Wind power forecast based on convolutional neural network with multi-feature fusion

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Abstract. As a renewable clean energy, wind energy has the characteristics of large storage and wide distribution. It is one of the important components of energy internet. However, its strong fluctuation, randomness and discontinuity affect the stable operation of power system. To reduce the impact of wind power on power network and improve the reliability of power prediction, a wind power forecast method based on convolutional neural network with multi-feature fusion is proposed. Firstly, the wind power is classified according to the change characteristic of the waveform. The feature of the wind power waveform is extracted by the convolution neural network (CNN). Then, a prediction model based on multi-feature fusion algorithm is established to accurately predict wind power. Finally, the corresponding simulation model is established to verify that the proposed method can effectively improve the reliability of wind power prediction.

1. Introduction

In recent years, environmental pollution and inadequate fossil energy production are more and more serious. To solve these problems, the utilization of renewable energy has become the focus of domestic and international research. Wind power is one of the renewable energy sources. It is characterized by low pollution, renewable and abundant resources comparing traditional energy sources[1]. Wind power generation technology is mature and widely favored. However, the strong fluctuation, randomness and discontinuity of wind energy bring great challenges to the stable operation of power system. To reduce the impacts on the power grid, it is necessary to accurately predict the wind power[2-3].

Wind power forecast methods are mainly based on physical model and statistical algorithm. The physical model analyzes the correlation between meteorological information and power change in time and space dimensions to realize the prediction of power fluctuation. This method requires a large amount of historical meteorological data. Statistical algorithm extracts, analyzes and predicts the characteristics of wind power waveform directly. However, traditional statistical algorithm cannot meet the accuracy of power prediction for the complexity of wind farm power characteristics and signal superposition of different scales. Reference [4] extracts the effective variables of meteorological data by causal detection method. According to the mapping relationship between wind power and meteorological factors, the power of wind is predicted and the error is corrected. In reference [7], the stochastic process of wind power generation is characterized by neural network to predict multiple scenarios of future wind power generation. Reference [5] proposed a method to identify time series
wind power, using dynamic programming recursive strategy to search for power variation. Reference [6] adopted the probability model based on the wind power climbing rate and the wind power forecast error to achieve the forecast. However, the accuracy of wind power prediction cannot be guaranteed for many factors affecting wind power and complex changes in power wave.

Therefore, this paper proposes a wind power prediction scheme based on convolutional neural network with multi-feature fusion (MFF-CNN). Convolution neural network (CNN) is used to classify and extract the features of wind power wave. According to the multi feature fusion algorithm, the corresponding weights are established for different features to realize the multi feature fusion. The forecast model is established to realize the accurate prediction of wind power. Through the actual wind power data of a wind power plant in China, the reliability of the method is verified by simulation.

2. Feature extraction of wind power waveform

Wind energy is a clean and renewable energy without pollution. It is affected by wind speed, wind direction, air density, temperature and other factors. Wind power is uncontrollable and random. The power waveform of wind farm is relatively stable when the temperature change is small and the air flow is slow. When strong low-pressure system (or cyclone), low-level jet stream, thunderstorm, gust or similar long-term extreme meteorological events occur, the power of wind farm will rise rapidly in a short time. While the relative meteorological events occur or the wind speed is higher than the cut-out wind speed, and some wind turbines are out of operation one after another, the wind farm power will decline rapidly in a short period of time. Wind power is divided into three categories according to the fluctuation process: large fluctuation, small fluctuation and random disturbance. Large fluctuation refers to the large fluctuation of wind power under abnormal conditions; Small fluctuation refers to the normal fluctuation of wind power due to weather changes; Random disturbance is a kind of random processing caused by a large number of high frequency random disturbances.[7]

The wind power sequence is normalized. The random disturbance power is identified by setting a threshold $\varepsilon$. Large fluctuation and small fluctuation are identified by duration time $T_k$, range $D_v$ and rise time $T_r$. Typical wind power waveform classification is shown in Figure 1.

![Figure 1. Wind power waveform classifications](image)

In Figure 1, each wave process grows from a corresponding local minimum to a maximum and then decays to another local minimum. The wave process formula is shown in formula (1).

$$W(T_i) = P_i, \quad i \in [t_{k,l}, t_{k,r}]$$

In formula (1), $W(T_i)$ is the wind power sequence; $T_i$ is the time series; $P_i$ is the power value; $t_{k,l}$ is the local minimum time point on the left side of the maximum power $t_{\text{max},k}$; $t_{k,r}$ is the local minimum time point on the right side of the maximum power $t_{\text{max},k}$.

For each fluctuation process, the feature quantity is extracted. Seven characterizations are used as the basis of multi feature fusion convolution neural network algorithm. Results as shown in Figure 2.
Figure 2. Wind power feature extraction sample

(1) $\Delta P_l, \Delta P_r$ are power amplitude changes.
(2) $\Delta t_l, \Delta t_r$ are time of rapid power change. $\Delta t_l$ is the time difference of power rising rapidly. $\Delta t_r$ is the time difference of power dropping rapidly.
(3) $\Delta P_l / \Delta t_l, \Delta P_r / \Delta t_r$ are climbing rate.
(4) $\Delta t$ is the total time of fluctuation process.

3. Wind Power forecast based on multi-feature fusion

3.1. Fundamentals of convolutional neural network

It is significant to extract the deep features of wind power signals for wind power ramp prediction. Convolutional neural network (CNN) can effectively extract the features of the original image by imitating the human visual perception mechanism\cite{12}. CNN is usually composed of convolution layer, pooling layer and full connection layer. The convolution layer is the most important part of CNN. CNN replaces the conventional matrix multiplication of at least one layer in the traditional neural network with convolution. It is an improvement of the traditional neural network. A filter is used to convolute the input in the convolution layer. The essence of each filter is a small matrix, and the corresponding characteristic graph can be obtained after convolution operation. CNN can automatically create filters and build dense and complete eigenvectors. It has been proved to be a very reliable method to extract deep features of data. In the same convolution layer, there is no connection between the neurons except the weights are shared. Therefore, CNN is more efficient comparing with the multi-layer perceptron with the same number of layers and neurons. Each convolution layer can be expressed by formula (2).

$$h^k_i = f((W^k \ast x)_j + b^k_j)$$ \hspace{1cm} (2)

In formula (2), $h^k_i$ is the output vector of convolution layer whose position is row $i$ and column $j$; $x$ is the input vector of the convolution layer; $f$ is the activation function; $W^k$ is the weight matrix of the convolution kernel connected to the feature graph $k$; $b^k$ is the offset vector of the feature map.

Pooling layer is another special layer of CNN. It can retain the main features by replacing the output of a particular location of the network with the statistics of nearby data. At the same time, the parameters and calculation amount of the next layer are reduced to prevent over fitting. Pooling methods mainly include maximum pooling and average pooling. Maximum pooling can get the maximum value which is the most important feature after convolution feature extraction. It also reduces the dimension of the data features extracted from the convolution layer, which effectively reduces the amount of calculation. The maximum pooling is selected in this paper.

In CNN, the convolution layer corresponding to each convolution kernel is actually the system used to judge the input characteristics. However, it is not clear about the operation rules of the system to judge the characteristics. The parameters of convolution kernel are adjusted by error back-propagation. The convolution kernel that adjusts parameters after training can complete the current convolution level to judge input characteristics. The CNN of a complex system composed of a certain
number of convolution layers can complete the extraction of the required complex features when all the single convolution layers can effectively complete the task of feature judgment.

3.2. Forecast model of multi-feature fusion

In this paper, a wind power forecast model based on convolutional neural network with multi-feature fusion (MFF-CNN) is proposed, which takes the waveform data as the input of the network. Convolution neural network (CNN) is used to extract 7 eigenvalues of waveform. Using multi feature fusion algorithm, these eigenvalues are fused respectively. Then the feature map is produced by sliding time window, and the subsequent calculation operation is carried out. This method takes advantage of CNN model extraction, improves the accuracy of the model and ensures the accuracy of power prediction. The structure of the prediction model is shown in figure (3).

![Figure 3. Structure of the prediction model](image)

The training data set D can be described as follows:

\[
D = \{(p_i, p_i', t_i, t_i', v_i, v_i', t_0)\}
\]  

(3)

In formula (3), \(p_i, p_i', t_i, t_i', v_i, v_i', t_0\) are seven eigenvalues of wind power waveform. The expression of training single feature image is as follows:

\[
\min_{w^D, \theta^D} \sum_{i=1}^{N} L(\text{softmax}(W^D g^D(d^i, \theta^D)), y^i)
\]

(4)

In formula (4), \(W^D\)is the weight; \(g^D(d^i, \theta^D)\) is the result of communication; \(y^i\) is the image tag; \(L(s, y) = - \sum y^i \log s^i\) is the cross entropy loss function expression. After feature fusion calculation, the expression of multi feature fusion is obtained as follows:

\[
\min_{w^F, \theta^F, \theta^F} \sum_{i=1}^{N} L(\text{softmax}(W^F[g^F, g^F]); \theta^F), y^i)
\]

(5)

In formula (5), \(g^F, \theta^F, \Theta^F\) is the parameter after feature fusion.

4. Simulation experiment of scheme feasibility

The wind power data of a wind farm in China in recent years are used as the data set in order to verify the scientificity and reliability of the model. Python is the programming language. The compilation environment is JetBrains Pychar 2018. The ram is 4 GB and the processor is Intel Core i5-8250u.
4.1. Accurate performance evaluation of forecast model.

In recent years, 2000 samples in wind farm are selected to test the model. 50% data are training set and the others are test set. Several groups of simulation experiments were carried out. Min-max standardization is used to transform the original data linearly. The data size is limited to [0,1]. Three indexes are selected as the standard in order to evaluate the prediction accuracy of the prediction model. The indexes are mean absolute percentage error (MAPE), mean absolute error (MAE) and root mean square error (RMSE). The proposed scheme (MFF-CNN) is compared with the traditional neural network prediction methods such as BPNN, ENN, CNN, LSTM and AM.

Table 1. Forecast error comparison between different algorithms

| Model Type | large fluctuation | small fluctuation |
|------------|-------------------|------------------|
|            | MAPE  | MAE  | RMSE | MAPE | MAE  | RMSE |          |
| MFF-CNN    | 0.046 | 44.32| 30.23| 0.032| 25.56| 20.54|          |
| BPNN       | 0.072 | 70.23| 50.01| 0.054| 60.56| 30.67|          |
| ENN        | 0.115 | 65.32| 55.39| 0.997| 60.06| 48.68|          |
| CNN        | 0.088 | 89.06| 58.11| 0.063| 80.12| 50.62|          |
| LSTM       | 0.096 | 74.26| 66.07| 0.083| 70.05| 60.74|          |
| AM         | 0.125 | 102.68| 85.67| 0.093| 88.54| 75.58|          |

Table (1) shows that the error percentage of the proposed scheme is less than 5% and the error value is within 40%. It has good prediction accuracy. The prediction accuracy of the prediction model for small fluctuation waveform is higher than that for large fluctuation waveform. The algorithm is better than the traditional prediction algorithm in three indicators comparing with different algorithms. Simulation results show that the algorithm has certain advantages in power prediction. The comparison between the predicted waveform and the actual waveform is shown in Figure (4). The two waveforms are basically coincident.

![Figure 4. Comparison between the predicted and actual waveform](image)

4.2. Prediction time performance evaluation of forecast model.

The MFF-CNN model is compared with the traditional neural network model by using the same data source. Compare the time when the prediction reliability is above 95%, 80% - 95%, 60% - 80% and below 60%. As shown in Figure (5).

![Figure 5. Comparison of prediction time performance](image)
In Figure (5), the total predicted time of 100 hours is used as the judgment basis. It can be seen that the prediction time of MFF-CNN prediction model with high reliability is higher than other traditional prediction schemes. Using the same data source, the model can predict a longer time.

### 4.3. Data window duration performance evaluation of forecast model.

By comparing the time window changes of the models, Table (2) can be obtained.

| Time Window (s) | MFF-CNN | BPNN | ENN | CNN | LSTM | AM |
|----------------|---------|------|-----|-----|------|----|
| 15             | 31      | 41   | 47  | 40  | 72   |

As can be seen from Table (2), MFF-CNN algorithm has the fastest speed and the shortest time window among many model algorithms.

### 5. Conclusion

In order to solve the problems of low accuracy and slow speed of wind power prediction, this paper proposes a wind power forecast scheme based on convolutional neural network with multi-feature fusion. The scheme is summarized as follows.

1. The wind power waveform is classified according to the fluctuation amplitude, and the corresponding feature extraction is carried out. Seven different features are extracted into convolution layer by convolution neural network. Sliding time window produces the feature map. Feature fusion algorithm fuses seven features. Finally, the weight is allocated to realize the accurate prediction of wind power.

2. The simulation experiment is carried out through the actual wind power data of a wind farm in China. In order to compare the proposed scheme with the traditional power prediction method, three indexes are proposed, including the accuracy of prediction, the requirement of data duration and the prediction time. Simulation results show that the scheme has certain advantages in three indexes.

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