New Energy Output Forecasting Method Considering Multi-zone Numerical Weather Forecast and Error Identification

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Abstract. In recent years, new energy has achieved rapid development in the whole world. However, with the gradual increase in the installed capacity of new energy, because of the uncertainty and volatility of new energy output, new energy has brought many impacts and challenges to the operation of the power system. In order to guarantee the safe and stable operation of the power system, the power system has to provide sufficient flexibility to cope with the volatility and uncertainty of the new energy output. Improving the prediction error accuracy of new energy output can effectively reduce the uncertainty of new energy output, so as to reduce the demand for power system flexibility, reduce the operating cost, and improve the system operation reliability. This paper utilizes the data mining technology to establish the prediction error identification module. Based on the data feature extracted from the wind power prediction input data, the potential abnormal wind power prediction error can be identified, and the original wind power output prediction result can be corrected, so as to improve the predication accuracy of the wind power generation. At the same time, in the prediction and identification process, the wind speed prediction data and historical wind power output data of neighbouring regional wind farms will also be utilized to improve the prediction accuracy of wind farm output in this region. The predicated time scale is 12 hours ahead of time, and the predicted result is the wind power output of the next 12 hours (a predicted resolution of 1 hour, and a total of 12 predicted values).

1. Overview

In recent years, new energy has achieved rapid development in the whole world. However, with the gradual increase in the installed capacity of new energy, because of the uncertainty and volatility of new energy output, new energy has brought many impacts and challenges to the operation of the power system [1]. In order to guarantee the safe and stable operation of the power system, the power system has to provide sufficient flexibility to cope with the volatility and uncertainty of the new energy output. Improving the prediction error accuracy of new energy output can effectively reduce the uncertainty of new energy output, so as to reduce the demand for power system flexibility, reduce the operating cost, and improve the system operation reliability.

The uncertainty of new energy output is mainly demonstrated by its large prediction error. The larger the prediction time scale is, the lower the prediction accuracy is. The accuracy of short-term wind power output forecasting method plays an important role in formulating the unit commitment and power generating plan. Therefore, it is in urgent need of studying ways to improve the accuracy of short-term wind power forecasting.

As previously mentioned, the wind power forecasting methods can be divided into three categories: the prediction method driven by physical models, the prediction method driven by data, and the combination of the two. There are many factors affecting wind power output, including wind speed, wind direction, temperature, fan model, fan position, topography, air density, wake effect and so on[2], in which, wind speed is recognized as the most important factor affecting wind power output. However, the wind speed prediction results usually come from third-party organizations such as the National Meteorological Service Station. Due to data contamination, defect, missing or other problems, the accuracy is not enough to fully support the wind power output prediction of the next stage. In order to solve the problem of bad data in wind speed prediction results, some scholars have already carried out research on the Numerical Weather Prediction (NWP) bad data identification [3].

However, these researches have shown their limitations: On the one hand, the prediction error is not only derived from the polluted, defected, missed or other bad data, but also comes from some data feature that could easily cause wind power prediction errors. The data feature which causes large deviations easily may be constituted by several consecutive data points. On the other hand, due to the time lag of the weather in the territory, the wind speed conditions in other regions have available information, which can be used as the reference for wind power prediction in the region. However, most of the current wind power prediction methods ignore such objective and useful information.

Literature [4] summarizes four common data features that can easily generate prediction errors, but the data feature should not be limited to these four types. At the same time, the literature [5], [6], and [7] not only use the available information of the power plant in this region, but also adopt the available information of the nearby wind power plant for wind power predication, which effectively improves the accuracy of wind power forecasting. Therefore, this paper proposes a wind power output prediction method that considers multi-region numerical weather prediction and error identification, thus effectively improving the accuracy of wind power forecasting.

This paper utilizes the data mining technology to establish the prediction error identification module. Based on the data feature extracted from the wind power prediction input data, the potential abnormal wind power prediction error can be identified, and the original wind power output prediction result can be corrected, so as to improve the predication accuracy of the wind power generation. At the same time, in the prediction and identification process, the wind speed prediction data and historical wind power output data of neighbouring regional wind farms will also be utilized to improve the prediction accuracy of wind farm output in this region. The predicated time scale is 12 hours ahead of time, and the predicted result is the wind power output of the next 12 hours (a predicted resolution of 1 hour, and a total of 12 predicted values).

2. Wind power output initial predication

Based on Artificial Neural Network (AN), this paper builds the wind power output prediction method. The predicted input data includes the wind speed and wind direction prediction data for the next 12 hours, wind speed and wind direction prediction data for the past 12 hours, and the wind power output measured value of the past 12 hours of this region and other regions, the output data is the predicted value of wind power output for the next 12 hours.

Artificial Neural Network adopts a Multi-Layer Perceptions (MLPs) with a hidden layer. The structure is a nonlinear function that can approximately express the common function under any accuracy. It is capable of forecasting the wind power out predication in the future 12 hours. In addition, it is usually required to carry out structural selection, so as to determine the number of neurons in each layer. In this paper, the final structure of the neural network in the wind power output prediction module uses 504 neurons of the input layer, 81 neurons of the hidden layer, and 12 neurons of the output layer. The input layer and the hidden layer adopt the log-sigmoid transfer function. The output layer adopts the linear transfer function. The BP (Back Propagation) method is used for the training. The gradient descent method with dynamics and adaptive learning speed is adopted to improve the BP neural network, so as to improve the problem that it is easily get trapped in locally optimal solution and it has a slow convergence speed.

3. Wind power predication error pattern identification

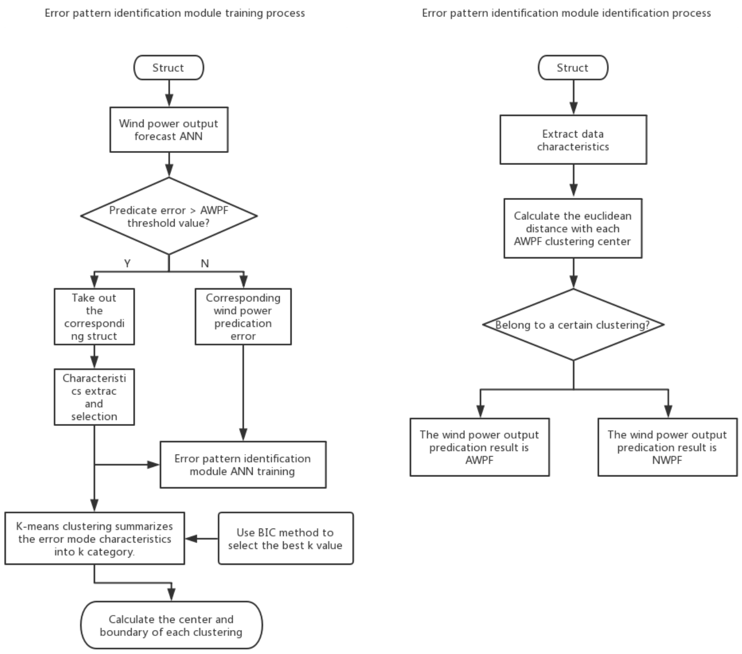

Figure 1. Flow chart of training and implementation of error pattern recognition module

The wind power prediction error pattern identification module is trained by using the historical accumulated data: first of all, all historical AWPFs are extracted according to the definition of AWPF; secondly, the wind power prediction input data corresponding to AWPF is conducted with feature extraction. In addition, the error pattern identification module is trained with this as the input and the wind power predication error corresponding to AWPF as the output. In the end, all AWPFs are classified based on BIC (Bayes Information Criterion) method and K-means clustering method, and the corresponding center and boundary of each cluster is obtained.

In the implementation process of error pattern identification: first of all, the wind power predication input data is conducted with the feature extraction, and then its Euclidean distance with each AWPF clustering center is calculated. When the distance is smaller than the set threshold value, the predication will be judged as AWPF, and then the predication result is corrected.

3.1. Historical AWPF Extraction

First, the AWPF is extracted from the historical data to form an AWPF set, which is recorded as S. The historical data is scanned, and every 12 points is a prediction result. Afterwards, it is required to compare the wind power practically measured value and the predicated value of the corresponding point. When the average prediction error of a certain prediction (a total of 12-point prediction results) exceeds the given threshold, the prediction is judged to be AWPF, and the corresponding data set will be placed in the set S.

3.2. AWPF Feature Extraction

Secondly, the feature vector of the data set that can represent AWPF from the set S. Under normal conditions, AWPF of the same type should have similar or approximate feature vectors, and vice versa. Future forecasts with similar or approaching feature vectors with the historical AWPF will also probably cause AWPF. If the relationship between the AWPF feature vector and the anomaly prediction error mode can be mined and applied in future predictions to identify the potential AWPF, the final prediction accuracy will be improved. In this paper, the feature candidate is constituted by the wind speed, wind direction, and wind power feature candidate of the local area and the adjacent area. The detailed conditions are as follows:

3.2.1. Wind speed data feature candidate

Wind speed predication peak and valley difference: The peak-to-valley difference of wind speed predication can describe the fluctuation of wind speed, as shown in the formula:

$$PV_s^x = max(\, WSF_t^x | WSF_t \in Struct_t^x) - min(\, WSF_t^x | WSF_t^x \in Struct_t^x)\; x = 0,1,2,\ldots,m \quad (1)$$

Wherein, the superscript x indicates different regions, the subscript s indicates the characteristic value related to the wind speed, the same below max (·) and min (·) respectively will return to the maximum and minimum values.

Wind speed predication average value: the average wind speed predication value can describe the wind speed, just as shown in the below formula:

$$\mu_s^x = \frac{\sum_{WSF_t^x \in Struct_t^x} WSF_t^x}{\mathrm{num}(WSF_t^x \in Struct_t^x)}, x = 0,1,2,\ldots,m \quad (2)$$

Wherein, $\mathrm{num}(\cdot)$ will return to the number of elements in the vector.

Maximum wind speed predication uphill value: The maximum wind speed predicted uphill value can reflect the demand for future wind power demand for the down regulation of the unit within the system, as shown in the formula:

$$RU_s^x = \max(WSF_{t+1}^x - WSF_t^x | WSF_t^x, WSF_{t+1}^x \in Struct_t^x), x = 0,1,2,\ldots,m \quad (3)$$

Maximum wind speed predication downhill value: The maximum wind speed predicted downhill value can reflect the future demand for wind power to adjust the up-regulation of the unit within the system, as shown in the formula:

$$RD_s^x = \max(WSF_t^x - WSF_{t+1}^x | WSF_t^x, WSF_{t+1}^x \in Struct_t^x), x = 0,1,2,\ldots,m \quad (4)$$

Wind speed predication standard deviation: The wind speed predication standard deviation can reflect the fluctuation intensity of the future wind power, as shown in the following formula:

$$\sigma_s^x = \sqrt{\frac{\sum_{WSF_t^x \in Struct_t^x} (WSF_t^x - \mu_s^x)^2}{\mathrm{num}(WSF_t^x \in Struct_t^x)}}, x = 0,1,2,\ldots,m \quad (5)$$

3.2.2. Wind direction data feature candidate

Peak-to-valley difference of wind direction predication value: Peak-to-valley difference of wind direction predication can describe the fluctuation of the wind direction, as shown in the following formula:

$$PV_d^x = max(\, WDF_t^x | WDF_t^x \in Struct_t^x) - min(\, WDF_t^x \big| {WDF_t^x}_t \in Struct_t^x\big)\; x = 0,1,2,\ldots,m \quad (6)$$

Wherein, the superscript *x* indicates different regions, and the subscript *d* indicates the characteristic value related to the wind direction, the same below.

Wind direction predication average value: The wind direction forecast average value can describe the general trend of the wind direction, as shown in the formula:

$$\mu_p^x = \frac{\sum_{WPO_t^x \in Struct_t^x} WPO_t^x}{\mathrm{num}(WPO_t^x \in Struct_t^x)}, x = 0,1,2,\ldots,m \quad (7)$$

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Maximum anticlockwise changing value of wind direction forecast: Maximum anticlockwise changing value of wind direction forecast can reflect the deviation of the future wind speed to anticlockwise direction, as shown in the formula:

$$RU_p^x = \max(WPO_{t+1}^x - WPO_t^x | WPO_t^x, WPO_{t+1}^x \in Struct_t^x), x = 0,1,2,\ldots,m \tag{8}$$

Maximum clockwise changing value of wind direction forecast: Maximum clockwise changing value of wind direction forecast can reflect the deviation of the future wind speed to clockwise direction, as shown in the formula:

$$RD_p^x = \max(WPO_t^x - WPO_{t+1}^x | WPO_t^x, WPO_{t+1}^x \in Struct_t^x)\ x = 0,1,2,\ldots,m \tag{9}$$

Wind direction forecast value standard deviation: Wind direction forecast value standard deviation can reflect the intensity of the future wind direction change, as shown in the formula:

$$\sigma_p^x = \sqrt{\frac{\sum_{WPO_t^x \in Struct_t^x}(WPO_t^x - \mu_p^x)^2}{\mathrm{num}(WPO_t^x \in Struct_t^x)}}, x = 0,1,2,\ldots,m \tag{10}$$

3.2.3. Wind power output characteristic value

Peak-to-valley difference of measured wind power output: Peak-to-valley difference of the actually measured wind power output can describe the fluctuation of the wind power output, as shown in the formula:

$$PV_p^x = max(WPO_t^x | WPO_t^x \in Struct_t^x) - min(WPO_t^x | WPO_t^x \in Struct_t^x) x = 0,1,2,\ldots,m \tag{11}$$

Wherein, the superscript x indicates different regions, and the subscript p indicates the characteristic value related to the measured wind power output, the same below.

Average value of measured wind power output: Average value of measured wind power output can describe the wind power output, as shown in the formula:

$$\mu_p^x = \frac{\sum_{WPO_t^x \in Struct_t^x} WPO_t^x}{\mathrm{num}(WPO_t^x \in Struct_t^x)}, \quad x = 0,1,2,\ldots,m \tag{12}$$

Maximum uphill value of measured wind power output: Maximum uphill value of measured wind power output can reflect the demand of the historical wind power to the downward regulation of the unit in the system, just as shown in the formula:

$$RU_p^x = \max(WPO_{t+1}^x - WPO_t^x | WPO_t^x, WPO_{t+1}^x \in Struct_t^x), x = 0,1,2,\ldots,m \tag{13}$$

Maximum downhill value of measured wind power output: Maximum downhill value of measured wind power output can reflect the demand of the historical wind power to the upward regulation of the unit in the system, just as shown in the formula:

$$RD_p^x = \max(WPO_t^x - WPO_{t+1}^x | WPO_t^x, WPO_{t+1}^x \in Struct_t^x), x = 0,1,2,\ldots,m \tag{14}$$

Standard deviation of the measured wind power output: Standard deviation of the measured wind power output can reflect the fluctuation intensity of the historical wind power, as shown in the formula:

$$\sigma_p^x = \sqrt{\frac{\sum_{WPO_t^x \in Struct_t^x}(WPO_t^x - \mu_p^x)^2}{\mathrm{num}(WPO_t^x \in Struct_t^x)}}, x = 0,1,2,\ldots,m \tag{15}$$

3.3. Error Pattern Identification Module

3.3.1. Training process

The feature vectors include a total of N=15(m+1) feature values, which correspond to k kinds of AWPFs, and k is unknown. As shown in Figure 2, these feature values are like the DNA of AWPF, and various types of AWPF are like different performances. Different DNAs will lead to different traits. In order to reveal the relationship between the two, data mining technology is required to explore the inner inside of the "black box." However, this "black box" is the error pattern identification module.

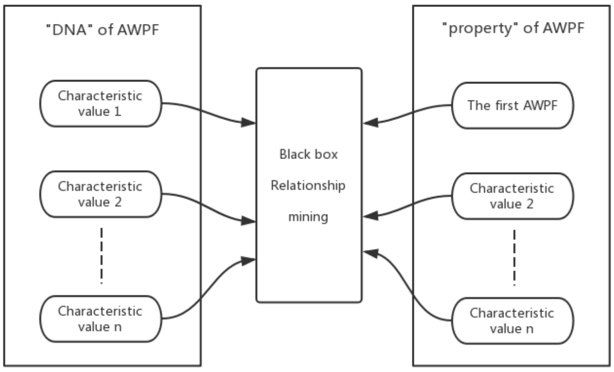

Figure 2. Diagram of the relationship between the data feature values and abnormal wind power predication error mode

The error pattern identification module also adopts the ANN method for modelling because ANN has the problem of over-fitting, namely bias-variance dilemma, which usually requires feature selection. A good feature selection model is designed to try to reduce the ratio between the complexity and the size of the training set. There are many related studies [8-10] on this aspect. In this paper, the feature selection process uses the Random Probe method [11] because it has the following advantages:

1) it does not depend on the probability distribution of characteristic values;

2) it can sort all candidate features;

3) the method has simple operation, high calculation efficiency and wide application field.

Specifically, probe features are firstly generated. These features are generated by the feature values in the random exchange feature vector, and the entire feature set is constituted by the uncorrelated feature set and the candidate feature set. After that, based on Gram-Schmidt orthogonalization, orthogonal forward regression is used to rank feature vectors. The probability that certain features in the irrelevant feature set rank better than the candidate features will be evaluated, and the given ranking boundary will eliminate the features that are ranked behind, so the boundary should eliminate as many irrelevant features as possible. Set *np* to indicate the number of uncorrelated features, because the uncorrelated feature set is generated by the feature values in the random exchange feature vector, so it has the same probability distribution as the original candidate feature set. The probability that the rank of the irrelevant feature is better than the candidate feature is evaluated as follows: the probability that the irrelevant feature rank is less than or equal to *r* is recorded as *nrp/np*, where *nrp* is the number of irrelevant features ranked after or the same as *r*. In the ranking process, when the *r* of $nrp/np > \delta$ appears, the ranking process finishes, and the ranking boundary value $r_0 = r - 1$, in which, δ is the given risk threshold. The literature [11] provides a specific example of the operation of the above method.

The ANN adopts a three-layer structure. The number of neurons in the input layer is equal to the number of features selected at the end, and the 12 neurons in the output layer and the hidden layer neurons are the square root of the product of the number of neurons in the input layer and the number of neurons in the output layer. The input layer and the hidden layer adopt the log-sigmoid transfer function, the output layer adopts the linear transfer function, and the training adopts the BP (Back Propagation) method. Each AWPF feature vector is used as an input, and the corresponding wind power prediction error is used as an output to train the error pattern identification module.

This paper uses the K-means clustering method to summarize k kinds of AWPF, and K-means clustering method needs to give the number of species in advance. Therefore, the BIC (Bayes Information Criterion) method is further used to obtain the optimal k value. Setting the center of k clusters as $C_k = (C_k^1, C_k^2, \dots, C_k^M)$, in which, M is the number of the characteristic values, namely, $M = 18(\mathrm{m} + 1)$. This paper utilizes the BIC method to determine the optimal k value. The formula is as follows:

$$BIC = log \prod_i \left[\frac{N_{C(i)}}{N}\frac{1}{\sqrt{2\pi}\sigma_{C(i)}} exp\left(-\frac{\|x_i - m_{C(i)}\|}{2\sigma_{C(i)}{}^2}\right)\right] - \frac{p \cdot log\, N}{2} \quad (16)$$

Wherein, N is the total number of the elements, $\mathrm{C(i)}$ represents the clustering of the element x_i, $\mathrm{N_{C(i)}}$ is the number of elements in the clustering $\mathrm{C(i)}$, then, $\mathrm{N} = \sum_\mathrm{i} \mathrm{N_{C(i)}}$. $\mathrm{m_{C(i)}}$ is the central vector of $\mathrm{C(i)}$, $\sigma_{\mathrm{C(i)}}$ is the standard deviation of the elements in $\mathrm{C(i)}$ to the clustering central distance. p represents the number of parameters in the statistics model, namely, $p = k \cdot M$. In the formula, the first part on the right side of the equal sign is the log approximation expression of k-means. The higher the value is, the more accurate the classification of the clustering is. The second part reflects the rising complexity of the model as the k value increases. When the value of k increases, the first part and the second part of the right side of the equal sign will also increase accordingly, and the BIC value will reach a peak value at a certain k value. The k value will be selected as the number of categories of the clustering.

3.3.2. Implementation process

Set the radius threshold of the kth clustering as e_k, with its size be equal to the maximum Euclidean distance between the element in the clustering and the clustering center, as shown in the formula:

$$e_k = max(\sqrt{\sum_{j=1}^{M}(F_{k,i}^j - C_k^j)^2} \quad (17)$$

In the formula, $F_{k,i}^j$ is the j^{th} characteristic value of the i^{th} element in the k^{th} clustering, M is the number of characteristics in each element.

The number, center and radius of clustering will be used as the basis for future AWPF identification. The error pattern identification module will evaluate whether the wind power prediction value of each point belongs to a certain type of potential AWPF. The identification method is as follows:

$$I(Struct_t) = \begin{cases} value\ of\ Struct_t \in k^{th}\ cluster\ , & \sqrt{\sum_{j=1}^{M}(F_t^j - C_k^j)^2} \le \alpha e_k \\ value\ of\ Struct_t \notin k^{th}\ cluster, & \sqrt{\sum_{j=1}^{M}(F_t^j - C_k^j)^2} > \alpha e_k \end{cases} \quad (18)$$

In the formula, I $(\cdot)$ is the AWPF discriminant function. As to each data set of wind power predication, whether it will lead to AWPF will be identified according to the function. The principle of discrimination is that when the distance between the feature vector of the data set and the center distance of a certain cluster is less than the threshold, the prediction will be judged as AWPF, otherwise, it will be judged as NWPF. $\mathrm{F_t^j}$is the j^{th} characteristic value of the prediction. $\alpha \in [0, 1]$ is the threshold adjustment parameter.

3.3.3. AWPF predication result correction

In predicting the future wind power output, the data structure $Struct_t$ will first be used to determine whether it will lead to potential AWPF: When it is judged as the potential AWPF, $Struct_t$ will be sent to the error pattern identification module in the first, and then correct each predication point of the initial wind power output predication result as formula (19) , otherwise, it will be directly sent to the wind power output prediction module for prediction.

$$WPF_t' = \frac{WPF_t}{1+ErrorRate(t)}, t = 1,2, \ldots ,12 \quad (19)$$

In which, WPF_t is the initial predicted wind power value at the time of t. WPF_t' is the final predicted wind power at the time of t. Error Rate is the output of the error pattern identification module, that is, the expected error amplitude of AWPF. Error Rate is constituted by 12 data points, which are corresponding to the 12 predication points in the wind power prediction results respectively.

4. Case analysis

4.1. Case Composition List
There are a total of four cases, as shown in Table 1.

Case 1-1 and Case 1-2 use only the data of this area for wind power prediction. Case 2-1 and Case 2-2 use both the data of the region and neighbouring area for wind power prediction. Case 1-1 and Case 2-1 do not carry out AWPF identification, and Case 1-2 and Case 2-2 carry out AWPF identification. Such case composition is conducive to the comparison and verification of the effects of multi-zone data sets and AWPF identification, respectively.

Table 1. Case composition

Name	Date set	Carry out AWPF identification
Case 1-1	Use only $Struct_t^0$, not use $Struct_t^x, x = 1,2,\dots,m$	No
Case 1-2	Use only $Struct_t^0$, not use $Struct_t^x, x = 1,2,\dots,m$	Yes
Case 2-1	Both use $Struct_t^0$, and $Struct_t^x, x = 1,2,\dots,m$	No
Case 2-2	Both use $Struct_t^0$, and $Struct_t^x, x = 1,2,\dots,m$	Yes

4.2. AWPF identification and data adjustment
Based on the historical wind power output measured value and the historical wind power output predicted value reproduced by the ANN method in this paper, the historical AWPF set, and then the extracted candidate features shall be conducted with the feature extraction. The uncorrelated feature sets are randomly generated by $Struct_t$, and δ is set to 5%. The final selected feature vector is:

$$\left(\mu_s^0, \mu_s^1, \mu_s^2, RU_s^0, RD_s^0, \mu_d^0, \mu_d^1, \mu_d^2, PV_p^0, \mu_p^0, RU_p^0, RD_p^0\right) \tag{20}$$

4.3. Predication result analysis
The RMSE results for each case are shown in Figure 3. The data-adjusted wind power output prediction method has obvious higher accuracy. At the same time, adopting the multi-region NWP data to predicate can also improve the predication accuracy, which verifies that the wind power output predication method of considering the numerical weather forecast and error pattern identification has a higher accuracy.

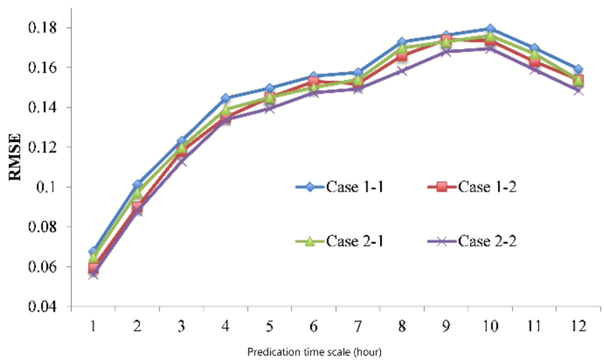

Figure 3. Comparison of each case RMSE result

5. summary
The difficulty in multi-zone absorption wind power is how to efficiently allocate flexible resources to address the uncertainty of wind power output. However, improving the accuracy of wind power output prediction is the most direct and effective way to reduce the uncertainty of wind power output.

Therefore, this paper proposes a wind power output prediction method considering multi-zone numerical weather prediction and error pattern identification. It can be seen from the analysis results of the example that the wind power output prediction method proposed in this paper can effectively identify the potential abnormal wind power prediction error mode and have a high accuracy of wind power output prediction.

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