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RBF neural network robust adaptive control for wind generator system

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1. Introduction

Among the main research subjects in the wind turbine domain, the control of wind generator system is considered an interesting application area for control theory and engineering. The control strategies must cope with the exacting characteristics presented by WECS such as the nonlinear behavior of the system, the random variability of the wind and external perturbations. Djohra et al. [1] model and simulate a wind turbine and an induction generator system as an electricity source in the southern parts of Algeria, and the obtained results have then been validated by the HOMER software confirming the effectiveness of the developed program. Jordi et al. [2] analyze and compares different control tuning strategies for a variable speed wind energy conversion system based on a permanent-magnet synchronous generator (PMSG), and the aerodynamics of the wind turbine and a PMSG have been modeled. Valenciaga et al. [3] presents the control of a variable-speed wind energy conversion system based on a brushless doubly fed reluctance machine, and the control design is approached using multiinput second-order sliding techniques. However, above-all papers have not considered the intelligent robust adaptive control method.

The radial basis function (RBF) neural network robust adaptive control for wind generator system is studied in particular in this work. The design procedure in this paper aims at designing stable neural network slide mode controller that guarantee the existence of the system poles in some predefined zone and wind speed precise tracking. More significantly, the controller design problem is reduced to Lyapunov stability problem. In this way, by solving the stability Lyapunov function, the feedback gains which guarantee global asymptotic stability and desired speed tracking control performance are determined.

The remainder of this paper is outlined as follows: Section 2 gives the problem formulation of wind generator system, and then, Section 3 shows the RBF Neural network robust adaptive control method. After that, Section 4 presents and discusses the simulation result. Finally, Section 5 draws some conclusions.

2. Problem formulation

In the first, we analyze the particular aerodynamic characteristics of windmills. Here the horizontal-axis type is considered. The output mechanical power available from a wind turbine is

$$P = 0.5\rho C_p (V_\omega)^3 A \tag{1}$$

where ρ is the air density, A is the area swept by the blades, V_ω is the wind speed, C_p is the power coefficient, and a nonlinear function of the parameter λ is given as $\lambda = \frac{\omega R}{V_\omega}$, where R is the radius of the turbine and ω is the rotational speed. C_p is approximated as $C_p = \alpha\lambda + \beta\lambda^2 + \gamma\lambda^3$ usually, where α, β, and γ are constructive parameters for a given turbine. The torque developed by the windmill is

$$T_t = 0.5\left(\frac{C_p}{\lambda}\right)(V_m)^2 \pi R^2 \tag{2}$$

The torque developed by the generator/Kramer drive combination is

$$T_g = \frac{3V^2 sR_{eq}}{\Omega_2[(sR_s + R_{eq})^2 + (s\omega_s L_{is} + s\omega_s L_{lr})^2]} \tag{3}$$

where

$$R_{eq} = \frac{s[n_2^2 sR_b + (n_1 |cos(\alpha)|)^2 R_s - n_1 |cos(\alpha)|]}{(n_2 s)^2 - (n_1 |cos(\alpha)|)^2}$$

$$R_b = R_r + 0.55R_f$$

$$\Gamma = 2n_2^2 R_b sR_s + (n_2 sR_s)^2 + n_2^2 (s\omega_s L_{ls} + s\omega_s L_{lr})^2 \tag{4}$$

with n_1 transformation rate between rotor and stator wounds; n_2 transformation rate between the Kramer Drive and the AC line; R_r, R_s, R_f Rotor, stator, and dc link resistance respectively; L_{ls} stator dispersion inductance; L_{lr} rotor dispersion inductance; α firing angle; ω_s synchronous pulsation; Ω_s synchronous mechanic rotational speed.

With the above mentioned content, ignoring torsion in the shaft, generator electric dynamics, and other higher order effects, the approximate system dynamic model is

$$J\dot{\omega} + \rho(x,\theta) = T_t(\omega, V_\omega) - T_g(\omega, V_\omega) \tag{5}$$

where J is the total moment of inertia, $\rho(x,\theta)$ means the dynamical uncertainties whose time-varying uncertain parameter θ appears nonlinearly, x represents any component of the system state, i.e. $x = [\omega, \dot{\omega}]^T$. We focus on the case where the uncertainties' admit a general multiplicative form, i.e., $\rho(x,\theta)=g(x,\theta)h(x,\theta)$, where the functions $\rho(x,\theta)$, $h(x,\theta)$ are assumed nonlinear and Lipschitzian in θ, $\theta=[\theta_1,\cdots\theta_p]^T\in R^p$.

The wind generator controlled system is configurated as Fig. 1.

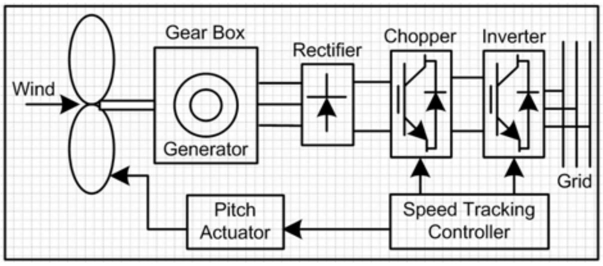

Fig. 1 General view of a wind generator controller system

In the following, $\|\bullet\|$ denotes the standard Euclidean norm. Note that all smooth or convex or concave functions satisfy the following Lipschitz condition.

Regarding (2) and (3), system model becomes

$$\dot{\omega}=\frac{1}{J}\left(0.5\rho\left(\frac{C_p}{\lambda}\right)\right)(V_\omega)^2\pi R^2-$$
$$-\frac{3V^2sR_{eq}}{\Omega_s[\Omega_2[(sR_s+R_{eq})^2+(s\omega_sL_{is}+s\omega_sL_{lr})^2]} \tag{6}$$

where R_{eq} depends nonlinearly on the control action $cos(\alpha)$ according to (4), C_p , λ and V_ω also depend on ω in a nonlinear way. Moreover, it is it is well known that certain generator parameters, such as wound resistance, are strongly dependent on factors such as temperature and aging. Thus a nonlinear adaptive control strategy seems very attractive. The shape of the generator curves allows a simple linearization on the expression for

$$T_g=-k_1\omega+k_2cos(\alpha) \tag{7}$$

As it can be verified, the proposed approximation is good in the required operation zone. The resulting expression for the whole system is then

$$\dot{\omega}=\frac{0.5}{J}\rho\left(\frac{C_p}{\lambda}\right)(V_\omega)^2\pi R^2-k_1\omega+k_2cos(\alpha)-\rho(x,\theta) \tag{8}$$

which has the standard normal form

$$\dot{\omega}+k_1\omega=k_2u+f(x) \tag{9}$$

here, $f(\cdot)$ mesns a nonlinear noise function [4], b represents a constant and $u=cos(\alpha)$.

3. RBF neural network robust adaptive control

3.1. RBF neural network approximate theory

In the field of control engineering, neural network is often used to approximate a given nonlinear function up to a small error tolerance. The function approximation problem can be stated formally as follows [5].

Definiti on 1: Given that $f(y):R^n\to R^m$ is a continuous function defined on the set $y\in R^n$ and $\hat{f}(W,y):R^{l\times m}\times R^n\to R^m$ is an approximating function that depends continuously on the parameter matrix W and y , the approximation problem is to determine the optimal parameter W^* such that, for some metric (or distance function) d

$$d(f(W^*,y),f(y))\le\varepsilon \tag{10}$$

for an acceptable small ε.

In this paper, Gaussian RBF neural network is considered. It is a particular network architecture which uses l numbers of Gaussian function of the form

$$\Theta(y)=exp\left(-\frac{(y-\mu)^2(y-\mu)}{\sigma^2}\right) \tag{11}$$

where $\mu=R^i$ is the center vector and $\sigma^2=R$ is the variance. Each Gaussian RBF network consist of three layers: the input layer, the hidden layer that contains the Gaussian function, and the output layer. At the input layer, the input spaceis divided into grids with a basis function at each node defining a receptive field in Rn Theoutput of the network $\hat{f}(W,y)$ is given by

$$\hat{f}(W,y)=W^T\Theta(y) \tag{12}$$

where $\Theta(y)=\left[\Theta_1(y)\Theta_2(y),...,\Theta_l(y)\right]^T$ is the vector of basis function.

In succeeding sections, we will use the aforesaid RBF neural networks (RBFNN) to approximate nonlinear function $f(\cdot)$, namely

$$f=W^T\Theta(y)+\varepsilon \tag{13}$$

where ε is network approximation difference which can be arbitrary small, and in our paper we assume the difference satisfy $|\varepsilon|<k$, $\Theta(y)$ is network activation function and y is network input.

Remark 1: In succeeding sections, we will use the aforesaid Gaussian RBF neural networks to approximate the nonlinear function $f(x)$, namely

$$f(x)=\{W\}^T\{\Theta(y)\}+\varepsilon \tag{14}$$

where ε is network approximation difference, $\{\Theta(y)\}$ is network activation function and y is network input.

3.2. RBF neural network control strategy

The tracking error of WT speed is defined as $e=\omega-r$. Regarding (9), the dynamics of system (8) in terms of the modified"velocity error"is expressed by

$$\dot{e}_\varepsilon + k_1 e_\varepsilon = k_2 u + f(x) \tag{15}$$

which can be further written as

$$\dot{e}_\varepsilon + k_1 e_\varepsilon = k_2 (u + k_2^{-1} f(x)) \tag{16}$$

It is assumed that the $f(x)$ is right-hand side in (9) can be represented by an ideal RBFNN as

$$f^*(x) = W^{*T}\Theta(x) + \varepsilon \tag{17}$$

where ε is reconstruction error of RBFNN the optimal weight matrix $W^* = [w_{ij}] \in R^{n\times n}$ satisfying that

$$W^* = \underset{W}{argmin}\left\{\sup_{x\in D}\left|\hat{f}(x\,|\,\hat{W}) - f(x)\right|\right\} \tag{18}$$

Here, D_x denotes the sets of suitable bounds of x. It is assumed that x never reaches boundary of D_x. In (18), $\hat{f}(x\,|\,\hat{W})$ is an estimation of $f(x)$, which can be approximated using an RBFNN as

$$\hat{f}(x\,|\,\hat{W}) = \hat{W}\Theta(x) \tag{19}$$

where $\hat{W}$ is adjustable weight matrix.

Now the proposed RBFNN robust adaptive control is give by

$$u = -k_2^{-1}\hat{f}(x\,|\,\hat{W}) \tag{20}$$

where $\hat{f}$ represents the proposed RBFNN adaptive controller which is used to approximate nonlinear function $f(x)$ in (9). In this way, using control law (20), close-loop system become

$$\dot{e} + k_1 e = \tilde{f}(x\,|\,\tilde{W}) \tag{21}$$

where $\tilde{f}(x\,|\,\tilde{W}) = f(x) - \hat{f}_{RBF}(x\,|\,\hat{W})$, with $\tilde{W} = W^* - \hat{W}$ denoting error of weight matrix.

Assumption 1: The reconstruction error $\varepsilon(x)$ is bounded, i.e. $\|\varepsilon\| \le c_\varepsilon$, for $\forall x \in D_x$ with known c_x.

Assumption 2: The norm of optimal weight matrix are bounded so that $\|W^*\| \le c_w$.

Consider the stability of the closed-loop system, we have the following theorem.

Theorem 1: The proposed RBF neural network adaptive controller defined by (20) enable wind generator system (8) to asaymptotically tracking a desired wind speed r and keep the MWEC performance. The adaptive law of is designed as

$$\dot{W} = k_2^{-1}\Lambda^{-1} e\Theta P \tag{22}$$

where $\Lambda = diag(\zeta_1, \zeta_2, \cdots, \zeta_n)$, $\zeta_1 > 0 (i = 1,2,\cdots,n)$ is gain matrix, and P is a positive definite solution of the following Riccati equation

$$PA + A^T P + P^T BB^T P + Q = 0 \tag{23}$$

where Q is a constant matrix with appropriate dimensions given in advance. Then:

(1) $x(t)$ in closed loop systems are uniformly ultimately bounded,

(2) if error $\varepsilon \in L_2$, i.e. $\int_0^\infty \varepsilon^2(t)dt < \infty$, trajectory tracking errors of WECS system tend to zero as time goes to infinity.

Proof. Consider a quadratic Lyapunov function candidate

$$V_1(t) = e^T(t)Pe(t) + Tr(\tilde{W}\Lambda\tilde{W}) \tag{24}$$

with $\tilde{W} = W^* - \hat{W}$. Taking the time derivative of V along (21) results in

$$\dot{V}(t) = e^T(A^T P + PA)e + \tilde{f}\Lambda^T Pe + e^T P\Lambda\tilde{f} + 2Tr(\tilde{W}\Lambda\dot{\tilde{W}}) = $$
$$= e^T(A^T P + PA)e + 2e^T P\Lambda\tilde{f} + 2Tr(\tilde{W}\Lambda\dot{\tilde{W}}) \tag{24}$$

Applying repeatedly the properties of trace of matrix and substituting (22) and (23) into (24) leads to

$$\dot{V}(t) = -e^T(P^T BB^T P + Q)e + 2x^T PB(\varepsilon + \tilde{W}\Theta) - 2Tr(\tilde{W}\Lambda\dot{\tilde{W}}) = -e^T(P^T BB^T P + Q)e + 2e^T PB\varepsilon + 2e^T PB\tilde{W}\Theta - 2Tr(\tilde{W}\Lambda\dot{\tilde{W}}) =$$
$$= e^T(P^T BB^T P + Q)e + 2e^T PB\varepsilon + 2Tr(\Theta^T\tilde{W}^T B^T Pe) - 2Tr(\tilde{W}\Lambda\dot{\tilde{W}}) = e^T(P^T BB^T P + Q)e + 2x^T PB\varepsilon + 2Tr[\tilde{W}^T(B^T Px\Theta^T - \Lambda\dot{\tilde{W}}]$$

According to (22), the equation above becomes

$$\dot{V}_1(t) = e^T(P^T BB^T P + Q)e + 2e^T PB\varepsilon = -e^T Qe - (B^T Pe - \varepsilon)^T(B^T Pe - \varepsilon) + \varepsilon^T\varepsilon \le -e^T Qe + \varepsilon^T\varepsilon \tag{25}$$

It is easy to get $\dot{V} \le -\lambda_{\min}(Q)\|x\|^2 + \|\varepsilon\|^2$, thus $V(x,\tilde{W})$ is negative outside the following compact set Ω_x

$$\Omega_x = \left\{x(t)\,|\,0 \le \|x(t)\| \le \sqrt{\frac{1}{\lambda_{min}(Q)}}\|\varepsilon\|\right\} \tag{26}$$

Assumption 2 implies that W is bounded (equivalently, $\tilde{W}$ is bounded), then $x(t)$ in close-loop systems are uniformly ultimately bounded.

Integration of (25) from $t = 0$ to ∞ can be rewritten as

$$\int_0^\infty e^T Qedt \le \int_0^\infty e^T edt + V(0) - V(\infty) \tag{27}$$

Then

$$\int_0^\infty \|x\|^2 dt \le \frac{k}{\lambda_{min}(Q)} \tag{28}$$

where $k = \int_0^\infty \varepsilon^T \varepsilon dt + V(0) - V(\infty)$. Then $V(0) - V(\infty) < \infty$ and $\int_0^\infty \varepsilon^2 dt < \infty$ with the fact that $V(t)$ is a non increasing function of time and low bounded, which implies $k < \infty$. From (28), it is clear that $x \in L_2$ is satisfied. The boundedness of $x(t)$ implies $x \in L_\infty$. From (21) and boundedness of $x(t)$, $\widetilde{W}(t)$, and $\varepsilon(t)$, one can get $\dot{x} \in L_\infty$, i.e. $x \in L_2 \cap L_\infty$. Thus, the result $lim_{t\to\infty} x(t)$ is achieved from Barbalats lemma [6]. Therefore, whole closed-loop system is asymptotically stable, i.e. trajectory tracking errors converge to zero as time goes to infinity.

According to above analysis, the architecture of close-loop system is shown in Fig. 2.

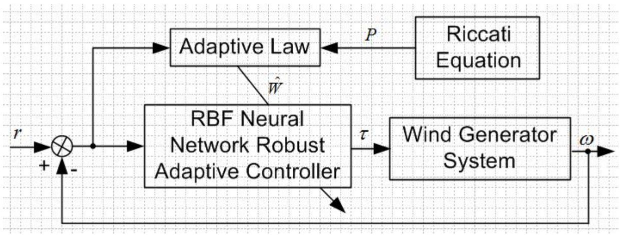

Fig. 2 Architecture of close-loop system

4. Simulation

Simulations are carried out using MATLAB 2006a. The overall system block diagram is depicted in Fig. 2. Here, set the turbine parameter value as $\rho = 1.7Ms^2 / M^4$, $R = 1.45M$, $J = 0.652Mm^2 / rad$, $\alpha = -0.35$, and give the wind generator parameters $R_f = R_s = 0.2\Omega$, $L_{ls} = 0.002Hy$, $n_1 = 2$, $n_2 = 2$.

The performance of the proposed controller is shown in comparison with the dynamical sliding mode power control [7]. The performances are depicted in Fig. 3 and Fig. 4 respectively with a pseudoaleatory sequence of step-shaped wind gusts. It is clearly that, with the RBF neural network adaptive controller, the closed loop converges rapidly to the desired optimal rotational speed. However, with the dynamical sliding mode power controller [7], there exists some obvious vibrations and deviations in the simulation. Therefore, it is evident that, for small

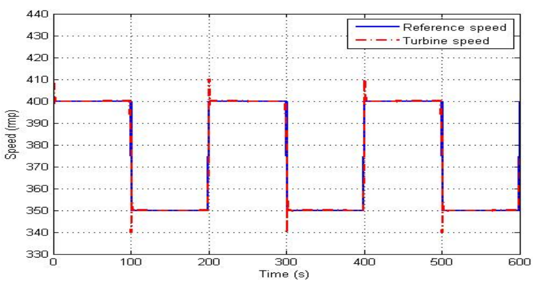

Fig. 3 Performance with our proposed method

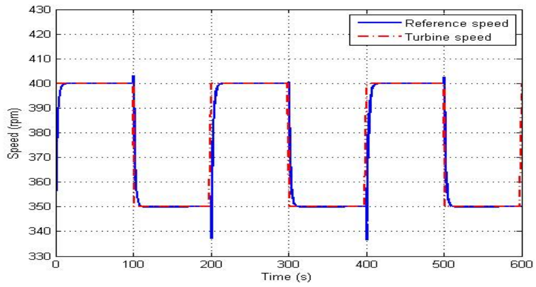

Fig. 4 Performance with method in [8]

errors, the neural network slide mode speed controller can drive the wind speed of wind generator system to the optimum operation point smoothly.

5. Conclusions

A RBF neural network robust adaptive control method for wind generator system is presented in this paper. The proposed RBFNN robust controller drives the wind speed tracking error to a given precision based on Lyapunov stability theory. The simulation shows that our control strategy owns the excellent performance in wind generator system than the exising result.

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VĖJO GENERATORIŲ SISTEMŲ SPECIALI INTENSYVI KONTROLĖ NAUDOJANT RBF NEURONINIUS TINKLUS

R e z i u m ė

Šiame darbe nagrinėjamas metodas vėjo generatorių sistemų specialiai intensyviai kontrolei atlikti naudojant RBF neuroninius tinklus,. Darbo tikslas – suprojektuoti specialius RBF neuroninių tinklų valdiklius, kurie leistų tiksliai stebėti vėjo kryptį. Be to, greičio kontrolės problemų sumažėja taikant Liapunovo stabilumo kriterijų. Šiuo būdu sprendžiant Liapunovo stabilumo funkcijas, gaunamas grįžtamasis ryšys, kuris garantuoja bendrą asimptotinį stabilumą ir norimą greičio efektyvumą. Šio skaitinio imitavimo rezultatai rodo, kad pasiūlytasis metodas yra pranašesnis už esamus.

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RBF NEURAL NETWORK ROBUST ADAPTIVE CONTROL FOR WIND GENERATOR SYSTEM

S u m m a r y

The RBF neural network robust adaptive control method of wind generator system is studied in this work. The design procedure in this paper aims at designing RBF neural network adaptive controllers that guarantee wind speed precise tracking. Moreover, the speed control problems are reduced to Lyapunov stability problem. In this way, by solving the stability Lyapunov functions, the feedback gains which guarantee global asymptotic stability and desired speed performance are determined. The results of numerical simulation showing the superiority of the proposed method than the existing result.

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