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A control of wind energy transformation systems via neural network

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Abstract
In this study a neural network-based adaptive control strategy for variable-velocity variable pitch wind energy transformation systems is suggested. It is based on neural network-based adaptive controller, which drives the tracking error to zero with user specified dynamics. The form of the network weight adaptation law for the neural network adaptive controller is derived from a Lyapunov stability theory. The numerical simulation showing the feasibility of the suggested method.

Keywords: Neural network; Wind energy transformation systems; control strategy

Introduction
Wind power is used to produce electricity or mechanical power and supplies it to homes, business, schools, etc. Wind turbine converts kinetic energy into mechanical energy and then the generator in the wind turbine converts this mechanical energy into electrical power [1-3]. Among the main research subjects in the wind energy domain, the control of wind energy transformation system (WETS) is considered an interesting application area for control theory and engineering. The control strategies must cope with the exacting characteristics presented by WETS such as the nonlinear behavior of the system, the random variability of the wind, usual uncertainties in both the aerodynamic and the electrical models and external perturbations[4]. Evangelista et al. Wind turbine consists of rotor, generator, tower that supports rotor, gear box, electrical cables, etc. It is classified into two major types; Horizontal Axis wind turbine and Vertical Axis wind turbine. Explore an adaptive second order sliding mode control strategy to maximize the energy extracted from the wind in a WETS. Pahlevaninezhad et al. [5] introduces a new control method to track the maximum power point for a WETS. However, above-all studys have not considered the intelligent robust adaptive control method.

A variable-velocity Variable-pitch WETS neural network adaptive control (NNAC) topology is studied in particular in this work. The design procedure in this study aims at designing stable NNAC controllers that make sure of the existence of the system poles in some predefined zone. The stability analysis and control design problems can be solved very efficiently by means of our control method. Since the arbitrary approach of the neural network, it offers more flexibility for combining several constraints on the closed loop system [6-7].

Equations
The output mechanical power available from a wind turbine is P [8].

$$P = 0.5\rho C_p (V_\omega)^3 A$$

Where,

ρ is the air density.

A is the area swept by the blades.

V_ω is the wind velocity.

C_p is called the power coefficient.

λ is given as a nonlinear function of the parameter.

$$\lambda = \frac{wR}{V_\omega}$$

Where,

R is the radius of the turbine.
ω is the rotational velocity.

$$C_p = \alpha\lambda + \beta\lambda^2 + \gamma\lambda^3$$

Where,
α, β, γ are constructive parameters for a given turbine.
This corresponds to an optimal relationship α_{opt} between ω and V_ω.

T_t is the torque of wind mill [8].

$$T_t = 0.5\left(\frac{C_p}{\lambda}\right)(V_m)^2 \pi R^2 \quad (1)$$

T_g is the torque of generator.

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

Where,

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

$$R_b = R_r + 0.55R_f,\ \Gamma = 2n_2^2 R_b sR_s + (n_2 sR_s)^2 + n_2^2(s\omega_s L_{ls} + s\omega_s L_{lr})^2 \quad (3)$$

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

α : firing angle.

Higher order effects, the approximate system dynamic and ignoring torsion in the shaft, generator electric dynamics model is

$$J\dot{\omega} + \rho(x,\theta) = T_t(\omega, V_\omega) - T_g(\omega, \alpha), \quad (4)$$

Where,

J : The total moment of inertia.
$\rho(x,\theta)$: 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 ncertainties 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, $\theta = [\theta_1, \cdots \theta_p]^T \in R^p$.

In the following, $\|\cdot\|$ denotes the standard Euclidean norm. Note that all smooth or convex or concave functions satisfy the following Lipschitz condition [8].
Definition 1: Functions and are said to be Lipschitzian in if there exist continuous functions such that the following inequalities:

$$\|g(x,\theta) - g(x,\bar{\theta})\| \le \sum_{j=1}^{p} L_j(x) \mid \theta_j - \bar{\theta}_j \mid,\ \|h(x,\theta) - h(x,\bar{\theta})\| \le \sum_{j=1}^{p} l_j(x) \mid \theta_j - \bar{\theta}_j \mid. \quad (5)$$

Regarding (1) and (2), system model becomes

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

Where,
R_{eq} depends nonlinearly on the control action $\cos(\alpha)$ according to (3), C_p, λ and V_ω also depend on 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 **[8]**. The shape of the generator curves allows a simple linearization on the expression for

$$T_g = -k_1\omega + k_2 \cos(\alpha) \quad (7)$$

As it can be verified, the suggested approximation is good in the required operation zone [8]. The resulting expression for the all system is then

$$\dot{\omega} = \frac{0.5}{J}\rho\left(\frac{C_p}{\lambda}\right)(V_\omega)^2 \pi R^2 - k_1\omega + k_2\cos(\alpha) - \rho(x,\theta) \qquad (8)$$

which has the standard normal form

$$\dot{\omega} + k_1\omega = k_2 u + f(x) - \rho(x,\theta) \qquad (9)$$

Here, $f(\cdot)$ is a nonlinear function, b is a constant and $u = \cos(\alpha)$.

Hypothesize 1. The reference output r is piecewise continuously time varying and uniformly bounded, and there is a known positive constant m_r such that $|r| < m_r$.

Lemma 1. ([8]) Given Lipschitzian functions $g(x,\theta)$, $h(x,\theta)$, let $L(x)$ and $l(x)$ be defined as

$$L(x) := \max_{j=1,2,\cdots,p} L_j(x),\ l(x) := \max_{j=1,2,\cdots,p} l_j(x).$$

Then, for $\theta \in R_+^p$, the following inequalities:

$$e(t)g(x,\theta)h(x) \le e(t)g(x,\theta)h(x) + |e(t)| \cdot \left\{ Ll(x)\left(\sum_{j=1}^{p}\theta_j\right)^2 + \left[\|h(x,0)\|L(x) + \|g(x,0)\|l(x)\right]\sum_{j=1}^{p}\theta_j \right\} \qquad (10)$$

hold true for any $e(t) \in R$.

In this study, Gaussian radial basis function (RBF) neural network is considered. It is a particular network architecture which uses l numbers of Gaussian function of the form

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

where $\mu \in R^i$ is the center vector.

$\sigma^2 \in R$ 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 R^n. The output of the network $\hat{f}(W,y)$ is given by

$$\hat{f}(W,y) = W^T\Theta(y) \qquad (11)$$

Where

$\Theta(y) = [\Theta_1(y) \quad \Theta_2(y) \quad \cdots \quad \Theta_l(y)]^T$ is the vector of basis function. Note that only the connections from the hidden layer to the output are weighted.

Gaussian RBF network has been quite successful in representing the complex nonlinear function. It has been proven that any continuous functions, not necessary infnitely smooth,can be uniformly approximated by a linear combination of Gaussians [9]. In succeeding sections, we will use the aforesaid RBF networks to approximate nonlinear function $f(\cdot)$, namely,

$$f = W^T\Theta(y) + \varepsilon \qquad (12)$$

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

Neural Network-based adaptive control

The tracking error of wind turbines velocity is defined as $e = \omega - \gamma$, In this way, the all error system can be

$$\dot{e} + k_1 e = k_2 u + f(x) - \rho(x,\theta) \quad (13)$$

Consider a quadratic Lyapunov function candidate

$$V_1(t) = \frac{1}{2}e^T(t)H(\omega)e(t) \quad (14)$$

Using the RBF neural network approximation for $f(x)$, its time derivative can be written as

$$\dot{V}_1(t) = e^T\left(\tau - W^T\Theta - f(x)\right) = e^T\left(\tau - W^T\Theta - ef(x)\right) \qquad (15)$$

where the notations on are neglected for simplicity. In view of relation (10), it follows that

$$\dot{V}_1(t) = e^T\left(\tau - W^T\Theta\right) + \left(eg(x,0)h(x,0)\right) + |e|\left\{ L(x)l(x)\left(\sum_{j=1}^{n}\theta_j\right)^2 + \left[\|h(x,0)\|L(x) + \|g(x)\|l(x)\right]\cdot\sum_{j=1}^{n}\theta_j \right\} \qquad (16)$$

With the describes

$$K(x)=[\omega_1 \quad \omega_2]=[L(x)l(x) \quad \|h(x)\|L(x)+\|g(x)\|l(x)],\ \beta=[\beta_1 \quad \beta_2]=\left[\left(\sum_{j=1}^{p}\theta_j\right)^2 \quad \sum_{j=1}^{p}\theta_j\right],\ \Phi(e,x)=\mathrm{sgn}(e)W(x), \quad (17)$$

the inequality (16) can be rewritten as

$$\dot{V}_1(t)=e^T\left(\tau-W^T\Theta\right)+s^T f_N(x)+e^T\Phi(e,x)\beta \quad (18)$$

The control input

$$\tau=-K_D e+W^T\hat{\Theta}+k-f_N(x)-\Phi(e,x)\hat{\beta} \quad (19)$$

conclude in

$$\dot{V}_1(t)\le -e^T K_D e+e^T\left[W^T\tilde{\Theta}-\Phi(e,x)\right]\tilde{\beta} \quad (20)$$

where $\tilde{\Theta}=\hat{\Theta}-\Theta$ and $\tilde{\beta}=\hat{\beta}-\beta$ are parameter errors and $K_D\in R$ is an arbitrary positive number.

To derive update laws for the parameter estimates, we employ the following Lyapunov function:

$$\dot{V}_1(t)=V_1(t)+\frac{1}{2}\left(\tilde{\Theta}^T\Gamma_\Theta^{-1}\tilde{\Theta}+\tilde{\beta}^T\Gamma_\beta^{-1}\tilde{\beta}\right) \quad (21)$$

where $\Gamma_\Theta,\Gamma_\beta$ are arbitrary numbers. It follows from (20) that

$$\dot{V}_1(t)\le -e^T K_D e+e^T\left[W^T\tilde{\Theta}-\Phi(e,x)\right]\hat{\beta}+\tilde{\Theta}^T\Gamma_\Theta^{-1}\tilde{\Theta}+\tilde{\beta}^T\Gamma_\beta^{-1}\tilde{\beta}. \quad (22)$$

Therefore, the following update laws:

$$\dot{\hat{\Theta}}=-\Gamma_\Theta W^T e,\ \dot{\hat{\beta}}=-\Gamma_\beta K^T(x)|e| \quad (23)$$

yield

$$\dot{V}_1(t)\le -e^T K_D e$$

The last inequality include that $V(t)$ is decreasing, therefore is bounded by $V(0)$.

A result of, $e(t)$ and $\tilde{a}(t)$ must be bounded quantities by virtue of definition (14). Given the boundedness of the reference trajectory r, one has $\dot{e}(t)\in L_\infty$ from the system dynamics(7).Also,relation(17)gives $K_D\cdot\int_0^T|e(t)|^2 dt\le V(0),\forall t>0$, i.e., $e(t)\in L_2$. Applying Barbalats lemma [9] yields $\lim_{t\to\infty}e(t)=0$ [8].

Matlab Simulation

Simulations are using MATLAB 2010 b to confirmly the performance of the neural network adaptive controller. The neural network adaptive controlled loops are showed in Fig. 1. Turbine velocity controlling performance are displayed in Fig. 2

Set the turbine parameters value,

$$\rho=1.7Ms^2/m^4,\ R=1.45M,\ J=0.652\,Mm^2/rad,\ \alpha=-0.35$$

The generator parameters value,

$$R_f=0.2\Omega,\ R_s=0.2\Omega,\ R_r=0.1\Omega,\ L_{ls}=0.001Hy,\ L_{lr}=0.002Hy,\ n_1=2,\ n_2=2$$

The output weights were normalized on random values between -1 and 1. The parameter was set to 0.03. In this figure, a sequence of step-shaped suddenly and hard wind is applied to the system. The resulting evolution of the closed loop converges rapidly to the desired optimal rotational velocity with simple first-order dynamics. It becomes evident that, for minimum errors, the neural network adaptive controller can drive the system to the optimum operation point accuracy [10, 11].

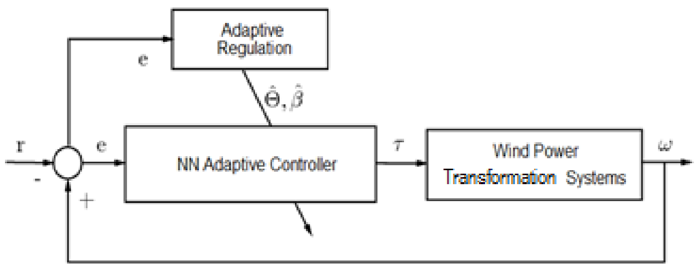

Fig. 1: Neural network adaptive controlled loops

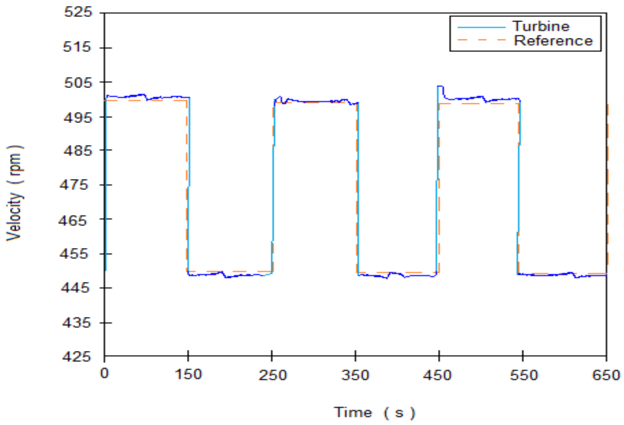

Fig. 2: Turbine velocity controlling performance

Conclusion

In this study, a neural network adaptive control algorithm for variable-velocity variable-pitch WETS is presented. The suggested intelligent controller drives the tracking error to zero with user specified dynamics. The form of the network weight adaptation law for the neural network adaptive controller is constituted from a Lyapunov stability theory. The empirical simulation shows which control strategy of this study the excellent performance in WETS.

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