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ADAPTIVE COMPOSITE NEURAL NETWORK CONTROL FOR VARIABLE SPEED WIND TURBINES

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Abstract. *This paper presents a new adaptive composite neural network control for variable speed wind turbines (VSWT), in order to improve the properties of VSWT. A novel output tracking control constraint method of neural network is designed to approximate the unknown nonlinear functions, since the dynamic model of VSWT is unknown. In the design of the observer and the controller, Lyapunov-function is used to prove state estimation error and parameter estimation (neural network weight) are uniformly ultimately bounded (UUB). In the part of simulation, the model of VSWT with a neural network observer which applies the new composite neural network method proposed is developed. A continuous reference input signal is selected to demonstrate the validity of the proposed constrained control algorithm.*
Keywords: Wind power, Composite neural network method control, RBF, VSWT, Adaptive back stepping

1. **Introduction.** In recent years, more and more attention is paid to the development of the wind power. Many countries in the world, like Canada, America, China, Spain, Germany, Italy, India, and France, are investing a lot of money in improving the utilization of wind energy [1,2]. Wind is a renewable energy with great potential, and the wind power does not need to consume fuel and does not produce air pollution [3].

Wind power turns the kinetic energy of the wind into the mechanical energy and converts the mechanical energy into the electricity kinetic energy via the use of the wind turbine. The wind wheel is a very important component which is composed of two or more impellers in the shape of propeller. Due to the fact that the size and direction of the wind often change and the speed of the wind wheel is relatively low, leading to the unstable speed, it is necessary to attach a transmission gear box to increase the rotation speed to the rated rotation speed of generator, and add a speed regulating mechanism for stable speed, and then connect to the generator before driving the generator [4].

With the development of control theory and technology applied to wind power generation, the wind power generator control system is improved from the initial fixed pitch and constant speed control to the current variable pitch and variable speed control. The variable speed wind generator has become the main control study object because it is widely used in the industry of wind power generation. Because of the factors of the inherent nonlinearity and uncertainty of wind turbine system and the existence of external operating condition effects, the controller designed by using the nominal linear system model makes the robust performance of the actual system poor and reliability low. Therefore, in recent years, people have tried to use the nonlinear robust control theory based on models for studies on the control of wind turbine generator systems. However, the current studies of wind turbine control system do not consider the control input constraint problem in the design process [5-7].

Due to the advantages of approximating any nonlinear function of neural network, it is widely used in various occasions like wind turbines. Many works have suggested neural networks (NNs) as powerful methods for approximation of arbitrary input-output mappings which can be applied to nonlinear control systems. Radial basis function networks are one of the useful methods. Radial-basis function (RBF) networks consist of a single hidden layer of nonlinear nodes, centered so that each of them is specialized on a particular zone of the input space. The desired response is obtained by adjusting weights connecting the hidden layer with a linear output node, with a training procedure [14]. Using RBF neural network has two main advantages. In the first place, the neural weights are tuned online without any pre-training phase. Secondly, the stability and performance of the closed-loop systems can be guaranteed effectively. Therefore, the adaptive composite RBF neural network control has become very suitable to control uncertain nonlinear dynamical systems like wind turbines. The ability of the online adaptation for approximation of nonlinear dynamics ensures a strong robustness when disturbances and uncertainties occur in the system [15].

By using the theory of neural network, the paper has designed a novel output tracking control constraint method of neural network. The contribution of this paper is proposing a new control method for the varying operating speed of a wind turbine which is different from general RBF neural network method. The method we proposed in this paper is a novel control strategy based on traditional RBF neural network method. Moreover, the input saturation problem is considered, too. This paper is organized as follows. In Section 2, the system model and problem formulation are given. In Section 3, the progress of model transformation is shown clearly. Then a new composite neural network method is proposed. The observer and controller design are developed in Section 3, too. Simulation results are presented to show the effectiveness of the proposed technique in Section 4. Finally, Section 5 makes a conclusion.

2. System Model and Problem Formulation.

The basic composition of VSWT includes three parts, that is wind turbines, growth container and generator. The block diagram of the variable speed wind turbine is shown in Figure 1 [6]. The rotor dynamic is described as

$$J_r\dot{\omega}_r = T_a - K_r\omega_r - B_r\int_0^t \omega_r(\tau)\mathrm{d}\tau - T_{ls} \tag{1}$$

And the generator dynamic is given as

$$J_g\dot{\omega}_g = T_{hs} - K_g\omega_g - B_g\int_0^t \omega_g(\tau)\mathrm{d}\tau - T_g \tag{2}$$

Because of the gearbox ratio, the following relationship (3) is obtained for the speed ω_r, ω_g, and torque T_{ls}, T_{hs}.

$$n_g = \frac{\omega_g}{\omega_r} = \frac{T_{ls}}{T_{hs}} \tag{3}$$

According to (1) to (3), since $J_t \neq 0$, we can obtain

$$\dot{\omega}_r = \frac{1}{J_t}\left(T_a - K_t\omega_r - B_t\int_0^t \omega_r(\tau)\mathrm{d}\tau - T_g\right) \tag{4}$$

where $J_t = J_r + n_g^2 J_g$, $K_t = K_r + n_g^2 K_g$, $B_t = B_r + n_g^2 B_g$, $T_g = n_g T_{em}$. T_a and T_{em} can be described as follows [6,11,12],

$$T_a = K_w \cdot \omega_r^2, \quad T_{em} = K_\phi \cdot c(I_f) \tag{5}$$

where K_w is a wind speed to power transfer parameter depending on factors like air density, radius of the rotor, the wind speed and the pitch angle. $c(I_f)$ is the flux in the

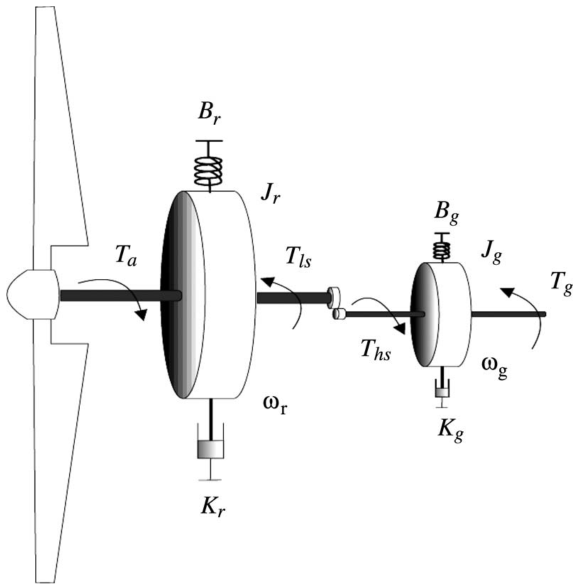

Figure 1. Schematic block diagram for the structure of VSWT

generating system function. The electrical subsystem dynamics of VSWT is governed by following equation.

$$\dot{I}_f = -\frac{R_f}{L} I_f + \frac{1}{L} u_f \tag{6}$$

Hence, from (4) to (6), the dynamic model of VSWT can be described as

$$\begin{aligned} \dot{\omega}_r &= \underbrace{\frac{K_w}{J_t}\omega_r^2 - \frac{K_t}{J_t}\omega_r - \frac{B_t}{J_t}\int_0^t \omega_r(\tau)\mathrm{d}\tau - \frac{n_g K_\phi}{J_t} c(I_f)}_{f_1(\omega_r,\theta_r,I_f)} \\ \dot{I}_f &= -\frac{R_f}{L} I_f + \frac{1}{L} u_f \end{aligned} \tag{7}$$

where angle $\theta_r = \int_0^t \omega_r(\tau)\mathrm{d}\tau$. Assume that function $f_1(\omega_r, \theta_r, I_f)$, R_f and L are all unknown.

The controller design and the stability analysis also require the desired reference trajectory to be first order integrable, that is

$$\int_0^T |\omega_d(\tau)|\,\mathrm{d}\tau < \infty$$

with T being finite (i.e., $\omega_d \in \mathcal{L}_1 \cap \mathcal{L}_\infty$ and $\dot{\omega}_d, \ddot{\omega}_d \in \mathcal{L}_\infty$).

3. Main Results.

3.1. **Model transformation.** Define new state $x_1 = \omega_r$, $x_2 = \dot{x}_1 = \dot{\omega}_r = f_1(\omega_r, \theta_r, I_f)$. Then the time derivative of x_2 can be expressed as

$$\begin{aligned} \dot{x}_2 &= \dot{f}_1(\omega_r, \theta_r, I_f) \\ &= \frac{\partial f_1(\omega_r,\theta_r,I_f)}{\partial \omega_r}\dot{\omega}_r + \frac{\partial f_1(\omega_r,\theta_r,I_f)}{\partial \theta_r}\dot{\omega}_r + \frac{\partial f_1(\omega_r,\theta_r,I_f)}{\partial I_f}\dot{I}_f \\ &= f(\bar{x}) + g(\bar{x})u_f \end{aligned} \tag{8}$$

with $\bar{x} = [\omega_r, \theta_r, I_f]^T$. Hence, the dynamic model of VSWT (7) is now transformed as

$$\dot{x} = Ax + B[f(\bar{x}) + g(\bar{x})u_f], \quad y = C^T x \tag{9}$$

where

$$A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad C = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

and $x = [x_1, x_2]^T$.

3.2. **Composite neural network.** Since the dynamic model (7) of VSWT is unknown, in this paper, neural network will be used to approximate the unknown nonlinear functions $f(\bar{x})$ and $g(\bar{x})$. At present, RBF neural network is widely implemented for function approximation. Here, we propose a composite neural network method for function approximation. For example, continuous unknown nonlinear function $h(\bar{x})$ is approximated by following

$$h(\bar{x}) = h_l(\bar{x}) + h_n(\bar{x}) = W^{*T} S(\bar{x}) + \varepsilon \tag{10}$$

where w_l^* and w_n^* are ideal constant weight vectors of linear and nonlinear parts of $h(\bar{x})$, and $W^* = \left[w_l^{*T}, w_n^{*T}\right]^T$, $S(\bar{x}) = \left[\bar{x}^{*T}, \sigma^T(\bar{x})\right]^T$. W^* is defined as Equation (11)

$$W^{*T} = \arg \min_{W \in \mathcal{R}^N} \left\{ \sup_{\bar{x} \in \Omega_{\bar{x}}} \left| h(\bar{x}) - W^T S(\bar{x}) \right| \right\} \tag{11}$$

and ε is the composite neural network's bounded approximation error, $\sigma(\cdot)$ is an activation function vector which is usually assumed to be a Gaussian function

$$\sigma_j(\bar{x}) = \exp\left(-\frac{\|\bar{x} - \mu_j\|^2}{\delta_j^2} \right), \quad j = 1, 2, \ldots, N-3$$

with $N-3$ being the number of RBF hidden layer neurons.

Hence, for continuous unknown nonlinear functions $f(\bar{x})$ and $g(\bar{x})$, there exist two composite neural networks $W_i^{*T} S_i(\bar{x})$, $i = 1, 2$. Then, the outputs of two composite neural networks are

$$\hat{f}(\bar{x}) = W_1^T S_1(\bar{x}), \quad \hat{g}(\bar{x}) = W_2^T S_2(\bar{x})$$

3.3. **Observer design.** Using the neural network approximations, the dynamic equation of a neural observer which estimates states in (9) is given as follows

$$\begin{aligned} \dot{\hat{x}} &= A\hat{x} + B\left[\hat{f}(\bar{x}) + \hat{g}(\bar{x})u_f\right] + L\left(y - C^T\hat{x}\right) \\ \hat{y} &= C^T\hat{x} \end{aligned} \tag{12}$$

where $\hat{x} = [\hat{x}_1, \hat{x}_2]^T$ is observed state, and $L = [l_1, l_2]^T$ is the observer gain vector. Define the state and output estimate errors as $\tilde{x} = x - \hat{x}$ and $\tilde{y} = y - \hat{y}$.

Theorem 3.1. *Consider the observer system (12), and let update laws for the parameters of neural systems be [16]*

$$\dot{W}_1 = \tilde{y}\Gamma_1 S_1(\bar{x}) - \kappa_1 \Gamma_1 W_1 \tag{13}$$

$$\dot{W}_2 = \tilde{y}\Gamma_2 S_2(\bar{x}) u_f - \kappa_2 \Gamma_2 W_2 \tag{14}$$

where $\Gamma_1 = \Gamma_1^T > 0$, $\Gamma_2 = \Gamma_2^T > 0$ *and* $\kappa_1 > 0$, $\kappa_2 > 0$. *Then, state estimation error and parameter estimation (neural network weight) are uniformly ultimately bounded (UUB). Consider the following Lyapunov-function candidate*

$$V = \underbrace{\tilde{x}^T P \tilde{x}}_{V_1} + \underbrace{\tilde{W}_1^T \Gamma_1^{-1} \tilde{W}_1 + \tilde{W}_2^T \Gamma_2^{-1} \tilde{W}_2}_{V_2} \tag{15}$$

The time derivative of V_1 is

$$\dot{V}_1 = \tilde{x}^T \left(\bar{A}^T P + P\bar{A} \right) \tilde{x} + 2\tilde{x}^T PB(\varepsilon_1 + \varepsilon_2 u_f) + 2\tilde{y} \left[\tilde{W}_1^T S_1(\bar{x}) + \tilde{W}_2^T S_2(\bar{x}) u_f \right] \tag{16}$$

We consider the algebraic Riccati-like equation

$$\bar{A}^T P + P\bar{A} + P^2 \le -Q \tag{17}$$

with $Q > 0$. Then,

$$\dot{V}_1 \le -\tilde{x}^T Q\tilde{x} + 2\tilde{y} \left[\tilde{W}_1^T S_1(\bar{x}) + \tilde{W}_2^T S_2(\bar{x}) u_f \right] + \Upsilon^2$$

$\dot{V}$ follows that

$$\dot{V} \le -\tilde{x}^T Q\tilde{x} + 2\kappa_1 \tilde{W}_1^T W_1 + 2\kappa_2 \tilde{W}_2^T W_2 + \Upsilon^2$$

Hence, $\dot{V}$ will become negative while

$$\|\tilde{x}\| > \sqrt{\frac{\kappa_1 \|W_1^*\|^2}{2\lambda_{\min}(Q)} + \frac{\kappa_2 \|W_2^*\|^2}{2\lambda_{\min}(Q)} + \frac{\Upsilon^2}{\lambda_{\min}(Q)}} = B_1$$

or

$$\|\tilde{W}_1^T\| > \sqrt{\frac{\|W_1^*\|^2}{4} + \frac{\kappa_2 \|W_2^*\|^2}{4\kappa_1} + \frac{\Upsilon^2}{2\kappa_1}} - \frac{\|W_1^*\|}{2} = B_2$$

or

$$\|\tilde{W}_2^T\| > \sqrt{\frac{\kappa_1 \|W_1^*\|^2}{4\kappa_2} + \frac{\|W_2^*\|^2}{4} + \frac{\Upsilon^2}{2\kappa_2}} - \frac{\|W_1^*\|}{2} = B_3$$

From above analysis, we can obtain all estimation errors are UUB.

3.4. **Controller design.** The uniform form of observer (12) is given as follows

$$\begin{aligned} \dot{\hat{x}}_1 &= \hat{x}_2 + l_1 \left(y - C^T \hat{x} \right) = \hat{x}_2 + \eta_1 \\ \dot{\hat{x}}_2 &= \hat{f}(\bar{x}) + \hat{g}(\bar{x}) u_f + l_2 \left(y - C^T \hat{x} \right) = \hat{g}(\bar{x}) u_f + \eta_2 \end{aligned} \tag{18}$$

where $\eta_1 = -l_1 \tilde{y}$, $\eta_2 = \hat{f}(\bar{x}) + l_2 \tilde{y}$.

Command filtered back-stepping control is different from back-stepping control, such as design procedure [11]. The block diagram of the proposed control algorithm for VSWT is depicted as Figure 2. Define the tracking error variables e_1 and e_2 which are introduced as follows

$$e_1 = \hat{x}_1 - x_1^c, \quad e_2 = \hat{x}_2 - \hat{x}_2^c \tag{19}$$

where x_1^c and $\hat{x}_2^c$ are the filtered-command of $\hat{x}_1$ and $\hat{x}_2$, respectively. Let us consider the candidate Lyapunov function

$$V_1 = \frac{1}{2} e_1^2$$

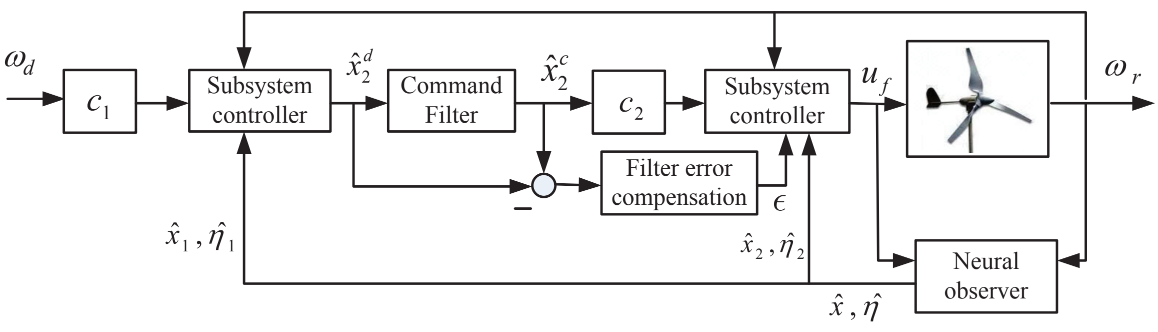

Figure 2. Proposed control method block diagram

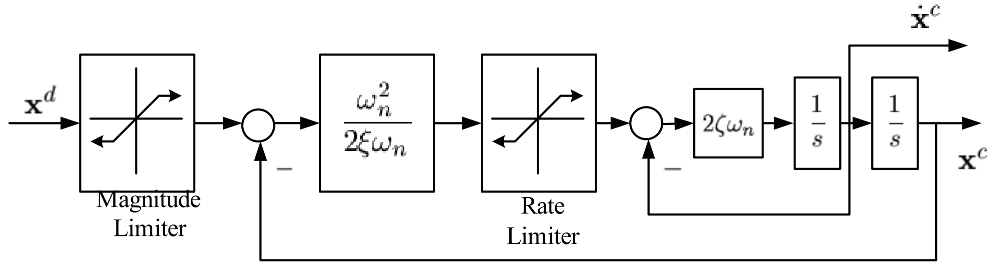

FIGURE 3. Structure of constrained command filters

The time derivative of V_1 with respect to time is given by

$$\dot{V}_1 = e_1\left(\hat{x}_2 + \eta_1 - \dot{x}_1^c\right) \tag{20}$$

The virtual controller (i.e., outer-loop controller) can be designed as

$$\hat{x}_2^d = \dot{x}_1^c - \eta_1 - c_1 e_1 \tag{21}$$

where c_1 is a positive definite matrix to be designed. Pass $\hat{x}_2^d$ through a filter, which is shown in Figure 3. Redefine tracking error $\bar{e}_1 = e_1 - \epsilon$, and design filter error compensation as

$$\dot{\epsilon} = -c_1\epsilon + \hat{x}_2^c - \hat{x}_2^d \tag{22}$$

We choose the Lyapunov function

$$V_2 = \frac{1}{2}\bar{e}_1^2 + \frac{1}{2}e_2^2$$

The time derivative of Lyapunov function V_2 is described as

$$\dot{V}_2 = -c_1\bar{e}_1^2 - c_2 e_2^2 \leq 0 \tag{23}$$

It means that $\bar{e}_1$, e_2 are uniformly ultimately bounded. Further, combined with the results of Section 3.3, we know all error signals of close-loop control system are bounded.

4. **Simulation Results.** In simulation, the system parameters of VSWT are chosen as the same as [11,13], which are considered as $R_f = 0.02\Omega$, $L = 0.001$H, $J_t = 24490$, $B_t = 52$, $K_t = 52$, $K_\omega = 3$, $n_g = 30$, $K_\phi = 1.7$, $c(I_f) = 1000 I_f$. And the reference angular velocity signal $\omega_d(t)$ is selected to be

$$\omega_d(t) = 2 + \sin(t)$$

We choose the 10 basis function nodes for each RBF neural networks. And the observer gain $L = [400, 800]^T$, weight-tuning parameters $\Gamma_1 = \text{diag}[5 \times 10^4]$, $\Gamma_2 = \text{diag}[5 \times 10^3]$, $\kappa_1 = \kappa_2 = 0.01$. The controller gains are selected as $K = [50, 50]^T$.

In this part, Figures 4 and 5 describe the great performances of the VSWT model and the RBF neural network observer. From Figure 4, we can see that the RBF neural network observer tracks the result from the VSWT model quite well via the novel adaptive composite neural network control method.

5. **Conclusion.** In this paper, an adaptive composite neural network control method which is robust to uncertainty in the wind turbine model was proposed for VSWT. The proposed method based on RBF can approximate the complex nonlinear dynamics of an uncertain wind turbine model and the simulation study shows the effectiveness of this method.

In the future, we will do more work focusing on the excitation fault problem of wind turbine generator. Further studies will be made to realize the fault tolerance control of wind turbine.

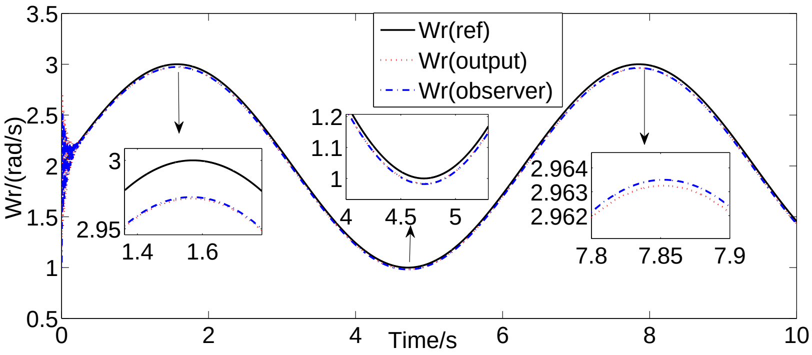

FIGURE 4. The reference signal and the results of the VSWT model and the RBF observer

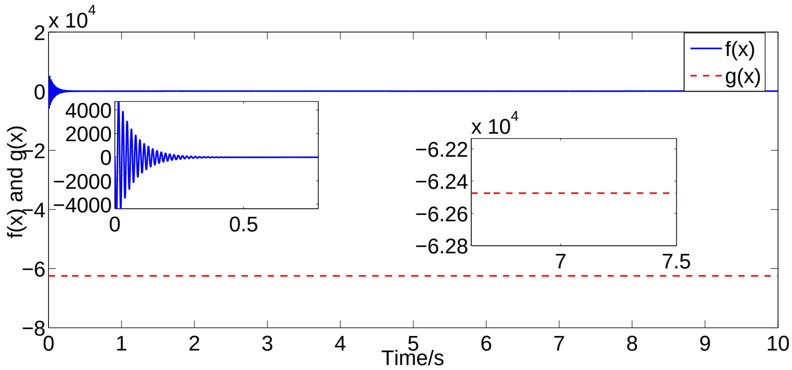

FIGURE 5. Results of $f(x)$ and $g(x)$ obtained via the method proposed

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