Global Energy Interconnection
Development and Cooperation Organization

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Volume 3 Number 2 April 2020 (140-148)
DOI: 10.14171/j.2096-5117.gei.2020.02.005

Global Energy Interconnection

Contents lists available at ScienceDirect
https: //www.sciencedirect.com/journal/global-energy-interconnection

Full-length article

Extreme scenario extraction of a grid with large scale wind power integration by combined entropy-weighted clustering method

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Abstract: Large-scale integration of wind power into a power system introduces uncertainties to its operation and planning, making the power system operation scenario highly diversified and variable. In conventional power system planning, some key operation modes and most critical scenarios are typically analyzed to identify the weak and high-risk points in grid operation. While these scenarios may not follow traditional empirical patterns due to the introduction of large-scale wind power. In this paper, we propose a weighted clustering method to quickly identify a system's extreme operation scenarios by considering the temporal variations and correlations between wind power and load to evaluate the stability and security for system planning. Specifically, based on an annual time-series data of wind power and load, a combined weighted clustering method is used to pick the typical scenarios of power grid operation, and the edge operation points far from the clustering center are extracted as the extreme scenarios. The contribution of fluctuations and capacities of different wind farms and loads to extreme scenarios are considered in the clustering process, to further improve the efficiency and rationality of the extreme-scenario extraction. A set of case studies was used to verify the performance of the method, providing an intuitive understanding of the extreme scenario variety under wind power integration.

Keywords: Wind power, Load, Weighted clustering, Entropy weight, Extreme scenario extraction.

1 Introduction

With the integration of large-scale renewable energy, the operation modes of traditional power systems have changed. The randomness and volatility of renewable energy have introduced uncertainties to power system planning and operation [1-3]. During the technical evaluation of a system planning scheme, it is time-consuming to analyze all the time-series scenarios of a horizontal-year grid operation. Therefore, several key scenarios are selected for analysis and verification. In traditional power system analysis, a small number of extreme scenarios are chosen. If the system is safe and stable in those scenarios, the system is said to be stable in all operation modes [4]. The selection of extreme scenarios is often based on empirical data such as historical information, experience, and judgment of system planners, thereby lacking theoretical support. In

Received: 16 November 2019/ Accepted: 26 February 2020/ Published: 25 April 2020

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particular, due to the uncertainty brought about by large-scale renewable energy integration, the existence of extreme scenarios of power grid operation in periods of relatively high power line load, or in some other typical period, is not known [5], which makes it difficult to extract the scenarios. Therefore, it is necessary to re-analyze, mine, and scan the grid operation scenarios to identify the high-risk or extreme scenarios of system operation, to improve the rationality of transmission network planning [6,7], economic dispatch [8] and efficiency of power grid operation load flow analysis [9], risk analysis and assessment [10,11], security and stability check [12,13], as well as help planners and decision makers conduct rapid technical feasibility assessment of a power grid and source planning schemes [14].

Extreme scenarios refer to the high-risk and worst operation scenarios from annual scenarios that will probably cause system instability, load flow violation, wind curtailment or load shedding, et al. The extraction of extreme scenario from a pool of operation scenarios with the worst wind power or load fluctuations in the transmission network planning is usually a manual process. It does not consider the temporal correlation between wind power and load; therefore, the extracted scenarios may not exist in the actual power system, resulting in a conservative planning scheme.

Time-series scenario analysis and scenario reduction [15-17], which capture the temporal variations of wind power and load and the correlation between load and wind power [18,19], is a reasonable and effective way to identify the extreme scenarios. In [20], the k-means clustering method was used to extract typical time-series scenarios for transmission network expansion planning by considering the correlation and spatial distribution characteristics between the time-series load and wind power, while wind power and load located closely are clustered in advance to reduce the clustering variables. In [12], an improved k-means clustering method was utilized to extract the key scenarios of a system time-series operation scenario set to perform a transient security risk assessment for large-scale power grid planning. In [21], from a planning point of view, a framework for the rapid stability scanning of future grid scenarios through an improved feature selection and self-adaptive PSO-k-means clustering algorithm was proposed. By clustering the time-series operation points spanning a long period of time, stability analysis was performed only on a small number of representative cluster centroids, instead of on the full set of operating conditions.

These studies provided various ideas and methods for scenario reduction. However, they do not provide a method to directly pick the extreme scenarios from the time-series operation scenarios, especially in the grid stability assessment for the planning stage.

The main contribution of this paper to existing research is a weighted-clustering-based extreme-scenario extraction framework that considers the spatiotemporal correlations of wind power and load from a planning perspective for the renewable energy sector. The research objective of this study is to enable the rapid identification of extreme scenarios of system operation with fewer data. Additionally, it uses the entropy weighted method to capture the characteristics of wind power and load fluctuations, while considering the varying impact of wind power and load on the extreme scenarios.

The rest of the paper is organized as follows: Section 2 outlines the typical scenario generation method as the basis of extreme scenario extraction. Section 3 introduces the extreme scenario extraction method, and Section 4 describes how to set the clustering weight according to a multi-influence factor. Section 5 details a case study to verify the effectiveness of the proposed method. Section 6 concludes the paper by discussing the results and their significance and implications, and the future direction.

2 Typical scenarios generation based on scenario clustering

Clustering is a common scenario reduction method in power systems. In this paper, the concept of scenario clustering is used to extract extreme scenarios. Meanwhile, typical operation scenarios should be obtained followed by the extreme scenario extraction because the scenarios far from the clustering center are regarded as extreme scenarios. The number of scenarios is reduced by clustering the original data in the time dimension. Thus, some typical scenarios can represent most of the time-series scenarios, while simultaneously maintain the time-series correlation between data.

Different from the online security evaluation at the system operation level, where more detailed and accurate clustering variables are utilized, offline security and stability evaluation from a system planning perspective aims at making a fast preliminary evaluation of the planning scheme. Therefore, the wind power and load in each node are selected as the clustering variables, and an annual time-series data of 8,760 hours is clustered in the time dimension to obtain the typical scenarios.

2.1 K-means clustering

The traditional k-means clustering algorithm assigns in advance data objects to the nearest class according to the principle of minimum distance to the k initial clustering centers selected, and divides the dataset into different categories through an iterative process, so that the criterion function for evaluating the clustering performance could be optimized [22].

For a given dataset, $x=\{x_i \mid x_i \in R^h, i=1,2,\ldots,t\}$, where h is the dimension of the data variable and i is the number of data in the dataset. The algorithm divides the data into k classes, which are C_1, C_2, ...,C_k, and c_1, c_2, ...,c_k are the clustering centers, respectively, defined as follows:

$$C_j = \frac{1}{N_j}\sum_{x_i \in C_j} x_i \tag{1}$$

where N_j is the number of samples in class C_j, and the similarity of data in class can be measured by the weighted Euclidean distance to the center:

$$d\left(x_i, x_j\right) = \sqrt{\sum_{v=1}^{h} w_v \left(x_{iv} - x_{jv}\right)^2} \tag{2}$$

where w_v is the weight of the data variable. In conventional clustering, w_v is generally set as 1. In this study, w_v is determined by factors that will be discussed in more detail in the following section. K-means clustering can be transformed into an optimization problem with the objective function shown below [23]:

$$\arg\min_{C} \sum_{i=1}^{k} \sum_{x_j \in C_i} \left\| x_j - c_i \right\|^2 \tag{3}$$

This is an NP problem, for which several efficient heuristic solution techniques have been proposed [22]. The clustering center derived by solving this problem will represent the typical scenarios.

2.2 Wind power-load time-series scenarios generation

Accurate wind power-load model featuring wind power and load fluctuation and their correlation characteristics is of great significance for the extraction of typical operation scenarios [24,25]. In general, the projected annual time-series wind power and load data can be directly processed as a combined scenario set, to maintain temporal correlation between data. Moreover, the wind power-load model can be developed based on historical data to generate more sample data. It is necessary to consider the correlation among different wind power values and the temporal correlation between wind power and load when constructing the wind power-load model and scenario set, otherwise unreasonable scenarios will be generated. Furthermore, the influence of the distribution characteristics of wind power and load also must be included in the scenario generation.

According to the hourly time-series data of each wind farm and load in the system, a combined wind power-load operation scenario set based on temporal correlation and geographical distribution characteristics was constructed, which is $S=\left[P_{it}^{\mathrm{w}}, P_{jt}^{\mathrm{l}}\right]$, i=1,2,…N_{w}, j=1,2,…N_{l}, t=1,2…,8760, where P_{it}^{w} and P_{jt}^{l} are the outputs of wind power and load, N_{w} and N_{l} are the number of wind farms and loads. Each period, t, corresponds to an operation scenario, with a total of 8,760 scenarios. Each operation scenario includes (N_{w}+N_{l}) variables. As shown in Fig. 1, the data points include two wind farms and one load, where each point represents a corresponding scenario.

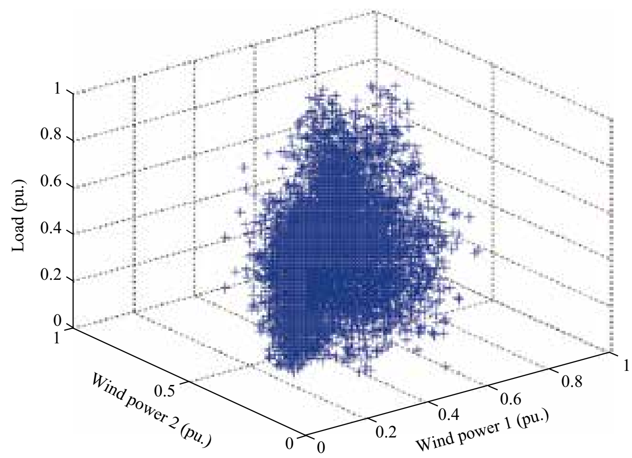

Fig. 1 Wind power-load scenario set

It is worth noting that if the dimension of variables in the scenario is too high, i.e., there are a large number of variables, steps should be taken to reduce it; otherwise, the clustering will become meaningless, including clustering of variables with the same characteristics [20] or prioritizing a portion of variables according to their importance to the analysis issues [11].

3 Extreme scenarios extraction

Based on the wind power-load time-series scenarios, several typical scenarios, which are the clustering center, are generated by clustering in the time dimension. In each cluster, edge points far away from these clustering centers are considered as the extremum corresponding to each typical scenario. Multiple typical scenarios will correspond to multiple extreme scenarios. The extraction process is shown in Fig. 2. The weighted Euclidean distance is utilized to measure the distance between the clustering center and the edge points.

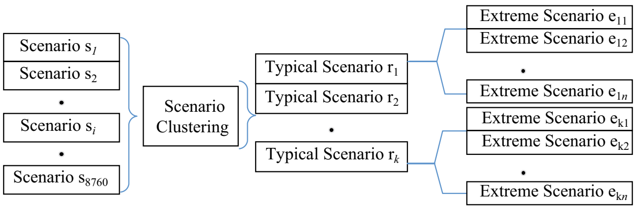

Fig. 2 Scheme for extreme-scenario extraction method

The extreme operating scenario is expressed as:

$$E = \{ e_i | \ d\left(e_i, c_i\right) = \max_{x_j \in C_i} d\left(x_j, c_i\right), \ e_i \in R^h, \ i = 1, 2, \dots, k \} \tag{4}$$

where i is the number of classes, and e_i is the edge points related to the i th class. If n edge points are taken from each class, i.e., each typical scenario corresponds to n extreme scenarios, then a total of $n \times k$ extreme operation scenarios will occur, which are defined as:

$$E^m = \{ e_i^m | d\left(e_i^m, c_i\right) = \max_{x_j \in C_i - e_i^q} d\left(x_j, c_i\right), e_i^m \in R^h, \ i = 1, 2, \dots, k, q = 1, 2, \dots, (m-1) \} \tag{5}$$

where m represents the extreme scenario at layer m corresponding to each typical scenario, $m = 1,2,\dots, n$.

Generally, the edge point of the first layer is the worst extreme scenario in each class.

The extreme scenarios are heavily depend on the typical scenarios, due to the use of the clustering method. Extreme scenarios may cover scenarios where wind power and load are extreme or even. That is, the extreme scenario is not only located at the outer contour of the sample data points, but also within the area bordered by the data points, which depends on the number of typical scenarios selected.

In order to improve the efficiency of the extraction method, a clustering evaluation index is proposed to determine the optimal clustering number. Refer to the sum of the squared error (SSE), which is one of the most widely used criterion of clustering [26], in this study, the sum of the weighted Euclidean distance between extreme points and their corresponding clustering centers is used, and we termed this sum the "extreme points squared error (EPSE)," which is defined as:

$$J_e = \frac{1}{k} \sum_{i=1}^{k} \left[\frac{1}{m} \sum_{x_j \in E_i} d\left(x_j, c_i\right) \right] \tag{6}$$

where E_i is the extreme points set corresponding to the i clustering center, k is the number of clusters.

4 Cluster variables weight settings

The cluster variables differ greatly by type, dimension, and importance. It is necessary to set the clustering weight such that it reflects the characteristics of different clustering variables.

The traditional Euclidean distance does not reflect the importance of each dimensional variable. For example, the contribution of variables of wind farms at different locations to the extreme scenarios will vary depending on the influence of the farm on the research problem. Thus, in the process of clustering, the importance is different. It is necessary to consider the importance of variables and set the subjective weights. Meanwhile, inherent information of variables should also be considered to reflect their contribution to the research problem through objective weights.

Therefore, this paper proposes the basis of k-means clustering different values of weight according to the volatility of different variables over time and the influence on extreme scenarios.

In terms of objective weight setting, variables with large temporal fluctuations often have a strong influence on the extraction of extreme scenarios. The greater the volatility of the variable, the farther the data edge point is from the cluster center point, and the more likely it is to contribute to the extreme edge point. Therefore, the fluctuation characteristics of variables can be used as an alternative for objective weight setting.

In terms of subjective weight setting, the influence of each variable on the study problem should be analyzed, and variables with a large impact should be given a larger weight. The weight can generally be obtained based on experience or machine learning sample training.

For example, considering the influence of variables on transient safety and stability analysis, the variable of wind farm capacity has an impact on the stability of the system. The greater the capacity of the wind farm, the larger the impact and the stronger the contribution to extreme scenarios. Therefore, it is necessary to set a larger weight for this variable.

4.1 Entropy weight method

The entropy weight method is an objective weighting method that is widely used in power system index evaluation and index weight setting [27,28]. The essence of this method is to measure the difference between the variable by the entropy value and then set the weight of each variable. It only reflects the volatility of the variable data and is independent of the type and relationship between variables.

According to its characteristics, entropy can be used to determine the dispersion of a variable. The greater the dispersion of the variable, the greater its influence (weight) on the comprehensive evaluation. Based on this principle, more accurate results were obtained by calculating the Euclidean distance between the scenarios with entropy-weighted variables than that by using only the Euclidean distance. For example, in the traditional method, although the variable data may have a large volume, it may not contain useful information, which results in bad clustering results. However, the entropy weight method was adopted to assign an objective weight to each variable, thus weakening the negative impact on the clustering.

Different variables have different dimensions. To compare the data of different variables, it must be standardized. For this study, data was compressed to the interval [0,1], and the process is shown below:

$$S_{ij} = \frac{P_{ij} - \min(P_{ij})}{\max(P_{ij}) - \min(P_{ij})} \tag{7}$$

The greater the volatility of the variable in the time dimension, the smaller the entropy value of the variable and the more effective the information it covers. Furthermore, the variable's contribution to the extreme scenario selection is greater, and hence a larger weight is required. Detailed steps to determine the weight by the entropy weight method are as follows. Let there be T scenario objects to be clustered in the time dimension, and each scenario contain (N_w+N_1) dimensional variables. Each variable is called a characteristic index, and its entropy value is expressed as [29]:

$$H_i = \frac{1}{\ln n}\sum_{j=1}^{T} f_{ij}\ln f_{ij} \tag{8}$$

$$f_{ij} = \frac{s_{ij}}{\sum_{j=1}^{T} s_{ij}} \tag{9}$$

where H_i is the entropy value of the characteristic index, i = 1, 2…(N_W + N_1), f_{ij} is the proportion of the j th object at the i th index, s_{ij} is data of the variable.

The entropy weight of the i th characteristic index is:

$$p_i = \frac{1 - H_i}{N_w + N_1 - \sum_{i=1}^{N_w+N_1} H_i} \tag{10}$$

When the variable is less volatile and H_i is larger, its clustering influence is smaller and its contribution to the selection of extreme scenarios is smaller. The greater the difference among the values of variables in the scenarios and the smaller the H_i, the greater the clustering influence of the variable and the greater the contribution to the selection of extreme scenarios. When all data of a variable in the scenarios are equal, $H_i = H_{max} = 1$, and its clustering influence is zero. Therefore, the importance of variables for clustering and extreme scenario extraction can be identified by different time-series data of wind power and load.

4.2 Subjective weight

Subjective weight means weighting the variable according to the importance of each variable to the clustering problem. In the entropy weight method, the weight of each index varies with the change of sample data, which means that the entropy weight is set based on the vertical time dimension. Giving a subjective weight to variables in the horizontal dimension will reflect more reasonably the contribution of clustering variables to extreme scenarios.

Since the capacity of wind power and load has a great influence on the extraction of extreme scenarios, this paper takes the capacity ratio of wind power and load as an alternative to subjective weighting.

4.3 Combination of subjective and objective weights

The combined method of subjective-objective weighting has been calculated in [30]. This combination is as follows,

$$w_i = \frac{p_i q_i}{\sum_{i=1}^{N_w+N_1} p_i q_i} \tag{11}$$

where p is the determined subjective weight and q is the objective weight determined by the entropy weight method, i = 1,2,…, (N_w+N_1).

The flowchart of the weighting process of a variable is shown in Fig. 3.

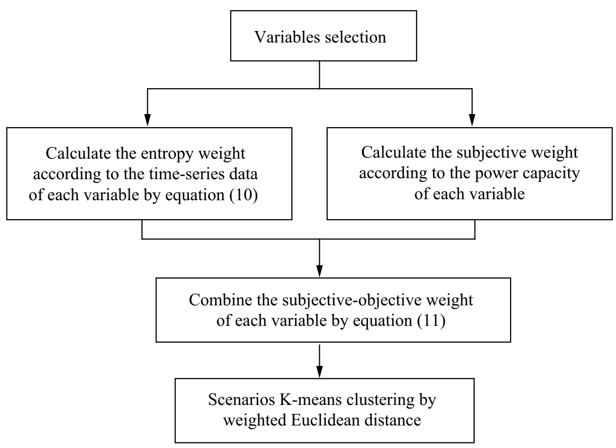

Fig. 3 Flow chart of weighting process of variable

5 Case study

To verify the effectiveness of the proposed extraction method, we selected two wind farms and one node load as the dominant variables. The fluctuation characteristics of wind power and load of these farms after normalization are shown in Fig. 4. The capacities of wind farms 1 and 2 are 100 and 50 MW, respectively. The maximum load of the node is 150 MW.

5.1 Shift in the extreme scenarios after wind power integration

In conventional transmission network planning, the scenario with the maximum load in a planning year is taken as the riskiest scenario to carry out safety verification for the planning scheme, which is generally the operation scenario with the highest network pressure. However, with large-scale intermittent renewable energy integration, the annual maximum load scenario is no longer the worst scenario of the planning scheme. The cluster number is set to 2, and the influence of wind power integration on extreme scenarios is compared. As shown in Fig. 5, the worst extreme wind power–load scenario extracted by the clustering method is no longer the scenario with the largest or smallest load, that is 8,759 h and 2,969 h, but 4,618 h and 8,151 h. The integration of wind power resulted in a shift in the extreme operation scenario of the system.

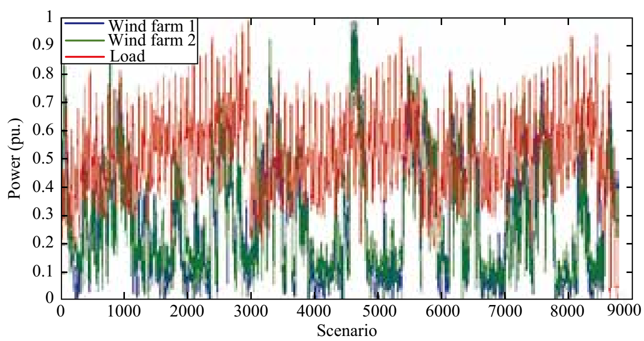

Fig. 4 Normalized data of wind power and load

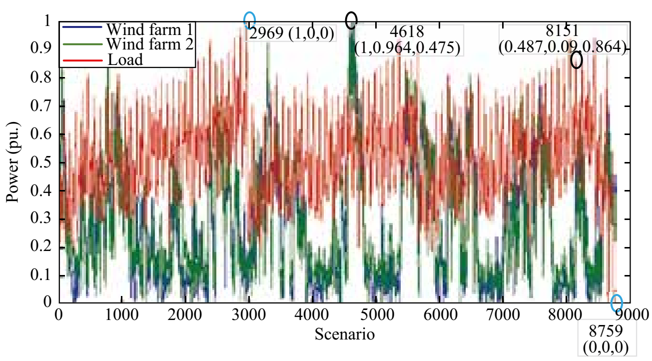

Fig. 5 Shift of extreme operation scenarios

5.2 Influence of weighted clustering and conventional clustering on extreme scenario extraction

The objective and subjective weights of variables were obtained from the entropy weight method and the capacity ratio, respectively, and then combined. As shown in Table 1, the original weights of the three variables are set to 0.33. The fluctuation of power of wind farm 1 is more severe than that of wind farm 2 (Fig. 4); therefore, the objective weight of wind farm 1 is larger than that of wind farm 2. In addition, both the capacity and subjective weight of wind farm 1 are twice those of wind farm 2. Despite having a high value, with the largest subjective weight of the three variables, the load power is less volatile than the wind power. This means the influence of the variable on the extreme scenario is weak, so its clustering combination weight is still small.

Table 1 Clustering variable weights

	Original weight	Subjective weight	Objective weight	Combined weight
Wind Farm 1	0.33	0.33	0.49	0.59
Wind Farm 2	0.33	0.17	0.43	0.27
Load	0.33	0.5	0.08	0.14

If the clustering number is taken as 3 and the number of extreme scenario layers as 5, the total number of extreme scenarios will be 15, with each class including 5 extreme points. The difference between the extreme scenarios obtained by the entropy weight clustering and conventional clustering methods were compared. Fig. 6 shows the projection of extreme scenarios on each dimension of the variables. It can be seen that the extreme points of one class coincide at a region in the curve where the wind power is high and the load is moderate. The extreme scenarios of the other two classes are quite different.

In the load variable dimension, the load levels of extreme scenarios extracted by the two methods were similar. However, in the wind power variable dimension, the wind power of extreme scenarios obtained by the entropy weight method covered a wider area, and it is more extreme at a lower level. This is because the entropy weighted clustering included the large fluctuations of wind power and considered the contribution of strong volatility of wind power to the scenarios. Therefore, more extreme scenarios can be extracted with accuracy and detail. However, because conventional clustering does not consider the contribution of volatility, the wind power level of the scenarios extracted by the method was relatively concentrated.

From Fig. 7, considering the subjective and objective weights, the extreme points obtained by combined weighted clustering are more concentrated in the wind farm 1 dimension than those obtained by the entropy weighted clustering, and the distribution is more scattered

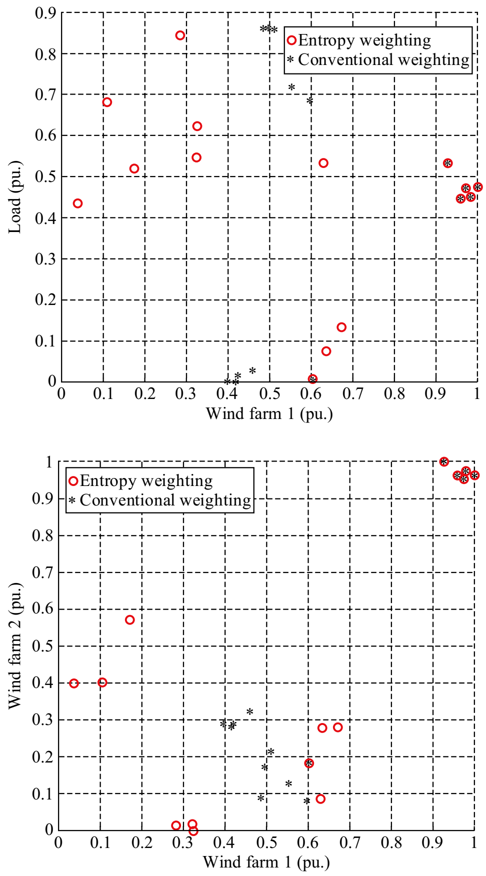

Fig. 6 Wind power and load distribution with entropy-weighted clustering vs. conventional clustering

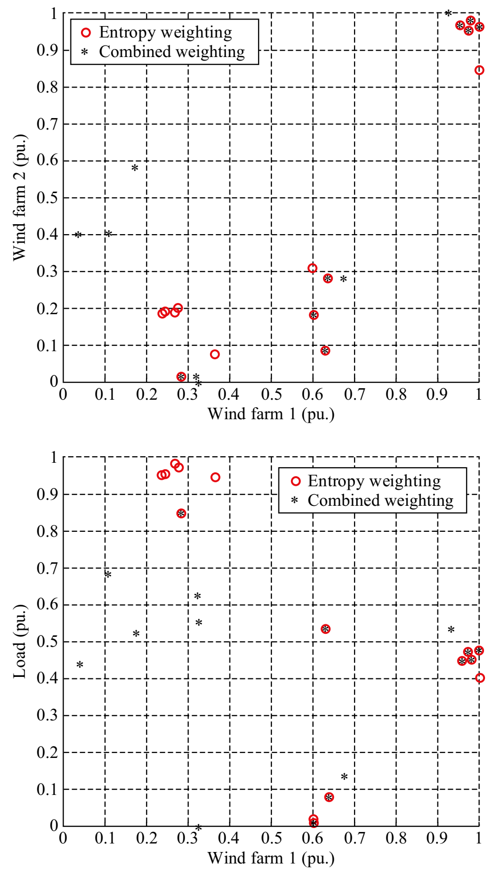

Fig. 7 Wind power and load distribution with entropy-weighted clustering vs. combined weighted clustering

and reasonable in the load dimension. This proves that wind farm 1 has a greater influence on the extreme scenarios. Additionally, the extreme scenario using the combined weighted clustering is consistent with the actual situation.

5.3 Influence of wind power distribution characteristics on extreme scenario extraction

To construct the wind power–load scenarios, the two farms were regarded as one variable regardless of the location of wind power. By taking the clustering number as 3, we obtained the worst extreme scenario numbered as [4618,8759,5656]. By considering their different geographical locations, the two wind farms were assumed as individual clustering variables, and the extreme scenario obtained by the clustering method was numbered as [4618,8151,8656]. The extreme scenarios shifted, and the corresponding wind-load scenario is shown in Table 2. Meanwhile, from Fig. 8, the wind-load operation scenario obtained by clustering, which considers the geographical distribution of wind power, is more extreme at the global level than that obtained by centralized clustering. The scenario also has higher load levels and lower wind power levels. Thus, the different geographical locations of wind power generation must be considered in the clustering method, to extract more extreme scenarios.

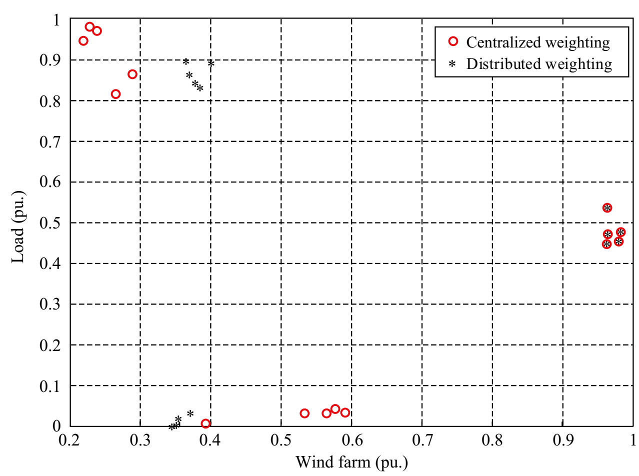

Fig. 8 Wind power and load distribution with distributed weighted clustering vs. centralized weighted clustering

Table 2 Comparison of extreme scenario with distributed clustering and centralized clustering

	[wind farm1, wind farm 2, load] (pu.)		
	Class 1	Class 2	Class 3
Distributed clustering	[1,0.96,0.48]	[0.49,0.09,0.86]	[0.71,0.45,0.04]
Centralized clustering	[1,0.96,0.48]	[0.42,0.28,0.86]	[0.38,0.42,0.04]

5.4 Influence of clustering number on extreme-scenario extraction

The number of clusters can be optimized according to a certain criterion. The optimization of extreme scenarios is consistent with that of typical scenarios. If the typical scenario clustering is the best, then the extreme scenarios based on the clustering is the worst.

More number of extreme scenarios with more comprehensive information can be derived as the clustering number increases. These extreme scenarios are the edge points of each class, but not necessarily those of the entire volume of sample data. It contains information on extreme cases that are otherwise missed by empirical methods or fewer clustering number, as the extreme points extracted are incomplete.

The growth of the clustering number, however, increases the computational requirements, and lead to the extraction of redundant extreme scenarios. From Fig. 9, the criteria of EPSE does not change much for clustering numbers above 3, i.e., increasing the clustering number does not yield positive feedback after reaching the inflection point. Therefore, the best clustering number in this case is 3.

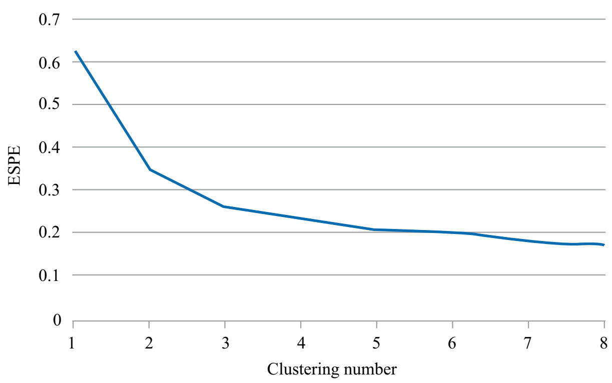

Fig. 9 Comparison of EPSE for different clustering numbers

6 Conclusions

This paper presents a framework for the extreme operation scenarios extraction of a power grid with large-scale wind-power integration based on the idea of weighted clustering, instead of traditional empirical methods. Under the framework, time-series wind power and load are chosen as the clustering object, the operation points farthest from the weighted Euclidean centers of the clusters are identified as extreme scenarios. With this contribution, weak points of grid operation with large-scale wind power integration can be picked for stability assessment and load flow analysis at planning stage. The results prove the effectiveness of the new method. It can enable planners to rapidly evaluate the operational safety of system planning schemes, and improve the rationality and science of the scenario analysis of large-scale power grids on stability.

In light of few clustering variables are chosen for the scenario extraction, only preliminary evaluation of the planning scheme with large-scale wind power integration can be made based on the scenarios. Future works should focus on practical transient stability analysis under the extreme scenarios. More influencing factors and variables must be considered in the analysis.

Acknowledgements

This work was supported by Innovation Fund Program of China Electric Power Research Institute (NY83-19-003).

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