A Lyapunov Based Switching Control to Track Maximum Power Point of WECS.

Mohammad Abu Jami'in, Jinglu Hu and Eko Julianto

Abstract—**The control system is a key technology to extract maximum energy from the incident wind. By regulating aerodynamic control, it is possible to adapt the changes in wind speed by controlling shaft speed. Thus, the turbine generator can track maximum power extracted from wind. In this paper, we propose a Lyapunov based switching control under quasi-linear ARX neural network (QARXNN) model to track maximum power of wind energy conversion system. The switching index is used to measure the stability of nonlinear controller and selects linear or nonlinear controller in order to ensure the stability. Interestingly, a simple switching law can be built utilizing the parameters of model directly. Finally, we have compared the proposed algorithm of switching controller with another algorithm. The results show that the proposed algorithm has better control performance.**

I. INTRODUCTION

It is possible for the turbine generator to operate in optimum power by tracking the optimum shaft speed. According to aerodynamic characteristic turbine blades, there is an unique optimal TSR with specific maximum aerodynamic efficiency for various wind speeds. Thus, the turbine generator has to work at the specific TSR by varying the turbine speed in order to maximize the power extracted from wind [1], [2]. The amount of power that can be converted depends on the accuracy of maximum power point tracking (MPPT), which is highly influenced by the accuracy of the control system. The effectiveness of the controller is intended to maximize the power output of the turbine, regardless of the type of generator used.

Some control techniques in wind energy conversion system (WECS) are designed based on nonlinear approach of wind turbine model using neural network (NN) or fuzzy neural network (FNN) [3], [4], [5], [6]. Neurocontroller (NC) or fuzzy logic controller (FLC) was proposed to control nonlinear system without the need mathematical description. However, as we know, fuzzy systems, neural networks, and neurofuzzy systems are nonparamtric or multiparametric models. The stability analysis of these models is difficult due to complexity of the nonlinear systems, and parameter tuning is generally a time-consuming process due to its nonlinear and multiparametric nature [7], [8]. In addition, NN and FNN are black-box models and have been criticized not user friendly since they neglect some good properties such as linear structure and simplicity. Especially, the linear structure is very useful and more favorable to certain applications such as nonlinear system control and fault diagnosis [9], [10].

In order to design controller using the prediction model parameters. We propose quasi linear autoregressive exogenous neural network (QARXNN) model as online identifier. It consists macro-part and core-part sub-models. Flexible nonlinear models are used to give the parameters for the input vector in macro part. Macro part sub-model has linear structure which is presented by the input vector and its coefficients. Thus, the controller is derived through inverse of model using its linear structure. Core-part sub model can be implemented using flexible nonlinear model such as NN, FNN, or wavelet network [11], [12], [13], [10]. The coefficients of regression vector consists of linear and nonlinear parts. Therefore, system identification can be performed using linear and nonlinear models hierarchically. If the system identified is linear, the coefficients converge to the specific value of constant. If the system is nonlinear, the coefficients will be time function [14]. Utilizing the linear and nonlinear parts, both linear and nonlinear control can be derived easily. A switching mechanism performs selecting linear and nonlinear controls in order to ensure closed loop control stability [11], [15], [8].

The nonlinear control stability is not global, for those problems, with only nonlinear controller cannot guarantee the bounded of the input-output closed-loop control [16]. To guarantee bounded controller, a switching mechanism was used to improve control accuracy and ensure the stability. In our previous research, the similar switching index named convergence index of error based switching control (CISC) was proposed to [17], [15]. However, the convergence index based switching control cannot capture much information of the dynamic behavior of the system dynamic because it only uses control error as switching variable [11], [8]. It is not efficient because unnecessary switch to the use linear control will be more often, resulting poor control accuracy.

In this paper, a Lyapunov based switching control using QARXNN model is designed and adapted to tracking a maximum power of the wind. Changes a wind speed causes the operating point of WECS system move from its optimum point. The objective of the controller is to keep the operating point of WECS always on its optimum point. We proposes a new switching index derived based on Lyapunov stability theory. The switching index only observes the stability of nonlinear control in order to activate linear or nonlinear controller. Switch to the use linear control if nonlinear control

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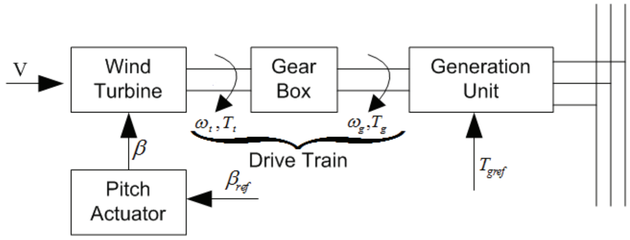

Fig. 1. Structural diagram of WECS systems.

is unstable. Change to the use nonlinear control to improve control accuracy. The proposed switching index can capture much behavior of system dynamics. Not only error but also one up to p-th differential error will be available as the switching variable. Thus, the controller can select to the use linear control more effective. Moreover, the switching formula can use the parameter of prediction model as switching variable. It comprises three parts: 1) linear robust adaptive controller (LRAC), 2) nonlinear robust adaptive controller (NRAC) and 3) switching mechanism

II. Dynamic Modeling of WECS System

The overall scheme for the WECS is given by Fig. 1. It is interconnected systems that consists of the wind turbine, the drive train, and the generation unit. The aerodynamic power P_m captured by the wind turbine is given by

$$P_m = 0.5\rho\pi Cp(\lambda, \beta)R^2V^3 \tag{1}$$

where $Cp(\lambda, \beta)$ represents the wind turbine power conversion efficiency, ρ is the air density (typically 1.25 kg/m3), R is radius of blades (in meter), $Cp(\lambda, \beta)$ is the wind-turbine power coefficient, and V is the wind speed (in m/s). The Cp is a function of the tip-speed ratio λ and blade pitch angle β (in degrees) in a pitch-controlled wind turbine. The λ is defined as the ratio of the tip speed of the turbine blades to wind speed, and is given by

$$\lambda = \frac{\omega_t R}{V} \tag{2}$$

where ω_t is the wind turbine shaft speed (in rad/s). The aerodynamic torque on the wind turbine rotor can be obtained by using the following relationships:

$$T_m = \frac{P_m}{\omega_t} = \frac{\rho\pi Cp(\lambda, \beta)R^3V^2}{2\lambda}. \tag{3}$$

Power coefficient Cp is a nonlinear function of the TSR λ and the pitch angle β and can be expressed as follows

$$Cp(\lambda, \beta) \quad = \quad 0.5176(\frac{116}{\lambda_i} - 0.4\beta - 5)e^{-21/\lambda_i} + 0.0068\lambda \tag{4}$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.008\beta} - \frac{0.035}{\beta^3 + 1}. \tag{5}$$

The curves have been obtained by plotting (4), which is commonly used in wind turbine simulators [18]. As we

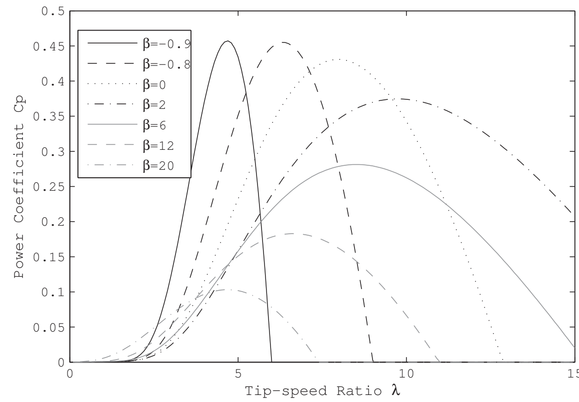

Fig. 2. Power coefficient versus tip-speed ratio for various blade pitches β.

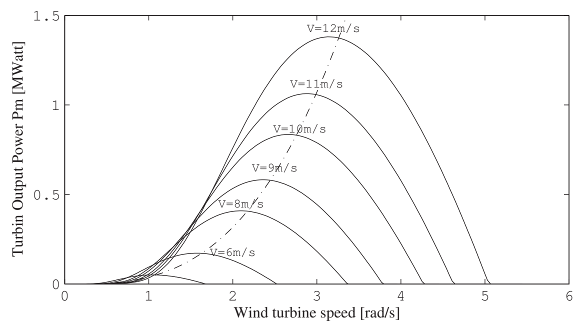

Fig. 3. Power-speed characteristics of wind turbines for various wind speeds at a pitch of 0^o.

can see on Fig. 2, the Cp-λ characteristics with different values of the pitch angle indicates that there is one specific λ at which the turbine is most efficient. In order to capture maximum power extracted from wind incident, a variable-speed wind turbine follows the Cp_{max} by varying the rotor speed to keep the system at λ_{opt}.

The objective of the proposed control is to maximize the power that the turbine extracts, which can be achieved if Cp is maximized. To maximize Cp, λ must be kept constant at its optimum value regardless of wind speed. Fig. 3 illustrates the steady-state power-speed characteristics (i.e., solid curves) and the maximum power point curve (i.e., dashed curve) attained for each wind speed at a pitch angle of 0^o.

The proposed MPPT technique seeks to retrieve the optimal rotor speed ω_t (i.e., the speed corresponding to the maximum generated power) for any instantaneous value of wind speed. Note in Fig. 1, the external input of the dynamic WECS are the set points of generator torque $T_{g,ref}$, the desired pitch β_{ref}, and wind speed signal V. The outputs of WECS can be measured that presented by the turbine rotor speed ω_t. The wind speed signals are fluctuated that can be assumed as a disturbance signal affecting uncertainty parameters of the WECS dynamics. The WECS dynamic can

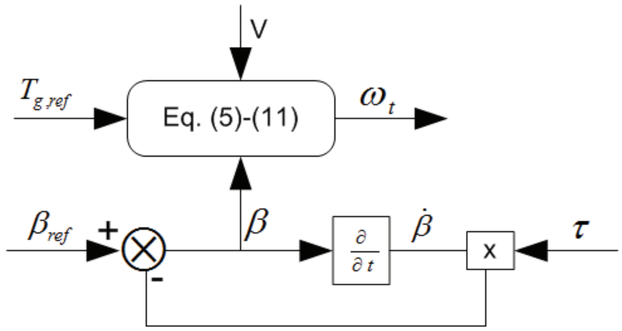

Fig. 4. Block diagram of nonlinear dynamic of WECS.

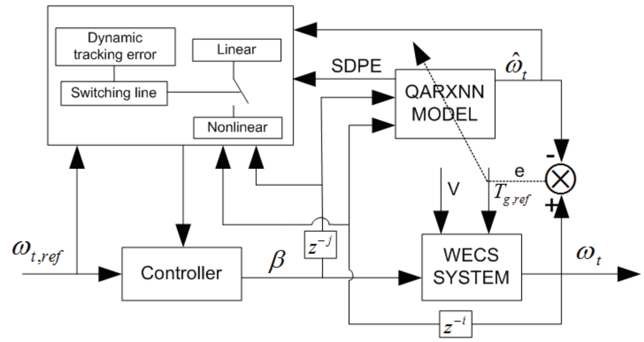

Fig. 5. MPPT controller of WECS bases QARXNN prediction model.

be described as follows:

$$\dot{\theta} = \omega_t - \omega_g \tag{6}$$
$$J_g\dot{\omega}_g(t) = K_s\theta + B_s\omega_t - B_s\omega_g + T_g(\omega_g, T_{g,ref}) \tag{7}$$
$$J_t\dot{\omega}_t(t) = -K_s\theta - B_s\omega_t + B_s\omega_g + T_m(\beta, V) \tag{8}$$

The generator torque T_g is a nonlinear function with the generator speed ω_g and the reference electromagnetic torque $T_{g,ref}$ as a variable. The generator usually operates in the linear region of its torque characteristics, which can be approximated in linear form as

$$T_g = B_g\omega_g - T_{g,ref}. \tag{9}$$

The pitch actuator is modelled as a first-order dynamic system with saturation in the amplitude and derivative of the pitch β as [19], [18]

$$\dot{\beta} = \frac{-1}{\tau}\beta + \frac{1}{\tau}\beta_{ref}. \tag{10}$$

Fig. 4 shows the dynamic of WECS model described in Equations (1)-(10). The control system acts to control blade pitch position in order to maximize the power extracted from wind, with the reference electromagnetic torque $T_{g,ref}$ set as constant. The system parameters are given as follows [1]:

Turbine and drive train parameters
R=30.30m, K_s=15.66x10^5 N/m,
Bs=30.29x10^2 $N.ms/rad$,
J_t=83.00x10^4 $kg.m^2$
Generator parameters
B_g=15.99 $N.ms/rad$, J_g=5.9 $kg.m^2$
Pitch actuator
τ=100 ms.

III. Control Strategy

A global scheme of the proposed control system is illustrated on Fig. 5. The control design is performed in two steps: 1) The online identification and prediction of WECS by using QARXNN model. By using the prediction model, the coefficients or state dependent parameter estimation (SDPE) can be obtained that consists of two parts: linear and nonlinear parts. 2) Deriving and implementing the control law based on the prediction model. In this step, the linear part is used to derive the linear adaptive and robust control (LRAC), and the sum of linear and nonlinear parts is used to derive nonlinear adaptive and robust control (NRAC). In order to ensure closed loop control stability, a switching mechanism is introduced between linear and nonlinear part of SDPE. The turbine speed is operated at MPPT point by controlling the pitch blade position with generator torque is assumed to be constant.

A. System Identification

Through performing Taylor series expansions [12], [13], nonlinear continuous function can be presented as

$$y(t) = \phi(t)^T\aleph(\phi(t)) \tag{11}$$

where $\aleph(\phi(t)) = [a_{(1,t)}\cdots a_{(n_y,t)}\ b_{(1,t)}\cdots b_{(n_u,t)}]^T$ is a Taylor coefficients, $\phi(t) \in R^{n=n_u+n_y}$ denotes the input vector with elements of $\phi(t) = [-y(t-1)\cdots -y(t-n_y)u(t-1)\cdots u(t-n_u)]^T$, n_u and n_y represents the orders of time delay in input-output data. $\aleph(\phi(t)) \in R^{n=n_u+n_y}$ denotes a kernel function that is used to give coefficients of the input vector. In our main theoretical, the assumption are made as follows:

Fig. 6 illustrates the quasi-linear ARX neural network in which multi perceptron neural network (MLPNN) is a core part of system modelling to parameterize the input vector. Incorporating to NN, the system modeling can be expressed as

$$y(t,\phi(t)) = \phi(t)^T\aleph(\phi(t)) \tag{12}$$
$$\aleph(\phi(t)) = W_2\Gamma W_1(\phi(t) + B) + \theta, \tag{13}$$

where $\Omega = \{W_1, W_2, B, \theta\}$. $W_1 \in R^{mxn}, W_2 \in R^{nxm}, B \in R^{mx1}$ are the weights matrix in the first layer, second layer, and bias vector of hidden nodes. $\aleph(\phi(t))$ is the coefficients or state dependent parameter estimation (SDPE)

In order to train QARXNN model, two sub-model are introduced as follows: $z_l(k) = y(t,\phi(t)) - \phi(t)^T[W_2(k)\Gamma W_1(k)(\phi(t) + B(k))]$ and $z_n(k) = y(t,\phi(t)) - \phi(t)^T\theta(k)$, where k denotes a sequence learning number. A hierarchical learning of the two sub-models performed in two steps: (1) LSE algorithm is used

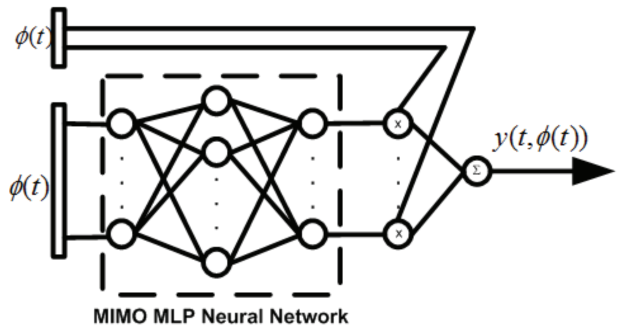

Fig. 6. Quasi-ARX neural network with MLP network as embedded systems.

to update θ and then is set as bias vector for MLPNN; (2) Performing backpropagation (BP) error algorithm to NN to give the coefficients for the input vector. In detail, the learning algorithms of the QARXNN model is performed step by step described as follows:

1) set $k = 0$ for initial conditions, $\theta(k) = 0$; and small initial values to $W_1(k)$, $W_2(k)$, and $B(k)$, then set $k = 1$, where k is the learning number.
2) calculate $z_l(k)$, then estimate $\theta(k)$ for by using a least-squares error algorithm.
3) calculate $z_n(k)$, then estimate $W_1(k)$, $W_2(k)$, and $B(k)$. It is realized by using the well-known back-propagation (BP) algorithm.
4) use the (13) to update $\aleph(\phi(t))$
5) stop if pre-specified conditions are met, otherwise go to Step 2, and repeat the estimation of $\theta(k)$, and $W_1(k)$, $W_2(k)$, and $B(k)$, set $k = k + 1$.

B. Controller Design

A model in (11) can be rewritten in the form of the relationship between the input vector and its coefficients as follows:

$$\begin{aligned} y(t) &= \hat{a}_{(1,t)}y(t-1) + \hat{a}_{(2,t)}y(t-2) + \\ &\quad \hat{a}_{(n_y,t)}y(t-n_y) + \hat{b}_{(1,t)}u(t-1) + \\ &\quad \hat{b}_{(2,t)}u(t-2) + \hat{b}_{(n_u,t)}u(t-n_u). \end{aligned} \tag{14}$$

where, $\hat{\aleph}(\phi(t)) = [\hat{a}_{(1,t)} \cdots \hat{a}_{(n_y,t)}\ \hat{b}_{(1,t)} \cdots \hat{b}_{(n_u,t)}]^T$ is a state-dependent parameter estimation. To derive the control signal, model in (14) can be rewritten as

$$u(t-1) = \frac{1}{\hat{b}_{1,t}}(y(t) + g(t)) \tag{15}$$

$$\begin{aligned} g(t) &= -\hat{a}_{(1,t)}y(t-1) - \hat{a}_{(2,t)}y(t-2) \\ &\quad -\hat{a}_{(n_y,t)}y(t-n_y) - \hat{b}_{(2,t)}u(t-2) \\ &\quad -\hat{b}_{(n_u,t)}u(t-n_u)). \end{aligned} \tag{16}$$

Equation (11) is regressed at time $(t + d)$ to calculate the output at d steps ahead of the prediction, described as follows:

$$y(t+d) = \phi^T(t+d)\hat{\aleph}(\phi(t+d)) \tag{17}$$

where, $\hat{\aleph}(\phi(t+d)) = [\hat{a}_{(1,t+d)} \cdots \hat{a}_{(n_y,t+d)}\hat{b}_{(1,t+d)} \cdots \hat{b}_{(n_u,t+d)}]^T$ is the coefficient of the input vector, $\phi(t+d) = [y(t+d-1)\ y(t+d-2) \cdots y(t+d-n_y)\, u(t+d-1)\, u(t+d-2) \cdots u(t+d-n_u)]^T$ is the input vector at d steps ahead of the prediction, and $\phi(t+d) = [y(t+d-1)\ y(t+d-2) \cdots y(t+d-n_y)\ u(t+d-2)\ u(t+d-3) \cdots u(t+d-n_u-1)\ \nu(t+d)]^T$. The online step ahead of the prediction, d is equal to one. From (17), we have the following:

$$u(t) = \frac{1}{\hat{b}_{1,t+1}}(y(t+1) + g(t+1)) \tag{18}$$

$$\begin{aligned} g(t+1) &= -\hat{a}_{(1,t+1)}y(t) - \hat{a}_{(2,t+1)}y(t-1) \\ &\quad - \cdots - \hat{a}_{(n_y,t+1)}y(t-n_y+1) \\ &\quad - \cdots - \hat{b}_{(n_u,t+1)}u(t-n_u+1)). \end{aligned} \tag{19}$$

where, $u(t)$ is a control signal corresponding to a nonlinear estimator by $\hat{\aleph}(\phi(t))$. For the control signal calculated by using a linear predictor, $\hat{\aleph}(\phi(t))$ is replaced with $\hat{\theta}$.

In order to guarantee control stability, the switching line is introduced between the linear part θ and the nonlinear part $\delta(\phi(t))$ of an SDPE, described as follows:

$$\hat{\aleph}(\phi(t)) = \hat{\theta} + \chi(t)\hat{\delta} \tag{20}$$

$$u(t) = \chi(t)u_n + (1 - \chi(t))u_l(t) \tag{21}$$

$$\hat{\delta} = \hat{W}_2\Gamma\hat{W}_1(\phi(t) + B) \tag{22}$$

where, u_l is a control signal calculated by the linear robust control that uses the parameters of the linear estimator $\hat{\theta}$, and u_n is a control signal from the nonlinear robust control that uses the parameters of the nonlinear estimator by summing $\hat{\theta}$ and $\hat{\delta}(\phi(t))$. $\chi(t)$ is a switching line which $\chi(t) = 1$ denoting nonlinear robust control and $\chi(t) = 0$ denoting linear robust control.

C. Switching Condition [11]

By utilizing SDPE, the dynamic tracking error can be stated as follows [11]:

$$\dot{E} = AE + BU + G. \tag{23}$$

where

$$A = \begin{pmatrix} 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 1 \\ -k_p & -k_{p-1} & \cdots & -k_1 \end{pmatrix}$$

$$B = \begin{pmatrix} \hat{b}_{1,t+1} & 0 & 0 & 0 \\ \hat{b}_{1,t+1} & -\hat{b}_{1,t} & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ c_1\hat{b}_{1,t+3-p} & -c_2\hat{b}_{1,t+2-p} & \cdots & (-1)^p c_{p+1}\hat{b}_{1,t+2-p} \end{pmatrix}$$

$$U = \begin{pmatrix} U(t) \\ U(t-1) \\ \cdots \\ U(t-p+1) \end{pmatrix}$$

$$G = \begin{pmatrix} -G(t+1) \\ -G(t+1) + G(t) \\ \vdots \\ -c_1G(t+3-p) + \cdots + (-1)^{p+1}c_{p+1}G(t+2-p) \end{pmatrix}$$

where A is a nonsingular matrix, c_n are binomial series coefficients such as $\binom{p}{r} = \frac{p!}{r!\,(p-r)!}, 0 \leq r \leq p$.

The nonlinear controller-estimation error U is defined as follows:

$$\begin{aligned} u(t) - u^*(t) &= \frac{1}{\hat{b}_{1,t+1}}(y(t+1) + \hat{g}(t+1)) - \\ &\quad \frac{1}{\hat{b}_{1,t+1}}(y^d(t+1) + g(t+1)) \\ &= \frac{1}{\hat{b}_{1,t+1}}(y(t+1) - y^d(t+1) + \\ &\quad \hat{g}(t+1) - g(t+1)) \\ U(t) &= \frac{1}{\hat{b}_{1,t+1}}(e(t+1) + G) \end{aligned} \tag{24}$$

where, $U = u(\cdot) - u^*(\cdot)$,$G = \hat{g}(\cdot) - g(\cdot)$, $\hat{g}(\cdot)$ are calculated using nonlinear predictor of QARXNN model. By performing the stability analysis based on Lyapunov theorem, the switching condition can be obtained as follows [11]:

$$\rho \leq -\frac{1}{2}(E^T Q E) + (\tilde{U} - \varepsilon)^T B^T P E + G^T P E, \rho \leq 0 \tag{25}$$

then $\lim_{t\to\infty} E(t) = 0$, $E(t) \to 0$ at $t \to \infty$, the tracking error e will converge to zero.

The switching line to change control action of linear part controller and nonlinear part controller. The model only with linear parameters has to work until the use of nonlinear parameters does not damage the stability of closed loop system. Therefore, the controller with using linear parameters $\hat{\theta}$ will work all the time, but the nonlinear parameters $\hat{\aleph}(\phi(t))$ will work under the switching sequence which is illustrated on Fig. 5. The controller law (21) work under the switching line as follows:

$$\chi(t) = \begin{cases} 1, & \text{if } \rho \leq 0 \\ 0, & \text{otherwise} \end{cases} \tag{26}$$

IV. Simulation and Results

The proposed MPPT control strategy is applied to arrange a pitch of blade β in order to track the angular velocities of a turbine operating at MPPT point. Wind speed is generated by an ARMA model that is created for the Swift Current site in Saskatchewan, Canada, based on data regarding the period from 1996 to 2003 appears in the following [20]. According to the wind modeling in which the mean observed wind speed of $\mu(t)$ = 12 m/s and the standard deviation (SD) of the observed wind speed of $\sigma(t)$ = 1.5. The result of wind profile modeling is shown by Fig. 7.

From the system modeling, an embedded system MLPNN of QARXNN is constructed with a three-layer neural network. The input vector of $\phi(t)$ is specified by the following: $\phi(t)$ is determined by $\phi(t) = [y(t-1)\, y(t-2)\, y(t-3)\, y(t-4)\, u(t-1)\, u(t-2)\, u(t-3)]^T$ with $n = 7$ equal to the sum of $n_u = 3$ and $n_y = 4$. The number of input nodes, hidden nodes, and output nodes is also the same as n. The constant learning rate of BP algorithm is selected by $\eta_{bp} = 0.1$ and gain of adaptive tracking control based on the QARXNN model are given by: $\gamma = 0.02$, $p = 4$.

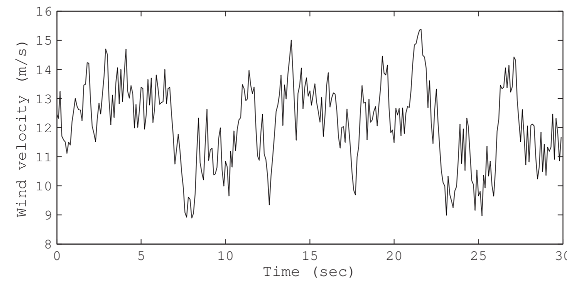

Fig. 7. Wind speed.

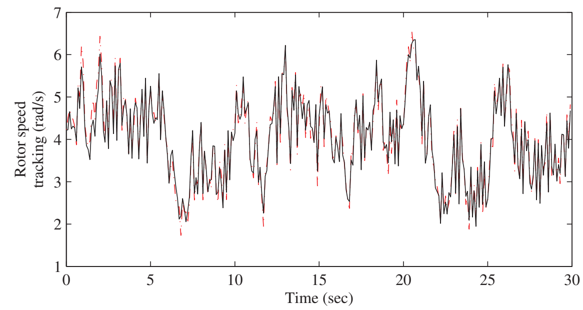

Fig. 8. Trajectory of ω_t (solid line: the proposed, dashed line: CISC)

The output responses and the tracking errors of the proposed controller compared with the CISC based switching of minimum variance control are shown in Fig. 8, Fig. 9. Fig. 10 illustrate the WECS response at the MPPT operating point. If the rotor speed can follow the specific speed references ω_t that satisfy to the specific λ, then the maximum power coefficient can be achieved. Thus, the power ratio will be equal to one. The MPPT accuracy shown by Fig. 11 illustrate tracking control accuracy defined as a ratio between the tracked MPPT power to aerodynamic power. Ratio of 1 indicates an accuracy of 100%.

V. Result and Discussion

In this paper we propose Lyapunov based switching controller applied for tracking control of WECS. Considering

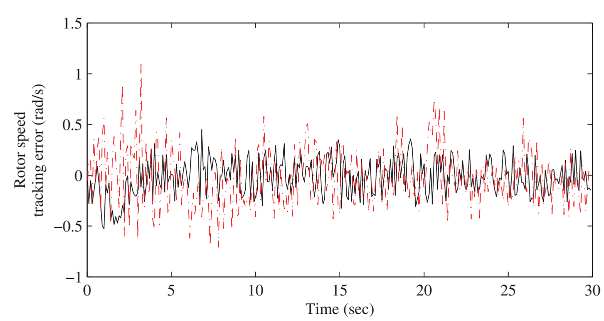

Fig. 9. Tracking error of turbine angular velocity (solid line: the proposed, dashed line: CISC).

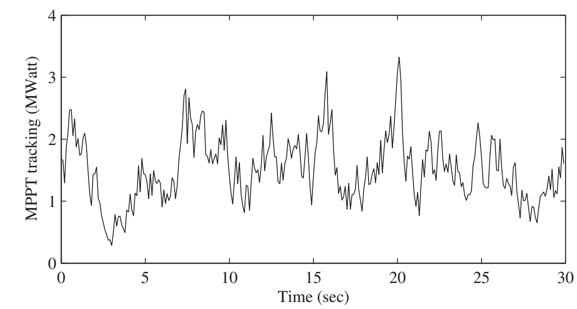

Fig. 10. Tracking MPPT power by using the proposed method

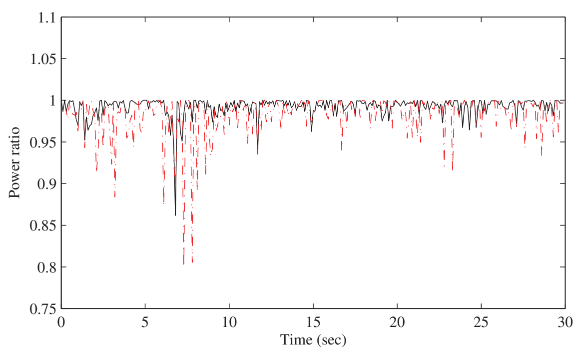

Fig. 11. The ratio between the tracked MPPT power to aerodynamic power (solid line: the proposed, dashed line: CISC).

traditional switching control (CISC) gain a poor performance due to less accurate measure to estimate the stability of nonlinear system. Traditional switching control cannot capture much information dynamic behavior of nonlinear system. Therefore, The controller will be unnecessary switch to the use linear controller, reduce the tracking control accuracy. In this paper, we applied the proposed algorithm to track maximum energy of WECS. We have compared our algorithm with another algorithm. The results show that the proposed algorithm has better performances.

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