Data-Driven Method Based Wind Power Characteristic Analysis and Climbing Identification

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Abstract. With the increasing penetration of wind power, how to accurately analyze characteristics of wind power becomes significant to the safe and stable operation of power system. This paper proposes a data-driven based wind power characteristic analysis and climbing identification method. Wind power climbing threshold is extracted firstly to construct climbing event dataset based on k-means clustering. 2D convolutional neural network-based climbing identification method is then proposed, with network parameters trained by transforming 1-dimensional wind power output records into a 2-dimensional matrix to identify future climbing events. Test results on practical wind farm show that the proposed method can effectively analyze characteristics of wind power, which has better climbing identification accuracy compared with traditional methods.

Keywords: Wind Power · Characteristic Analysis · Climbing Identification

1 Introduction

Wind power output is highly correlated with environmental factors. With the influence of complex weather scenarios, characteristics of wind power output change, and the occurrence of corresponding climbing events poses great challenges in developing scheduling plans for power system [1–5]. Consequently, accurate and reliable wind power characteristic analysis and climbing identification under complex weather scenarios is an important basis for the modern smart grid operation and scheduling, and is an important condition for achieving wind power penetration in the future [6, 7].

According to whether judged by the wind power forecasting results, climbing identification methods can be divided into direct methods and indirect methods [8–10]. Indirect identification methods are based on wind power forecasting results, and the models used contain three main types: physical models based on numerical weather forecasts, statistical models using historical data, and integrated models combining the two. However, the calculation errors of the models usually affect the accuracy of climbing identification results. By contrast, the direct identification method obtains the identification mechanism by training from historical climbing data, and then directly predicts the climbing event

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characterization quantity (such as slope magnitude, duration or slope rate, etc.), becoming popular in recent years. However, due to the complexity of the climbing problem, the existing methods still suffer from the problem of low accuracy [4, 5].

This paper proposes a data-driven based wind power characteristic analysis and climbing identification method. Wind power climbing threshold is extracted firstly to construct climbing event dataset based on k-means clustering. 2D convolutional neural network-based climbing identification method is then proposed, with network parameters trained by transforming 1-dimensional wind power output records into a 2-dimensional matrix to identify future climbing events. Test results on practical wind farm show that the proposed method can effectively analyze characteristics of wind power, which has better climbing identification accuracy compared with traditional methods.

2 Data-Driven based Wind Power Characteristic Analysis and Climbing Identification Method

2.1 Wind Power Output Characteristics

Supposing P_{ti} means the magnitude of wind power output at time t_i, then the characteristics of wind power output under given period $t_0 - t_0 + \Delta t$ can be shown in Eqs. (1)–(4).

$$\mathrm{A_1} = \mathrm{abs}\left(\mathrm{P_{t_{i+1}}} - \mathrm{P_{t_i}}\right)\ \mathrm{t_i} \in [\mathrm{t_0}, \mathrm{t_0} + \Delta\mathrm{t}] \tag{1}$$

$$\mathrm{A_2} = \max\left[\mathrm{P_{t_0}} : \mathrm{P_{\Delta t + t_0}}\right] - \min\left[\mathrm{P_{t_0}} : \mathrm{P_{\Delta t + t_0}}\right] \tag{2}$$

$$\mathrm{A_3} = \frac{\mathrm{P_{\Delta t + t_0}} - \mathrm{P_{t_0}}}{\Delta\mathrm{t}} \tag{3}$$

$$\mathrm{A_4} = \frac{\mathrm{sum}\left[\mathrm{P_{t_0+1}} : \mathrm{P_{\Delta t + t_0 + 1}}\right] - \mathrm{sum}\left[\mathrm{P_{t_0}} : \mathrm{P_{\Delta t + t_0}}\right]}{\Delta\mathrm{t}} \tag{4}$$

2.2 Extraction for Climbing Threshold

K-means algorithm is a division-based clustering algorithm. It uses distance to measure the similarity between samples, which can divide the sample set into K clusters. The mean vector of a cluster is the center of mass of the cluster, as shown in Eq. (5).

$$\boldsymbol{\mu}_i = \frac{1}{|C_i|} \sum_{x \in C_i} x \tag{5}$$

The purpose of k-means algorithm is to find K centroids to obtain the minimum distance between the centroid and the sample, that is, to minimize the squared error E. The smaller squared error E is, the higher the similarity of the samples in the cluster is. The squared error E can be expressed as Eq. (6).

$$E = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \boldsymbol{\mu}_i\|^2 \tag{6}$$

Specifically, the calculation process of k-means is as follows.

(1) Supposing there exists a sampling set $X = \{x_1,x_2, \ldots ,x_n\}$, K samples are chosen at random as the initial center of mass
(2) The distance between the rest of the samples in the sample set and the center of mass is calculated, and the samples are grouped with the nearest center of mass.
(3) After all samples are grouped into sets, the centroid of each set is recalculated.
(4) Finally, this process is repeated continuously until the minimum distance between the calculated new centroid and the old centroid is less than the set threshold, that is, the minimization squared error E is less than the expected value, then the algorithm is considered to converge.

In this paper, characteristics of wind power output records (1)–(4) under historical periods are constructed into matrix **P**, which is further divided into different clusters by using K-means algorithm. Then wind power climbing threshold is extracted, as shown in Fig. 1.

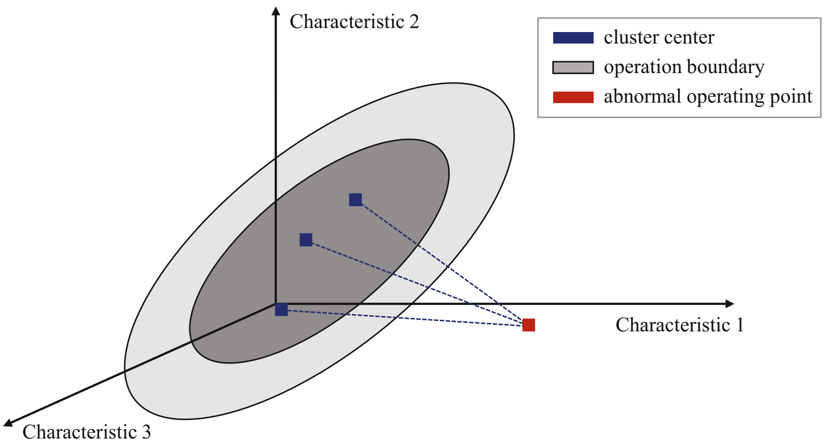


Fig. 1. Extraction for wind power climbing threshold

2.3 2D Convolutional Neural Network-Based Climbing Identification

Convolutional neural network (CNN) is a kind of feedforward neural network that includes convolutional computation and deep structures, which is known as one of the representative algorithms of deep learning. The network is modeled after the biological perceptual mechanisms, and the convolutional kernel parameters shared within the implicit layers and the sparsity of inter-layer connections allow convolutional neural network to feature lattice pointing with small computational effort. In general, CNN algorithms include 1D CNN, 2D CNN and 3D CNN, among which, in 1D CNN, the kernel slides along one dimension and is often used for the processing of temporal data, 2D CNN is often applied to the recognition of image-based text, and 3D CNN is mainly used for medical images and video-based data recognition. The basic structure of CNN is shown in Fig. 2.

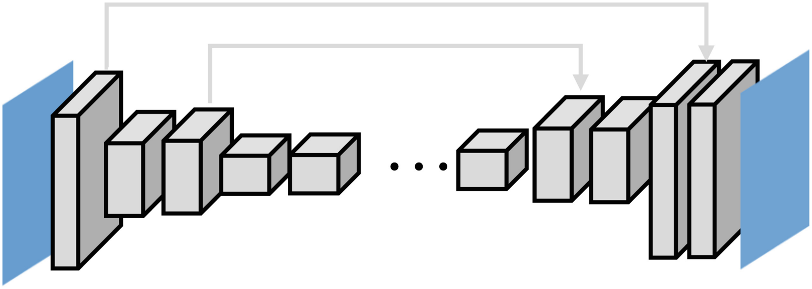


Fig. 2. Basic structure of CNN

Specifically, a convolutional neural network usually consists of the following structures.

1. convolutional layer: the convolutional layer, also called feature extraction layer, is mainly used to extract the features of the input data, each different convolutional kernel extracts different features of the input data, the more convolutional kernels in the convolutional layer, the more features of the input data can be extracted.
2. pooling layer (Pooling), also called down-sampling layer, the main purpose of which is to reduce the amount of data processing and speed up the training network while retaining useful information.
3. flat layer: the data dimension is made to change due to the passage of filters, and the role of this step is to convert the data to be processed into a one-dimensional vector corresponding to the neural units of the input layer before being fed to the neural network.
4. hidden layer, normalization layer, fully connected layer, output layer, etc.

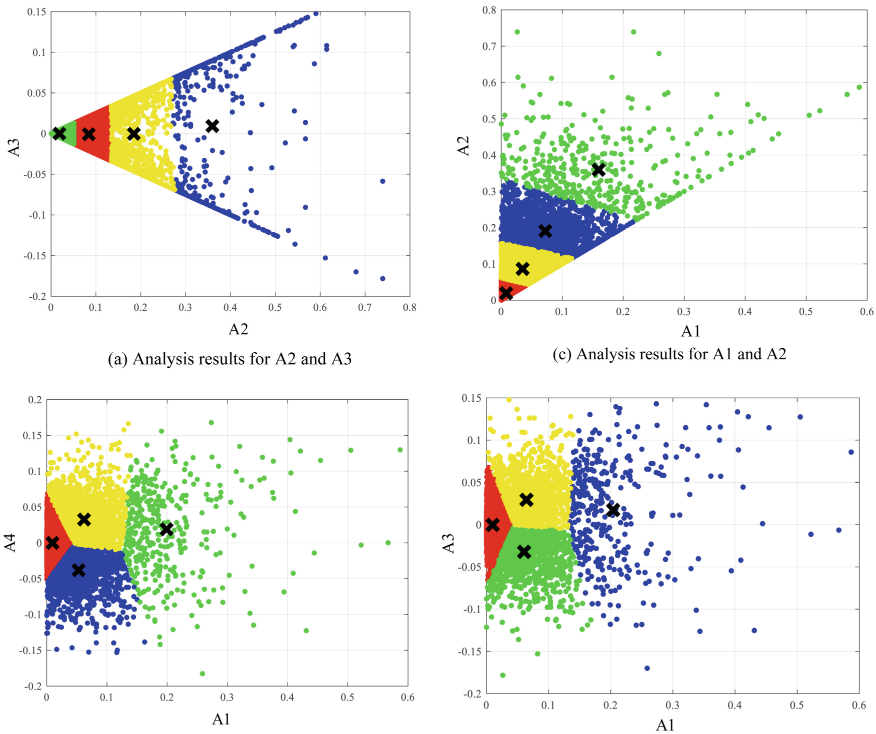
Considering the inherent correlation between different characteristics, in this paper, 2D convolutional neural network-based climbing identification method is then proposed, with network parameters trained by transforming 1-dimensional wind power output records into a 2-dimensional matrix to identify future climbing events.

3 Case Study

Case study is conducted on practical wind farms in China, firstly, the analysis results for wind power output characteristics is discussed, which is utilized to determine the climbing threshold. Then the comparison results for the climbing identification between different methods are analyzed.

3.1 Analysis Results for Climbing Threshold Extraction

The calculation results of different indexes are shown in Fig. 3. It can be found that the clustering of wind power output characteristics can be accurately realized based on the proposed method, and the threshold can be extracted on this basis.



(a) Analysis results for A2 and A3

(c) Analysis results for A1 and A2

(b) Analysis results for A1 and A4

(d) Analysis results for A1 and A3

Fig. 3. Analysis results for climbing threshold extraction

3.2 Analysis Results for Climbing Identification

The results of climbing identification are shown in Fig. 4. And the comparison results of different methods under different wind power output periods are shown in Tables 1 and 2. It can be found that the proposed method can realize climbing identification more accurately than other methods.

4 Conclusion

This paper proposes a data-driven based wind power characteristic analysis and climbing identification method. Wind power climbing threshold is extracted firstly to construct climbing event dataset based on k-means clustering. 2D convolutional neural network-based climbing identification method is then proposed, with network parameters trained by transforming 1-dimensional wind power output records into a 2-dimensional matrix to identify future climbing events. Test results on practical wind farm show that the proposed method can effectively analyze characteristics of wind power, which has better climbing identification accuracy compared with traditional methods.

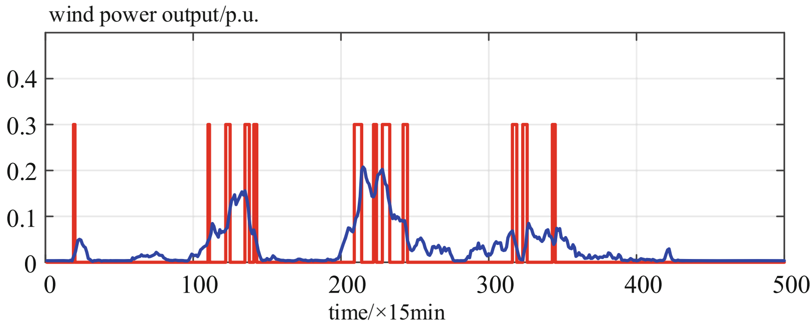


Fig. 4. Analysis results for climbing identification

Table 1. Comparison results of different methods under period 1

	SVM	BPNN	LSTM	CNN	PM
Accuracy (%)	94.74	90.18	92.58	95.09	98.15

Table 2. Comparison results of different methods under period 2

	SVM	BPNN	LSTM	CNN	PM
Accuracy (%)	93.1	87.9	91.3	94.04	97.39

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