Research on Power Control of Wind Power Generation Based on Neural Network Adaptive Control

Hai-ying DONG(董海鹰), Chuan-hua SUN(孙传华)
(*School of Automation & Electrical Engineering, Lanzhou Jiaotong University, Lanzhou* 730070, *China*)

Abstract – For the characteristics of wind power generation system is multivariable, nonlinear and random, in this paper the neural network PID adaptive control is adopted. The size of pitch angle is adjusted in time to improve the performance of power control. The PID parameters are corrected by the gradient descent method, and Radial Basis Function (RBF) neural network is used as the system identifier in this method. Simulation results show that by using neural network adaptive PID controller the generator power control can inhibit effectively the speed and affect the output power of generator. The dynamic performance and robustness of the controlled system is good, and the performance of wind power system is improved.

Key words – *wind power generation*; *power control*; *PID adaptive control*; *neural network*

Manuscript Number: 1674-8042(2010)02-0173-05

dio: 10.3969/j.issn.1674-8042.2010.02.18

1 Introduction

Wind energy is clean, renewable and inexhaustible. Its stable power-generating capacity can be developed on large-scale and commercially in a short time. So the research and development of efficient and reliable wind power generation system has become hot spots in the field of world energy technology research. In Ref. [1], the speed signal of wind turbine is used, and the pitch angle of the variable speed of the constant-frequency wind turbine is controlled by PI control, but the control effect is not ideal. In Ref. [2], wind turbine's pitch control is deviced according to fuzzy PID control theory. This method is effective to improve the pitch control effect of the wind power system, but the selection rules of fuzzy rules are based on the designer's experience with blindness. In Ref. [3], wind turbine's blade pitch angle is adjusted to capture the largest wind energy by the neural network. This method improves the system's control performance, but the steady-state error is relatively large. In Ref. [4], the Back Propagetion (BP) neural network and the RBF neural network are combined to achieve the wind turbine's pitch control. This method improves the tracking accuracy of wind turbine controller, but the algorithm is larger. In Ref. [5], wind turbine's pitch controller is designed according to the auto disturbance rejection control theory. This method improves the system's dynamic performance of constant power output region, but it is nonlinear robust control method based on process errors. In addition, fuzzy neural network, adaptive control, sliding mode variable structure control combined with more control strategies, and so on, are used widely in the wind turbine's pitch control.

In this paper, for the characteristics of wind power generation system is multivariable, nonlinear and random. RBF neural network adaptive PID tuning methods are adopted. This control method uses the ability of neural network self-learning and approximating any nonlinear function, to suppress the random disturbances of wind power system suffering wind speed changes and improve the generator's output power. The simulation results show that neural network adaptive control is used in wind turbine's power control, which can satisfy the power control requirements of wind power generation system.

2 Wind turbine pitch control theory

According to aerodynamics, the expression of the wind turbine generating power is

$$P = \frac{1}{2}\rho\pi C_P(\lambda,\beta)R^2 v^3 = T\omega, \tag{1}$$

where P is the wind turbine's output power, W; ρ is the air's density, kg/m^3; v is wind turbine's positive wind speed, m/s; T is the wind turbine's torque, Nm; ω is the wind turbine's speed, rad/s; R is the radius of the wind

* **Received**: 2010-03-16
Project supported: This work was supported by the Science and Technology Major Special Projects Gansu (No. 0801GKDA058)
Corresponding author: Hai-ying DONG(hydong@mail.lzjtu.cn.)

turbine, m; C_P is the power coefficient of the wind turbine; β is the pitch angle, (°); and $\lambda = \omega R/v$ is the tip speed ratio.

The degree of wind turbine getting natural energy is defined as the power coefficient of the wind turbine. According to the relevant reference [9], the power coefficient of the wind turbine can be approximately described as

$$C_P = (0.44 - 0.0167\beta)\sin[\frac{\pi(\lambda - 3)}{15 - 0.3\beta}] - 0.001\,84(\lambda - 3)\beta. \quad (2)$$

From Eq. (2), the characteristic curve of available pitch control of the wind turbine is shown in Fig. 1.

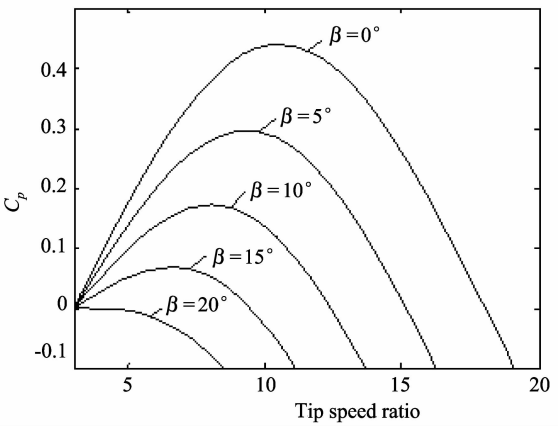

Fig. 1 Characteristic curve of pitch control

The following two conclusions can be reached from Fig. 1:

1) When pitch angle β is fixed, the wind energy utilization coefficient is the unique maximum;

2) When the tip speed ratio λ is an arbitrary value and pitch angle $\beta = 0°$, the wind energy utilization coefficient is relative maximum. With the pitch angle β increasing, C_P decreases.

These two conclusions provide theoretical base for the electric pitch control: When the wind speed is lower than the rated value, the pitch angle β is set 0 °, so that the wind energy utilization coefficient is kept at the maximum $C_{P\max}$ to capture maximal wind energy. When the wind speed is higher than the rated value, the wind turbine's pitch angle is real-time adjusted in order to change wind turbine's output power and keep the output power around rated power. The pitch control technology is used in high wind speed stage.

In this paper, neural network adaptive power regulator is used, and wind turbine's operation circle is studied when the wind speed is above the rated value. The principle structure of wind turbine pitch control is shown in Fig. 2. The system's input is the error signal of generator rated power when compared with the measured actual power. This signal is put into the RBF neural network adaptive controller. In accordance with control algorithms, the pitch angle is adjusted to obtain the referential pitch angle. The input of electric pitch servo system is the error signal of the actually measured pitch angle compared with the referential pitch angle.

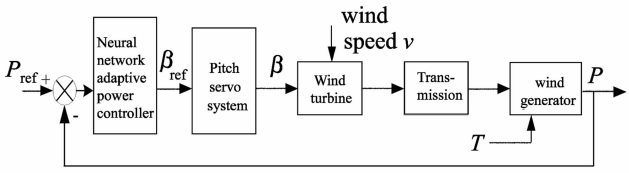

Fig. 2 Structure of variable pitch wind turbine control

3 Studies of generator power neural network control

3.1 Control theory of RBF neural network adaptive PID

RBF neural network is a three feedforward network with a single hidden layer. Because it simulates the neural network structure of the human brain partial adjustment and each covering receptive field, RBF neural network is a local approximation network to prove that it can arbitrary accuracy approximate to any continuous function[10-11]. Its basic structure is shown in Fig. 3.

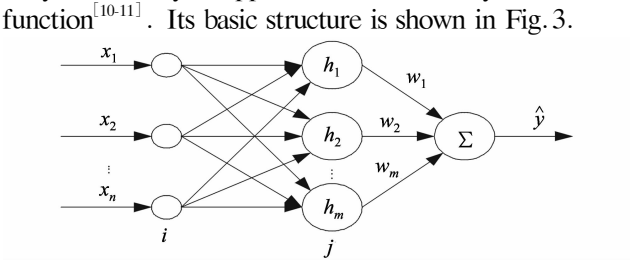

Fig. 3 RBF neural network model

The basic structure of RBF neural network adaptive PID control system is shown in Fig. 4. It is composed of the PID controller, RBF neural network identifier and the controlled object.

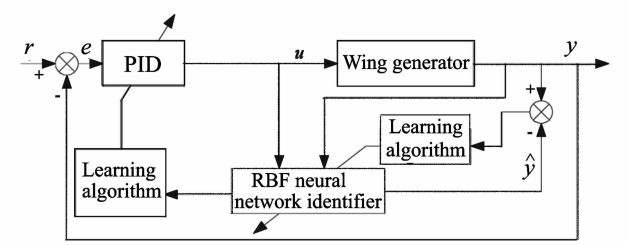

Fig. 4 Structure of RBF neural network adaptive PID control system

The system controlled object is real-time online identified in the control process by RBF neural network identifier, and proportion parameters, integral parameters and differential parameters of PID controller are real-time adjusted so that a simple PID controller is provided with self-learning and adaptive capacity.

3.2 Adaptive tuning PID controller parameters

An incremental PID controller is used in designing this method. The control error is described as

$$\varepsilon(k) = r(k) - y(k). \tag{3}$$

The three inputs of the PID controller are described as

$$\begin{aligned} xc(1) &= e(k) - e(k-1), \\ xc(2) &= e(k), \\ xc(3) &= e(k) - 2e(k-1) + e(k-2). \end{aligned} \tag{4}$$

The control algorithm is described as

$$u(k) = u(k-1) + \Delta u(k), \tag{5}$$

$$\begin{aligned} \Delta u(k) = {} & k_p(e(k) - e(k-1)) + k_i e(k) + \\ & k_d(e(k) - 2e(k-1) + e(k-2)). \end{aligned} \tag{6}$$

In Eq. (6), k_p, k_i, k_d are respectively the proportional parameter, the integral parameter and the differential parameter of the unified power wind turbine control system.

The PID tuning error indicators are described as

$$E(k) = \frac{1}{2}e^2(k), \tag{7}$$

k_p, k_i, k_d are adjusted according to the gradient descent method.

$$\begin{cases} \Delta k_p(k) = -\eta_p \dfrac{\partial E(k)}{\partial k_p(k)} = \\ \qquad -\eta_p \dfrac{\partial E(k)}{\partial y(k)} \dfrac{\partial y(k)}{\partial \Delta u(k)} \dfrac{\partial \Delta u(k)}{\partial k_p(k)} = \\ \qquad \eta_p e(k) \dfrac{\partial y(k)}{\partial \Delta u(k)} xc(1), \\ k_p(k) = k_p(k-1) + \Delta k_p(k). \end{cases} \tag{8}$$

$$\begin{cases} \Delta k_i(k) = -\eta_i \dfrac{\partial E(k)}{\partial k_i(k)} = \\ \qquad -\eta_i \dfrac{\partial E(k)}{\partial y(k)} \dfrac{\partial y(k)}{\partial \Delta u(k)} \dfrac{\partial \Delta u(k)}{\partial k_i(k)} = \\ \qquad \eta_i e(k) \dfrac{\partial y(k)}{\partial \Delta u(k)} xc(2), \\ k_i(k) = k_i(k-1) + \Delta k_i(k). \end{cases} \tag{9}$$

$$\begin{cases} \Delta k_d(k) = -\eta_d \dfrac{\partial E(k)}{\partial k_d(k)} = \\ \qquad -\eta_d \dfrac{\partial E(k)}{\partial y(k)} \dfrac{\partial y(k)}{\partial \Delta u(k)} \dfrac{\partial \Delta u(k)}{\partial k_d(k)} = \\ \qquad \partial_d e(k) \dfrac{\partial y(k)}{\partial \Delta u(k)} xc(3), \\ k_d(k) = k_d(k-1) + \Delta k_d(k). \end{cases} \tag{10}$$

In Eq. (8)~(10), η_p, η_i and η_d are respectively the learning rates of k_p, k_i and k_d, $\dfrac{\partial y(k)}{\partial \Delta u(k)}$ is Jacobian matrix of the controlled object. It indicates the sensitivity of the controlled object output vs the input, and it can be obtained by RBF neural network identifier.

3.3 RBF neural network identifier

In this paper, the structure of radial basis function neural network is a 3-6-1 type, and the three inputs of the network identified are $\Delta u(k)$, $y(k)$ and $y(k-1)$. $\boldsymbol{X} = [x_1, x_2, x_3]^T$ is the network input vector. The radial basis function vector of RBF network is $\boldsymbol{H} = [h_1, h_2, h_3, h_4, h_5, h_6]^T$, and the Gaussian function is

$$h_j = \exp\left(-\frac{\| \boldsymbol{X} - \boldsymbol{C}_j \|^2}{2b_j^2}\right), j = 1,2,\cdots,6, \tag{11}$$

the center vector of network j node is

$$\boldsymbol{C}_j = [c_{j1}, c_{j2}, c_{j3}]^T, \tag{12}$$

the network base width vector is

$$\boldsymbol{B} = [b_1, b_2, \cdots, b_6]^T. \tag{13}$$

The base width parameters of j node are b_j, and they are bigger than zero. The network weight vector is

$$\boldsymbol{W} = [w_1, w_2, \cdots, w_6]^T. \tag{14}$$

The identified network output is

$$\hat{y}(k) = w_1 h_1 + w_2 h_2 + \cdots + w_6 h_6. \tag{15}$$

The function of identifier performance index is

$$J_1 = \frac{1}{2}(y(k) - \hat{y}(k))^2. \tag{16}$$

Based on the gradient descent method, the iterative algorithm of output power, the node centers and the node base width parameters are

$$\begin{aligned} w_j(k) = {} & w_j(k-1) + \eta(y(k) - \hat{y}(k))h_j + \\ & \alpha(w_j(k-1) - w_j(k-2)), \end{aligned} \tag{17}$$

$$\Delta b_j = (y(k) - \hat{y}(k)) w_j h_j \frac{\| \boldsymbol{X} - \boldsymbol{C}_j \|^2}{b_j^3}, \tag{18}$$

$$\begin{aligned} b_j(k) = {} & b_j(k-1) + \eta \Delta b_j + \\ & \alpha(b_j(k-1) - b_j(k-2)), \end{aligned} \tag{19}$$

$$\begin{aligned} \Delta c_{ji} = {} & (y(k) - \hat{y}(k)) w_j \frac{x_j - c_{ji}}{b_j^2}, \\ & i = 1,2,3, \end{aligned} \tag{20}$$

$$\begin{aligned} c_{ji}(k) = {} & c_{ji}(k-1) + \eta \Delta c_{ji} + \\ & \alpha(c_{ji}(k-1) - c_{ji}(k-2)). \end{aligned} \tag{21}$$

In Eq. (17)~(21), η is the learning rate, α is the momentum factor. When adaptive PID parameters of the unified wind turbine power control system are tuned, Jacobian matrix algorithm is required. It is

$$\frac{\partial y(k)}{\partial \Delta u(k)} \approx \frac{\partial \hat{y}(k)}{\partial \Delta u(k)} = \sum_{j=1}^{6} w_j h_j \frac{c_{ji} - x_1}{b_j^2}. \tag{22}$$

In Eq. (22), $x_1 = \Delta u(k)$.

4 The simulation and analysis of generator neural network adaptive control

4.1 Simulation model foundation

In the domestic 1 MW double-fed asynchronous generator group, when the wind speed changes from the rated wind speed (12.5 m/s) to the cutting out wind speed (25 m/s), the pitch control mode is used. In this paper, the simulation study of wind turbine power regulation stages is made, when the wind speed is higher than the rated wind speed. According to the wind turbine pitch control rule, the Matlab/Simulink simulation model of the wind turbine is set up, as shown in Fig. 5.

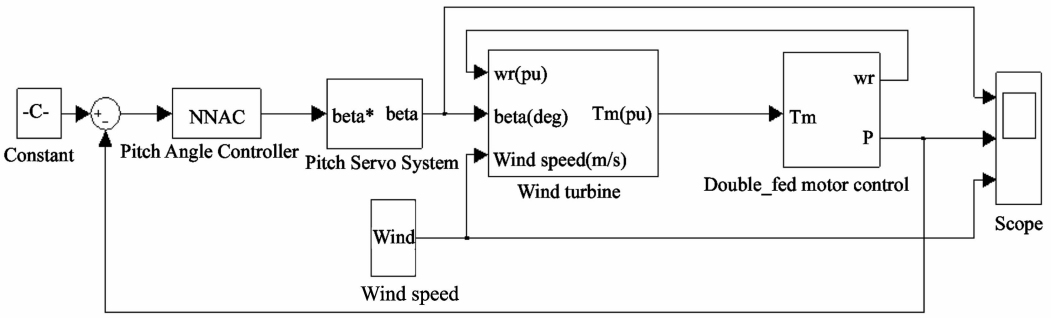

Fig. 5 Simulation model of pitch wind power system

4.2 Simulation results and analysis

In this paper, the study and design is based on theparameters of the domestic 1 MW double-fed asynchronous generator. The main technology parameters are: the wind wheel speed ranges from 11.1 r/min to 22.1 r/min, the wind wheel radius is 30 m, the cutting into wind speed is 4 m/s, the rated wind speed is 12.5 m/s, the cutting out wind speed is 25 m/s, the generator's pole number is 2, the generator's rated power is 1 MW, the rated frequency is 50 Hz, the stator windings' rated voltage is 690 V and rotor windings' rated voltage is 690 V.

In this paper, adaptive RBF neural network PID controller of the unified wind turbine power is achieved by the S function. The initial parameters are: $\boldsymbol{X} = [0,0,0]^{\mathrm{T}}$, $\boldsymbol{H} = [0,0,0,0,0,0]^{\mathrm{T}}$, $\boldsymbol{C}_j = 30 * \mathrm{ones}(3,6)$, $\boldsymbol{B} = 40 * \mathrm{ones}(6,1)$, $\boldsymbol{W} = 10 * \mathrm{ones}(6,1)$, $\alpha = 0.05$, $\eta = 0.25$, $\eta_{\mathrm{p}} = 0.8$, $\eta_{\mathrm{i}} = \eta_{\mathrm{d}} = 0.2$, $k_{\mathrm{p}} = 200$, $k_{\mathrm{i}} = k_{\mathrm{d}} = 0$. The given input wind speed of the system is shown in Fig.6. The pitch angle output curve of PID control and neural network control are respectively shown in Fig.7(a) and (b). The power output curve of PID control and neural network control are respectively shown in Fig. 8(a) and (b).

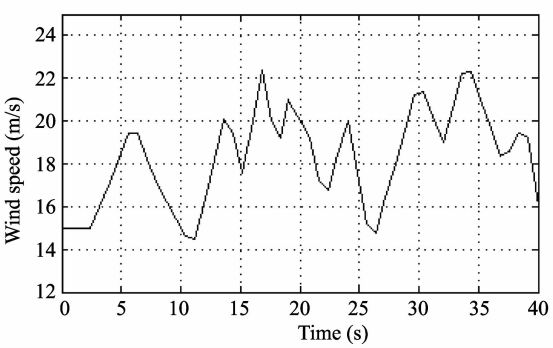

Fig. 6 Wind speed curve

The simulation results show that when the wind speed exceeds the rated value, the double-fed induction generator is accelerating (it takes about 2.5 s). So the output power is less than the rated power, and the pitch angle is maintained at 0°. When the generator's start-up phase is ended and the wind speed exceeds the rated value, the output power is larger than the rated power. So the size of the pitch angle is enlargened by the pitch system to reduce the output power and maintain the output power at the rated power. The results of the PID control, compared with the results of neural network control show that the pitch angle is adjusted with real-time wind speed, and wind turbine's output power P is stably maintained at the rated power by neural network adaptive control in power control.

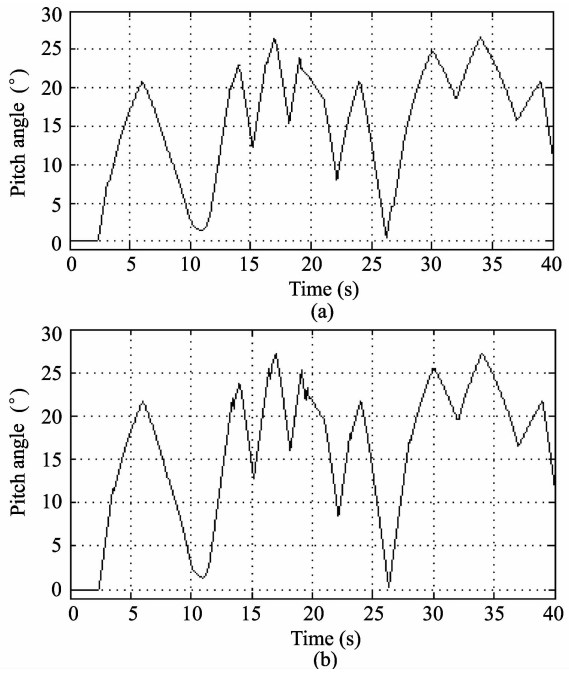

Fig. 7 Pitch angle output curve of power control: (a) Pitch angle output curve based on PID control, (b) Pitch angle output curve based on neural network PID control

5 Conclusion

In this paper, neural network adaptive control is used in the generator power control system. The simulation results show that the control system has good dynamic performance by PID neural network control algorithm. This algorithm can effectively inhibite the system's nonlinearity and parameter's variability. The system's robustness and anti-interference ability are enhanced, and the power control performance of wind power system is im-

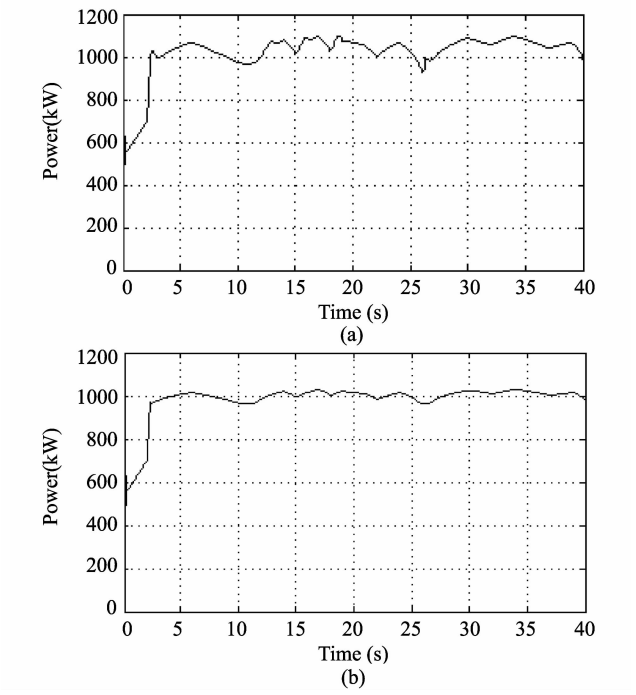

Fig. 8 Wind turbine's power output curve: (a) Power output curve based on PID control, (b) Power output curve based on neural network control

proved by neural network adaptive control. Therefore, neural network adaptive control is used in the wind turbine's power control, which can maintain the output power at the rated power and satisfy the requirements of wind turbine power control.

References

[1] M. Aminian, F. Aminian, 2000. Neural-network based analogcircuit fault diagnosis using wavelet transform as preprocessor. *IEEE Trans Circuits Syst-*Ⅱ, 44(3): 151- 156.

[2] Xin-fu Song, Bo Liang, 2009. Wind power system pitch control based on fuzzy self-learning emendation control theory. *Power System Protection and Control*, 37(16): 50-53.

[3] Hui Li, K. L. Shi, P. G. McLaren, 2005. Neural-network-based sensorless maximum wind energy capture wth compensated power coefficient. *IEEE Transactions on Industry Applications*, 41(6): 1548-1556.

[4] Bang-sheng Fu, Bing-xin Wu, Xiao-lei Wang, 2009. Design of pitch-controlled system based on neural network. *Journal of Zhongyuan University of Technology*, 20 (5): 56-59.

[5] Chang-liang Xia, Zhan-feng Song, 2007. Pitch Control of Variable Speed Constant Frequency Wind Turbines Based on Active-disturbance-rejection Controller. Proceedings of the CSEE, p. 91-95.

[6] T. Senjyu, R. Sakamoto, N. Urasaki, et al, 2006. Output Power Leveling of Wind Farm Using Pitch Angle Control with Fuzzy Neural Network. Power Engineering Society General Meeting, p. 18-22.

[7] Kun Qian, Shou-sheng Xie, Mei-yan Gao, 2004. Applications of adaptive control to variable speed wind turbine system. *Control Engineering of China*, 11(1): 76-78.

[8] Yao-jie Sun, Long-yun Kong, Wei-xiang Shi, 2004. Robust sliding mode control of variable-speed wind power system. *Power Electronics and Motion Control Conference*, 3: 1712-1716.

[9] Abdin Ezzeldin S, Xu Winlsonm, 2000. Control design and dynamic performance analysis of a wind turbine induction generator unit. *IEEE Trans. on EC*, 3(15): 91-96.

[10] Da-zhi Wang, Zhen-lei Wang, 2001. Identification and Control of Induction Motor Using Artificial Neural Network. Proceedings of the Fifth International Conference on Electrical Machines and Systems. Shenyang, p. 751-754.

[11] Chao Yang, Huai-chun Zhou, Xu-sheng Zhou, 2008. PID cascade control system of power plant combustion with RBF network self-tuning. *J. Huazhong Univ. of Sci. & Tech.*, 36(7): 57-59.