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A novel combinational evaluation method of voltage and reactive power in regional power grid containing renewable energy

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Abstract: The output of renewable energy is strongly uncertain and random, and the distribution of voltage and reactive power in regional power grids is changed with the access to large-scale renewable energy. In order to quantitatively evaluate the influence of renewable energy access on voltage and reactive power operation, a novel combinational evaluation method of voltage and reactive power in regional power grids containing renewable energy is proposed. Firstly, the actual operation data of renewable energy and load demand are clustered based on the K-means algorithm, and several typical scenarios are divided. Then, the entropy weight method (EWM) and the analytic hierarchy process (AHP) are combined to evaluate the voltage qualified rate, voltage fluctuation, power factor qualified rate and reactive power reserve in typical scenarios. Besides, the evaluation results are used as the training samples for back-propagation (BP) neural networks. The proposed combinational evaluation method can calculate the weight coefficient of the indexes adaptively with the change of samples, which simplifies the calculation process of the indexes' weight. At last, the case simulation of an actual regional power grid is provided, and the historical data of one year is taken as the sample for training, evaluating and analyzing. And finally, the effectiveness of the proposed method is verified based on the comparison with the existing method. The evaluated results could provide reference and guidance to the operation analysis and planning of renewable energy.

Key words: adaptive weighting coefficient, combinational evaluation, renewable energy, typical scenarios

Nomenclature

U1 is the voltage qualified rate, N_{sat} is the number of samples qualified by monitoring point voltage, N is the total number of monitored samples, U2 is the voltage fluctuation, $V_{\max}$ is the maximum voltage of the period, $V_{\min}$ is the minimum voltage of the period, U3 is the power factor qualified rate, $N_{\text{sat}.p}$ is the number of qualified samples of monitored power factor, U4 is the reactive power reserve, $Q_{\max}$ is the maximum voltage in a period of time, Q_L is the reactive power demand of power load, J is the intra-class distance, x_v is the v-th $(v = 1, 2, \ldots, V)$ data, u_z is the z-th $(z = 1, 2, \ldots, k)$ clustering center, x_{ij}, x_i represent, respectively, the i $(i = 1, 2, \ldots, m)$ data under the index of j $(j = 1, 2, \ldots, n)$, y_{ij} is the i-th data under the j-th index after normalization, p_{ij} is the information entropy contained in the i-th data of the j-th index, H_j is the entropy value of the j-th index, B_j is the weight coefficient of the j-th index, $\boldsymbol{A}$ is the judgment matrix, U_{aj} is the a-th $(a = 1, 2, \ldots, n)$ data in the j-th column of the judgment matrix, W_j is the weight of the j-th index of the judgment matrix, $\lambda_{\max}$ is the maximum characteristic root of the judgment matrix, ω_j is the j-th index weight of the standardized judgment matrix, B_j represents the weights of the EWM, ω_j represents the weights of the AHP, Z_j represents the weights of the EWM-AHP, $\widetilde{\text{U}}1$ is the average voltage fluctuation, $\widetilde{V}_{bds}$ is the maximum voltage fluctuation allowed by China standard, Q_{sL} is the conventional reactive power reserve, G is the finally evaluation scores, S is the number of nodes of hidden layers, m, n represent the number of nodes in the input layer and the output layer, respectively, α is the constant from 1 to 10.

1. Introduction

With the increasingly prominent issues of energy security, ecological environment and climate change, accelerating the development of renewable energy has become the universal consensus and concerted action of the international community. It is the main measure to promote the development of energy transformation and respond to global climate change, but there are still some problems in the utilization and consumption of renewable energy [1, 2]. After a high proportion of renewable energy sources is connected to the power system, the burden of system adjustment is increased. Conventional power sources not only need to meet load changes, but also need to balance the output fluctuations of renewable energy sources [3]. While the output of renewable energy exceeds the adjustment range of the system, the power system must be controlled to ensure the dynamic balance of the system, which would lead to the abandonment of the wind turbine (WT) generator system and photovoltaic (PV) power generation [4]. Voltage and reactive power are the key factors to limit the improvement of renewable energy absorption capacity [5]. In this regard, some scholars have done related researches on the reactive power operation evaluation system and evaluation methods.

Referring to the evaluation system of voltage and reactive power operation, the regional power grid under automatic voltage control (AVC) is evaluated successively in references [6–9], from the aspects of control effect, loss reduction benefits, equipment configuration and strategy evaluation, etc. Based on the evaluation model and evaluation indexes containing reactive power equipment configuration, the reactive power operation of the regional power grid is quantitatively evaluated in reference [9]. The above studies mostly focused on the optimization analysis and evaluation of the reactive power operation of the system, but the multi-scenario operation of renewable energy is not considered.

In view of the research on the voltage and reactive power evaluation of regional grids containing new energy, reference [10] used Stockwell transform and fuzzy clustering to evaluate the power quality in a distribution system with high wind energy penetration. The reference [11] considered the power quality of the renewable energy grid connected in different scenarios where wind energy and photovoltaic power energy are mixed. In order to ensure the voltage stability margin within a sufficient range, the reference [12] adopted a stochastic programming method to evaluate and enhance the voltage stability of the power system in the presence of wind power.

The evaluation of voltage and reactive power is a multi-objective evaluation problem. Existing research mainly focuses on the determination of weights among multiple objectives. At the beginning, the most widely used methods include the entropy weight method (EWM) and analytic hierarchy process (AHP) to calculate the weight [13]. The EWM can determine the objective weight of multiple evaluation indexes. The AHP can refer to historical operating data to determine subjective and objective weights and select reasonable solutions. The problem of multi-objective comprehensive evaluation can be solved by the combination of the EWM and AHP (EWM-AHP) [14], and some relevant studies have been conducted in the fields of power quality assessment [15] and fault identification [16]. Existing EWM-AHP methods have studied voltage and reactive power evaluation, but there are still some problems. The weight of the EWM is mostly dependent on historical data, and the weight should be recalculated while the data changes, which is a cumbersome process. The Back Propagation (BP) neural network can determine the weight coefficient adaptively according to the training samples [17]. Therefore, if the evaluation result of the EWM-AHP method could be taken as samples and trained with the BP neural network, the problem that the weight depends on the data can be solved and the calculation efficiency can be improved.

This paper proposed a combination evaluation method based on the EWM-AHP and BP neural network, which can adaptively determine index weights of multi-objective functions to simplify the calculation process of weights. Firstly, the K-means algorithm is used to cluster the historical operation data of a regional power grid and divide the typical scenarios. Secondly, based on the four indexes of voltage qualified rate, power factor qualified rate, voltage fluctuation, and reactive power reserve, the EWM-AHP method is used to comprehensively score each typical scenario. The higher the score, the better the voltage and reactive power operation of new energy connected to the grid. Then, we used the sample set generated by the combined evaluation method to train the BP neural network. Finally, the effectiveness of the proposed combined evaluation method is verified by the prediction and comparison with the actual operating data of the region.

The structure of this paper is as follows. Evaluation indexes of voltage and reactive power of renewable energy connected to the regional power grid are presented in Section 2. The detailed process of building a combined evaluation method based on the EWM-AHP and BP neural network, and the analysis of the dynamic interactions for the combination evaluation are depicted in Section 3. To demonstrate the effectiveness of the proposed combination evaluation method, simulations are examined in Section 4. Finally, some conclusions are drawn in Section 5.

2. Evaluation indexes of voltage and reactive power of renewable Energy connected to regional power grid

The difference of renewable energy access to the regional power grid is mainly reflected in location, capacity, etc. And different access methods have different impacts on the regional power grid [18].

Voltage and reactive power operation evaluation indexes are the key to voltage and reactive power operation and regulation of the regional power grid, which could provide a reference for safe and stable operation and management of the regional power grid. Generally, voltage and reactive power evaluation indexes contain voltage qualified rate, voltage fluctuation, power factor qualified rate, reactive power compensation configuration, etc. Among them, the power factor is a coefficient that measures the efficiency of electrical equipment. The low power factor indicates that the reactive power used by the circuit for alternating magnetic field conversion is large, which reduces the utilization rate of the equipment and increases the power supply loss of the line. When the user's power factor increases, the reactive power it draws from the power system will be reduced, so the voltage loss will also be reduced, thereby improving the user's voltage quality [19]. The impact of voltage fluctuations is a common cause of complaints about low power quality. Voltage fluctuations in the power grid are usually caused by changes in the load state [20]. Therefore, the four evaluation indexes shown in Fig. 1 are selected to comprehensively evaluate the voltage and reactive power of the regional power grid with renewable energy.

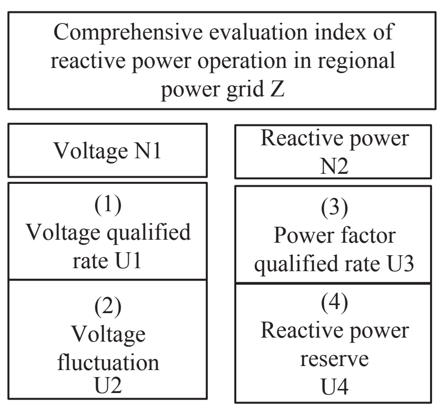


Fig. 1. Comprehensive evaluation indexes of voltage and reactive power operation in regional power grid

2.1. Voltage qualified rate

The voltage qualified rate is one of the important indexes to evaluate power quality, which directly affects the social benefits of power grid companies and consumer evaluation. The calculation formula is as follows [21]:

$$\mathrm{U1} = \frac{N_{\mathrm{sat}}}{N}, \tag{1}$$

where: U1 is the voltage qualified rate; N_{sat} is the number of samples qualified by monitoring point voltage, and N is the total number of monitored samples.

2.2. Voltage fluctuation

The nonlinearity and three-phase imbalance of load have a great impact on power quality [22]. Voltage fluctuation is the key index and the calculation formula is as follows:

$$\mathrm{U2} = V_{\max} - V_{\min}\,, \tag{2}$$

where: U2 is the voltage fluctuation in a period of time; $V_{\max}$ is the maximum voltage of the period, and $V_{\min}$ is the minimum voltage of the period.

2.3. Power factor qualified rate

Power factor is closely related to power loss and voltage drop. The calculation of the index is as follows:

$$\mathrm{U3} = \frac{N_{\text{sat}.p}}{N}\,, \tag{3}$$

where: U3 is the power factor qualified rate and $N_{\text{sat}.p}$ represents the number of qualified samples of the monitored power factor.

2.4. Reactive power reserve

Reactive power reserve has an important function on ensuring the voltage stability of the system [23]. In principle, the index should be at least 10%~15% in the regional power grid, which is calculated as follows:

$$\mathrm{U4} = \frac{\left(\sum Q_{\max} - \sum Q_L\right)}{\sum Q_{\max} \times 100\%}\,, \tag{4}$$

where: U4 is the reactive power reserve; $Q_{\max}$ is the maximum voltage in a period of time, and Q_L is the reactive power demand of power load.

3. Combined evaluation method based on EWM-AHP and BP neural network

3.1. Basic idea of the combinational evaluation method

In order to solve the problem that results from the strong dependence of the EWM-AHP method on historical data and cumbersome calculation processes, a combination evaluation method is proposed by combining the EWM-AHP method with BP neural networks. The basic idea is that the EWM-AHP method is used to evaluate historical data, and the evaluation results are used as training samples for BP neural networks. The flow chart of the method proposed is shown in Fig. 2.

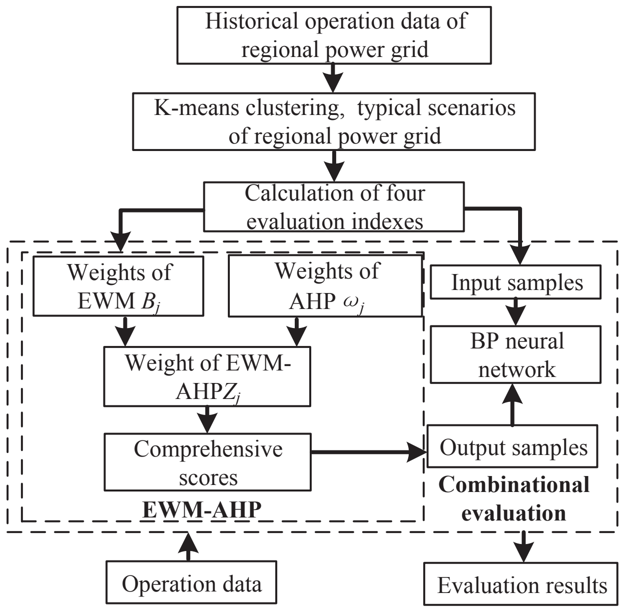


Fig. 2. The structure of combinational evaluation method based on BP neural networks

3.2. Typical scenarios for division of regional power grid with renewable energy

Considering the volatility and complexity of regional power grid operation data, a K-means clustering algorithm is used to cluster historical operation data [24] and classify typical scenarios. A K-means clustering algorithm has a simple principle and it is suitable for a variety of data types. The Euclidean distance is taken as the similarity index. The clustering goal is to minimize the sum of the squares of the intra-class distance J, and the objective function is shown as follows:

$$J = \sum_{z=1}^{k} \sum_{v=1}^{m} \|x_v - u_z\|^2, \tag{5}$$

where: x_v is the v-th ($v = 1, 2, \ldots, V$) data; u_z is the z-th ($z = 1, 2, \ldots, k$) clustering center.

The K-means clustering analysis process is shown in Fig. 3. The actual operation data of the regional power grid mainly includes the output power of WTs, the output power of PV and the load data of the regional power grid. Clustering of these three types of data is carried out respectively, and the data of the whole year is divided into the collection of multiple typical scenarios. The operating state of the regional power grid is analyzed and evaluated by using typical scenarios.

3.3. Sample generation based on EWM-AHP method

In the proposed method, the historical data are evaluated by the EWM-AHP method, which could be treated as training samples for BP neural networks. Firstly, the EWM determines the objective weights of the four evaluation indexes; secondly, the subjective weights of the four evaluation indexes are determined based on the AHP method; finally, the two weights are

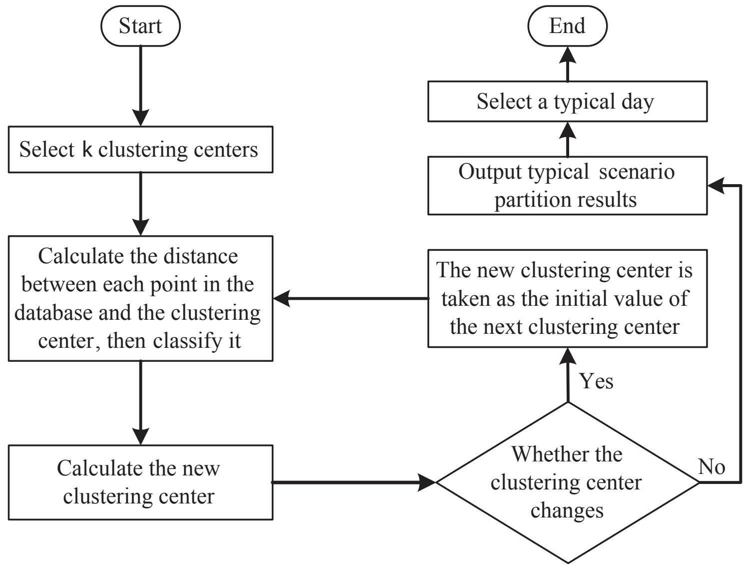


Fig. 3. The process of K-means clustering analysis

combined according to the multiplication product method to calculate the final scores of the four evaluation indexes.

1. Multi-objective evaluation based on the EWM

The EWM can be applied to solve multi-objective evaluation problems. The objective weight of multiple evaluation indexes can be determined by information entropy from a number of given alternatives. According to the fluctuation of information entropy, the evaluation index with higher importance is given a higher weight. The calculation process of the EWM is shown as follows:

$$\begin{cases} y_{ij} = \dfrac{x_{ij-\min(x_i)}}{\max\left(x_i\right) - \min(x_i)} \\ p_{ij} = \dfrac{y_{ij}}{\sum\limits_{i=1}^{n} y_{ij}} \\ H_j = -\left(\dfrac{1}{\ln(n)}\right) \sum\limits_{i=1}^{n} p_{ij} \ln p_{ij} \\ B_j = \dfrac{\left(1 - H_j\right)}{\sum\limits_{i=1}^{n} H_j} \end{cases}, \tag{6}$$

where: x_{ij}, x_i represent, respectively, the i ($i = 1, 2, \ldots, m$) data under the index of j ($j = 1, 2, \ldots, n$), y_{ij} is the i-th data under the j-th index after normalization, p_{ij} is the information entropy contained in the i-th data of the j-th index, H_j is the entropy value of the j-th index, B_j is the weight coefficient of the j-th index. If $p_{ij} = 0$, $H_j = 0$.

2. Multi-objective evaluation based on the AHP

The comprehensive evaluation of voltage and reactive power is a complex problem that is interrelated and mutually restricted by multiple indexes. The AHP can better solve such problems [25], and determine the subjective weight of each evaluation index based on the judgment matrix made by expert experience. The specific judgment matrix will be discussed in Section 4.3. The calculation process is given as follows:

$$\begin{cases} W_j = \sqrt[n]{\prod_{j=1}^{n} U_{aj}} \\ \lambda_{\max} = \dfrac{1}{n} \sum_{j=1}^{n} \dfrac{(\boldsymbol{A}W)_j}{W_j} \\ \omega_j = \dfrac{W_j}{\sum_{i=1}^{n} W_j} \end{cases}, \tag{7}$$

where: $\boldsymbol{A}$ is the judgment matrix, U_{aj} is the a-th ($a = 1, 2, \ldots, n$) data in the j-th column of the judgment matrix, W_j is the weight of the j-th index of the judgment matrix, $\lambda_{\max}$ is the maximum characteristic root of the judgment matrix, ω_j is the j-th index weight of the standardized judgment matrix.

3. Evaluation method based on the EWM-AHP

As shown in Eq. (8), the objective weights of the four indexes obtained by the EWM and the subjective weights of the four indexes obtained by the AHP are combined by the multiplication product method to obtain the weight coefficients of the EWM-AHP method. According to Eq. (9), the comprehensive evaluation scores of the four indexes are obtained.

$$Z_j = \frac{\omega_j B_j}{\sum_{j=1}^{4} \omega_j B_j}, \tag{8}$$

$$G = Z_1 P_V + Z_2 * \sum \frac{\left|1 - \widetilde{\mathrm{U}}1\right|}{\widetilde{V}_{bds}} + Z_3 P_p + Z_4 * \left(1 - \frac{\left|Q_{sL} - \sum \widetilde{\mathrm{U}}2\right|}{Q_{sL}}\right), \tag{9}$$

where: B_j represents the weights of the EWM; ω_j represents the weights of the AHP; Z_j represents the weights of the EWM-AHP; $\widetilde{\mathrm{U}}1$ is the average voltage fluctuation; $\widetilde{V}_{bds}$ is the maximum voltage fluctuation allowed by the China standard; Q_{sL} is the conventional reactive power reserve, and G is the final evaluation score.

3.4. A combination evaluation method of voltage and reactive power based on BP neural network

BP neural networks with reference to the biological nervous system, which is a multilayer overall structure, have adaptive matching weight coefficients and handle a large number of input parameters of complex problems. The BP neural network is trained by the sample set generated by the EWM-AHP method, and then the voltage and reactive power combination evaluation of the regional power network is carried out by using the trained neural network. Fig. 4 shows the sample training process.

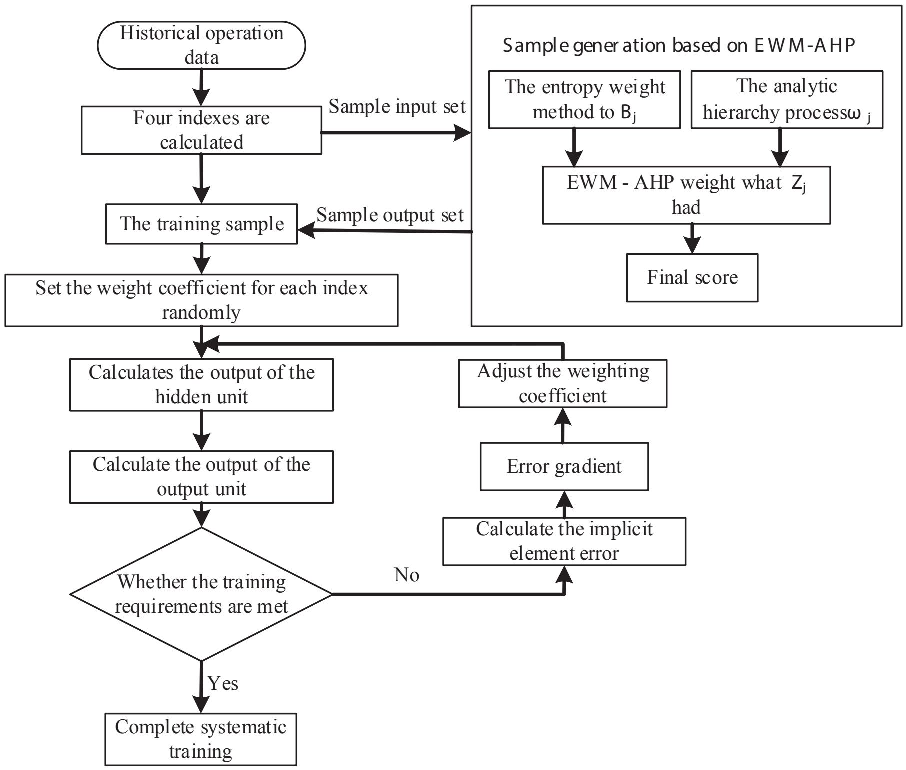


Fig. 4. Sample generation and training process of combinational evaluation method

The number of nodes in the input layer and output layer of BP neural networks is usually determined by function characteristics. The number of nodes in the hidden layer can be determined by Eq. (10),

$$S = \sqrt{m + n} + \alpha, \tag{10}$$

where: S is the number of nodes of the hidden layer; m, n represent the number of nodes in the input layer and the output layer, respectively; α is a constant from 1 to 10.

4. Case studies

4.1. Example introduction

The effectiveness of the proposed combination evaluation method is verified with an actual regional power grid, and the simplified topology of the regional power grid is shown in Fig. 5.

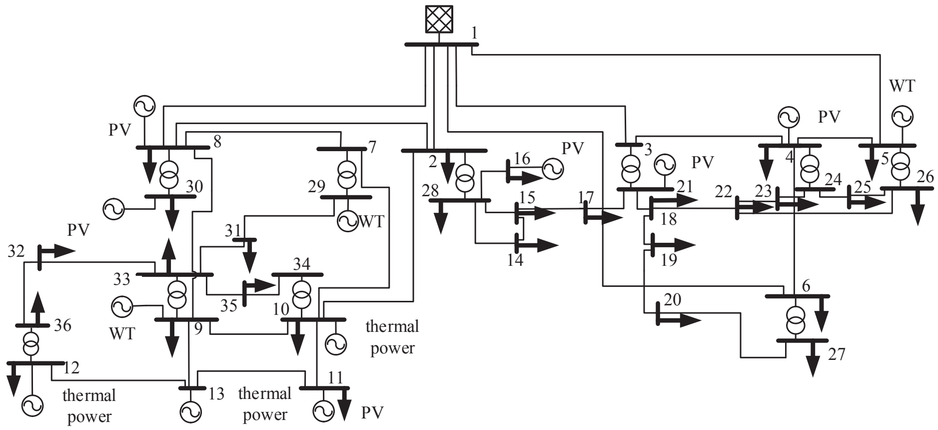


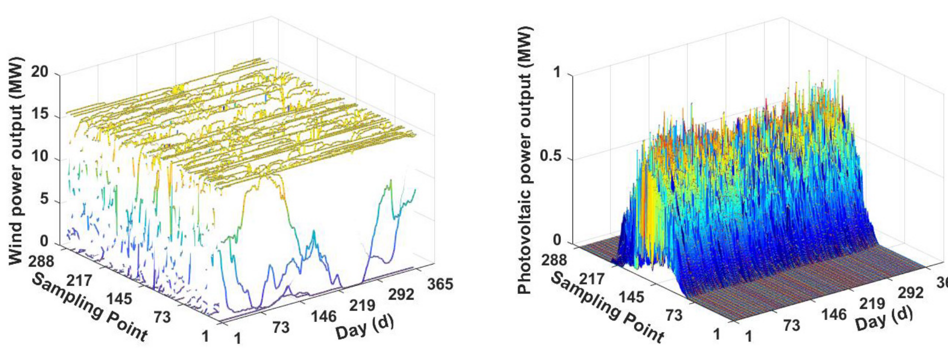
Fig. 5. Simplified topology of an actual regional power grid

The simplified regional power grid contains 36 nodes, including two voltage levels, 220 kV and 110 kV. The maximum load of the regional power grid is 1200 MW. The power supply contains 3 thermal power stations, 5 WT stations and 4 PV stations. The maximum output of renewable energy is 890 MW. The renewable energy information is shown in Table 1.

Table 1. Detailed information of renewable energy stations

Access bus	Energy	Installed capacity/MW
4, 11, 16, 21	PV	300, 170, 30, 30
5, 8, 9, 29, 30	WT	140, 700, 80, 30, 30

The historical output of renewable energy in this region in a certain year is shown in Fig. 6, in which the sampling interval of historical data is 5 minutes, 288 points per day and the sampling duration is 365 days.



(a) (b)

Fig. 6. One year's historical output data of renewable energy in a certain area: the output power of WT (a); the output power of PV (b)

4.2. Typical scenarios of division based on K-means algorithm

Clustering one-year historical operating data and dividing typical scenarios, the calculation process is as follows:

First determine the number of clusters k in the K-means algorithm. The three data of total load, the output power of the WT and the output power of PV are clustered, and the average distance D within the cluster under different numbers of clusters is shown in Fig. 7.

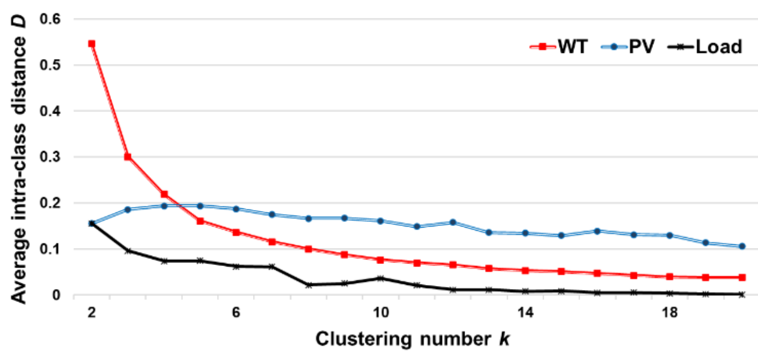
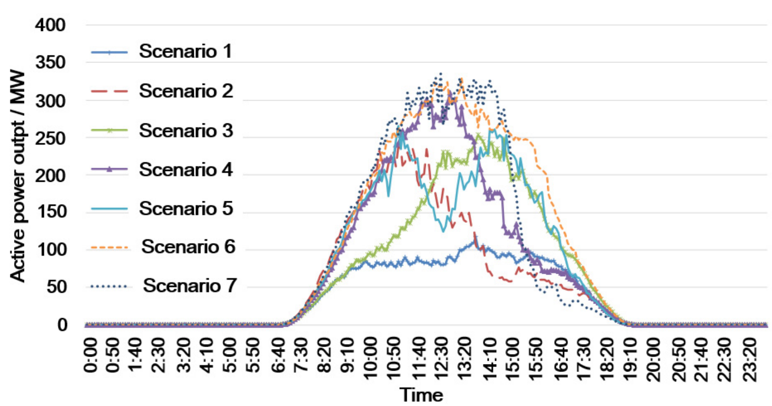
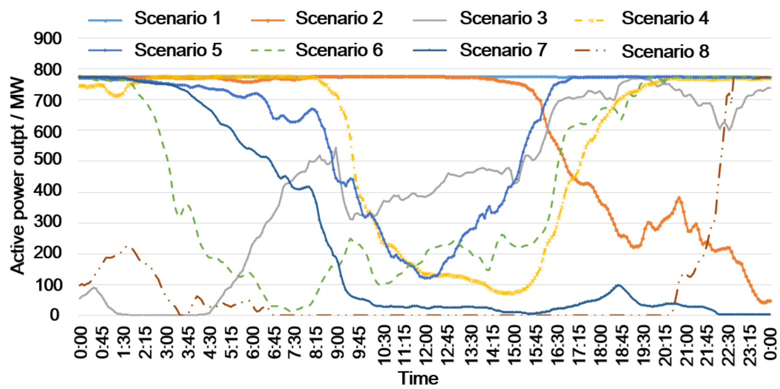


Fig. 7. Average intra-class distance under different number of clusters

As shown in Fig. 7, k represents the clustering numbers. The intra-class average distance between the load and WT tends to be stable while $k = 8$; and the intra-class average distance of PV tends to be stable while $k = 7$. The number of clusters is determined according to the objective function of the clusters, and a total of 7*8*8 typical scenarios are obtained. Besides, the typical scenarios are shown in Fig. 8. Set up a simulation model of the actual regional power grid in Matpower software, the scenario reduction is carried out [26], and the historical data is merged into each typical scenario. A total of 107 scenarios are obtained, and there are no remaining scenarios in the historical data. In addition, four evaluation indexes of voltage qualified rate, voltage fluctuation rate, power factor qualified rate and 24-hour reactive power reserve in each typical scenario were obtained.



(a)



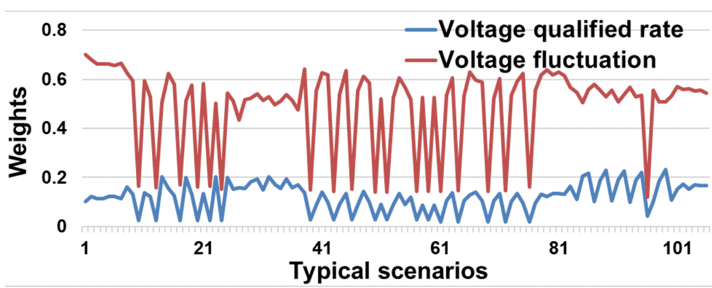
(b)

Fig. 8. Typical scenarios: (a) PV typical scenarios; WT typical scenarios (b)

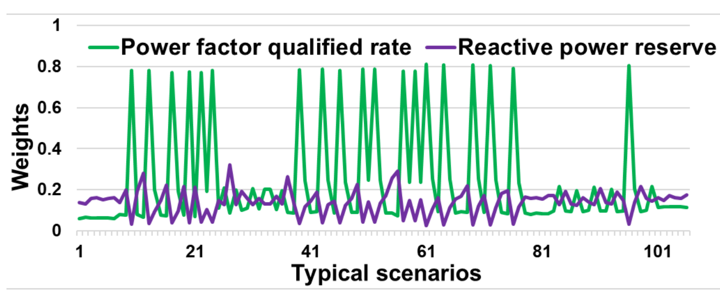
4.3. Combinational evaluation of sample generation based on EWM-AHP

1. Objective weights of evaluation indicators with the EWM

The objective weights of the four evaluation indexes are calculated by the EWM and the weights of the four indexes in each typical scenario are shown in Fig. 9.



(a)



(b)

Fig. 9. The weights are obtained by EWM: voltage indexes (a); reactive power indexes (b)

Voltage quality generally includes three indexes: voltage offset, voltage fluctuation, and three-phase voltage unbalance. Since this paper did not consider the low-voltage station area and the three-phase voltage imbalance, only the first two indexes were selected. Voltage fluctuation is the amount of change and fluctuation within a period of time, and the voltage qualified rate is to count whether all nodes are out of limit. The difference between the maximum weight and the minimum weight of the voltage qualified rate and the power factor qualified rate are 0.5082 and 0.8486, respectively; the difference between the maximum weight and the minimum weight of voltage fluctuation and reactive power reserve is 0.3988 and 0.3617, respectively. Therefore, the weight fluctuations of the voltage qualified rate and the power factor qualified rate are more obviously than that of voltage fluctuation and reactive power reserve.

2. Subjective weights of evaluation indexes with the AHP

The subjective weights of the four evaluation indexes are calculated by the AHP. The four voltage and reactive power evaluation indexes are scored by experts, and the judgment parameter matrix $\boldsymbol{A}$ is constructed according to the 1~9 scaling method. Tables 2 and 3 are the scaling method and the judgment parameter matrix $\boldsymbol{A}$, respectively.

Table 2. The meaning of each scale

Scale	Meaning
1	Indicates that two factors are of equal importance compared to
3	Indicates that compared to two factors, one factor is slightly more important than the other
5	Indicates that compared with two factors, one factor is obviously more important than the other
7	Indicates that compared to two factors, one factor is more important than the other
9	Indicates that compared to two factors, one factor is extremely important than the other
2, 4, 6, 8	The median of the above two adjacent judgments
reciprocal	If A is compared with B if the scale is 3, then B is 1/3 compared with A

Table 3. Comparison matrix $\boldsymbol{A}$

	U1	U2	U3	U4
U1	1	1/5	1/3	1/2
U2	5	1	2	3
U3	3	1/2	1	2
U4	2	1/3	1/2	1

The element a_{ij} in the judgment matrix table indicates the significance of the index i compared with the index j. When $i = j$, the two indexes are the same, they are equally important and recorded as 1, which explains that the main diagonal element is 1. After obtaining the judgment matrix $\boldsymbol{A}$, the results of calculating the weights of each index are shown in Table 4.

Table 4. The results of AHP

Index	First-level weight ω_{Ui}	Evaluation index	Second-level weight ω_{Ui}	Weight ω_{Ui}
Voltage N1	0.5	Voltage qualified rate U1	0.0940	0.0940
		Voltage fluctuation U2	0.5122	0.5122
Reactive power N2	0.5	Power factor qualification rate U3	0.2246	0.2246
		Reactive power reserve U4	0.1691	0.1691

The weights of voltage qualified rate U1, voltage fluctuation U2, power factor qualified rate U3 and reactive power reserve U4 are 0.0940, 0.5122, 0.2246 and 0.1691, respectively. Besides, the weight of the voltage fluctuation is significantly higher than the other three indexes.

4.4. Evaluation of typical scenarios based on EWM-AHP

The four evaluation indexes are comprehensively weighted by Eq. (8) using the multiplication product method, and the four evaluation indexes are combined to get a comprehensive score from Eq. (9). The results are shown in Fig. 10. In the regional power grid, the evaluation scores of 365 days are greater than 0.6, accounting for 97.26% of the annual operation time. It is indicating that the operation state of voltage and reactive power in the regional power grid is stable.

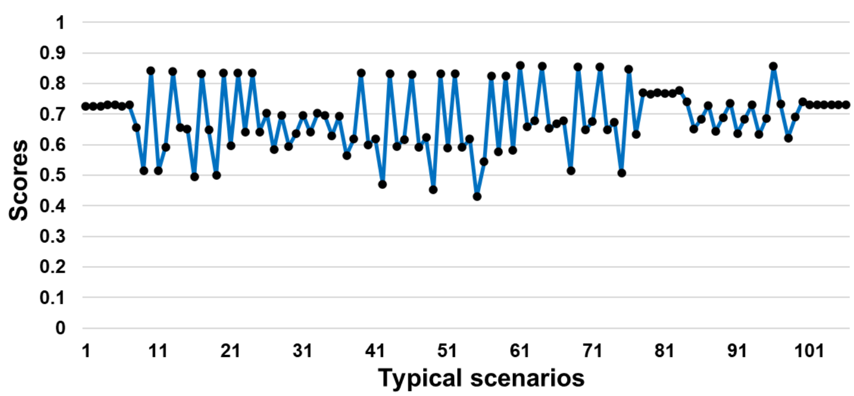


Fig. 10. Comprehensive evaluation results of EWM-AHP

From the evaluation results of the four levels, one day is respectively selected as a typical day for analysis, as shown in Table 5. It can be seen from the Table 5 that the voltage qualified rate and power factor qualified rate of the days evaluated as “superior” are relatively high. This is because the reactive power distribution on that day is reasonable, and the low reactive power reserve scores indicate that the higher reactive power utilization rate leads to the system voltage. The fluctuation is high, so the voltage fluctuation score is also low. In the same way, the power factor qualified rate of the days evaluated as "good" and "medium" is the highest, and the voltage qualified rate is relatively lower. This is because the short-term high-intensity application of reactive power has a greater impact on the grid voltage. In the days evaluated as "inferior", the reactive power reserve is relatively small, and there is a large amount of reactive power flowing in the power flow of the power grid, which causes large fluctuations in the power grid voltage.

Table 5. The score of each evaluation level on typical days

Grade	Evaluation indicators				Comprehensive weight of four evaluation indexes				Source
	U1	U2	U3	U4	Z1	Z2	Z3	Z4	
Superior	0.9117	0.5063	0.9420	0.0376	0.0254	0.1632	0.7794	0.0319	0.8412
Good	0.7894	0.6611	0.9970	0.8754	0.1153	0.6646	0.0605	0.1596	0.7304
Medium	0.8573	0.4663	0.9970	0.7352	0.1986	0.5426	0.1103	0.1485	0.6424
Inferior	0.9443	0.4325	0.9970	0.2269	0.1328	0.5759	0.0761	0.2153	0.4992

Scores of 10 days are lower than 0.6, accounting for 2.74% of the annual operating time. The peak-valley difference of load in 9 days are 303 MW, and the fluctuation of renewable energy output in 1 day is 760 MW. So, the greater the fluctuation of renewable energy output and load demand, the more obvious the voltage fluctuation, and the worse the reactive power operation state.

4.5. Combinational evaluation results based on EWM-AHP and BP neural network

Evaluation results obtained by the EWM-AHP are used as training samples for BP neural networks, and the historical data of a single month in the following year is evaluated and analyzed with the two methods.

The BP neural network is designed as a three-layer structure. The inputs are the four evaluation indexes, and the output is the comprehensive scores. The maximum number of training iterations is 10 000, and the convergence error is 0.001. The evaluation results of the proposed combinational method and EWM-AHP method are shown in Table 6.

According to Table 6, the average error of the two evaluation methods is 3.82%. The number of days that evaluation scores more than 0.6, calculated with the EWM-AHP method and the proposed combinational method, was 27 and 29, respectively. The comparison results verified the effectiveness of the proposed combinational evaluation method.

The EWM-AHP method has strong dependence on historical data. While the operation state of the regional power grid changes, the weight coefficient of each index should be recalculated. In the combination evaluation method, BP neural networks can adaptively adjust the weight of each index according to the samples, which could simplify the calculation process of weight and reduce the operation time. The program of the EWM-AHP method and the combinational evaluation

Table 6. Comparison of evaluation results between combinational evaluation and EWM-AHP

Day	Comprehensive evaluation	EWM-AHP	Day	Comprehensive evaluation	EWM-AHP
1	0.7489	0.7767	16	0.7998	0.7937
2	0.7414	0.7582	17	0.7392	0.7930
3	0.6832	0.7388	18	0.7675	0.7597
4	0.8986	0.7208	19	0.7774	0.7441
5	0.7600	0.7906	20	0.7832	0.7443
6	0.7446	0.7338	21	0.8108	0.7705
7	0.7360	0.7617	22	0.7387	0.7231
8	0.7341	0.7548	23	0.7469	0.7438
9	0.8641	0.8073	24	0.7556	0.7791
10	0.7359	0.7314	25	0.7362	0.7659
11	0.7361	0.7312	26	0.7350	0.7521
12	0.5008	0.6634	27	0.7432	0.6968
13	0.7782	0.7348	28	0.7348	0.7677
14	0.7250	0.6796	29	0.7360	0.7904
15	0.7015	0.7440	30	0.7734	0.7574

method was run 50 times in the same simulation environment, and the average calculation time was 0.0654 s and 0.0080 s, respectively. The comparison results show that the calculation speed of the combinational evaluation method is significantly faster than that of the EWM-AHP method.

5. Conclusions

A novel combinational evaluation method based on the EWM-AHP and BP neural network is proposed. An actual regional power grid was provided for simulation verification, and the following conclusions are drawn:

1. The combinational evaluation method takes the evaluation results of the EWM-AHP method as the training samples for BP neural networks. Combined with the EWM-AHP method and BP neural network, the reactive power operation of the regional power grid is evaluated from the perspectives of voltage qualified rate, voltage fluctuation, power factor qualified rate and reactive power reserve. The effectiveness of the proposed combination evaluation method is verified compared with the EWM-AHP method.
2. The combinational evaluation method determines the weight of each evaluation indicator using the BP neural network, which can adaptively adjust the weights of evaluation indexes with the training samples. Compared with the EWM-AHP method, the weight calculation

process is simplified. With the simulation analysis of an actual regional power grid, the calculation speed of the proposed combination evaluation method is significantly better than that of the EWM-AHP method.

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References

[1] Sharif A., Raza S.A., Ozturk I., Afshan S., *The dynamic relationship of renewable and nonrenewable energy consumption with carbon emission: a global study with the application of heterogeneous panel estimations*, Renewable Energy, vol. 133, pp. 685–691 (2019), DOI: 10.1016/j.renene.2018.10.052.

[2] Ossowska L.J., Janiszewska D.A., *Toward sustainable energy consumption in the European Union*, Archives of Electrical Engineering, vol. 23, no. 1, pp. 37–48 (2020), DOI: 10.33223/epj/119371.

[3] Zhang W.Q., Zhang X.Y., Huang S.W., Xia Y.K., Fan X.C., *Evolution of a transmission network with high proportion of renewable energy in the future*, Renewable Energy, vol. 102, pp. 372–379 (2017), DOI: 10.1016/j.renene.2016.10.057.

[4] Zhou Q., Wang N.B., Shen C.Y., Zhao L., Wang D.M., Zhang J.M., *Analysis of the reasons and prospect for the abandonment of new energy power in China*, Proceedings of the 2016 5th International Conference on Energy and Environmental Protection, Shenzhen, China (2016).

[5] Tang Z.Y., Hill D.J., Liu T., *Two-stage voltage control of subtransmission networks with high penetration of wind power*, Control Engineering Practice, vol. 62, pp. 1–10 (2017), DOI: 10.1016/j.conengprac.2017.02.013.

[6] da Costa J.N., Passos J.A., Henriques R.M., *Loading margin sensitivity analysis in systems with significant wind power generation penetration*, Electric Power Systems Research, vol. 175, pp. 1–9 (2019), DOI: 10.1016/j.epsr.2019.105900.

[7] Cai Y., Wang Z.C., Li Y., Cao Y.J., Tan Y.D., Tang X., *A novel operation of regional power grids in china: the generator voltage-class-reduction scheme*, IEEE Access, vol. 7, pp. 132841–132850 (2019), DOI: 10.1109/ACCESS.2019.2939925.

[8] Kumar V.S.S., Reddy K.K., Thukaram D., *Coordination of reactive power in grid-connected wind farms for voltage stability enhancement*, IEEE Transactions on Power Systems, vol. 29, pp. 2381–2390 (2014), DOI: 10.1109/TPWRS.2014.2300157.

[9] Liu Q.J., Yu L.F., Li Z.H., Zeng J., Chen S.Y., *Regional grid voltage reactive power optimization strategy based on voltage qualification rate evaluation function*, 2018 International Conference on Power System Technology, Guangzhou, China, pp. 3875–3882 (2018).

[10] Mahela O.P., Khan B., Alhelou H.H., Siano P., *Power quality assessment and event detection in distribution system with wind energy penetration using S-transform and fuzzy clustering*, IEEE Transactions on Industrial Informatics, vol. 16, no. 11, pp. 6922–6932 (2020), DOI: 10.1109/TII.2020.2971709.

[11] Mahela O.P., Khan B., Alhelou H.H., Tanwar S., *Assessment of power quality in the utility grid integrated with wind energy generation*, IET Power Electronics, vol. 13, no. 13, pp. 2917–2925 (2020), DOI: 10.1049/iet-pel.2019.1351.

[12] Swain S., Ray P.K., *Short circuit fault analysis in a grid connected DFIG based wind energy system with active crowbar protection circuit for ride through capability and power quality improvement*, International Journal of Electrical Power and Energy System, vol. 84, pp. 64–75 (2017), DOI: 10.1016/j.ijepes.2016.05.006.

[13] Wang S.X., Ge L.J., Cai S.X., Wu L., *Hybrid interval AHP-entropy method for electricity user evaluation in smart electricity utilization*, Journal of Modern Power Systems and Clean Energy, vol. 6, pp. 701–711 (2018), DOI: 10.1007/s40565-017-0355-3.

[14] Huang Y.S., Jiang Y.Q., Wang J., Li J., *Adaptability evaluation of distributed power sources connected to distribution network*, IEEE Access, vol. 9, pp. 42409–42423 (2021), DOI: 10.1109/ACCESS.2021.3066206.

[15] Du J., Cai C., Xie Z.J., Geng M.Z., *Comprehensive energy efficiency evaluation of municipal power grid based on TOPSIS method*, 2020 5th Asia Conference on Power and Electrical Engineering, Chengdu, China, pp. 829–833 (2020).

[16] Xu J.Z., Tong G.Q., Chen Q., Wu M., *A new evaluation method of the fault recovery scheme for medium-low voltage dc distribution network*, 2020 5th Asia Conference on Power and Electrical Engineering, Chengdu, China, pp. 1730–1735 (2020).

[17] Cheng Y.M., Liu C., Wu J., Liu H.M., Lee I.K., Niu J., Cho J.P., Koo K.W., Lee M.W., Woo D.G., *A back propagation neural network with double learning rate for PID controller in phase-shifted full-bridge soft-switching power supply*, Journal of Electrical Engineering and Technology, vol. 15, no. 6, pp. 2811–2822 (2020), DOI: 10.1007/s42835-020-00523-5.

[18] Li J.J., Zhang M.Y., Li Z.G., Zhang T., Zhang Q., Chi C., *Study on grid planning method considering multiple energy access*, 2018 International Conference on Smart Grid and Electrical Automation, Changsha, China, pp. 59–62 (2018).

[19] Malengret M., Gaunt C.T., *Active currents, power factor, and apparent power for practical power delivery systems*, IEEE Access, vol. 8, pp. 133095–133113 (2020), DOI: 10.1109/ACCESS.2020.3010638.

[20] Wiczynski G., *Determining location of voltage fluctuation source in radial power grid*, Electric Power Systems Research, vol. 180, pp. 1–10 (2020), DOI: 10.1016/j.epsr.2019.106069.

[21] Hong Y., Bie Z.H., Li G.F., Liu S.Y., Berizzi A., *The integrated reliability evaluation of distribution system considering the system voltages adjustment*, 2017 1st IEEE International Conference on Environment and Electrical Engineering and 2017 17th IEEE Industrial and Commercial Power Systems Europe, Milan, Italy (2017).

[22] Truong D.N., Ngo V.T., *Estimation of parameters associated with individual sources of voltage fluctuations*, International Journal of Electrical Power and Energy Systems, vol. 65, no. 2, pp. 425–431 (2015), DOI: 10.1109/TPWRD.2020.2976707.

[23] Zhang W.M., Zhang Y.X., *The reactive power and voltage control management strategy based on virtual reactance cloud control*, Archives of Electrical Engineering, vol. 69, no. 4, pp. 921–936 (2020), DOI: 10.24425/aee.2020.134639.

[24] Bian H.H., Zhong Y.Q., Sun J.S., Shi F.C., *Study on power consumption load forecast based on K-means clustering and FCM-BP model*, Energy Reports, vol. 6, pp. 693–700 (2020), DOI: 10.1016/j.egyr.2020.11.148.

[25] Chen Z., Du Z.B., Zhan H.Q., Wang K., *An evaluation method of reactive power and voltage control ability for multiple distributed generators in an islanded micro-grid*, 2018 International Conference on Power System Technology, Guangzhou, China, pp. 1819–1825 (2018).

[26] Lin C.F., Fang C.Z., Chen Y.L., Liu S.Y., Bie Z.H., *Scenario generation and reduction methods for power flow examination of transmission expansion planning*, 2017 IEEE 7th International Conference on Power and Energy Systems, Toronto, Canada, pp. 90–95 (2017).