Research on Variable Pitch Pre-compensation Control Method Based on Wavelet Neural Network Wind Speed Prediction

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Abstract

At present, because of the proportion of wind power in the world is increasing, the stability of wind power generation is particularly important. According to the wind speed, adjusting the wind turbines in real time to obtain the optimal pitch angle is a common method to stabilize the output power and voltage, suppress the frequent adjustment of the pitch angle, and prolong the service life of the mechanical equipment. Aiming at the problem that the pitch angle mechanical adjustment has hysteresis, this paper proposes a variable pitch pre-compensation control method based on wind speed prediction. Firstly, the wind speed is predicted by the improved cyclic wavelet neural network with error feedforward compensation (E-FFD-WNN), and the pitch angle is pre-compensated according to the change rate of wind speed and the trend of wind power. The results of the experiment show that the improved wavelet neural network can pre-dict the wind speed better and the error is small. At the same time, the pre-compensation control method for the pitch angle can stabilize the output power and reduce the adjustment range of the pitch angle, from which can extend the service life of the equipment.

Keywords

Wind power generation, Short-term wind speed prediction, Pitch angle pre-adjustment, Cyclic wavelet neural network.

1. Introduction

At present, the energy demand and environmental pollution (pollution, acid rain, greenhouse effect, etc.) caused by the consumption of fossil energy are becoming more and more serious, and non-polluting renewable energy is a very important way to solve this problem[1-2], Therefore, it has received extensive attention. Among them, wind energy develops most rapidly due to its characteristics of pollution-free and renewable. Wind power generation is currently the most important form of utilization of wind energy, but it is greatly affected by the characteristics of wind speed fluctuation and randomness. Because the adjustment of the pitch angle of the large fan has short-term hysteresis, accurate prediction of wind speed and pre-compensation adjustment of the pitch angle can be used to stabilize the wind farm output power and smooth pitch angle fluctuation to prolong the mechanical life and improve the wind energy. System reliability and so on are of great significance.

According to the time scale, wind speed prediction can be divided into long-term prediction and short-term prediction. At present, there are many methods for predicting wind speed, such as continuous prediction method [3], Kalman filtering method [4], time series analysis method [5], neural network method [6], support vector machine method [7], etc. [8]. With the development of neural networks, advances in machine learning, and continuous improvement of prediction methods, the prediction results of short-term wind speeds are becoming more and more accurate. Wavelet neural network is a neural network model based on wavelet transform. The nonlinear wavelet base is used to replace the nonlinear excitation function of neurons. The wavelet transform and neural network are organically combined to give full play to their advantages.

When the wind speed is higher than the rated wind speed, the fan needs to output constant power through the pitch control method. A good control strategy can reduce the power fluctuation caused by various factors, thus ensuring the smooth output of power. In [9], the affine nonlinear model of wind turbine is established. The dif-ferential geometric feedback linear transformation is used to realize the global accurate linearization of the model. The pitch controller of the rotor speed feedback is used to solve the high wind speed zone. Speed regulation and constant power control issues, but this method is computationally intensive and requires high performance com-puting equipment support. Reference [10] considers the relationship between power and pitch angle at high wind speeds, establishes the sensitivity relationship between the two and designs the pitch controller.

In this paper, considering the instability of wind speed, and the input power of large wind turbines under high wind speed will be affected by the change of wind speed, and the variation of the pitch angle of large wind turbine is affected by mechanical inertia with short-term hysteresis. A method based on Wavelet Neural Network with Error Feedforward Compensation (E-FFD-WNN) is proposed to predict the wind speed, and a pre-compensation control method is proposed for the change of the pitch angle. By comparing with other methods, it can be found that the dynamic performance of the system can be improved while improving the accuracy of wind speed prediction, so that the output power can be stabilized near the rated value while slowing down the fluctuation of power, pitch angle and rotor speed.

2. Wavelet neural network and wind speed prediction

2.1 Wavelet neural network

Wavelet Neural Network (WNN) is a network based on BP neural network topology. Compared with time series, BP neural network, etc., wavelet neural network has local information that can fully extract signals; it has strong adaptive ability, so it can learn various functions; it can avoid local optimal problem of BP neural network and simple structure The advantages of fast convergence and so on. The neural network used in this paper uses the wavelet basis function as the transfer function of the hidden layer node, and the signal forward propagation while the signal propagates backward. Therefore, it is a feedforward neural network with feedback.

The wavelet neural network is divided into an input layer, a hidden layer, and an output layer. There are M neurons in the input layer, L nodes in the hidden layer, and N neurons in the output layer (where M, L, and N are positive integers). The structure is shown in Figure 1.

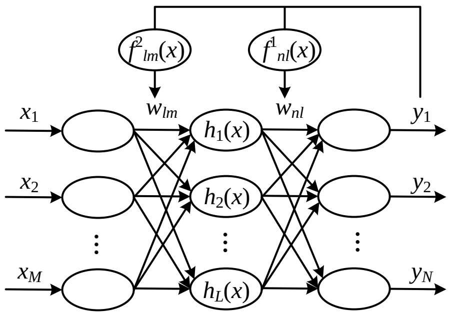

Fig.1 Wavelet neural network structure

In the figure, $f_{nl}^{1}(x)$ and $f_{lm}^{2}(x)$ are the weight correction functions of the hidden layer to the output layer and the input layer to the hidden layer, respectively. The neuron excitation function of the WNN hidden layer was selected by experiment:

$$\mathrm{h}(t) = e^{(-t^2/2)}\cos(1.75\times t) \tag{1}$$

Where $t=(\frac{x-b}{a})$, a is the translation factor of the wavelet function and b is the scaling factor of the wavelet function. In order to achieve the desired goal of the training results, the specified error should be made as small as possible. That makes (2) as small as possible.

$$E=\sum_{p=1}^{P}E^{p}=\frac{1}{2P}\sum_{p=1}^{P}\sum_{n=1}^{N}\left(d_{n}^{p}-y_{n}^{p}\right) \quad (2)$$

Where, d_n^p and y_n^p are the expected output and actual output of the nth node of the output layer respectively, and there are P input and output. In order to achieve the above objectives, it is necessary to constantly adjust the weight of the input layer to the hidden layer and the hidden layer to the output layer, as well as the translation factor a and the scaling factor b. The weight update formula is:

$$w_{lm}\left(t+1\right)=w_{lm}\left(t\right)+\eta_{1}\sum_{m=1}^{p}\delta_{lm}+\lambda\vartriangle w_{lm}\left(t\right) \quad (3)$$

Where $t=(\frac{x-b}{a})$, $w_{lm}\left(t\right)$ and $w_{lm}\left(t+1\right)$ are the weights between the input layer node m and the hidden layer node l before and after the update; η_1 is the learning rate between the input layer and the hidden layer for the purpose of optimization. The hidden layer to the output layer adopts different learning rates η_2; λ is a momentum factor; $\vartriangle w_{lm}\left(t\right)$ is a momentum term.

For the sake of simplicity, only the weight and factor calculation formulas between the input layer and the hidden layer are listed below, and the update of the weight $w_{nl}\left(t+1\right)$ between the hidden layer and the output layer is similar.

The update expressions for the translation factor and the scaling factor are:

$$a_{l}\left(t+1\right)=a_{l}\left(t\right)+\eta_{1}\sum_{m=1}^{p}\delta_{a_{l}}+\lambda\vartriangle a_{l}\left(t\right) \quad (4)$$

$$b_{l}\left(t+1\right)=b_{l}\left(t\right)+\eta_{1}\sum_{m=1}^{p}\delta_{b_{l}}+\lambda\vartriangle b_{l}\left(t\right) \quad (5)$$

Where, $\delta_{a_l}=\frac{\partial E_n^p}{\partial a_l}$, $\delta_{b_l}=\frac{\partial E_n^p}{\partial b_l}$; $a_l\left(t\right)$, $a_l\left(t+1\right)$, $b_l\left(t\right)$, and $b_l\left(t+1\right)$ respectively represent the translation factor and the expansion factor before and after the update; $\vartriangle a_l\left(t\right)$ and $\vartriangle b_l\left(t\right)$ are the momentum items of the translation factor and the expansion factor, respectively.

When adjusting the network weights, generally follow the rules: the learning rate can be too large when learning the initial stage, thus speeding up the learning, and when the learning effect is getting better and better, close to the optimal state, the learning rate needs to be appropriately reduced to prevent the shock. Can not converge. The number of hidden layer nodes in the wavelet neural network uses a number of training observation errors to select a suitable number.

2.2 Wind speed prediction of error feedforward compensation wavelet neural network

Considering that the wavelet neural network has a certain error in the prediction of wind speed, and this situation is especially obvious at special points. Wavelet neural networks are a great test when the wind speed is suddenly rising sharply or drastically, and when the wind speed is rising to falling or falling to the extreme point of rising. Therefore, a method of variable factor error forward compensation is proposed. The error of this moment is multiplied by a dynamic factor, and then compensated to the next predicted value to achieve the purpose of improving the prediction accuracy. The specific implementation method is iterated as shown in equations (6) and (7).

$$e\left(t\right)=x\left(t\right)-\tilde{y}\left(t\right) \quad (6)$$

$$\tilde{y}(t+1)=y(t+1)+\sigma e(t) \quad (7)$$

Where: $x(t)$ is the actual wind speed input at time *t*; $y(t+1)$ is the actual predicted output when *t+1* time is not corrected; $\tilde{y}(t)$ and $\tilde{y}(t+1)$ are corrected wind speeds corrected at time *t* and *t+1* respectively; $e(t)$ is the corrected wind speed at time *t*. The error value between the output and the actual wind speed input; σ is the variable factor.

The value range of σ should be between 0 and 1. The specific choice is to decrease with the increase($e(t)$) of the error. This is to prevent over-compensation when the error forward compensation is performed, thus generating a damped oscillation phenomenon.

In the initial stage, the network needs to learn the historical data first. When the real wind speed is measured at one moment, the learned wind speed is used to predict the wind speed at the next moment. Since the wind energy is uninterrupted when the wind farm is connected to the grid and the wind speed changes are subject to strong interference, the forecast network for short-term wind speed will not be suitable for continuous forecasting, which requires the network to have continuous self-renewal capability. Based on this, this paper adopts the method of cyclically predicting wind speed, that is, every interval (set to Ts) or when the difference between the predicted wind speed and the actual wind speed is greater than 0.5m/s, the wavelet neural network training is immediately renewed and updated. The weights and factors are used to replace the inapplicable network, while the evaluation is suspended until the new network after training is used for prediction. The forecast flow chart is shown in Figure 2.

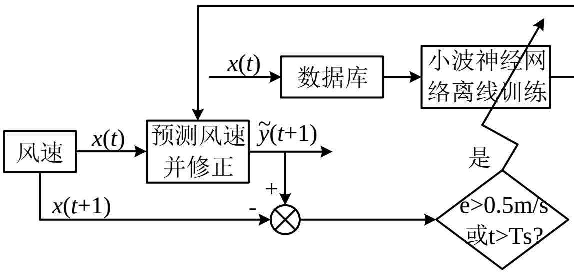

Fig.2 Wind speed prediction flow chart

The database is continuously updated and records the 1000 wind speed data with the most recent time; $x(t)$ and $x(t+1)$ are the input wind speeds at time *t* and *t+1* respectively; $\tilde{y}(t+1)$ is the output wind speed at time *t+1* predicted and corrected according to historical data.

3. Design of pre-compensation control method for pitch angle

Since the mechanical adjustment of the pitch angle has short-term hysteresis, this paper adopts the method of pre-compensation regulation to achieve the purpose of suppressing the sudden change of the pitch angle and stabilizing the output power.

3.1 Wind turbine mathematical model

Wind energy is the kinetic energy generated by air flow, and the work of variable speed pitch wind turbines is to convert wind energy into electrical energy. It needs to be converted into mechanical energy before being converted into electrical energy. According to the aerodynamic principle, the power equation obtained by the wind turbine can be obtained as follows:

$$P_m=\frac{1}{2}C_{\mathrm{p}}(\lambda,\beta)\rho\pi R^2V_{\mathrm{wind}}^3 \quad (8)$$

Where: $C_{\mathrm{p}}(\lambda,\beta)$ is the wind energy utilization coefficient; λ is the tip speed ratio; β is the pitch angle; ρ is the air density (1.225 kg/m3 at 15 ° C sea level average pressure); R is the rotation of the fan rotor Radius, m; V_{wind} is the input wind speed, m/s.

The actuator of the pitch is realized by the hydraulic device. Since the large mechanical equipment has a certain inertia, the variation of the pitch angle will cause a certain delay, that is, the change of the pitch angle has a short time lag. Based on this paper, the compensation pre-control method based on the predicted wind speed is proposed to alleviate the hysteresis of the mechanical device, so as to achieve the purpose of stabilizing the output power and the rotor speed. At the same time, it can suppress the frequent change of the pitch angle and extend the mechanical equipment. The purpose of the service life. It can be seen from the formula (8) that under the condition that the air density is constant and the rotor radius is constant, in order to stabilize the output power above the rated wind speed, the utilization factor of the wind energy should be adjusted. The wind power available at a certain wind speed is related to and . Due to the small fluctuation of the actual speed around the rated speed under high wind speed, it is basically unchanged here, so when the wind speed is constant, the equation can be regarded as basically unchanged according to formula (9), then the stable output power is best. The method is to adjust the pitch angle in time. It is assumed that time t is the current time, and the next time of the current time is recorded as time *t+1*, and time is brought to λ , β , V_{wind}^3 , etc., unless otherwise specified, the default is the current time state (ie, the time *t* is status).

The ratio of the speed of the tip circumference to the wind speed is recorded as the tip speed ratio λ , which is calculated as follows:

$$\lambda(t)=\frac{\omega(t)R}{V_{\mathrm{wind}}(t)}=\frac{\pi n(t)R}{30V_{\mathrm{wind}}(t)} \tag{9}$$

Where: $n(t)$ is the current speed of the wind wheel, r / min; $\omega(t)$ is the angular frequency of the current wind wheel, rad / s.

Before calculating the power of the wind turbine, the utilization coefficient $C_{\mathrm{p}}(\lambda,\beta)$ of the wind energy is required, and the wind energy utilization coefficient can be approximated as a nonlinear function of the tip speed ratio λ and the pitch angle β . The calculation method is as follows:

$$C_{\mathrm{p}}(\lambda,\beta)=c_1(\frac{c_2}{\lambda_i}-c_3\beta-c_4)e^{\frac{-c_5}{\lambda_i}}+c_6\lambda \tag{10}$$

where:

$$\frac{1}{\lambda_i}=\frac{1}{\lambda+b_1\beta}+\frac{b_2}{\beta^3+1} \tag{11}$$

Where: $c_1 \sim c_6$, b_1 , and b_2 are the fitting parameters of $C_{\mathrm{p}}(\lambda,\beta)$. The parameters corresponding to the model built in this paper are 0.5176, 116, 0.4, 5, 21, 0.0068, 0.008, and -0.035, respectively.

According to the Betz theory, the energy obtained by the wind wheel from the natural world is limited. In theory, the wind energy utilization coefficient $C_{\mathrm{p}}(\lambda,\beta)$ of the wind turbine is at most 0.593, and the wind energy utilization coefficient of the three-blade blade is 0.52 to 0.55. Since some conversion losses are also considered, the current optimal wind energy utilization factor is between 0.46 and 0.48.

3.2 Pitch angle pre-compensation control method

When the actual wind speed is greater than the rated wind speed, in order to maintain the maximum power output, the pitch angle of the fan blades should be adjusted in time so that the wind energy utilization coefficient reaches the most advantageous, so the corresponding power and pitch angle need to be measured in time. Since this paper first predicts the wind speed and then pre-compensates the wind turbine pitch angle, this paper also needs to obtain the corresponding current wind speed, predicted wind speed and estimated power at the next moment in time. According to the predicted wind speed ($\hat{V}_{\text{wind}}(t+1)$) at the next moment, the current time $C_{\text{p}}(\lambda,\beta)$ combines the equation (8) to obtain the power of the next time (t+1 time), as shown in the following equation:

$$\hat{P}_m(t+1)=\frac{1}{2}C_{\text{p}}(t)\rho A\hat{V}_{\text{wind}}^3(t+1) \tag{12}$$

Where $A=\pi R^2$, Which is the area swept by the rotor rotation; $\hat{P}_m(t+1)$ is the estimated power of the next moment.

Therefore, the rate of change of power and wind speed can be obtained as:

$$\Delta P_m=\hat{P}_m(t+1)\text{-}P_m(t) \tag{13}$$

$$\Delta V_{\text{wind}}=\hat{V}_{\text{wind}}(t+1)\text{-}V_{\text{wind}}(t) \tag{14}$$

According to the wind speed and the rate of change of power, PID compensation is performed on the pitch angle respectively. At the same time, combined with the wavelet neural network, the wind speed is predicted cyclically. Under the condition that the actual wind speed is greater than the rated wind speed, the overall pre-compensation control is shown in Figure 3:

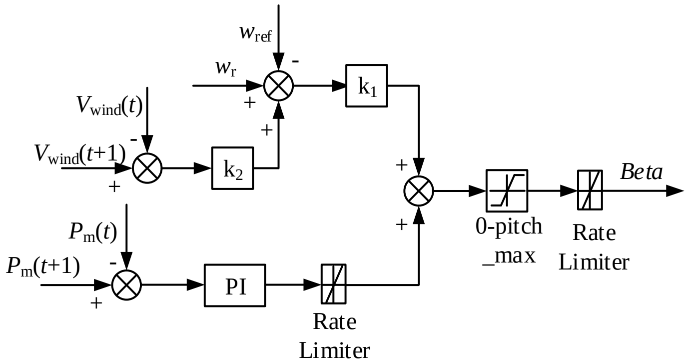

Fig.3 Pitch angle precompensation control chart

4. Experimental results and analysis

4.1 Wind speed prediction experiment

The sample is the wind speed record of a certain place in China in 2015, and 1000 sample data are selected as historical data for learning. In order to facilitate the study of pitch angle pre-compensation regulation, the last 100 data of 1000 sample data selected are greater than the rated wind speed. The wind speed data, the 100 data is used as the inspection data of the predicted data.

In order to verify the superiority of the proposed model and method, the prediction results of the variable-factor error forward compensation wavelet neural network model (E-FFD-WNN) proposed in this paper are respectively compared with the nonlinear autoregressive model (NAR, Nonlinear Auto). Regressive models), wavelet neural network (WNN) prediction results are compared.

The hidden layer nodes of the wavelet neural network are selected as L=6, and the learning rates from the input layer to the hidden layer and the hidden layer to the output layer are respectively $\eta_1=0.01$ and $\eta_2=0.001$, and the maximum number of iterations is set to 1000 times. The autoregressive order of NAR (Nonlinear Autoregressive Model) was selected as 3 orders, and the number of hidden layer neurons was 15

In this paper, the prediction effect of the model is tested by comparing the predicted data with the actual data. There are three evaluation indicators: average absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE). As shown in equations (15), (16), (17):

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|x(t)-\tilde{y}(t)\right| \tag{15}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(x(t)-\tilde{y}(t)\right)^2} \tag{16}$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{x(t)-\tilde{y}(t)}{x(t)}\right| \tag{17}$$

Figure 4, Figure 5 and Figure 6 show the prediction results of the same wind speed data by different methods. The actual value is compared with the predicted value. Figure 7 is the error comparison chart of the three methods.

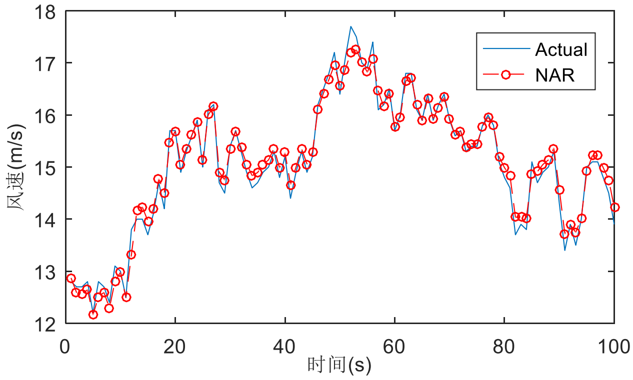

Fig.4 NAR wind speed prediction

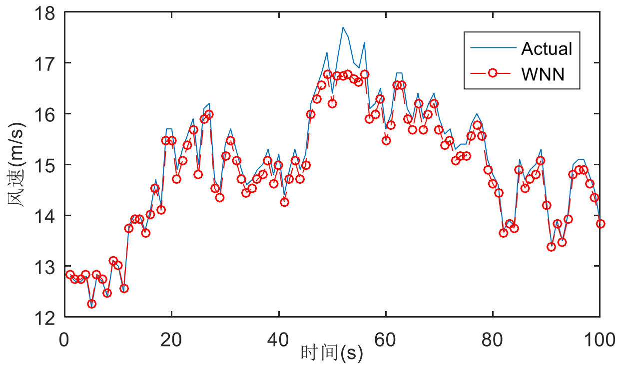

Fig.5 WNN wind speed prediction

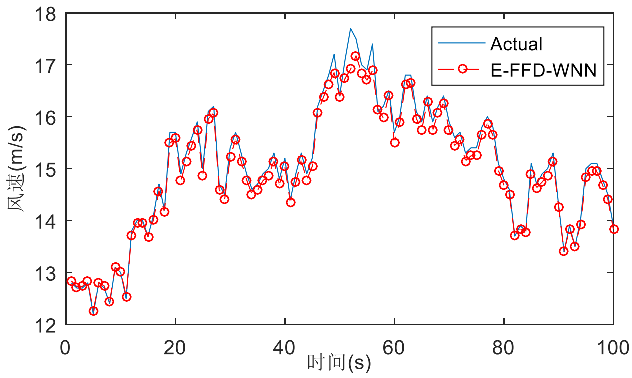

Fig.6 Error feedforward compensation WNN wind speed prediction

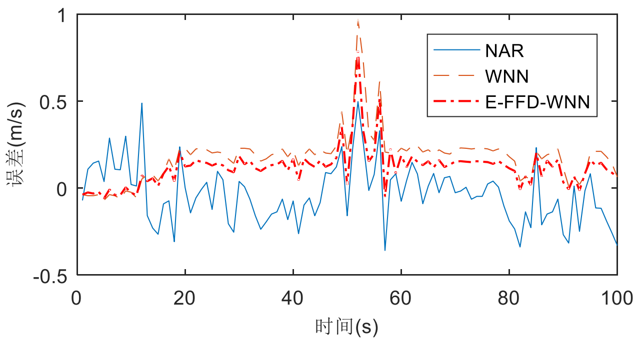

Fig.7 Three model error comparison

It can be seen from Fig. 4 that the nonlinear autoregressive model (NAR) is not accurate enough to predict the wind speed when the wind speed fluctuates more frequently. Whenever the wind speed changes suddenly or changes from high to low, the NAR predicts the result. Larger errors, but predictions are more accurate during successive ascent or descent phases. As can be seen from Fig. 5, the wavelet neural network (WNN) is more accurate than the NAR model in predicting small fluctuations, but when the mutation occurs and the prediction error value at the maximum point of the wind speed is much larger than the prediction error of the NAR, it can be seen that the wavelet neural network is more Suitable for predicting wind speeds with small fluctuations. Figure 6 shows the prediction results of wind speed based on error feedforward compensation wavelet neural network (E-Feedforward-WNN, E-FFD-WNN). It can be seen from the figure that the prediction error is large near the most wind speed, and the other moments are close to the actual value. Figure 7 shows the error comparison of the three methods. It can be clearly seen that the E-FFD-WNN designed in this paper has the smallest error in the three methods, and the fluctuation of the error is also small, only when the wind speed is abruptly changed. A large error will occur. At the moment of maximum wind speed, the prediction error needs to be improved compared with the NAR, but the overall error curve is in a gentle state with little fluctuation.

Combining the three model prediction error data shown in Table 1 with FIG. 4, FIG. 5, FIG. 6, and FIG. 7, it can be found that the improved wavelet neural network method greatly improves the wind speed abrupt change and the maximum wind speed prediction. When the wind speed fluctuates slightly, the prediction results of wavelet neural network based on error feedforward compensation are more accurate than the predictions of NAR and WNN. Therefore, the error feedforward compensation wavelet neural network proposed in this paper is more accurate than NAR and WNN in predicting wind speed, which increases the prediction advantage of WNN when the wind speed fluctuates slightly and makes up for the shortcoming of WNN when the wind speed is suddenly changed. Therefore, the overall prediction error and local error are further reduced.

Tab.1 Parameter of variable parameter model

Model	MAE(m/s)	RMSE(m/s)	MAPE(%)
NAR	0.1363	0.1729	0.92
WNN	0.1881	0.2297	1.20
E-FFD-WNN	0.1279	0.1638	0.82

4.2 Pitch angle precompensation simulation experiment

In order to enable the wind turbine to emit rated power at high wind speeds and not overspeed, the control module is required to continuously command the pitch to the system. Moreover, since the mechanical adjustment device of the pitch angle has a certain hysteresis, the adjustment of the pitch angle has a certain delay, which causes the pitch to change frequently and the output of the active power to fluctuate.

In order to verify the feasibility of the pitch angle pre-compensation control method proposed in this paper, a 9MW wind farm consisting of 6 1.5MW was built in MATLAB/Simulink and simulated. In order to study the variation of the pitch angle and the power, the selected wind speed is a high wind speed that is greater than the rated wind speed and is in a constantly changing state.

Figure 8 shows the experimental wind speed and pitch angle changes.

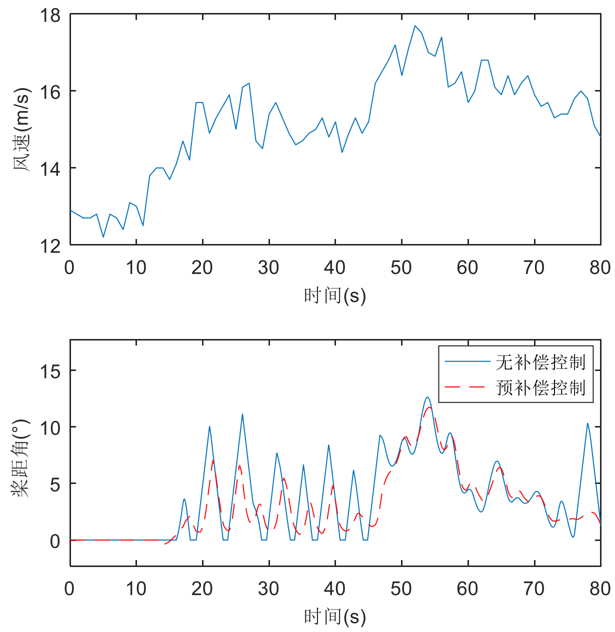

Fig.8 Comparison of wind speed and pitch angle

As can be seen from Figure 8, it took about 15 seconds from the start of the wind turbine to the point where the rated output power was reached. When the wind speed changes, the pitch angle change without pre-compensation measures is more obvious, and it can be found that the fluctuation range is large and prone to sudden changes; when the pre-compensation regulation is adopted, the pitch angle changes less than before. With less significant fluctuations, the overall curve is smoother. Therefore, it can be shown that the pitch angle pre-compensation regulation strategy proposed in this paper can reduce the frequent adjustment of the pitch angle and prolong the service life of the mechanical equipment.

Figure 9 shows the generator speed when the pre-compensation control strategy proposed in this paper is adopted.

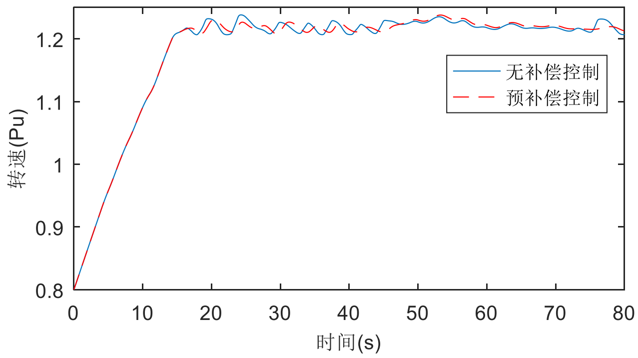

Fig.9 The change of speed output

It can be seen from Fig. 9 that after adopting the pitch angle pre-compensation control strategy, the generator speed can reach the rated speed, and it fluctuates slightly around 1.21 pu, which is less affected by the wind speed fluctuation, and the speed fluctuation is smaller than when no measures are taken. The speed fluctuates and the whole is in a smooth state.

Figure 10 shows the active power output from the wind farm before and after the pre-compensation control method.

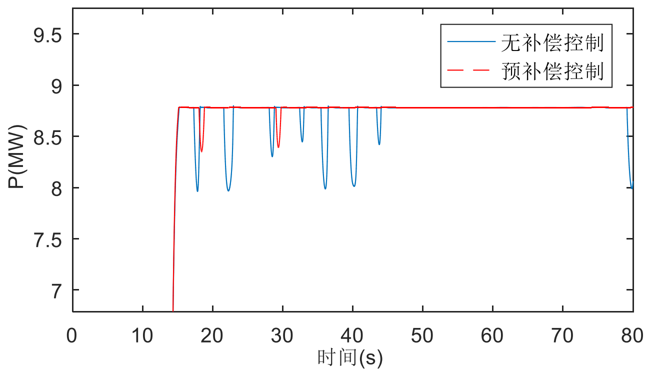

Fig.10 Active power output

As can be seen from Fig. 10, the active power generated by the wind farm reaches a steady state for the first time in about 15 seconds. When the wind speed fluctuates around 15m/s, the active power generated by the wind farm fluctuates significantly. When the pitch angle pre-compensation regulation is adopted, the fluctuation frequency of the active power becomes smaller, and the amplitude of the fluctuation also decreases greatly. It can achieve the purpose of stable output active power.

The simulation results in Fig. 8, Fig. 9 and Fig. 10 show that compared with the ordinary pitch angle control, the pitch angle pre-compensation regulation method based on wind speed prediction designed in this paper, through the prediction of wind speed, according to wind speed and power The change situation gives a certain compensation to the pitch angle in advance, which can effectively suppress the influence of wind speed change on the wind turbine. The method proposed in this paper can stabilize the output of active power, reduce the frequent large fluctuation of the pitch angle, and suppress the fluctuation of the generator speed, making the whole wind power generation system more stable and prolonging the service life of the mechanical equipment.

5. Conclusion

This paper first proposes a wavelet neural network based on error feedforward compensation, which improves the accuracy of short-term wind speed prediction. Then, the pre-compensation control of the pitch angle is designed. The wind power generation system under high wind speed is improved by pre-compensating the pitch angle. Op-erating status. The variable pitch pre-compensation control method based on error feedforward compensation for wavelet neural network wind speed prediction can not only effectively predict short-term wind speed, but also can suppress generator speed fluctuations and reduce frequent large fluctuations of pitch angle, and finally achieve stable active power. Output and stabilize the purpose of the wind power system.

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