Research Article

Wind Turbine Anomaly Identification Based on Improved Deep Belief Network with SCADA Data

Xiafei Long,1 Shengqing Li,1,2 Xiwen Wu,3 and Zhao Jin3

1School of Electrical and Information Engineering, Hunan University of Technology, Zhuzhou, Hunan 412007, China
2Hunan Photovoltaic Smart Grid Control Engineering Research Center, Zhuzhou, Hunan 412007, China
3Hunan New Energy Development Co., Ltd, Guodian Power, Changsha 410016, China

Correspondence should be addressed to Shengqing Li; 2205456745@qq.com

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This article presents a novel fault diagnosis algorithm based on the whale optimization algorithm (WOA)-deep belief networks (DBN) for wind turbines (WTs) using the data collected from the supervisory control and data acquisition (SCADA) system. Through the domain knowledge and Pearson correlation, the input parameters of the prediction models are selected. Three different types of prediction models, namely, the wind turbine, the wind power gearbox, and the wind power generator, are used to predict the health condition of the WT equipment. In this article, the prediction accuracy of the models built with these SCADA sample data is discussed. In order to implement fault monitoring and abnormal state determination of the wind power equipment, the exponential weighted moving average (EWMA) threshold is used to monitor the trend of reconstruction errors. The proposed method is used for 2 MW wind turbines with doubly fed induction generators in a real-world wind farm, and experimental results show that the proposed method is effective in the fault diagnosis of wind turbines.

1. Introduction

Wind power is considered one of the most promising forms of renewable energy sources, which has been widely used in the world [1–3]. However, it results in a higher failure rate than expected because the wind turbine (WT) is exposed to adverse environmental conditions. The operation and maintenance (O&M) costs account for approximately 15–20% of the gross income of onshore wind farms and 30–35% of offshore wind farms [4]. Therefore, condition monitoring (CM) and fault diagnosis technology can achieve preventive maintenance before the malfunction happens. Many kinds of condition monitoring and fault diagnosis techniques, such as acoustic emission [5–8], vibration analysis [9–12], strain measurement [13], electrical effects analysis [14], and ultrasonic testing techniques [15], have been developed to minimize downtime as well as the O&M costs. The recent review in [16] included a comprehensive survey of the existing fault diagnosis technologies for wind turbines with qualitative and quantitative methods, and the fault diagnosis system is also described in this paper. However, most of these methods have not been universally used in wind farms because they are mostly based on the analysis of mechanical signals emitted during the operation process and require a large number of extra sensors, thus resulting in high-deployment costs.

As an important part of wind power equipment, the supervisory control and data acquisition (SCADA) can remotely collect equipment operating data [17]. It has the advantages of providing complete information, improving efficiency, and correctly mastering the operating status of the system. Moreover, it can also help to monitor the health condition of wind turbines. However, currently, there is no effective state evaluation algorithm in most SCADA systems. Only when the sampled data exceed the given threshold can the alarm signal of the wind turbine components be given. At this point, the fault may have deteriorated to a certain level. In order to further improve the fault diagnosis rate and
reduce the high-deployment costs, it is of significant academic value and application prospect to establish an evaluation algorithm and model using SCADA data.

In recent years, the measurement data that come from the SCADA system of a wind farm is used for condition monitoring and fault diagnosis [18–21]. On the one hand, it has achieved remarkable results in reducing the wind turbines downtimes and improving the reliability of wind power. On the other hand, it has become profitable to integrate multisource data signals including mechanical and electrical signals in the wind turbines for analysis. A large number of data mining and abnormal identification methods have been applied to improve diagnostic accuracy upon integrating different condition parameters of the SCADA system. In [22–24], the prediction models composed of conditional parameters of the wind turbine are established by the neural networks. In [22], the historical SCADA data, its current SCADA data, and some wind turbines’ current SCADA data from other wind farms are used to train and test these models. The study in [23] proposes an online wind turbine fault detection system through the multilayer neural network technology using SCADA data. The study cases show the effectiveness of this method. However, in these researches, the input parameters of the model are selected based on domain knowledge, without considering the correlation between the parameters which are associated with other signals that are measured simultaneously. In [24], a method for cointegration analysis of wind turbine fault diagnosis is presented based on the SCADA data. In this current research, six condition parameters are selected for cointegration verification, and abnormal problems can be detected through this method. It is worth pointing out that the proposed approach in [24] assumes that the cointegration relationship is unique; however, in actual situation, the cointegration relationship may be diverse. In [25], an AutoRegressive with Xogenous input model for wind turbine bearing fault is established using SCADA data. However, the choice of manual intervention parameters in this method noticeably affects the accuracy of the model. A deep learning method of a layerwise encoder network for the CM of wind turbine main bearing through SCADA data is proposed in [26]. However, the selection of the number of neurons in the hidden layer and the learning rate parameters have a significant impact on the prediction accuracy.

For different target condition parameters, the different sample data selected from the WT SCADA system will have a significant impact on diagnostic accuracy. However, to the best of our knowledge, little research has been carried out on the effects of the selected condition parameters for WT fault diagnosis model. Aiming to these problems, in this article, a novel fault diagnosis algorithm for WTs based on the whale optimization algorithm (WOA)- deep belief networks (DBN) using SCADA data is proposed. The proposed novel fault diagnosis algorithm can automatically analyze a large number of SCADA data with a low sampling rate. Furthermore, the input condition parameters of this fault diagnosis model are selected based on domain knowledge and the correlation between conditional parameters. This method effectively solves the problem of difficult fault diagnosis of the wind turbine, reduces the installation cost of fault diagnosis equipment, and improves the economic benefit of the wind farm.

The structure of the article is presented in the following manner. The wind turbine and the SCADA system are introduced in Section 2. Section 3 describes the condition parameter selection, the model performance analysis, and the exponentially weighted moving average (EWMA) thresholds method. The whale optimization algorithm, deep belief networks technology, and the WOA-DBN approach are presented in detail in Section 4. In Section 5, a framework of the WT condition monitoring using SCADA data is discussed. In Section 6, the field example is investigated to prove the effectiveness of the proposed method. The conclusions are summarized in Section 7.

2. Wind Turbine and SCADA System

2.1. Description of Wind Turbine. As illustrated in Figure 1, the wind turbine studied in this article is mainly composed of the rotor system, main shaft, gearbox, generator, converter, and so on. And the capacity of the system is 2 MW. The wind energy captured by the rotor system blades is converted into mechanical energy, and then, the main bearings transmit mechanical energy to the generator through the gearbox, while increasing lower rotor speed of the wind turbine to a higher speed. Finally, the generator converts mechanical energy into electrical energy. The simulation and the wind turbine operational principle are discussed [27, 28].

Wind turbines work in complex and varied environments consistently, resulting in frequent failures and high O&M costs, and it should be noted that the longest mean time to repair corresponds to the blade failure, followed by the gearbox and the generator [29].

2.2. Wind Turbine SCADA System. The SCADA system is a data acquisition and monitoring control system, which plays a vital role in the collection, management, and transmission of wind turbine real-time data. The data acquisition of each WT is then transmitted to the data information to the monitoring control system through equipment such as optical fiber and switches. As shown in Figure 2, the monitoring control system provides the interface, picture, and service operation for the wind farm operators to understand all kinds of information of the wind field. The monitoring software provides users with online monitoring, alarm reception, remote control, and operational data charts, using a friendly and flexible user graphical interface, which can real-time monitor the relevant data of wind turbine operation.

However, relying solely on the SCADA alarm system does not accurately grasp the operation status of the wind turbine. Due to the wide setting of the alarm threshold, when the system issues an alarm, the fault may have deteriorated to a serious degree, which cannot prevent the failure. In order to improve the fault diagnosis rate and prevent faults in
advance, the SCADA data used in this study were derived from the 2 MW onshore wind turbines of a wind farm in Central China. The continuous monitoring data from March 2018 to September 2018 were collected.

3. Prediction Model Development

3.1. Parameter Description and Processing. Up to 97 different types of condition parameters are measured and provided in the SCADA system of a wind farm, including wind speed, wind power, and temperature of different components. However, not every parameter plays a decisive role. For various fault classifications, the choice of parameters will be different, which will lead to different diagnostic models. In order to improve accuracy rates and reduce the diagnostic time, the input condition parameters for each model are selected based on domain knowledge and the correlation between parameters. For example, the relationship between wind speed and the wind power, and the relationship between the oil sump temperature of the wind gearbox and wind power are shown in Figures 3(a) and 3(b), respectively.

The selection of input condition parameters has a high impact on simplifying the model and ensuring prediction accuracy. Firstly, according to the judgment of expert domain knowledge, a total of 49 condition parameters are selected. Secondly, after judging the correlation coefficient as shown in equation (1), where $r$ denotes the Pearson correlation, $n$ is the length of the condition parameter, $x_i$ and $y_i$
are the $i_{th}$ sample point corresponding to different parameters, $\overline{x}$ and $\overline{y}$ denote the average of the condition parameters, and different parameters are selected as shown in equation (1). Finally, the selected conditional parameters are modeled to assess the health of the wind turbine. In this step, according to the expert domain knowledge and the size of correlation between the condition parameters, the type and number of parameters selected are different for different prediction models, which is beneficial to the increase in prediction accuracy and the decrease in prediction time.

$$r = \frac{\sum_{i=1}^{n} (x_i - \overline{x}) (y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \overline{x})^2 \cdot \sum_{i=1}^{n} (y_i - \overline{y})^2}}$$

$$= \frac{n \sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \cdot \sum_{i=1}^{n} y_i}{\sqrt{n \sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2} \cdot \sqrt{n \sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2}}$$  \hspace{1cm} (1)

3.2. Performance Analysis. As shown in equations (2)–(4), the root mean square error (RMSE), the mean absolute percentage error (MAPE), and the mean absolute error (MAE) are used to evaluate the performance of the predictive model.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{m} (x(I) - \overline{x}(I))^2}{m}},$$

$$\text{MAPE} = \frac{1}{m} \sum_{i=1}^{m} \frac{|x(I) - \overline{x}(I)|}{x(I)} \times 100\%,$$

$$\text{MAE} = \frac{1}{m} \sum_{i=1}^{m} |x(I) - \overline{x}(I)|,$$  \hspace{1cm} (4)

where $x(I)$ and $\overline{x}(I)$ represent the actual and predicted values of the $I_{th}$ sample and $m$ is the number of the test samples.

3.3. The Reconstruction Errors and Exponentially Weighted Moving Average Thresholds. The reconstruction error between the actual value and the predicted value of the dataset is used as the detection quantity of the wind turbine state trend. The EWMA [26] threshold is used to monitor the trend of the reconstruction error to realize the fault monitoring and abnormal state determination of the wind power equipment because the trend of reconstruction error will change significantly under normal operating conditions and fault conditions. The reconstruction error $\rho_e$ is given by

$$\rho_e = \|x(I) - \overline{x}(I)\|^2.$$  \hspace{1cm} (5)

Based on the above analysis, the threshold control chart is sensitive to detect a small drift of the mean value in the process, and the exponential weighted moving average is used to set the control line to monitor the fluctuation of reconstruction error. The statistics ($\kappa_t$) of the EWMA control chart are

$$\kappa_t = \lambda \rho_{et} + (1 - \lambda)\kappa_{t-1},$$  \hspace{1cm} (6)

where $\lambda$ represents the weight of history $\kappa_t$ on the current EWMA statistic, $\lambda \in (0, 1]$, and denotes the time. The mean and variance of the statistics are obtained by equation (7), where $\mu_{\kappa_t}$ and $\sigma_{\kappa_t}^2$ denote the mean and variance of the statistics, respectively, $\mu_{\rho_e}$ is the mean of the $\kappa_t$ of the wind power equipment, and $\ell_t$ represents the sampling length.

$$\mu_{\kappa_t} = \mu_{\rho_e},$$

$$\sigma_{\kappa_t}^2 = \frac{\sigma_{\rho_e}^2}{\ell_t} \left[ \frac{\lambda}{2 - \lambda} \right] \left[ 1 - (1 - \lambda)^{2\ell_t} \right].$$  \hspace{1cm} (7)

Therefore, the upper and lower bound functions of EWMA control charts for wind power equipment based on time $t$ are expressed as

Figure 3: (a) Relationship between wind speed and wind power. (b) Relationship between oil sump temperature of the wind gearbox and wind power.
RBM consists of a visual layer further introduced in [37]. From Figure 5, it can be seen that the machine (BM) proposed by Ackley in [36], which was when negative and positive phases of the training process continues until the final RBM is completed. Trained RBMs are stacked to form DBN; for the DBN classification model with \( n \) hidden layers, the joint probability \( p(y, h^1, h^2, \ldots, h^n) \) of the whole DBN is given as

\[
p(y, h^1, h^2, \ldots, h^n) = p(y | h^1) p(h^1 | h^2) \ldots (h^{n-1} | h^n),
\]

(10)

where \( p(h^{n-1} | h^n) \) is the conditional distribution between the \((n−1)_{th}\) hidden layer and then \( n_{th}\) hidden layer.

Figure 5 shows the RBM as the development of Boltzmann machine (BM) proposed by Ackley in [36], which was further introduced in [37]. From Figure 5, it can be seen that RBM consists of a visual layer \( y \) containing \( m \) visible units \((y_1, y_2, \ldots, y_m)\) and a hidden layer \( h \) containing \( l \) hidden units \((h_1, h_2, \ldots, h_l)\). Typically, the visible units follow the Bernoulli or Gaussian distribution, whereas the hidden units usually follow the Bernoulli distribution. The state of the RBM is generally evaluated using an energy function:

\[
E(y, h; \theta) = -\sum_{i=1}^l \sum_{j=1}^m \omega_{ij} y_j h_i - \sum_{j=1}^m b_j y_j - \sum_{i=1}^l c_i h_i,
\]

(11)

where \( \theta = \{\omega_{ij}, c_i, b_j\} \) denotes network parameters, \( \omega_{ij} \) is the weight between hidden unit \( h_i \) and visible unit \( y_j \), and \( c_i \) and \( b_j \) are the bias of the \( i_{th}\) hidden variable and the \( j_{th}\) visual variable, respectively. The negative and positive phases of the RBM learning can be mathematically expressed as

\[
L_U(t) = \zeta \cdot \mu_{\nu} + K \sigma_{\nu} \cdot \frac{1 - (1 - \lambda)^{2l}}{2 - \lambda},
\]

\[
L_L(t) = \zeta \cdot \mu_{\nu} + K \sigma_{\nu} \cdot \frac{\lambda^{1 - (1 - \lambda)^{2l}}}{2 - \lambda},
\]

where \( K \) is a value of 2 and 3, in which 2 is taken as the fault warning limit and 3 is taken as the fault detection warning limit, \( \zeta \) is a value of 3, and the equipment is in the safe zone when \( L_U < L_U(t) \). The principle is shown in Figure 4.

4. Whale Optimization Algorithm and Deep Belief Network Approach

4.1. Deep Belief Network Approach. Deep belief network, which was first proposed by Hinton [30], is a kind of generative depth model, and it has become a widely used deep structure in the field of research and applied science [31–33]. As shown in Figure 5, the structure of DBN consists of a number of restricted Boltzmann machines (RBM) stacked layer by layer [31, 34], while extracting important information and critical features through deep data mining. Based on the RBM learning rule, the data conversion process from the visible layer to the hidden layer is completed by a sigmoid activation function [35]. The hidden layer of the first RBM is considered a visible layer of the second RBM and so on. The training process continues until the final RBM is completed. Trained RBMs are stacked to form DBN; for the DBN classification model with \( n \) hidden layers, the joint probability \( p(y, h^1, h^2, \ldots, h^n) \) of the whole DBN is given as

\[
p(y, h^1, h^2, \ldots, h^n) = p(y | h^1) p(h^1 | h^2) \ldots h^{n-1} | h^n),
\]

(10)

where \( p(h^{n-1} | h^n) \) is the conditional distribution between the \((n−1)_{th}\) hidden layer and then \( n_{th}\) hidden layer.

4.2. The Whale Optimization Algorithm. The WOA, which mimics the social behavior of humpback whales, is known as a nature-inspired metaheuristic optimization algorithm, proposed by Mirjalili and Lewis [38]. As shown in Figure 6, this social feeding behavior of humpback whales is called the bubble-net predation strategy. This optimization algorithm is becoming more and more popular in engineering applications because it does not require gradient information, relies on relatively simple concepts, is easy to implement, and can bypass local optimization to find global optimality [39]. As can be seen from Figure 6, whales attack their prey by spiraling upward and contracting their encirclement.

A mathematical model of the WOA algorithm can be obtained by combining the three aspects of encircling prey, bubble-net attacking predation strategy, and hunting prey. The encircling prey behavior can be represented by

\[
\vec{D} = |\vec{C} \vec{Y}^* (t) - \vec{Y} (t)|,
\]

\[
\vec{Y} (t + 1) = \vec{Y}^* (t) - \vec{A} \cdot \vec{D},
\]

(17)

where \( t \) is the current iteration, \( \vec{C} \) and \( \vec{A} \) denote coefficient vectors, \( \vec{Y} \) represents the position vector, and \( \vec{Y}^* \) indicates the position vector of the best solution currently obtained, and it should be updated in each iteration if there is a better solution. The \( \vec{C} \) and \( \vec{A} \) are obtained as

\[
\vec{C} = 2 \cdot \vec{r},
\]

\[
\vec{A} = 2 |\vec{r} - \vec{a}|,
\]

(18)

where \( \vec{r} \) denotes a random vector in \([0, 1]\) and \( \vec{a} \) linearly drops from 2 to 0 throughout the process.

According to the behavior of the humpback whale, the mathematical model of the bubble-net attacking predation strategy is as
\[
\bar{Y}(t + 1) = \left| \bar{Y}^*(t) - \bar{Y}(t) \right| + e^{bl} \cdot \cos(2\pi l) + \bar{Y}^*(t),
\]

where \( b \) is a constant that defines the logarithmic spiral shape and \( l \) is a random number between \(-1\) and \(1\). It is worth noting that the whale swims in the spiral shape to the prey while shrinking the encirclement. To model this synchronous behavior, it is assumed that there is a probability of \( P_i \) to choose the contraction enclosing mechanism and a probability selection spiral model of \( 1 - P_i \) to update the position of the
whale during optimization. The mathematical model can be expressed as

\[
\vec{Y}(t + 1) = \begin{cases} 
\vec{Y}^* (t) - \vec{A} \cdot \vec{D}, & \text{if } P < P_i; \\
\vec{Y}^* (t) - \vec{Y}(t), & \text{if } P \geq P_i.
\end{cases}
\]  

(20)

On hunting prey stage, the mathematical model is given as

\[
\vec{D} = |C \vec{Y}_{rand} - \vec{Y}|;
\]

\[
\vec{Y}(t + 1) = \vec{Y}_{rand} - \vec{A} \cdot \vec{D},
\]  

(21)

where \( \vec{Y}_{rand} \) denotes a random position vector (a random whale) selected from the current population.

The WOA algorithm begins with a set of random solutions. In each iteration, the search agent updates its location based on a randomly selected search agent or the best solution obtained so far. The random search agent is selected when \( \vec{A} > 1 \), and the best solution is chosen when \( \vec{A} < 1 \) for updating the search agent location. According to the \( P_i \) value, the WOA algorithm can switch between either spiral motion or circular motion. Finally, the WOA algorithm is terminated according to the satisfaction of termination criteria.

4.3. Deep Belief Networks Optimized by Whale Optimization Algorithm. The random initialization of DBN’s network parameters is easy to cause local optimization. For this reason, this article uses the WOA to globally optimize the DBN network parameters and provide the DBN reliable initialization parameters, and the global optimal solution is terminated based on the maximum number of iterations. In order to reduce the fluctuation of prediction accuracy caused by the artificial selection of the DBN network parameters, the WOA is used to optimize the learning rate of the DBN network (\( \eta \)) and the number of the hidden neurons in each layer of the RBM (\( m_i \)) to obtain the highest accuracy in the global sample space.

\[
\min f(\eta, m_i) = \frac{1}{n} \sum_{l=1}^{n} (x(l) - \tilde{x}(l))^2,
\]

\[
s.t. \; \eta \in \eta_{best}, \quad m_i \in \{m_{1_{\text{best}}}, \ldots, m_{n_{\text{best}}}"},
\]

(22)

In this article, the WOA algorithm is used to optimize the parameter combination of the DBN model, and the fitness function is selected as equation (22), where \( x(l) \) and \( \tilde{x}(l) \) represent the actual and predicted values of the \( l_{th} \) sample and \( m_i \) denotes the number of hidden neurons in \( i_{th} \) layer of the RBM, respectively.

The flowchart of the WOA-DBN algorithm is shown in Figure 7, and it can be summarized and described as follows:

(i) Step 1. Initialize the WOA algorithm parameters.

The maximum number of iterations, the population size of whales, and the variable dimensions and their ranges are set.

(ii) Step 2. Randomly initialize the generated whale’s position.

(iii) Step 3. Calculate the fitness of the individual group, according to the objective function (equation (19)), and find the position of the current global optimal solution as the target position.
(iv) Step 4. Update the individual whale location.
(v) Step 5. Determine whether the algorithm satisfies termination conditions. If the maximum number of iterations is reached, the optimal parameters of DBN are output to establish the prediction model; otherwise, return to Step 3.
(vi) Step 6. Obtain the best parameters. When the maximum number of iterations is reached, the global optimal solution is obtained.
(vii) Step 7. Generation of the DBN prediction model. According to the model training, the fault prediction results are obtained.
(viii) Step 8. The validity of the model is verified by examples.

5. The Framework of the WT Condition Monitoring Using SCADA Data

5.1. Implementation of the Proposed Method. In this work, the WOA-DBN approach is employed for WT fault diagnosis using SCADA data. Figure 8 shows the application of the present proposed method, and it can be summarized as follows:

(i) Step 1. Collect the SCADA data. As the research object, the same type of wind turbine was selected, and the original operation data of the WTs were extracted from the wind farm SCADA system.
(ii) Step 2. Process the SCADA data. Firstly, the condition parameters are selected from the original operational data based on expert domain knowledge. Then, the SCADA data are further processed according to the wind farm accident operation record. Finally, the accident operation data and the error data in the SCADA system are deleted.
(iii) Step 3. Select the input and output parameters for each model. (1) Select the output parameters of each model through expert domain knowledge; (2) calculate the correlation between the parameters by the Pearson correlation coefficient (equation (1)); and (3) when the correlation coefficient value between the output parameter and the remaining parameters is greater than a certain value, these parameters are used as input parameters.
(iv) Step 4. Normalize the selected SCADA data to get samples. It can obtain the preprocessed data
samples to test or train the prediction model after normalizing the SCADA data.

(v) **Step 5.** Randomly divide the samples into testing and training sample. Normalize the selected SCADA data to get samples. The ratio of the testing dataset to the training dataset is randomly set. The testing samples are applied to validate the prediction model, and the training samples are adopted to train this model.

(vi) **Step 6.** Optimize the DBN parameters by the WOA. In order to improve the situation that the DBN method is easy to fall into local optimum, the WOA technology is used to optimize the learning rate and the number of hidden neurons in $i_{th}$ layer of the RBM.

(vii) **Step 7.** Train the DBN prediction model and analyze its performance. The three prediction models of the whole wind turbine, WT gearbox, and WT generator are trained separately, and the prediction model is evaluated using the RMSE, MAPE, and MAE indicators.

(viii) **Step 8.** Apply the DBN prediction model to the actual wind farm and evaluate the results. The SCADA data of the actual wind field are input into the prediction model to evaluate the condition of the wind turbine, and the economic benefits of the wind farm are analyzed under the method.

6. The Example Verification

The WT example verification units, which are located in the hills at an altitude of about 1,700 meters originate from a wind farm in Central China. As shown in Figure 9, a total of 25 wind turbines (2-MW) are sent to 110kV step-up substation through three collector lines in this wind farm.

The SCADA analysis data, collected from March 2018 to September 2018, derived from 4 WTs (#3, #11, #12, and #19) with the same type in this article.

6.1. Data Acquisition and Preprocessing. The wind speed of the SCADA data used for modeling is between 3.5 m/s and 25 m/s by statistically sorting the operational data and accident records of the wind farm, and the sampling interval of these data is 10 minutes. In this way, a data matrix with 8209 lines and 97 columns is obtained. Based on domain knowledge, the data can be further processed to obtain a data matrix, which contains 8209 rows and 49 columns.

In order to improve the accuracy of the prediction, the data matrix is further processed by the Pearson correlation coefficient, and the health prediction model of the whole WT is taken as an example to illustrate. Firstly, the wind power is taken as the output, the correlation coefficients of 49 selected conditional parameters are calculated, and those with correlation larger than 0.896 (shown in Figure 10) are selected as input parameters. Secondly, according to the previous step, the condition parameters of three different types of health prediction models can be obtained, as shown in Table 1, where GNT. denotes the generator and T. denotes the temperature. The third row represents the output condition parameters of the three prediction models, and the remaining rows represent the input condition parameters of the prediction models. Figure 11 shows the boxplot of the 12 condition parameters in the whole WT prediction model, where ST.W. represents the stator winding. Finally, the corresponding two columns of parameter values in Table 1 are modeled separately for the WT generator and the WT gearbox, and the performance analysis values of various models are obtained.

6.2. Experimental Results. The WOA-DBN-based method is used to recognize the fault classification of WTs. The programs are run in the MATLAB R2017a environment, where 80% of the samples are randomly exploited for training, and the remaining are used for the test of the fault diagnosis performance. The WOA parameters are set as follows: the maximum number of iterations is set as 10, the population size of whales is set to as 40, the variable dimensions are set as 2, and their ranges are set to as [100 100] and [1 1 0.01], respectively. The DBN parameters are set to as follows: the number of train iterations is determined to be 10, the batch size is selected to be 2, and a network with an output unit is set up. On the basis of these parameters, the performance of the trained WOA-DBN prediction model is shown in Table 2. The predicted results produced by the proposed method are shown in Figures 12(a), 12(b), and 12(c).

After the model training is completed, according to the historical data of the wind farm, the SCADA fault data of the three sets of the wind turbine, gearbox, and generator are searched separately, and the validity of the model for fault detection is verified according to the content proposed in Section 3.3. According to the on-site accident record book, some data of wind turbine, wind power gearbox, and the whole machine before failure are collected, and then, the EWMA method is used to verify whether the WOA-DBN model can judge the health status of wind power equipment in advance. As shown in Figures 12(d), 12(e), and 12(f), the simulation results show that the proposed method can accurately judge the fault types of wind power equipment.

From Figure 12(d), it can be concluded that the fault data samples of the wind turbine generator are predicted by the model, and only the EWMA value of one data sample does not exceed the upper limit of the alarm value. Considering the influence of singularity point, it can be judged that the wind turbine generator has been faulted. According to the fault records of the wind farm, three days after the operation of the unit, the “generator temperature alarm” message issued by the SCADA system indicates that the generator has failed. Similarly, from Figure 12(e), it can be seen that all EWMA of the fault data samples corresponding to the wind power gearbox exceeds its alarm upper limit value, and it can be judged that the gearbox has been faulted and needs to be checked and further processed. The fault alarm results of the whole machine show that 15% of the EWMA value of the fault data sample does not exceed its upper limit of the alarm...
value as seen in Figure 12(f). Although it is judged by the WOA-DBN method that the probability of failure of the unit is large, in order to avoid the occurrence of fault misjudgment, it should be further judged according to the experience of the field staff whether the unit should be shut down for inspection.

6.3. Economic Analysis. Checking the on-site operation record found that the #12 wind turbine was out of operation for 42 days due to gearbox damage failure at 14:05 on August 5, 2018, and the gearbox needed to be replaced. Five days before the failure of the gearbox, the field data are collected, and the method proposed in this article is used for condition monitoring and analysis. It is found that this method can accurately judge the alarm value of the wind power gearbox exceeding the upper limit. If the machine was stopped and checked in time, the whole damage accident of the gearbox could be avoided and only the high-speed axle of the gearbox would need to be replaced. According to the analysis of the wind field, it usually takes about 15 days to replace the high-speed bearing of the gearbox. Taking Nangao Gear as an example, the direct cost of hoisting and purchasing the gearbox is about 116,427 $, while the
maximum cost of replacing a high-speed shaft of the gearbox is not more than 36,383 $. The detailed statistics are shown in Table 3, where it can be concluded that the fault prediction method proposed in this article could have reduced the direct economic loss about 115,949 $.

In addition, according to the on-site operation records of #47 wind turbine, at 18:20 on January 7, 2019, the #47 wind turbine was shut down for 54 days due to generator failure, and the generator needs to be replaced. 10 days before the generator failure, the field data are collected, and the method proposed in this article to carry out condition monitoring and fault diagnosis analysis. The results show that 80% of the alarm value of the wind turbine is over the upper limit. According to the auxiliary analysis of the on-site operators, if the wind turbine is shut down for inspection in time, the occurrence of the cleaning accident of the generator can be avoided, and only the rear bearing of the generator needs to be replaced. Using the data of wind field for analysis, it usually takes only 3 days to replace the generator rear bearing. Take the wind turbine as an example, the replacement cost of the generator is about 90,154 $, while the maximum cost of replacing the rear bearing is not more than 1600 $. The specific statistical results are shown in Table 4. It can be seen that the fault prediction method proposed in this article can reduce the direct economic loss about 175,498 $.
### Table 2: Prediction model performance.

| Model classification                  | Input parameter                      | RMSE | MAE  | MAPE (%) |
|---------------------------------------|---------------------------------------|------|------|----------|
| WT generator prediction model          | GNT. bearing T. (B) (°C)               | 1.62 | 1.55 | 4.57     |
| WT gearbox prediction model            | Gearbox oil sump T. (°C)              | 0.75 | 0.58 | 1.05     |
| Whole WT prediction model              | Wind power (kW)                       | 21.44| 13.96| 5.4      |

![Graphs](image_url)

**Figure 12:** Continued.
All in all, the method can effectively monitor the condition of the wind turbine and reduce the operation and maintenance cost of the wind farm.

7. Conclusions

A novel method for the fault diagnosis of a wind turbine based on the WOA-DBN approach using the SCADA data is presented in this article. The SCADA data are preprocessed based on domain knowledge and the Pearson correlation coefficient. Three prediction models, namely, the whole wind turbine, the wind power gearbox, and the wind power generator, are established in this article. The simulation results show that the proposed method has high prediction accuracy. Field examples further show that this method can realize the condition monitoring of wind turbines and reduce the operation and maintenance costs of wind farms. This method can effectively detect the fault of a wind turbine based on SCADA data and can provide a new idea for the health management of wind turbine in the data center of wind farm. It is a supplement to the deficiency of current fault detection methods. However, in this study, the SCADA data can only be used to judge the failure of the wind turbine equipment. Specifically, some types of failure need to be further verified by relevant technical means, which is a problem to be solved in the follow-up study.
Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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