shown in Fig. 3 indicate that the method employed for calculating objective and subjective proportions is nearly mutually complementary with each other. For example, the objective values of voltage margin indexes (k_{q1}) are high while the subjective values of voltage margin indexes (k_{p1}) are low. Finally, the comprehensive weights of indices $\boldsymbol{\omega}_{\text{com}}$ defined by Eq. (8) are obtained as Eq. (26).

$$\boldsymbol{\omega}_{com} = \begin{bmatrix} 0.0800 & 0.2285 & 0.2184 & 0.2531 & 0.1081 & 0.2099 & 0.1181 & 0.1079 & 0.0689 & 0.1780 \\ 0.1268 & 0.2279 & 0.2414 & 0.2375 & 0.1095 & 0.2256 & 0.1319 & 0.1197 & 0.1751 & 0.0953 \\ 0.1335 & 0.2279 & 0.2341 & 0.2440 & 0.1096 & 0.2254 & 0.1051 & 0.0724 & 0.1139 & 0.1148 \\ 0.1201 & 0.2279 & 0.2305 & 0.2484 & 0.1087 & 0.2217 & 0.1462 & 0.1021 & 0.1704 & 0.2376 \\ 0.0618 & 0.2327 & 0.2184 & 0.2458 & 0.0985 & 0.1961 & 0.1223 & 0.1429 & 0.1068 & 0.2157 \\ 0.0733 & 0.2278 & 0.2264 & 0.2339 & 0.0857 & 0.1986 & 0.1492 & 0.1426 & 0.1432 & 0.2156 \\ 0.1076 & 0.2299 & 0.2183 & 0.2472 & 0.0972 & 0.1964 & 0.1016 & 0.0876 & 0.0369 & 0.1341 \\ 0.0658 & 0.2288 & 0.2359 & 0.2536 & 0.1093 & 0.2041 & 0.0606 & 0.0773 & 0.1198 & 0.1662 \\ 0.0802 & 0.2284 & 0.2199 & 0.2532 & 0.1092 & 0.2109 & 0.0846 & 0.0756 & 0.0513 & 0.1565 \\ 0.1171 & 0.2279 & 0.2348 & 0.2446 & 0.1095 & 0.2208 & 0.1128 & 0.0896 & 0.1282 & 0.1318 \\ 0.0723 & 0.2285 & 0.2465 & 0.2335 & 0.1086 & 0.2022 & 0.1458 & 0.1680 & 0.2263 & 0.1526 \\ 0.0997 & 0.2280 & 0.2404 & 0.2380 & 0.1093 & 0.2154 & 0.1641 & 0.2176 & 0.2680 & 0.1930 \\ 0.1007 & 0.2280 & 0.2324 & 0.2456 & 0.1093 & 0.2133 & 0.1642 & 0.2285 & 0.2579 & 0.2298 \\ 0.0781 & 0.2287 & 0.2217 & 0.2515 & 0.1089 & 0.1999 & 0.1732 & 0.2460 & 0.2401 & 0.3390 \end{bmatrix}_{14\times10} \quad (26)$$

Table 1
Fuzzy-topsis results for the 14 wind farms of the hami grid.

No.	Y^+	Y^-	D^+	D^-	C_i
1	0.0381	0.0006	0.1204	0.0503	0.2800
2	**0.0420**	**0.0009**	**0.1467**	**0.0731**	**0.3763**
3	**0.0737**	**0.0032**	**0.1219**	**0.0434**	**0.4271**
4	0.0961	0.0016	0.1467	0.0642	0.3639
5	**0.0947**	**0.0034**	**0.0843**	**0.0473**	**0.2311**
6	**0.0480**	**0.0083**	**0.1482**	**0.0518**	**0.2673**
7	**0.0936**	**0.0027**	**0.1204**	**0.0873**	**0.4592**
8	0.0407	0.0007	0.1269	0.0584	0.3360
9	0.0496	0.0012	0.1226	0.0516	0.2990
10	0.0340	0.0004	0.1286	0.0483	0.3664
11	0.0384	0.0009	0.1243	0.0535	0.3154
12	**0.0749**	**0.0010**	**0.1379**	**0.0429**	**0.2693**
13	0.0340	0.0002	0.1399	0.0535	0.3177
14	0.0322	0.0002	0.1232	0.0575	0.2988

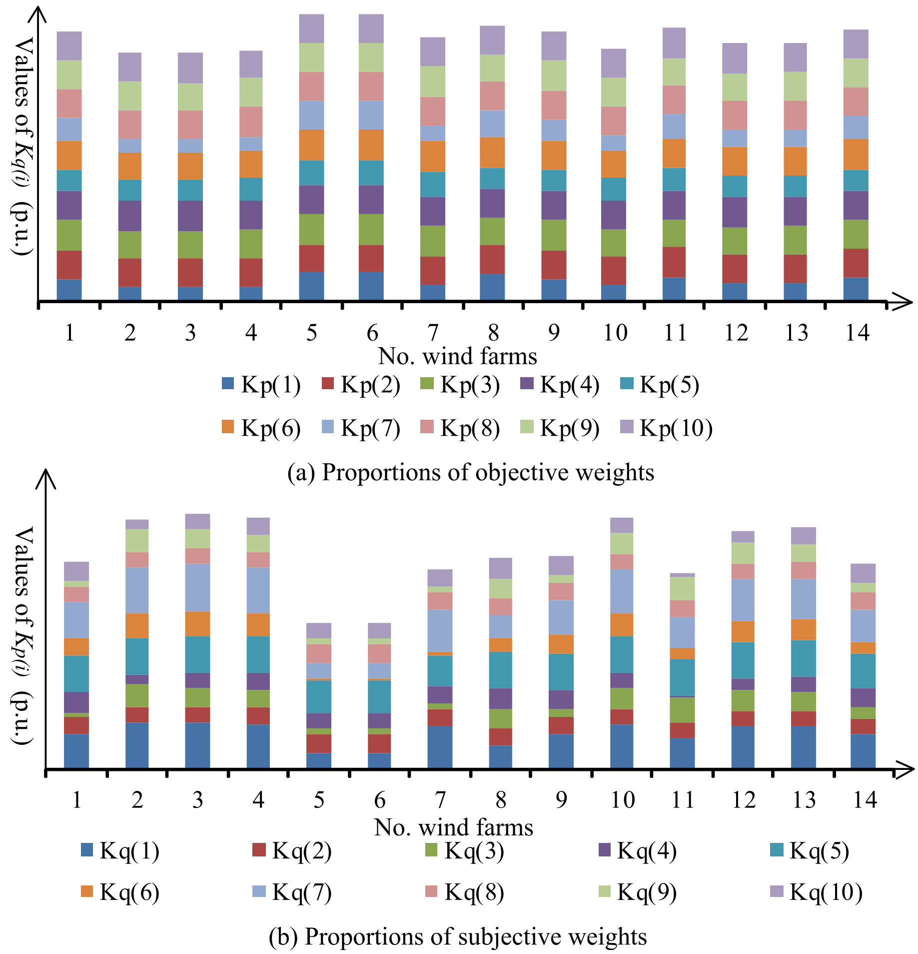


Fig. 3. Proportions of variously determined weights for the 14 wind farms of the Hami grid.

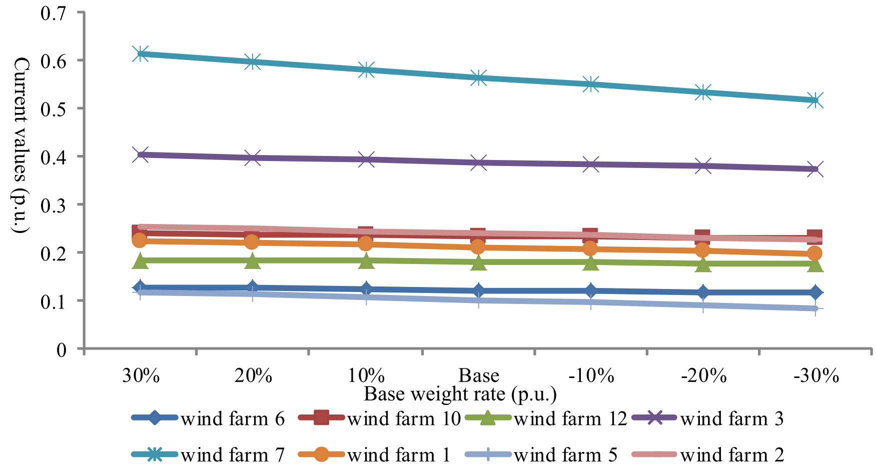
4.3. Rank final results by using Fuzzy-TOPSIS

Fuzzy-TOPSIS is employed to obtain a final ranking of system components in terms of the voltage stability, considering system functionality and proportionality. Firstly, reviewing the general information of three regional wind groups, experts group provided the linguistic ratings for the performance of 14 wind farms of the Hami grid. Secondly, Y^+ and Y^- were calculated using Eqs. (19) and (20), and the values of C_i were obtained using Eqs. (21) and (23). The results for the overall computational process are listed in Table 1.

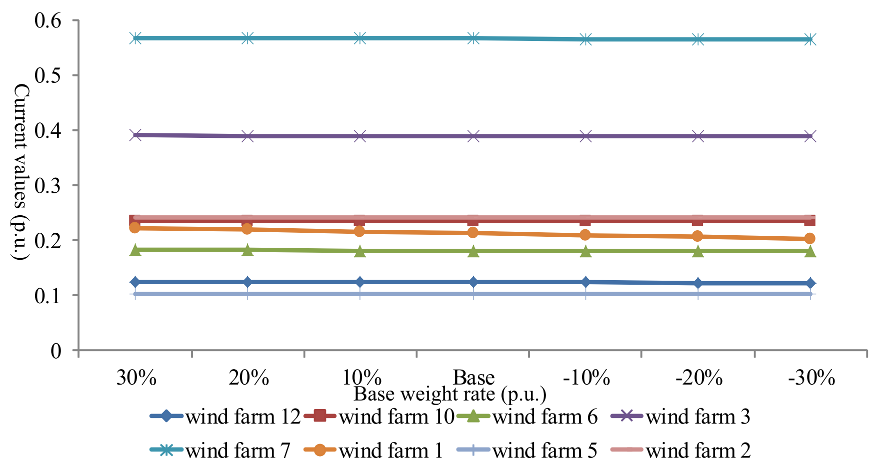
We can draw the following conclusions according to the obtained values of C_i in Table 1: wind farm 7 (Shisanjianfang) is a relatively robust component of the studied power grid; however, the maximum value of C_i obtained indicates that wind farm 5 (WYT) is the weakest component. Moreover, the most stable and unstable wind farms are marked in bold in the Table 1. We note that wind farm 5 is most sensitive to disturbances, and could cause a power failure in the case of a serious fault. Thus, wind farm 5 should be a focal monitoring region. The results of finding the most stable and unstable bus bar are also consistent with the PMU analysis results which are applied by Hami Power Company. Moreover, different kinds of index are compared with each other in order to further verify the superiority and comprehensive of the proposed method, as

Table 2
Final ranking of 14 wind farms of hami grid from most robust to weakest of different kinds of methods.

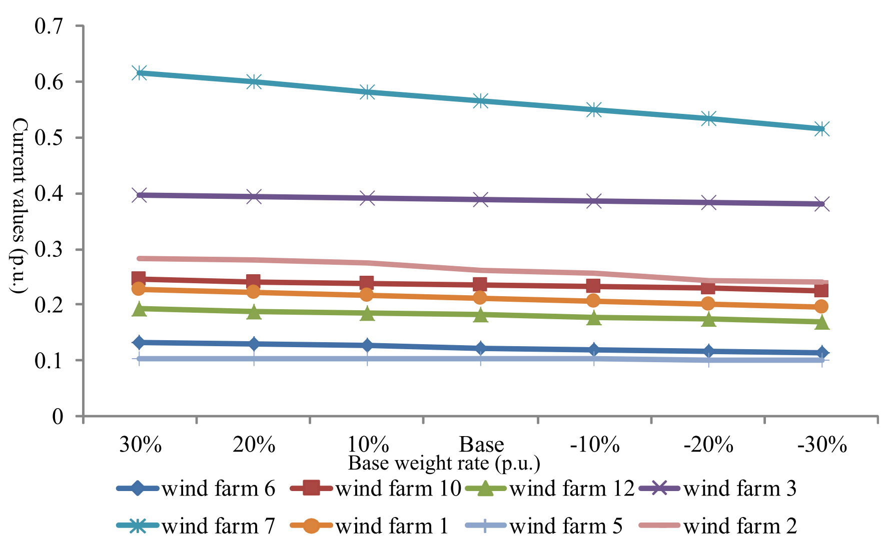
No.	Wind farm	MCDM	X1	X2	X5	X6	X9	X10
1	Wast MMH	7	5	5	14	5	8	8
2	East MMH	3	6	4	6	7	10	9
3	Hongxing	2	8	2	5	1	1	2
4	West WYT	10	4	10	4	6	3	11
5	WYT	4	9	6	3	4	7	7
6	East WYT	8	2	12	1	9	9	5
7	Shisanjianfang	13	13	9	2	14	2	13
8	KH Naomaohu	11	12	13	9	11	5	4
9	Naomaohu	9	11	8	11	13	11	6
10	South Yandun	14	10	3	12	12	6	12
11	North Yandun	1	1	1	8	10	4	1
12	West Yandun	12	14	11	10	8	13	10
13	West Kushui	6	3	14	13	3	12	3
14	East Kushui	5	7	7	7	2	14	14



(a) X_1



(b) X_5



(c) X_{10}

Fig. 4. Sensitivity analysis results of three sub-criteria X_1, X_5, and X_{10} of eight wind farms.

seen in Table 2.

Table 2 lists the ranking of wind farm stability for the Hami grid in the order from highest to lowest for the individual indices employed and for the multi-index system proposed in this work. As shown in the table, different ranking results are generally obtained by applying different indices under equivalent conditions. For example, wind farm 7 is deemed the most stable based on P-V curve and sensitivity analyses while wind farm 3 is deemed the most stable based on Q-V curve analysis, and wind farm 7 is far down the list. As discussed, this is the result of the different mathematical relations for the physical quantities of a power system employed by the individual indices. Thus, the results demonstrate the necessity of applying a comprehensive voltage stability assessment for power grids. Moreover, the results of the proposed method present the nearly same ranking results for the weakest and the most stable bus bars obtained using other methods for the study case, implying the dependability of the approach.

4.4. Sensitivity analysis

In Section 2, the values of weights are determined according to the proposed comprehensive weight calculation method. However, weight values could be changed with applying other kinds of methods. Thus, we conduct a sensitivity analysis to identify the effects of ten sub-index on the comprehensive voltage stability evaluation in the fourteen selected wind farms analyzed in this study. Sensitivity analysis is the method that can testify the stability and robustness of the proposed method [26]. The normal Step is to increase or decrease some indexes and then see the final rank results again. The method can be proved as robustness and reasonable when the rank results remain the same. According to Fig. 1, ten sub-criteria are divided into four analysis levels, namely PV and QV curves, sensitive analysis, modal analysis, and time domain simulation analysis. We suppose ten initial sub-criteria of each level change at rates of 30%, 20%, 10%, 0%, -10%, -20% and -30%, respectively (all base weights are shown in Eq. (26)). And then see the final rank results again to testify the validity of the proposed method. We choose three sub-criteria which are indexes X_1, X_5, and X_{10} to make comparisons. Meanwhile, the other parameters remained unchanged. For example, the rest nine indexes remain the same value when index X_1 changed. The voltage stability of wind farms will then be recalculated, as well as their ranks. Since there are fourteen alternatives, only most four stable and unstable wind farms (rank results), which are wind farms 1, 2, 3, 5, 6, 7, 10 and 12 present in Fig. 4.

It can be seen in Fig. 4 that the final score of each alternative decreases when the weight of sub-criteria X_1, X_5, and X_{10} becomes less important. Thus, they are most sensitive to these weights. Meanwhile, the scores of all wind farms have small variations, no matter how the sub-criteria X_1, X_5, and X_{10} change. However, no matter how these weights change, the 7th wind farm keeps the first ranking and the 5th wind farm keeps the last ranking as the base case. It can be verified that the voltage stability analysis of wind farms using the proposed comprehensive weights calculation method is robust.

5. Conclusion

In this paper, a method for conducting voltage stability analysis in power systems is presented. Ten voltage stability indices are integrated to form a multi-criteria index system to identify the weakest bus. The integration process employs the MCDM method based on a combination of the subjective AHP method and the objective entropy method to set the weights of the various indices in a comprehensive fashion. Moreover, the Fuzzy-TOPSIS method is adopted to rank the system components of a power grid, and thereby identifying weak buses. Sensitivity analysis is performed to verify the robust and effective of the proposed weight calculation approach. The experimental results and analysis for the wind farms of an actual power grid in Hami City, China have demonstrated that the proposed method represents an innovative approach for determining the weakest bus in power systems.

The originality of the paper comes from its integration of EW-AHP based on LCEV and Fuzzy-TOPSIS for weak bus bar selection by distinguishing the most stable and unstable bus bar from generic power grid for the first time in literature. The result aims to guide researchers and other investors to easily forecast power grid projects' stable performance and decide accordingly. The entire computational process was programmed using the C programming language. The next stage of this research will be to design complete application software based on the original programming, and apply it in actual power grid operations to analyze the voltage stability of power systems.

Declarations

Author contribution statement

Jiahui Wu: Conceived and designed the experiments; Wrote the paper.

Haiyun Wang: Performed the experiments.

Lei Yao, Zhi Kang: Analyzed and interpreted the data.

Qiang Zhang: Contributed reagents, materials, analysis tools or data.

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Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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