Research on Fan Operation Evaluation and Error State Judgment Relying on Improved Neural Network and Intelligent Computing

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Abstract. Fan, as the most commonly used mechanical equipment, is widely used. In order to solve the problem of fan bearing fault diagnosis, this paper analyzes the main factors affecting fan spindle speed and power generation in operation. The input and output parameters of the performance prediction model are determined. The performance prediction model of wind turbine is established by using generalized regression neural network, and the smoothing factor of GRNN is optimized by comparing the prediction accuracy of the model. Based on this model, the sliding data window method is used to calculate the residual evaluation index of wind turbine speed and power in real time. When the evaluation index continuously exceeds the pre-set threshold, the abnormal state of wind turbine can be judged. In order to obtain wind turbine blades with better aerodynamic performance, a blade aerodynamic performance optimization method based on quantum heredity is proposed. The Bézier curve control point is used as the design variable to represent the continuous chord length and torsion angle distribution of the blade, the blade shape optimization model aiming at the maximum power is established, and the quantum genetic algorithm is used to optimize the chord length and torsion angle of the blade under different constraints. The optimization results of quantum genetic algorithm and classical genetic algorithm are compared and analyzed. Under the same parameters and boundary conditions, the proposed blade aerodynamic optimization method based on quantum genetic optimization is better than the classical genetic optimization method, and can obtain better blade aerodynamic shape and higher wind energy capture efficiency. This method makes up for the shortcomings of traditional fault diagnosis methods, improves the recognition rate of fault types and the accuracy of fault diagnosis, and the diagnosis effect is good.

Keywords: Air blower, Aerodynamic model, Neural network, Optimize.
1. Introduction
With the continuous development of actuator technology, various types of actuators have been widely used in different industries [1]. Such as industrial, medical, aviation and many other fields. Actuator control related technologies have also been widely discussed in the society, mainly for the problem of actuator end-impact [2].

With the development of optimization technology, researchers at home and abroad have carried out research on the field of fan structure optimization and achieved some research results. The researchers use the multi-optimization design method, one is the conventional gradient-free optimization method, and the other is the adjoint-driven optimization design method, in which the response surface is created by two-dimensional and three-dimensional numerical results. The design parameters are solved by correlating the geometric sensitivity of the model and the sensitivity diagram of the adjoint surface. The numerical results show that, compared with the original blade profile, the flow from the root to the middle of the non-design point of the optimized blade profile is greatly improved, the total pressure recovery coefficient is increased to a certain extent, the fan total pressure ratio is greatly increased, and the adiabatic efficiency is basically unchanged.

Because of its strong self-learning ability, industrial neural network is widely used in the field of modeling, prediction and diagnosis of complex industrial processes. When the common neural networks such as BP and Elman are used for modeling, the network structure can not be optimized automatically, and the convergence speed and accuracy of the model are related to the training algorithm, and sometimes it is easy to fall into local optimization. As a kind of neural network based on mathematical statistics, the generalized regression neural network replaces the transfer function with the probability density function, obtains the joint probability density between the independent variable and the dependent variable from the observed samples, and calculates the regression value of the dependent variable directly, which has the advantages of fast learning speed, strong approximation ability and few adjusting parameters.

This paper aims to iteratively optimize the target model based on genetic algorithm and neural network algorithm, and compares the results obtained by classical genetic algorithm and quantum genetic algorithm by setting different boundary constraint conditions. The results show that quantum genetic algorithm has better optimization performance when the same parameters and constraints are applied, and can significantly improve the aerodynamic performance of the blade while satisfying the good morphology of the blade.

2. System principle and equation

2.1. Pneumatic structure and working principle of Fan
The control system based on pneumatic actuator is shown in figure 1. The main core components are composed of air cylinder, sensor, inertial mass device, displacement sensor, controller, pressure sensor and flow proportional valve.

Wind turbine blades can be simplified as shown in Fig. 1. The blades are divided into several blade elements along the spanwise direction, and the global force on the blades can be obtained by integrating the force on each blade element. The theoretical framework of wind turbine blade aerodynamic performance optimization by quantum genetic algorithm is shown in the figure.
2.2. Mathematical modeling
In this paper, the force balance, pressure and flow of pneumatic actuator system are mathematically modeled.

(1) System force balance equation:

\[ F + p_1 A_1 + p_2 A_2 = P_i A_i \]  
\[ (1) \]

F -- force sensor to detect pressure;
A1 and A2 -- respectively represent the effective cross-sectional area of the piston in the left and right chambers of the air cylinder;
P1 and P2 -- respectively represent the pressure of the left and right chambers of the air cylinder;
Pa and Ar -- respectively represent the atmospheric pressure and the effective cross-sectional area of the pressure cylinder rod.

(2) Pressure differential equation:

\[ V_i = V_{i0} + A_i (I + x), i = 1 \square 2 \]  
\[ (2) \]

(3) Flow equation:

\[ q = \begin{cases} 
CA_i P_s \rho_0 \sqrt{\frac{T_0}{T}}, & P_s \leq b \\
CA_i P_s \rho_0 \sqrt{\frac{T_0}{T}} \left[ 1 - \left( \frac{P_s - b}{P_b} \right) \right], & b < \frac{P_s}{P_b} \leq 1 
\end{cases} \]  
\[ (3) \]

3. Quantum genetic optimization of aerodynamic performance

3.1. Variable setting
Using the control points of Bezier curve to represent the chord length and twist Angle corresponding to the blade element can reduce the design variables and improve the efficiency of programming and
operation. Described by a five-control point Bezier curve the chord length and twist Angle of wind turbine blades. In \( (c_{xi}, c_{yi}; t_{xi}, t_{yi}, i \in [1, 5]) \), \( (c_{xi}, c_{yi}) \) and \( (t_{xi}, t_{yi}) \) are respectively the coordinates of the control points of chord length and twist Angle. The abscissa of the control points is kept unchanged, and the ordinate is taken as the design variable: \( (c_{yi}; t_{yi}, i \in [1, 5]) \)

![Bezier curves describe the length of the string](image)

**Fig.2** Bezier curves describe the length of the string

### 3.2. The objective function

The annual power generation of a wind turbine can be expressed by the product of the average annual power and the annual power generation time. Therefore, this paper selects the output power \( P \) of the wind turbine as the target parameter to establish an optimization model.

The optimization objective function can be expressed as:

\[
\max (P) = \left( c_{yi}, t_{yi}, \quad i \in [1, 5] \right)
\]  

(4)

### 4. Generalized regression neural networks

#### 4.1. Overview of the model

Generalized Regression Neural Network is a new type of nonlinear regression feedforward neural network model proposed by Specht. Its structure includes input layer, mode layer, summation layer and output layer.
4.2. Model building

Assumptions:

\[ D_i^2 = (X - X_i)^T (X - X_i) \]  

\( X \) is the learning sample currently input; \( X_i \) is the n-dimensional input vector of the i th sample in the training set. \( D_i^2 \) represents the square of the Euclidean distance between the current learning sample \( X \) and \( X_i \). In the equation layer, Gaussian function is taken as the activation kernel function, and the output of the i th neuron is the exponential form of Euclidean distance square \( D_i^2 \) between \( X \) and \( X_i \):

\[ P_i = \exp \left( -\frac{D_i^2}{2\sigma^2} \right), \quad i = 1, 2, \cdots, N \]  

The summation layer consists of two units, which are used to calculate the numerator and denominator of the output layer. Wherein, the first unit corresponds to the output vector dimension \( m \), \( j=1, 2, \cdots, m \) nodes. Output \( S_j \) of the j th node is the \( i = 1, 2 \) in the network training set.

\[ Y_i = [y_{i1}, y_{i2}, \cdots, y_{im}]^T \]  
is the output vector of \( N \) samples \( i \) is the weighted sum of the output \( P_i \) of the j th element \( Y_i \) and the i th neuron in the mode layer (that is, \( Y_j \) is taken as the connection weight between the i th neuron Pi in the mode layer and the j th neuron in the summation layer), and its calculation formula is:

\[ S_j = \sum_{i=1}^{N} y_{ij} P_i, \quad j = 1, 2, \cdots, m \]
Output $S_D$ is the sum of the output $P_i$ of each node in the mode layer (as the common denominator of the calculation of each node in the output layer), and its calculation formula is:

$$S_D = \sum_{i=1}^{N} P_i$$  \hspace{1cm} (8)

The number of neurons in the output layer is the same as the y-dimension $m$ of the output vector, and the output of each neuron is the division of the two summation results in the summation layer,

$$y_j = \frac{S_j}{S_d}, \hspace{0.5cm} j = 1, 2, \ldots, m$$  \hspace{1cm} (9)

The key to improve the prediction accuracy is to select the appropriate smoothing parameter values, which should be optimized by combining the prediction test results of model training samples and test samples.

5. Control algorithm

5.1. Algorithm to choose

Compared with the fan, the working condition is more complex, and the calculation of the air volume needs to take into account the coupling relationship between the driving depth and the underground environmental parameters, as well as the requirement of the minimum wind speed, so it is very difficult to establish the mathematical model of fan speed regulation in capital construction, and the traditional PID feedback adjustment algorithm is difficult to meet the requirements. Therefore, in order to ensure the integration of various parameters, the speed regulation model of the construction fan system adopts BP neural network algorithm and uses MATLAB programming language to construct the mathematical model.

5.2. Fault feature extraction of vibration signal

Four kinds of bearing fault signals tested by the wind turbine sensor are the test data. First, a sinusoidal signal polluted by white noise is constructed, and the step $\mu = 0.015$ is taken. The NLMS adaptive filter is used to verify the denoising effect. The results are shown in the figure. In the figure, $d (n)$ is a sinusoidal signal. The difference between white noise, $d (n)$ and $y (n)$ is the de-noised signal, which is very close to the sinusoidal waveform.
Four kinds of original bearing fault signals after noise reduction are decomposed by three-layer wavelet using orthogonal wavelet basis db5, and the squares of wavelet coefficients of each frequency band are added to get the energy of each frequency band. The energy distribution characteristics of various fault signals are analyzed, the probability of each node is calculated, and the energy ratio of each node is calculated. The specific energy distribution spectrum of each frequency band of the fault signal is shown in the chart. As can be seen from the figure, except that the signal energy distribution of the bearing normal signal is the most obvious in the frequency band 1, the distribution is the most obvious and concentrated in the frequency band 3 and 7.
The four fault types were represented by binary coding, and 15 groups of data of different fault types were taken as training samples, while the remaining 20 groups of data were taken as test samples. Particle swarm optimization algorithm and local neighborhood search algorithm are used to optimize the weight of the neural network. The fault features with binary coding as input are mainly the energy proportional coefficients of frequency band 3 and 7. Y1 and Y2 are outputs of the improved BP neural network model respectively, which are used to output four types of faults represented by binary code. The hidden node output model is:

$$h(j) = f\left(\sum W_{ij} x_i - \theta_j\right)$$

Output node output model is:

$$y_k = f\left(\sum W_{ik} h_j - \theta_k\right)$$

![Fig.6 BP output - target error](image)

6. Conclusion
Based on the previous model, this paper puts forward a method of fan operation state evaluation and early warning based on GRNN. This method is based on the data of normal operation state and does not need any prior knowledge of abnormal state. By using the feature extraction method of NLMS-WP fusion, the interference of fault noise signal is effectively removed, and the energy distribution characteristics of different frequency bands of fan bearing fault signal are extracted. Using the improved BP neural network to identify and judge the fault type, compared with the single wavelet packet feature extraction method, this method has a higher recognition rate in bearing fault feature extraction and classification, and can reflect the running state information of fan bearing more comprehensively. The wind turbine condition detection and early warning software is developed with the above method, and verified by the real historical fault cases of wind turbine. It shows that this method can detect the abnormal state of wind turbine timely and correctly. It is of great significance for wind turbine operation state early warning and maintenance decision-making.

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