2014 International Joint Conference on Neural Networks (IJCNN)
July 6-11, 2014, Beijing, China

Adaptive Control of Wind Turbine Generator System Based on RBF-PID Neural Network

Zhanshan Wang, Zhengwei Shen, Chao Cai
School of Information Science and Engineering,
Northeastern University,
The State Key Laboratory of Synthetical Automation for Process Industries, Liaoning, People's Republic of China
zhanshan_wang@163.com

Kaili Jia
Shandong Liaocheng Power Supply Company
Shandong, People's Republic of China

***Abstract*—Wind turbine generator system(WTGS) is a complex multi—varies nonlinear system with the characteristics of time—varying, strong coupling and multi—interference. Wind speed is affected by many factors , the magnitude and direction are random. There are numerous of factors such as temperature, weather, environment and so on that affect wind turbine generator system, result in the WTGS cannot be guaranteed safety operation and constant output power. With the characteristic of strongly nonlinear, delay and uncertainty, the WTGS cannot be given an ideal control using traditional PID controller. Although the neural network control can solve the problems of nonlinear and uncertainty, it belongs to nonlinear approximation in essentially and cannot eliminate the error in steady state. In order to improve wind turbines behavior, an adaptive control method based on RBF-PID neural network is presented in this paper. This algorithm synthesizes the mechanical and electrical characteristics. System identification is part of the controller. At high wind speed, pitch angle is adjusted to keep rated output power using neural network adaptive controller. The RBFNN is used as the identifier of the WTGS. According to the identification information and the given learning speed, PID parameters are modified on line. The Matlab simulation results at random wind speeds show the controller can effectively improve the performance of variable pitch control.**

I. INTRODUCTION

Wind power generation has several good properties such as environmental friendly, large capacity, easy to develop large scale wind farm and be therefore considered most promising renewable energy resource [1].And because of energy shortage and environment pollution, the renewable energy, especially wind energy, has attracted more attentions all over the world .Large-scale wind turbine is currently the main form of network operation of wind energy [2].Variable speed and variable pitch wind generating technology is getting increasing recognition for its characteristic of high efficiency and practicability over constant speed wind turbine generator system.

In recent years, several research efforts have been devoted to address the topic of this paper. At present, a variety of effective methods to control the wind power system has been developed, but it's still not perfect. K. R. Kosoric and A. R. Katancevic considering mechanical and electrical dynamic characteristics of wind turbine, gives the online adjustment of generator exciting winding voltage nonlinear adaptive control law, the method can realize to the reference speed gradually tracking, but real-time parameter estimation is one of the main faults[3]. Based on the wind speed signal, PI controller is designed for variable speed constant frequency wind turbine pitch control of the wind turbine system, but the effect is still not ideal[4]. It is very difficult to obtain the proper result by using open loop control or general PID control. A control scheme for limiting the power of the variable pitch wind turbine based on the differential geometry feedback linearized theory is proposed to keep the rotational speed and output power at the rated value [5]. In addition, fuzzy adaptive and variable structure control technology has also been applied in pitch control [6]-[7].

RBF neural network has the general advantages of neural networks, such as multidimensional nonlinear mapping ability and generalization ability, the parallel information processing ability, etc., but also has a strong ability to cluster analysis, the advantages of simple learning algorithms [8]-[10]. Wind turbine is a typical complex multivariable nonlinear system, in addition to large environmental impact, wind speed, temperature, etc., there are many other interference factors, seriously affecting the wind turbine generator system to maintain a constant power output [11]-[12].With the characteristic of strongly nonlinear, delay and uncertainty, the WTGS cannot be given an ideal control using traditional PID controller. Although the neural network control can solve the problems of nonlinear and uncertainty, it belongs to nonlinear approximation in essentially and cannot eliminate the error in steady state. In order to improve wind turbines behavior, we designed an adaptive control method based on RBF-PID neural network , using neural network real-time regulating PID parameters can get more satisfactory control effect[13]-[15].

Because of the unique technical characteristics of the adjustable pitch control, it is often applied to wind turbine generator systems to ensure the constant output power above the rated power and the safe operation of WTGS [16]-[17].Adaptive control of wind turbine generator system based on RBF-PID neural network is adopted in this paper. At high wind speed, in order to effectively regulate the absorption of wind turbine power and limit the load of rotor does not exceed the design value. Pitch angle is adjusted to keep rated output power using adaptive control based on RBF-PID neural network [18]-[20]. Through this method, it can be more effective control of the wind turbine operation, greatly improving the defects caused by the other control strategies, with good control accuracy, enhance the operation performance of the whole system.

This paper is organized as follows: The mechanism of variable pitch wind power system model is given in section 2. And the proposed establishment of the RBF neural network and model is presented in section 3. In section 4, simulation results show quite good performance of the proposed approach from the basis of the mathematical model. Followed by conclusion in section 5.

II. MECHANISM OF VARIABLE PITCH WIND TURBINE SYSTEM MODEL

A wind turbine is a complex system because the knowledge from the areas of aerodynamics and mechanical, electrical, and control engineering is applied. Variable-speed wind turbines are designed to achieve maximum aerodynamic efficiency over a wide range of wind speeds. The electrical system of a variable-speed wind turbine is more complicated than that of a fixed-speed wind turbine. A typical wind turbine generator system primarily consists of wind turbine, rectangular of transformer, generator and the variable blade servo system. Variable pitch wind turbine mainly including pitch controller, mechanical drive system, turbine, pitch actuator and doubly-fed induction generator (DFIG)[21].The structure of wind turbine generation system is shown in Fig.1.

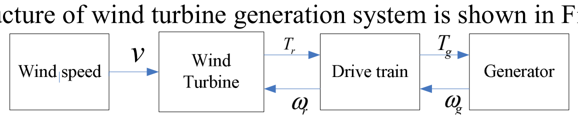

Fig. 1. Wind turbine scheme

In Fig.1, v wind speed, T_r aerodynamic torque, T_g generator torque in the rotor side, ω_r rotor speed, ω_g generator speed.

When the wind speed is higher than the rated wind speed, wind turbine system is a complex nonlinear time-varying one. An aerodynamic model of the wind turbines is a common part of the dynamic models of the electricity-producing wind turbines. The power and aerodynamic torque mathematical models are given by [22]:

$$P_r = \frac{1}{2} C_p(\lambda, \beta) \rho \pi R^2 v^3 \quad (1)$$

$$T_r = \frac{1}{2} C_T(\lambda, \beta) \rho \pi R^2 v^3 \quad (2)$$

Where P_r is the turbine power absorption, R is the radius of wind wheel, ρ is the density of air, C_p is the power coefficient, β is the blade pitch angle of wind turbine, λ is the tip speed ratio, the ratio between blade tip speed and wind speed at hub height, C_T is the aerodynamic torque coefficient. $C_T(\lambda, \beta)$ is torque coefficient with the relationship to $C_P(\lambda, \beta)$

$$C_p(\lambda, \beta) = C_T(\lambda, \beta)\lambda . \quad (3)$$

The power coefficient C_p depends on the blade pitch angle β and the tip speed ratio λ is defined as

$$\lambda = \frac{\omega_r R}{v} \quad (4)$$

Coefficient C_p utilization of wind energy is a function of the tip speed ratio λ and pitch angle β, precise calculation need air dynamics and finite element analysis. The speed of wind turbine has to be changed with wind speed for capturing maximum power, so that optimum tip speed ratio is maintained. If the wind speed is not change, the higher of the value of C_p, the higher the efficiency changing from the wind energy to the mechanical energy. In this paper, we can express (5) approximately as a nonlinear function of λ and β :

$$C_p(\lambda,\beta) = (0.44 - 0.0167\beta)\sin[\frac{\pi(\lambda-3)}{15-0.3\beta}] - 0.00184(\lambda-3)\beta \quad (5)$$

When the stable operation of the system, for a fixed pitch β , there exists an optimum tip speed ratio λ and maximum wind energy utilization coefficient of C_P remain unchanged, but when the wind speed reaches the maximum value changes relative to the wind, it will have the optimum pitch angle β, the largest wind energy utilization coefficient C_P . In the above rated wind speed, the system uses the variable pitch control, and coordinated control of electromagnetic torque of the generator, the output power of wind speed and the system has a good performance in tracking the rated value.

III. ADAPTIVE CONTROL BASED ON RBF-PID NEURAL NETWORK

A. RBF neural network

RBF neural network is Radial Basis Function Neural Network, what it's generated has a strong biological background. In a region of the cerebral cortex, local regulation and overlapping receptive field is the characteristic of the human brain response [23]-[24]. The basic structure of RBF neural network is shown in Fig.2.

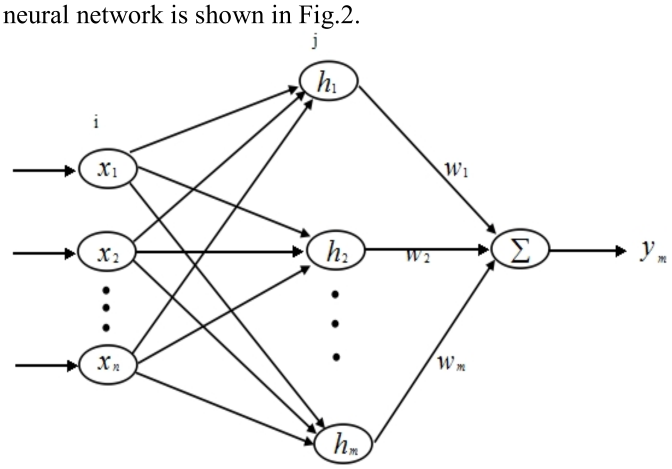

Fig. 2. The basic structure of RBF neural network

From the picture, we can see that RBFNN is a three layer forward network. The map from input to output is nonlinear while the map from hidden layer to output is linear, which can improve learning speed greatly. The input layer nodes only transmit the input signal to the hidden layer, function of hidden layer nodes (basis functions) by using the Gauss function, and the output layer node is usually a simple linear function. RBF has the characteristics of simple structure, fast learning speed, and it can overcome the problem of over fitting, and has a parallel computing capabilities and non-linear capabilities [25].

B. RBF neural network learning algorithm

In the structure of RBF neural network, $H=[h_1,h_2,...h_m]^T$ is the radial basis vector, $X=[x_1,x_2,...x_m]^T$ is the input vector, h_j is Gaussian function, which can be described as[26]-[27]

$$h_j=\exp\left(-\frac{\|X-C_j\|^2}{2b_j^{\,2}}\right), j=1,2,...,m \tag{6}$$

$B=[b_1,b_2,...b_m]^T$ is the basis width vector. The output vector of the network is given by

$$y_m(k)=w_1h_1+w_2h_2+...+w_mh_m \tag{7}$$

The weight vector of the network is given by

$$W=[w_1,w_2,...w_m]^T \tag{8}$$

C. Controller Design

From the above we have learned some of basic algorithms and structure of the RBF neural network. In this part, we will focus on the design adaptive control system based on RBF-PID neural network [28].The adaptive control system based on RBF-PID neural network structure as shown in Fig.3.

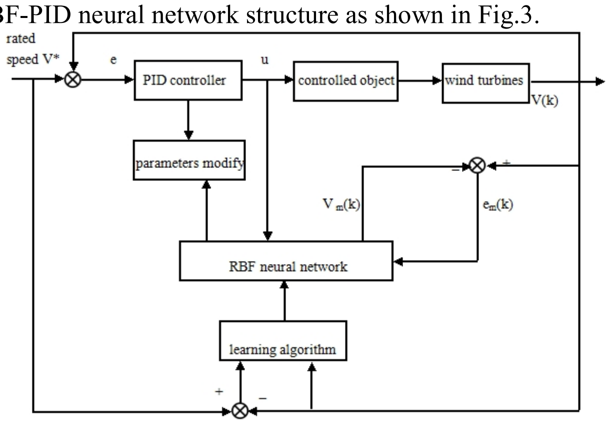

Fig. 3. The structure of PID control system based on RBF neural network

From the picture, we can see that the system input $V*$ is the rated speed of the wind turbine, and the actual speed of the wind turbine as the system output $V(k)$ .The network input values are $[u(k),y(k),y(k-1)]$, and u is the PID output value. The controller consists of two parts:

The first part is the PID controller, direct closed-loop control was carried out on the controlled object, passing parameters based on neural network, the automatic on-line adjusting the three parameters k_p , k_i , k_d and the PID controller is calculated results is passed to the controlled object and RBF network.

Another part is the neural network, according to the system operation state, through each layer of the neural network self-learning, neural network parameters self-tuning, pass the output to the PID controller, to correct the parameters in the PID.

Assume the input vector of identifier is given by:

$$X=[u(k),y(k),y(k-1)]^T \tag{9}$$

$u(k)$, $y(k)$ are the control signal and output signal of controlled object respectively. The approximation error is $e_m(k)=y(k)-y_m(k)$. The performance function of system can be selected as

$$J_m=0.5(e_m(k))^2 \tag{10}$$

According to the gradient descent method, the weight value, center vector, basis width can be calculated from[29]:

$$w_j=w_j(k-1)+\eta(y(k)-y_m(k))h_j+\alpha(w_j(k-1)-w_j(k-2)) , \tag{11}$$

$$\Delta b_j=(y(k)-y_m(k))w_jh_j\frac{\|X-C_j\|}{b_j^{\,3}} , \tag{12}$$

$$b_j(k)=b_j(k-1)+\eta\Delta b_j+\alpha(b_j(k-1)-b_j(k-2)) \tag{13}$$

$$\Delta c_{ji}=(y(k)-y_m(k))w_j\frac{x_j-c_{ji}}{b_j^{\,2}} , \tag{14}$$

$$c_{ji}(k)=c_{ji}(k-1)+\eta\Delta c_{ji}+\alpha(c_{ji}(k-1)-c_{ji}(k-2)) \tag{15}$$

Where η is the learning speed, α is the momentum factor.

When $e_m(k)$ is in the acceptable range, the Jacobian information can be got, the sensitivity information between input and output, which can be described as:

$$\frac{\partial y(k)}{\partial u(k)}=\frac{\partial y_m(k)}{\partial u(k)}=\sum_{j=1}^{m}w_jh_j\frac{c_{ji}-x_1}{b_j^{\,2}} , \tag{16}$$

In the formula $x_1=u(k)$ .The incremental PID is used in this paper, the control error is given by

$$e(k)=r(k)-y(k) \tag{17}$$

Assume the input of RBFNN based self-turning PID controller is given by

$$X_c(k)=[x_{c1}(k),x_{c2}(k),x_{c3}(k)]^T=\begin{bmatrix} e(k) \\ e(k)-e(k-1) \\ e(k)-2e(k-1)+e(k-2) \end{bmatrix} \tag{18}$$

According to the incremental PID algorithm, the control variable is be given by

$$u(k) = 2u(k-1) + k_p(e(k) - e(k-1)) + k_i e(k) + k_d(e(k) - 2e(k-1) + e(k-2)) , \quad (19)$$

The index of the neural network is defined as：

$$E(k) = \frac{1}{2}(e(k))^2 , \quad (20)$$

According to the gradient method, k_p, k_i, k_d can be modified by:

$$\Delta k_p = -\eta_P \frac{\partial e(k)}{\partial k_p} = -\eta_P \frac{\partial e(k)}{\partial y(k)} \frac{\partial y(k)}{\partial u(k)} \frac{\partial u(k)}{\partial k_p} = \eta_P e(k) \frac{\partial y(k)}{\partial u(k)} xc_1(k) , \quad (21)$$

$$\Delta k_i = -\eta_I \frac{\partial e(k)}{\partial k_i} = -\eta_I \frac{\partial e(k)}{\partial y(k)} \frac{\partial y(k)}{\partial u(k)} \frac{\partial u(k)}{\partial k_i} = \eta_I e(k) \frac{\partial y(k)}{\partial u(k)} xc_2(k) , \quad (22)$$

$$\Delta k_d = -\eta_D \frac{\partial e(k)}{\partial k_d} = -\eta_D \frac{\partial e(k)}{\partial y(k)} \frac{\partial y(k)}{\partial u(k)} \frac{\partial u(k)}{\partial k_d} = \eta_D e(k) \frac{\partial y(k)}{\partial u(k)} xc_3(k) \quad (23)$$

Where $\partial y / \partial u$ the Jacobian identification information which is obtained by identifier, η_P, η_I, η_D is the proportional learning speed, integral learning speed and differential learning speed, respectively.

In order to confirm whether the system reaches the target requirement, the rated speed of the wind turbine V^* is given as the input of the controller. The output of controller is the actual speed of the wind turbine $V(k)$. Regulating the pitch for blades of the wind speed change, the output electric power of the generator can be controlled. The RBFNN is used as the identifier of the WTGS. According to the identification information and the given learning speed, PID parameters are modified on line.

IV. SIMULATIONS RESULTS AND ANALYSIS

A. Simulation background

A wind turbine of classic design is composed of tower, nacelle, hub and rotor blades. The type fan comprises a horizontal axis wind turbine and vertical axis wind turbine. Since the structure is the design of common turbine, as they are shown in Fig. 4- Fig. 5. The wind/solar hybrid controller, inverter, storage battery are shown in Fig.4. The simulated user load side contains: Three-phase unbalance load compensation and automatic multi-load modeling, as shown in Fig.5.

Fig. 4. Wind/solar hybrid controller

Fig. 5. Simulated user load side

B. The performance of the controller

The wind turbine considered in this study is variable speed, variable pitch one. Take the wind turbine systems in our laboratory as the background. The Simulation is investigated with a rated 600KW variable pitch wind turbine. The structure of the NN is chosen as 2-21-1. The initial value of the weight W_1 and W_2 is set as -0.1 and 0.1 respectively, the initial values of other weights in this network is set to 0.01. Activation function is set to unipolar S-shaped function $[\bar{\sigma}(z)] = \frac{1}{1+e^{-z}}$. The applied input wind speed profile of value is shown in Fig.6.

As the state vector z_1, z_2 in Section 2, z_1 denotes $\omega_r^* - \omega_r$, where ω_r^* is the rated rotate speed. When the rotate speed rated value is $22.3(r \cdot \min^{-1})$, as Fig. 7 shows, the angular velocity variations remain smooth, without big fluctuations, the proposed neural network adaptive controller clearly results in a good tracking performance.

The pitch angle and generator output is maintained near the rated value (Fig.8)

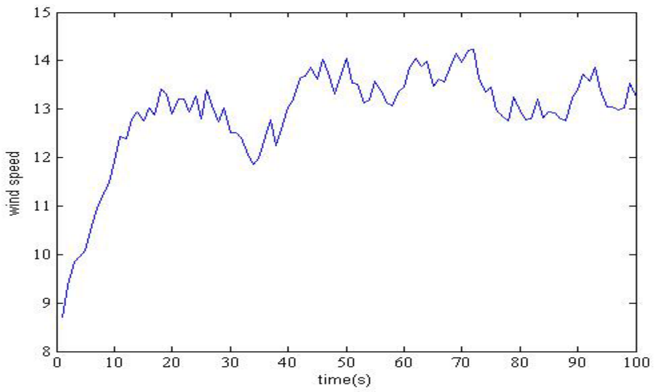

Fig. 6. Wind speed

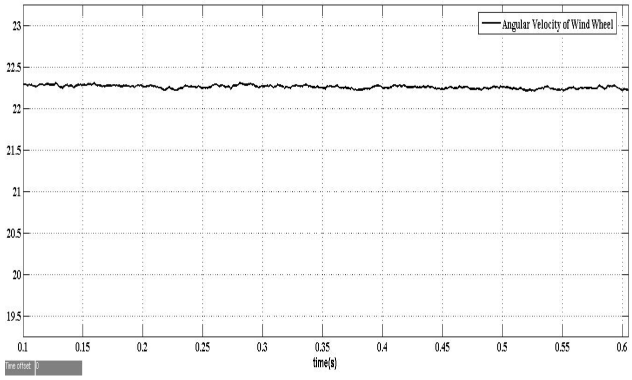

Fig. 7. Rotate speed

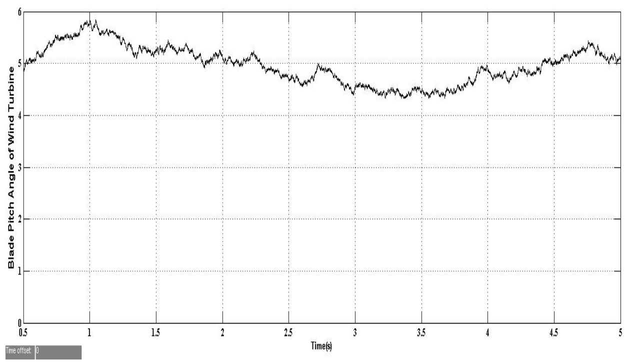

Fig. 8. Pitch angle

C. *The contrast of the two kinds of controller*

The method presented in reference [5] is a feedback linearization control based on the affine model of wind turbine. Comparing to the method proposed in this paper, the wind speed of the feedback linearization controller and the PID controller based on RBF neural network has different reaction. As it is shown in Fig.9, The wind speed of PID controller based on RBF network has a smaller overshoot than the feedback linearization controller. Experimental results also deliver a conclusion that the PID controller based on RBF network has a good performance in tracking the rated value and getting smooth output with less susceptibility to disturbances.

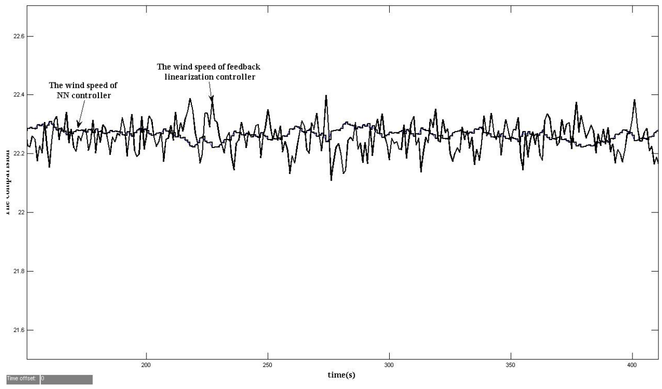

Fig. 9. The comparison of wind speed

V. CONCLUSION

With the characteristic of strongly nonlinear, delay and uncertainty, the WTGS cannot be given an ideal control using traditional PID controller. In order to achieve system optimization and reliable operation, a control strategy which employs neural network adaptive controller to achieve power control is put forward. The variable speed generator system can obtain smooth and steady output power and generator rotation speed. Simulation results indicate that proposed control method is able to be more effective control of the wind turbine operation, greatly improving the defects caused by the other control strategies, with good control accuracy, enhance the operation performance of the whole system. Therefore, suggested control strategy can obtain optimal and reliable operation of the wind turbine generator system. The adaptive controller based on RBF-PID neural network is proposed clearly in the good control precision. Notable is, here the proposed control method can be easily extended to other nonlinear systems.

ACKNOWLEDGMENT

This work was supported by the National Natural Science Foundation of China (Grant Nos. 61074073 and 61034005), the Fundamental Research Funds for the Central Universities (Grant Nos. N130504002 and N130104001), and SAPI Fundamental Research Funds (Grant No. 2013ZCX01).

REFERENCES

[1] Y. Tohbai, G. Wu, and H. Guo, "A basic study on construction and control of offshore wind power generation system," *Transmission and Distribution Conference and Exposition: Asia and Pacific,* Seoul, pp.1-4, Oct. 2009.

[2] K. Kosoric and A. Katancevic, "Wind changes influence on control of power systems with high percentage of wind power," *IEEE Power Engineering Society General Meeting, 2003, pp. 2337-2339, Jul. 2003.*

[3] Y. Song, B. Dhinakaran, and X. Bao, "Control of wind turbines using nonlinear adaptive field excitation algorithms," *Proceedings of the American Control Conference,* Chicago, pp. 1551- 1555, Jun. 2000.

[4] J. Slootweg and W. Kling, "Aggregated modeling of wind parks in power system dynamics simulations," *IEEE Power Tech Conference Proceedings, Bologna*, pp. 1-6, Jun. 2003.

[5] J. Yang and J. Zheng, “Feedback linearization control of constant output power for variable pitch wind turbine,” *Control Theory and Applications,* vol.29, no. 10, pp. 1365-1370, 2012.

[6] X. Zhang, D. Xu, Y. Lv, and Y. Liu, “Adaptive fuzzy control for large-scale variable speed wind turbines,” *Journal of System Simulation,* vol.16, no.3, pp. 573-577, Mar. 2004.

[7] Y. Sun, L. Kong,W. Shi, B. Cao, and Z. Yang, “Robust sliding mode control of variable-speed wind power system,” *Power Electronics and Motion Control Conference*, Xi’an, pp. 1712-1716, Aug. 2004 .

[8] X. Wang and H. Shao, “The theory of RBF neural network and its application in control,” *Information and Control*, vol.26, no.4, pp.272-284, Aug. 1997.

[9] Y. Zhou and Z. Hu, “The theory of RBF neural network and its application in control,” *Journal of Wuhan University of Science and Engineering*, vol.20, no.5, pp.40-42, May 2007.

[10] H. Guo and H. Dong, “Research on wind speed prediction based on fuzzy neural network,” *Electric Drive Automation*, vol.34, no.3, pp.1-5, Jul. 2012.

[11] X. Zhang, D. Xu, and Y. Liu, “Control strategy for Variable speed fixed pitch wind turbines,” *J. North China Electric Power University,* vol.31, no.5, pp.37-43, Sept. 2004.

[12] T. Dai, B. Song, and S. Shu, “Study on the wind energy resources assessment in wind power generation,” *2nd International Conference on Artificial Intelligence, Management Science and Electronic Commerce* Deng Leng, pp. 6804-6807, Aug. 2011.

[13] X. Yao and X. Zeng, “A wind power control systems based on neural network theory,” *Control And Decision*, vol.12, supp1, pp.482-487, Jul. 1997.

[14] A. Gogdare, A. Doroudi, and M. Ghaseminejad, “A new method to mitigate voltage fluctuation of a fixed speed wind farm using DFIG wind turbine,” *Proceedings of 17th Conference on Electrical Power Distribution Networks,* Tehran, pp. 6804-6807, May 2012.

[15] J. Ekanayake, H. Lee, X. Wu, and N. Jenkins, “Dynamic modeling of doubly fed induction generator wind turbines,” *IEEE Trans. Power Systems,* vol. 18, no. 2, pp. 803-809, May 2003.

[16] W. Gao, Z. Zhu, M. Jing, J. Chu, and F. Wang, “Adaptive fuzzy control based on the neural network for the wind turbines variable pitch system,” *J. Wuhan University Tech.,* vol.30, no.4, pp. 533-536, Aug. 2008.

[17] Y. Sun, L. Wang, G. Li, and J. Lin, “A review on analysis and control of small signal stability of power systems with large scale integration of wind power,” *International Conference on Power System Technology*, Hangzhou, pp. 1-6, Oct. 2010.

[18] M. Narayana, G. Putrus, and M. Jovanovic, “Predictive control of wind turbines by considering wind speed forecasting techniques,” *Proceedings of the 44th International Universities Power Engineering Conference,* Glasgow, pp. 1-4, Sept. 2009.

[19] F. Hughes, O. Anaya-Lara, and N. Jenkins, “Control of DFIG based wind generation for power network support,” *IEEE Transactions on Power Systems*, vol. 20, no. 4, pp. 1958-1966, Nov. 2005.

[20] M. Narayana and G. Putrus, “Optimal control of wind turbine using neural networks,” *Proceedings of the 45th International Universities Power Engineering Conference,* Cardiff Wales, pp. 1-5, Aug. 2010.

[21] X. Yao, L. Guan, Q. Guo, and X. Ma, “RBF neural network based self-Tuning PID pitch control strategy for wind power generation system,” *International Conference on Computer, Mechatronics, Control and Electronic Engineering,* Changchun, pp. 482-485, Aug. 2010.

[22] Z. Ji, H. Feng, and Y. Shen, “Data-drive predictive control for wind turbine pitch angle,” *Control Engineering of China*, vol. 20, no. 2, pp. 327-330, Mar. 2013.

[23] W. Wang, J. Cheng, and H. Wang, “Application of fuzzy neural network control on the variable speed pitch regulated generator,” *J. Xinjiang University*, vol. 21, no. 1, pp. 8-10, Feb. 2004.

[24] B. Boukhezzar and H. Siguerdidjane, “Nonlinear control of variable speed wind turbines without wind speed measurement,” *44th IEEE Conference on Decision and Control,* pp. 3456-3461, Dec. 2005.

[25] W. Gao and R. Rastko, “Neural network control of a class of nonlinear systems with actuator saturation,” *IEEE Trans. Neural Network,* vol. 17, no. 1, pp. 147-156, Jan. 2006.

[26] X. Song, J. Liu, and Y. Huang, “Variable pitch control of wind power generation based on RBF neural network tuning PID control，” *Power System and Clean Energy*, vol. 25, no. 4, pp. 49-53, Apr. 2009.

[27] Y. Luo, H. Zhang, and Q. Zhang, “Neural network adaptive controller design based on a novel dead-zone compensator,”*Acta Electronica Sinica*, vol. 36, no. 11, pp. 2113-2119, Nov. 2008.

[28] Y. Song, B. Dhinakaran, and X. Bao, “Variable speed control of wind turbines using nonlinear and adaptive algorithms,”*Wind Engineering and Industrial Aerodynamics J.,* vol. 85, no.3, pp. 293–308, Apr. 2000.

[29] Z. Wang, Y. Tian, L. Chen, and Q. Guo, “Pitch angle control strategy based on RBF neural network,” *Acta Energiae Solaris Sinica*, vol. 32, no. 5, pp. 623-626, May 2011.