A Fault Diagnosis Algorithm for Wind Turbine Blades Based on BP Neural Network

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Abstract. As one of the most critical wind power generation components, wind turbine blades play a key role in generating wind power. Aiming at the problem that the wind turbine blades are subjected to multiple loads in combination, the crack problem is easy to occur. Through the analysis of the macroscopic expansion mechanism and microscopic damage mechanism of short cracks and main cracks, the hidden relationship between crack appearance and damage nature is deeply explored. A fault diagnosis algorithm for wind turbine blades established on the basis of the BP neural network is raised. On the multi-discriminator fusion network structure, BP neural network algorithm is used to train the multi-feature sample data including wind turbine blades, so that the network parameters tend to convergence and gradually approach the real tag. The experimental analysis shows that the algorithm effectively diagnoses and evaluates the damage degree of the blade structure, and has a high recall rate and accuracy, which proves the effectiveness and robustness of the algorithm.

1. Introduction

With continuous development of the national economy in recent years, the industries across China are also developing energetically. In particular, the wide application of wind power generation has created increasingly high demands on safe and reliable wind turbine blades in the field of generating wind power. China is a major resource country rich in wind resources. Thus wind power generation, as a new energy power industry, is supplying abundant wind power. As an important component of the wind turbine generator set, wind turbine blade is quite essential in wind power generation. Due to its requirement on the wind speed, the wind turbine generator set [¹] is generally deployed in harsh environment of Northeast China, Northwest China, the Southwest Plateau, and coastal areas. The large work area makes it difficult for artificial monitoring. As a result, wind turbine blades and other devices are not monitored and keep working at a high work load. Due to the above factors, the damage rate of wind turbine blades is high and the damage cycle varies. Wind turbine blades normally have the faults of crack, breakage and dent. If these faults are not detected and handled in time, a turbine blade may break. It may lead to shutdown and power failure in lesser cases. In severe cases, it may burn the generator and cause chain reactions, leading to a heavy economic or asset loss [²]. Therefore,
national guidelines and strategies on green development and environmental-protection should be adopted to enhance the competitiveness of the wind power generation industry. It is urgent to study effective and trustworthy ways to diagnose the faults on wind turbine blades of the wind power generator set. Thanks to the development of AI technology in recent years, the fault diagnosis of wind turbine blades \cite{3} becomes more and more intelligent. Now there occur more fault prediction methods with rising prediction accuracy. There are many ways of predicting the time series: the ARMA model \cite{4} has high accuracy of predicting linear systems, yet is unsuitable for the modeling and prediction of non-linear systems. The modeling of gray forecasting model doesn’t need the calculation and statistical of characteristic quantity. Also, it is suitable for predicting not only all non-linear changes but also the indicators with exponential growth and the indicators with other tendencies. However, it has a high gray level and its accuracy can hardly be improved.

Artificial Neural Network \cite{5} has been a popular research topic emerged in the AI field in the 1980s. The BP neural network (based on Error Backpropagation Training, BP) \cite{6} is applied to the simulation of the structure and function of the brain’s neural system. Its practical application in industry and technological studies is the most mature. The neural network carries out non-linear propagation calculation through the mapping relationship between attributes and tags. Thus rules can be automatically summarized from the internal attributes and tags of data to find internal laws and connections. Currently, the BP neural network is mainly applicable to such fields as mode recognition \cite{7} and AI \cite{8}. Its application in the environmental evaluation and prediction of industrial scenarios has higher accuracy than traditional industrial algorithms.

The paper mainly adopted the BP neural network and the expert decision-making method deduced from function thresholds. In the integrated system, the neural network was used to process deep perception data. The function threshold deduction was used to display shallow key information. It aimed to combine the functional threshold deduction and deep-learning neural network into the neural network integrated diagnosis system to analyze the fault of wind turbine blades. The fusion algorithm used in the paper mainly includes two knowledge layers: Firstly, the system based on key attribute judgment mainly adopts the joint judgment calculation based on experience thresholds. Secondly, the system based on the reception field propagation of the deep network mainly adopts the non-linear correlations between the deep attributes and tags of the BP neural network.

2. Materials and Research Methodology

2.1 Sample Collection

Wind turbines are generally installed in areas rich in wind energy resources such as grasslands, deserts and coastal areas. The working environment of wind turbines is very harsh, and they have been exposed to extreme high and low temperature environmental conditions with heavy humidity and high dust for a long time. As a result, the key components of the wind turbine are often affected by special weather outside. Moreover, the maintenance of wind power equipment is very difficult, so ensuring reliable and stable long-term operation is the most fundamental requirement. The research object of the paper is centered on the working environment of wind turbine blades. According to former introduction \cite{9}, the real-time detection of the state of wind turbine blades involves the following sensors and devices: (1) Detect transmission through sound analysis and noise test; (2) Apply infrared sensing for infrared detection; (3) Use fiber optical grating sensors to check cracks; (4) Calculate the differences of sound propagation through ultrasonic detectors; (5) Calculate and detect resistance difference through circuit principles.

The boundary conditions of the simulation results, such as vibration frequency and force, are based on the actual working conditions of the wind turbine blades. Environmental sensors are used to abstract features of the surrounding environment. Structural responses and signals are processed into damage features. Through acoustic emission testing, noise signals are collected. Through infrared detection, the thermal distribution map is monitored. The crack signals are collected through the optical grating. The ultrasonic wave detects the difference signals in wind turbine blades. The internal
strain state is detected by the resistance strain. Please refer to Figure 1-5 for the simulation effect of characteristic signals.

Figure 1 shows the distribution of all blade feature data in a special highlight form. Figure 2 shows the root mean square value of the blade signal during the sampling period, represented by V. Voltage signal is related to the size of the acoustic emission, easy to measure, and not affected by the threshold. It is mainly suitable for continuous leaf signal activity evaluation. Figure 3 shows the average value of the signal level within the sampling time, expressed in Db. The information and usage provided are similar to RMS (Root Mean Square). Level signals are particularly useful for continuous blade signals that require high amplitude dynamic range and low time resolution. It is also used to measure the background noise level of blade signals. Figure 4 shows the area under the envelope of the blade signal detection. The power signal reflects the relative degree of failure. The power signal is not sensitive to the threshold, operating frequency and propagation characteristics. It is also used to identify the type of fault source. Figure 5 shows the sound wave signal in the process of passing through the blade. It reflects the location of the blade failure.

![Thermal distribution](image)

**Figure 1.** Thermal distribution.

![Voltage signals](image)

**Figure 2.** Voltage signals.

![Level signals](image)

**Figure 3.** Level signals.
Acoustic emission testing mainly refers to collecting the acoustic emission signals produced when the blade is working particularly with cracks, expansion, and other mechanical faults. At the same time, the emission principles of such signals are analyzed with the signal processing method of time-frequency analysis. Infrared detection refers to measuring the radiation of an object with the noctovisor, calculating the temperature distribution, and converting the thermal distribution of the object into visible images that include the detected object’s surface temperature, namely the thermal distribution diagram. Optical grating detection mainly refers to deploying optical grating sensors at different positions of the blade and monitor the structural damage of wind turbine blades in a real-time manner, so as to abstract the characteristics of damage signals. Ultrasonic testing refers to abstracting the difference features of ultrasonic reflection energy and the penetration time based on the differences between the acoustic characteristics of blades. Resistance strain detection refers to taking resistance strain gauge as a sensor component and adding the strain gauge onto the detected object. The resistance changes when the object’s force-deformation extends or shrinks, which shows the value of strain on the surface or in the component.

Figure 4. Power signals.  
Figure 5. Ultrasonic detection.

In consideration to data collection methods and accuracy, the paper collected the monitoring data from papers on diagnosing problems of wind turbine blades, and the documents on the wind turbine structure design. It also studied the primary work environment of wind turbine blades, time for investment and production, and the collected values of the work environment.

2.2 Diagnosis of Damage on Wind Turbine Blades Based on Neural Network

Suppose n damage parts are taken as category tags and recorded as \{Y_1, Y_2, ..., Y_n\}. Then the damage level of different parts \(Y_i\) is in the range of [0.1 - 1.0].

Different damage features of turbine blades \(M\) \(\{X_i\}_{i=1}^{M}\) and the tags of turbine blade damage \(\{Y_1, Y_2, ..., Y_m\}\) are defined as training samples. \(X_i\) represents the damage features of wind turbine blade samples. Each wind turbine blade sample corresponds to different damage features \(M\{X_i\}_{i=1}^{M}\); \(i\) in \(Y_i\) refers to the damaged part of the present sample. The \(Y_i\) value is the damage level.

According to the definition of training samples, the recognition of damaged parts and the damage-level tasks are abstracted into convex optimization problems. The below is the formula of convex optimization:

\[
\max_{R, \{V_i\}_{i=1}^{M}} \prod_{i=1}^{M} P(\hat{Y}_i = Y | X_i, V_i) \\
R \geq 0, \{V_i\}_{i=1}^{M} \geq 0
\]

(1)

Wherein, \(R\) indicates the weight of the neural network parameter; is the category tag of current prediction; \(P(\hat{Y}_i = Y | X_i, V_i)\) is the prediction of current tag on the Softmax layer \(^{[10]}\) of the neural network [0.0-1.0]. If \(Y_i \geq 0.3\), it refers to the damage issues of \(Y_i\) classified component; the
corresponding relationship between the damage level and the value of $\hat{Y}_i$ is {0.3-0.5: I, 0.6-0.7: II, 0.8-1.0: III}.

The solution of the concave optimization is implemented as follows:

$$\max_{\{Y_i\}_{i=1}^M} \sum_{i=1}^M \left( \log p_{V_i,Y}^i + \sum_{j \in V_i} \log p_{V_j,Y}^i \right)$$

$$= \max_{\{V_i\}_{i=1}^M} \sum_{i=1}^M \left( \log p_{V_i,Y}^i + \sum_{j \in V_i} \log p_{j,N+1}^i - \log p_{V_i,N+1}^i \right)$$

In the formula, $i$ is the input loss feature of wind turbine blade; $y$ is the category tag for the loss of wind turbine blade $i$; $j$ is the judgment results of the $j$ category tag of wind turbine $i$; $R$ is the weight parameter of the neural network.

2.3 Composition of the BP Neural Network

BP neural network is constituted by two parts: the forward transmission of information and the backward transmission of errors. The forward transmission of operation signals: Through the concealed layer, the input signals are conveyed from the input to the output layers. In the forward propagation of operating signals, the weight and offset of the network remain permanent. At the same time, the state of neurons on each layer only affects the state of neurons on the following layer. If the expected output cannot be achieved at the output layer, it can be shifted to the backpropagation of error signals.

The backpropagation of error signals: The differences between the real input and desired output of the network are defined as error signals. In transmitting error signals in backward direction, the error signals are conveyed from the output layer to the input layer. Meanwhile, the weight of the network is adjusted by the error feedback in the backpropagation. The application of weight and the continuous modification of the deviant values make the real output of the network closer to the desired output. The following factors are mainly considered by the BP neural network: The confirmation of network layers, the quantity of nodes at the input layer, the quantity of nodes at the output layer, and the quantity of nodes at the hidden layer.

**Figure 6.** BP neural network model.

BP neural network is primarily demonstrated on the present 3-layer BP neural network. The damage feature is converted into the feature matrix and taken as network input. The fc_1 layer, fc_2
layer, and Eltwise layer are added to change softmax. As Figure 7 shows, the \text{fc}_1 layer is used to map the input loss feature into a characteristic vector; The \text{fc}_2 layer is used to map the judgment results of the threshold algorithm\cite{11} into characteristic vectors; the Eltwise layer is used to combine the positions of the \text{fc}_1 layer and the \text{fc}_2 layer. The softmax layer then makes one classification and discrimination for each position (tag) to output the predicted discriminate value of each position (tag).

2.4 Two-stage Network Design

The current designs of mainstream network structure are mainly divided into one-stage network and two-stage network. The one-stage network is simple in structure, fast in speed and poor in effect. The two-stage network mainly combines multiple algorithms into the fusion discrimination. It requires multiple operation, testing and classification procedures. Although the algorithm has a low speed, its accuracy is quite high. Please refer to Figure 7 for the algorithm structure of the paper.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{algorithm_structure.png}
\caption{Algorithm structure diagram.}
\end{figure}

The main procedures of the fusion algorithm are as follows:

Apply the principle of encoding-decoding\cite{12}. Firstly, the loss features of wind turbine blades are input into the \text{fc}_1 layer at the front end of the coding layer network. Next, \text{fc}_1 turns such features into feature vectors through matrix transformation and normalization and inputs them on the convolution layer. The convolution network has a total of 16 layers. Lastly, the dimension reduction process is carried out for 1x1 convolution layers to turn such layers into the Feature Map. The Feature Map is then input into the back end of the network\cite{13}.

At the front end of the decoding layer network, the loss features of wind turbine blades form the threshold classification matrix through threshold discriminator. Next, the threshold classification matrix is input into the \text{fc}_2 layer and form feature vectors through matrix transformation and normalization. Such feature vectors undergo 1x1 dimension-reduction operation and form the New Feature Map with the same dimensions at the back end of the encoder network\cite{14}.

The Feature Map and New Feature Map of the encoder back end are fused through the Eltwise layer. Next, 3x3 convolution is carried out and eventually get Feature Map\cite{15}.

The above Feature Map is input into the Softmax layer and make one discrimination operation for \( Y_i \) of each category to work out the corresponding value of \( Y_i^y \). Suppose Feature Map is a K-dimensional vector, the classification formula of Softmax is:

\[ \sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \]  

(2)

The threshold algorithm of the above fusion algorithm set a threshold for each predicted category
label $Y_i$ through the experience value. Next, a formula is worked out through deduction:

$$
egin{align*}
Y_1^* &= w_1^1 X_1 + w_1^2 X_2 + \ldots + w_m^1 X_m \\
Y_2^* &= w_1^2 X_1 + w_2^2 X_2 + \ldots + w_m^2 X_m \\
&\vdots \\
Y_n^* &= w_1^n X_1 + w_2^n X_2 + \ldots + w_m^n X_m
\end{align*}
$$

(3)

In the formula, $Y_i^*$ is the prediction value of $Y_i$ tag in the threshold algorithm of current samples. $w_j^i$ is the critical value of attribute $X_i$ at the $Y_i$ label.

2.5 Iteration of BP Algorithm

The main procedures of the BP algorithm iteration$^{[10]}$ are as follows:

**Stp1:** Initialize the threshold parameter and weight of the network; confirm the error function; set the accuracy rate and maximum times of learning $M$;

**Stp2:** Suppose there is neuron $h_1$; the activation function is the sigmoid function; figure up the forward propagation and solve $o_1$:

$$
\begin{align*}
net_{h_1} &= w_1^1 i_1 + w_2^1 i_2 + b_1^1 \\
on_{h_1} &= \frac{1}{1 + e^{-net_{h_1}}} \\
net_{o_1} &= w_5^1 o_{h_1} + w_6^1 o_{h_2} + b_2^1 \\
on_{o_1} &= \frac{1}{1 + e^{-net_{o_1}}}
\end{align*}
$$

**Stp3:** Calculate the total error through input values of $o_1$ and $o_2$.

$$
E_{total} = \sum \frac{1}{2}(o_1 - o_2)^2
$$

**Stp4:** Introduce the above total error into the calculation of partial derivatives through chain rules and work out the parameter variation of $w_5$;

$$
\frac{\partial E_{total}}{\partial w_5} = \frac{\partial E_{total}}{\partial o_{o_1}} \frac{\partial o_{o_1}}{\partial net_{o_1}} \frac{\partial net_{o_1}}{\partial w_5}
$$

$$
\frac{\partial E_{total}}{\partial w_5} = \delta_{o_1} o_{h_1}
$$

**Stp5:** Update the weight value of the hidden layer in reference to the above methods of calculating partial derivatives and following out $(h_1) \rightarrow net (h_1) \rightarrow w_1$:

$$
\begin{align*}
\frac{\partial E_{total}}{\partial w_1} &= \frac{\partial E_{total}}{\partial o_{h_1}} \frac{\partial o_{h_1}}{\partial net_{h_1}} \frac{\partial net_{h_1}}{\partial w_1} \\
\frac{\partial E_{total}}{\partial o_{h_1}} &= \frac{\partial E_{o_1}}{\partial h_1} + \frac{\partial E_{o_2}}{\partial h_1} \\
\frac{\partial o_{h_1}}{\partial net_{h_1}} &= \frac{1}{1 + e^{-net_{h_1}}} \left(1 - \frac{1}{1 + e^{-net_{h_1}}}ight) \\
\frac{\partial net_{h_1}}{\partial w_1} &= w_1^1 i_1 + w_2^1 i_2 + b_1^1 \\
\frac{\partial E_{total}}{\partial w_5} &= \delta_{o_1} o_{h_1}
\end{align*}
$$

2.6 BP Algorithm Implementation

This paper mainly implemented the BP algorithm through Matlab. It first listed the input function
(environmental features, structural response, and the damage features produced by processing signals, noise signals, thermal distribution diagram, crack signals, structural difference signals in wind turbines, internal strain state) and target vectors (predicted values of five predicted faults on wind turbine blades)\(^\text{[16]}\). Take 270 sets of data as the train set and 30 sets of data as the test set. Secondly, train the BP neural network model: 1. The BP neural network initializes the weight; 2. The input data is propagated forward through the input layer, convolutional layer, fully connected layer, and Softmax layer to obtain the output value; 3. Find the error between the output value of the network and the target value; 4. When the error is greater than our expected value, the error is transmitted back to the network, and the errors of the input layer, convolutional layer, fully connected layer, and Softmax layer are obtained in turn. The error of each layer can be understood as the total error of the network, how much the BP neural network should bear. When the error is equal to or less than our expected value, the training ends; 5. Perform weight update based on the calculated error. Then enter the second step. Finally, The BP neural network was tested with the test set.

3. Results and Analysis

3.1 10-fold Cross-Validation

In the 10-fold cross validation\(^\text{[17]}\), the data set \(D\) is divided into ten exclusive sub-sets with the same size (folded), including \(D_1, D_2, D_3\ldots\) The model undergoes \(k\) times of iteration training and tests, with each iteration \(i \in \{1, 2, \ldots, k\}\). Also, the iteration follows the same rule: Trained on \(D \setminus D_i\) and tested on \(D_i\).

3.2 Evaluation Standards

An important role of formulating statistical indicators with the effective model effect is to objectively evaluate its efficiency or the predictive success. To achieve this aim, a set of measurement formulas is necessary to determine the performances of the predictor. Here the standards put forward in\(^\text{[17]}\) are applied to the calculation of visualized and comprehensible indicators.

According to the standard, the correct prediction rate for turning the faults of wind turbine blades into the series is defined by the following definition:

\[
\begin{align*}
Sn &= 1 - \frac{N^-}{N^-} \\
Sn &= 1 - \frac{N^-}{N^-} \\
Acc &= 1 - \frac{N^- + N^-}{N^+ + N^-} \\
MCC &= \frac{1}{\sqrt{1 + \frac{N^- - N^+}{N^+} \left(1 + \frac{N^- - N^-}{N^-}\right)}} 
\end{align*}
\]

\(N^+\) is the total number of series formed by the positive fault samples of the studied wind turbine blades; \(N^+\) is the series of positive samples wrongly predicted by the classifier into blade faults. \(N^-\) is the total number of the series formed by the negative samples of faults on studied wind turbine blades. \(N^-\) is the series of negative samples wrongly predicted by the classifier into blade faults.

Sn is sensibility; Sp refers to specificity; Acc indicates accuracy; Mcc is the coefficient of model stability. These four measurement indicators are generally used to record the discriminator’s prediction results. The performances of the predictor are quantitatively measured from four different perspectives. In statistical analysis, Sn is also known as the true positive rate; (1- Sp) is called to be the false positive rate.
3.3 Experimental Results

Predicting the positions of faults on wind turbine blades refers to finding the non-linear mapping relationship between the input attributes and predicted values of environmental features, structural response, the damage features produced by processed signals, noise signals, thermal distribution diagram, crack signals, the difference signals in blades and internal strain state through modeling training. The ten-fold cross validation method and the train data are used in the BP neural network, threshold model and fusion discrimination algorithms for training. Figure 8 shows the loss iteration graph of training.

![Figure 8. Loss iteration graph.](image)

Based on Figure 3, the model tends to converge when the algorithm iterates for the 1300th times. Next, 30 sets of data are used to test the model and the comparison model [18]. The differences between the prediction value and the real measured tag calculated according to each evaluation standards are shown in Table 1.

| Evaluation Method       | Sn(%)   | Sp(%)   | Acc(%) | Mcc(%) |
|-------------------------|---------|---------|--------|--------|
| BP algorithm            | 78.31   | 81.65   | 79.97  | 60     |
| Threshold Discrimination| 73.92   | 74.29   | 74.66  | 49     |
| The algorithm           | 87.86   | 84.70   | 86.27  | 73     |

To verify the robustness of this algorithm, the ROC curve is used to measure the quality of the classifier’s performances. The vertical coordinate Y is Sn (the real positive rate). The horizontal coordinator X is the false positive rate or 1-Sp. Figure 9 shows the ROC curve.
According to Table 1, the Acc and Mcc of the fault diagnosis algorithm for wind turbine blades in the paper are respectively 86.27% and 0.73 when the times of iteration reaches 3,000\cite{19}. It can predict the faults of wind turbine blades more accurately. As Figure 3 indicates, the ROC curve of the fault diagnosis algorithm for wind turbine blades is significantly better than the BP value and the threshold value of the comparison algorithm. The ROC curve has the AUC values of 0.9548, 0.9488 and 0.9258 respectively. According to quantitative indicators, the robustness and accuracy of the algorithm put forward in the paper have been significantly improved than those of previous algorithms\cite{20}.

3.4 Experimental Analysis

There are various reasons for the faults on wind turbine blades in the wind power generator set. Due to the changing natural environment, abundant damage parts, the complex composition of the generator set, and numerous key links, the fault diagnosis of wind turbine blades is more difficult than that of other industrial devices\cite{21}. The paper put forward a fault diagnosis algorithm for wind turbine blades based on BP neural network. Based on characteristic attributes of the wind power generator set, intelligent algorithms from the frontier computer field were introduced to deeply excavate the superficial factors and internal connections of information related to faults on wind turbine blades\cite{22}. The proposed algorithm sensitively perceives the weak, non-linear, and instant fault signals of wind turbine blades, which effectively predicts and judges the types and damage of faults.

To prove the real effect of the algorithm used in the paper, the paper conducted a comparative simulation experiment of frontier algorithms and the proposed algorithm based on several sets of wind turbine blade data. Meanwhile, several evaluation indicators were introduced to make statistical calculation and analysis of experimental results\cite{23}. According to the experimental analysis, the algorithm effectively discriminated and evaluated the damage of the blade structure, and several evaluation indicators were better than those of compared diagnosis algorithms. It proved the fusion diagnosis algorithm put forward by the paper has high effectiveness and robustness.

4. Conclusion and Significance

The paper conducted an in-depth study and analysis of diagnosing and predicting faults on wind turbine blades of the wind power generation set. Meanwhile, it put forward a fault diagnosis algorithm based on frontier scientific algorithms and technology. The algorithm has two advantages: For one thing, it guides the wind power generator set to make real-time monitoring and intelligent discrimination of wind turbine blades, thereby effectively preventing financial loss and increasing the economic benefits of wind power generation for the country. For another, it has referential values and significance for industrial detection and control system within the industry.
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