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Nonlinear Adaptive Control for Wind Energy Conversion Systems Based on Quasi-ARX Neural Networks Model

Mohammad Abu Jami'in, *Member, IAENG,* Imam Sutrisno, *Member, IAENG,* and Jinglu Hu

***Abstract*—A wind turbine, by itself, is already a fairly complex system with highly nonlinear dynamics. Wind speed and torque fluctuations can change the dynamic parameters of wind energy conversion systems (WECS), so that the parameter will be a function of time. The quasi-ARX neural networks are nonlinear models, while the multi-layer parceptron (MLP) network is an embedded system to give the unknown parameters of the regression vector. Unknown parameter is the coefficient of nonlinear autoregressive moving average (ARMA) models and consists of two parts, linear and nonlinear parts. With a quasi-ARX model as an identifier, we design an adaptive controller for WECS. Logic switch function is used to ensure the stability and control accuracy. In this paper, the objective of WECS controller is to track the maximum power point tracking (MPPT) is used to maximize the power output of the wind turbine. However, from user's point of view, there are two majors. First, quasi-ARX neural network model is used to identification and prediction of nonlinear system, and second, by using using minimum variance controller with switching law, the proposed model successfully is used to track MPPT of WECS.**

***Index Terms*—wind energy conversion systems (WECS), quasi-ARX neural networks, nonlinear parameter estimation, wind turbine control, switching controller.**

I. Introduction

THE growing concern over environmental degradation resulting from combustion of fossil fuels and fluctuating oil prices has raised awareness about alternative energy options [1], [2]. Wind energy is non-depletable, site-dependent, nonpolluting, and potential sources of alternative energy options. The wind generation rely purely on weather conditions; the highest level of energy injected into the electricity grid can occur at times when the cost of the electricity is also high. This will improve the high capital intensive installation cost required for such renewable energy generation systems to be recovered earlier and hence improve future investment opportunities [3].

There are many challenges for designing an effective control system for the wind energy conversion systems (WECS). The system variables must be regulated in the presence of severe fluctuations in the input turbine power caused by erratic variations in the wind speed. Fluctuations in turbine power can lead to harmful effects on the system [4]. Large variations in the drive train torsional torque can occur, thus reducing the life time of the mechanical parts of the system. Another challenge is the presence of nonlinearity in the system dynamics and the continuous variation of the operating point depending on the average wind speed. The control system must cope with these variations to ensure good performance over the whole range of operation of the WECS. The One of control strategy are made based on identification and prediction of WECS systems such as model predictive control (MPC) [5].

The estimated parameters neural networks have been used to identify and control nonlinear dynamical systems because of its ability to approximate arbitrary map to any desired accuracy [6]. Some researchers have used neural networks directly to identify and control nonlinear systems [6], [7]. However, from a user's point of view, there are two major criticisms on those neural network models. One is that their parameters do not have useful interpretations. The second is that they do not have a friendly interface for controller design and system analysis [8], [9]. Quasi-ARX model is a nonlinear model constructed by neural network. Based on Taylor expansion series, nonlinear system has a linear correlation between the information vector and its nonlinear coefficients [10], [11], [12]. Nonlinear coefficients serve as the parameters of ARX model, can be executed by using multi-input multi-output model, and also can be implemented by neuro fuzzy, wavelet, radial basis function, and multi layer parceptron (MLP) networks [13].

The control system is the key technology of the wind energy conversion process in order to extract maximum energy from the incident wind. Thus, maximum power point tracking (MPPT) control schemes have been reported which operate by varying the generator speed in order to optimize wind turbine aerodynamic efficiency [14]. The effectiveness of controller is to track maximum power point tracking which are employed to maximize the wind turbine output power. In this work, we propose a nonlinear adaptive controller by using quasi-ARX neural networks model as an identifier. A MLP neural networks is embedded system injected to the quasi-ARX model as a kernel and the nonlinear parameters are its output. By using the quasi-ARX model as a predictor, we estimate nonlinear parameters and design an adaptive feedback controller derived from the output of predictor.

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Mohammad Abu Jami'in and Imam Sutrisno are with the Graduate School of Information Production and Systems Waseda University, Kitakyushu 808-0135, Japan, and Shipbuilding Institute of Polytechnic Surabaya (Politeknik Perkapalan Negeri Surabaya), Jalan Teknik Kimia Kampus ITS Sukolilo Surabaya, 60111, Indonesia,(e-mail: mohammad@ruri.waseda.jp and imams3jpg@moegi.waseda.jp).

Jinglu Hu is with the Graduate School of Information Production and Systems Waseda University, Kitakyushu 808-0135, (e-mail: jinglu@waseda.jp).

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II. Dynamic Modeling of WECS System

A. Wind Speed Modeling

The power produced by a wind turbine generator (WTG) at a particular site is highly dependent on the wind regime at that location. There is a number of ways that wind speed can and has been modeled in power system reliability evaluation. This method uses the ARMA model to predict wind speeds in the reliability evaluation process and is designated as the ARMA approach. An ARMA model with p autoregressive terms and q moving average terms is denoted as $ARMA(p, q)$. The ARMA model created for the Swift Current site in Saskatchewan, Canada based on 1996 to 2003 data is shown in the following [15]:

$$\begin{aligned} s(t) &= 1.1772s(t-1) + 0.1001s(t-2) - 0.3572s(t-3) \\ &\quad +0.0379s(t-4) + \nu(t) - 0.5030\nu(t-1) \\ &\quad -0.2924\nu(t-2) + 0.1317\nu(t-3) \\ &\quad \nu(t) \in (0, 052476^2). \end{aligned} \tag{1}$$

The simulated wind speed at hour t, designated as $V(t)$, can be calculated as follows:

$$V(t) = \mu(t) + \sigma(t)s(t). \tag{2}$$

where $\mu(t)$ is the mean observed wind speed at hour and $\sigma(t)$ is the standard deviation of the observed wind speed at hour.

B. Dynamic Modeling of WECS

The power captured by a wind turbine is given by

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

where 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 coefficient $Cp(\lambda, \beta)$ depends on the pitch angle of the blades β (in degrees) and the tip-speed ratio λ, which is defined as the ratio of the linear velocity of the blade tip ($\omega_t R$) to the wind speed V as follows:

$$\lambda = \frac{\omega_t R}{V} \tag{4}$$

where ω_t is the wind turbine shaft speed (in rad/s).

The relation of Cp versus λ of a three-blade horizontal-axis wind turbine for various blade pitch angles β is illustrated in Fig. 1. The curves have been obtained by using the following equation that is commonly used in wind turbine simulators [5], [16]:

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

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.008\beta} - \frac{0.035}{\beta^3 + 1}. \tag{6}$$

WECS can be structured into several interconnected subsystem models as shown in Fig. 2. This system consists of wind turbine, a drive train, and a generation unit.

The objective of the proposed control is to maximize the power that the turbine extracts. This can be achieved if Cp is maximized. To maximize Cp, λ must be kept constant at its optimum value , regardless of the wind speed. Fig. 3 illustrates the steady-state power-speed characteristics (solid

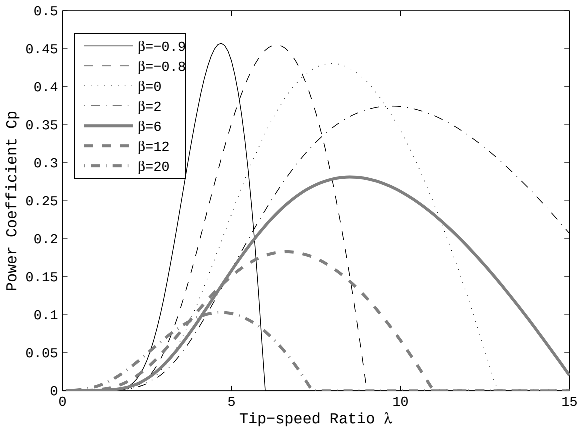

Fig. 1. Power coefficient versus tip-speed ratio, for various blade pitch angles β.

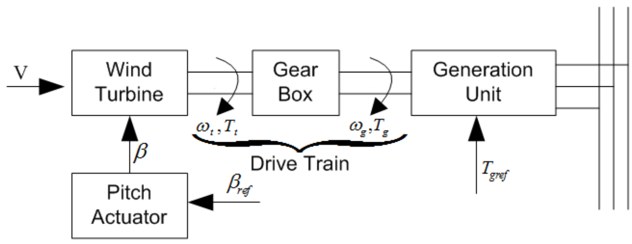

Fig. 2. Structural diagram of WECS systems.

curves) and the maximum power point curve (dashed curve) attained at each wind speed, for a blade pitch angle of 0^o. The aerodynamic torque on the wind turbine rotor can be obtained using the following relationships:

$$T_m = \frac{P_m}{\omega_t} = \frac{\rho\pi Cp(\lambda, \beta)R^3V^2}{2\lambda}. \tag{7}$$

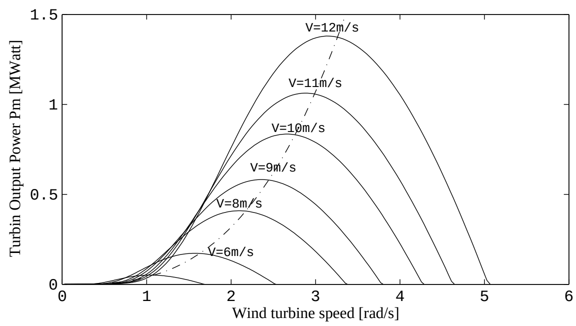

Fig. 3. Power-speed characteristics of wind turbine, for various wind speeds at pitch angle 0^o.

The basic idea of the proposed MPPT technique is to retrieve the optimal rotor speed ω_t (meaning the speed corresponding to the maximum generable power) for any instantaneous value of the wind speed. In Fig. 2, the input signals coming from the turbine control system are the generator torque set point $T_{g,ref}$ and the desired pitch angle β_{ref}. The measured outputs are assumed to be the turbine rotor speed ω_t. The wind speed V is the disturbance signal

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affecting the WECS. Its model is given as

$$\begin{aligned} \dot{\theta} &= \omega_t - \omega_g & (8) \\ J_g\dot{\omega}_g(t) &= K_s\theta + B_s\omega_t - B_s\omega_g + T_g(\omega_g, T_{g,ref}) & (9) \\ J_t\dot{\omega}_t(t) &= -K_s\theta - B_s\omega_t + B_s\omega_g + T_m(\beta, V) & (10) \end{aligned}$$

The generator torque T_g is a nonlinear function of ω_g and the control variable $T_{g,ref}$. The generator usually operates in the linear region of its torque characteristic which can, therefore, be approximated by a linear form

$$T_g = B_g\omega_g - T_{g,ref}. \qquad (11)$$

The pitch actuator is modelled as a first-order dynamic system with saturation in the amplitude and derivative of the pitch angle β as [4], [5].

$$\dot{\beta} = \frac{-1}{\tau}\beta + \frac{1}{\tau}\beta_{ref}. \qquad (12)$$

It can be seen that the overall WECS model described in (3)-(12) is nonlinear. Fig. 4 shows the block diagram of a control scheme to track the optimal rotor speed to maximize the power that the turbine extracts. The control

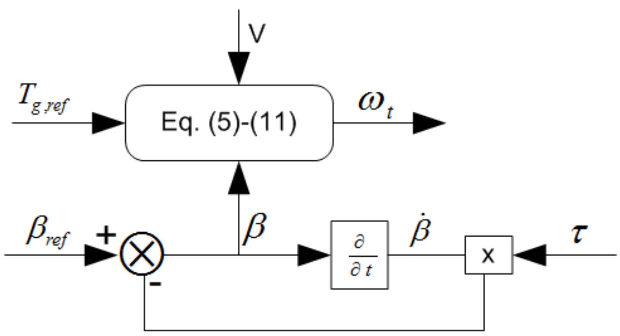

Fig. 4. Block diagram of nonlinear dynamic of WECS.

system acts on the generator in order to apply the reference electromagnetic torque $T_{g,ref}$ and on the pitch actuator in order to control the pitch angle of the blades β. The system parameters are given as follows [17]:
Turbine and drive train parameters
R=30.30m,K_s=15.66x10^5N/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

To control a given system, the controller design includes two steps: the first step for identification and prediction of WECS by quasi-ARX neural network model; and the second step for deriving and implementing control law. In Fig. 5, we shows the adaptive controller scheme based on quasi-ARX model. To regulate turbine speed at MPPT operating point is performed by using blade pitch control, with generator torque assumed to be constant.

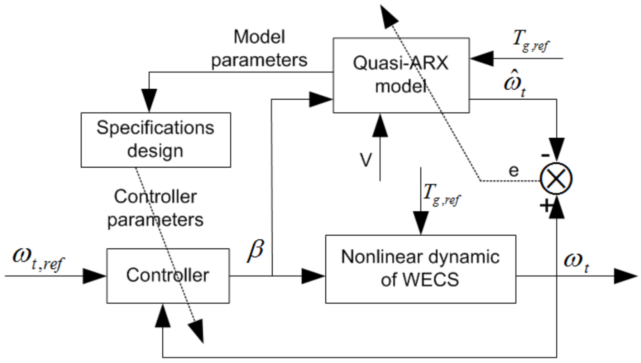

Fig. 5. Block diagram of the MPPT controller of WECS.

A. System Identification

Through using Taylor expansion series [8], [10], nonlinear continuous function can be presented as

$$y(t) = y_0 + \phi^T(t)\aleph(\phi(t)) + e(t) \qquad (13)$$

where $\aleph(\phi(t)) = [a_{(1,t)} \cdots a_{(n_y,t)}\ b_{(1,t)} \cdots b_{(n_u,t)}]^T$ and $\phi(t) = [-y(t-1) \cdots - y(t-n_y)\ u(t-1) \cdots u(t-n_u)]^T$ are Taylor coefficients (nonlinear parameter estimation) and the information or input regression vector, respectively. $\phi(t) \in R^{n=n_u+n_y}$, n is the dimension of information vector, equals to the sum of n_u and n_y that represent orders of time delay in input and output data. $\aleph(\phi(t)) \in R^{n=n_u+n_y}$ is a function called as the core-part sub-model to parameterize the input regression vector. $e(t)$ and y_0 are gaussian white noise added to the system and initial condition of output, respectively.
Assumption 1. The pairs of the input and output of training data are bounded.
Assumption 2. The input and output of nonlinear function $\aleph(\phi(t))$ are bounded.

By performing Taylor expansion series, nonlinear system is decomposed into linear correlation between the information vector and its coefficients. It is the same in form like ARX model with nonlinear coefficients. If the system is linear, then the coefficients are constant; and if the system is nonlinear, then the coefficients are not constant or nonlinear. By putting nonlinear function into its coefficients, quasi-linear ARX model is defined as follows,

$$\begin{aligned} y(t,\phi(t)) = b_{(1,t)}u(t-1) + \cdots + b_{(n_u,t)}u(t-n_u) \\ - a_{(1,t)}y(t-1) - \cdots - a_{(n_y,t)}y(t-n_y). \quad (14) \end{aligned}$$

The system identification are performed by quasi-ARX neural network model is shown in Fig. 6. The embedded of MLP network of quasi-ARX model has input dimension of $\phi(t)$ is equal to n, the number of hidden layer is m and the number of output layer is n. The quasi-ARX incorporating neural network can be expressed as,

$$\begin{aligned} y(t,\phi(t)) &= \phi^T(t)\aleph(\phi(t)) & (15) \\ \aleph(\phi(t)) &= W_2\Gamma W_1(\phi(t)+B)+\theta. & (16) \end{aligned}$$

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 the first and the second layer. $\theta \in R^{nx1}$ is the bias vector of output nodes, and Γ is the diagonal nonlinear operator with identical sigmoidal elements on hidden nodes.

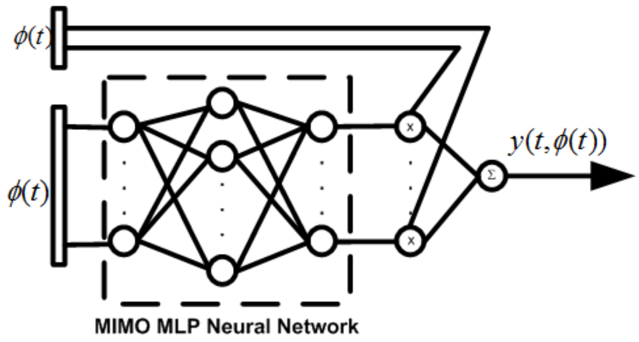

Fig. 6. Quasi-ARX neural network with MLP network as embedded systems.

If model in (15) satisfies to mapping the input-output of the system, and **Assumption 1.** and **Assumption 2.** are fulfilled, then we can estimate the output of the system at time $(t+d)$. The equation (15) is regressed at time $(t+d)$ to calculate the output at d step ahead prediction, described as,

$$y(t+d,\phi(t+d)) = \hat{b}_{(1,t+d)}u(t+d-1)+\cdots+ \hat{b}_{(n_u,t+d)}u(t-n_u+d) - \hat{a}_{(1,t+d)}y(t-1+d) - \cdots - \hat{a}_{(n_y,t+d)}y(t-n_y+d) \quad (17)$$

where, $\phi(t+d) = [y(t+d-1)\ y(t+d-2)\cdots y(t+d-n_y)\ u(t+d-1)\ u(t+d-2)\cdots u(t+d-n_u)]^T$, for online step ahead prediction d is equal to one.

The learning algorithm for quasi-ARX model is performed by the back propagation error algorithm for embedded MLP network and LSE algorithm for the to update θ. Let we introduce two sub-models $z_l(k) = y(t,\phi(t))-\phi(t)[W_2(k)\Gamma W_1(k)(\phi(t)+B(k))]^T$, and $z_n(k) = y(t,\phi(t)) - \phi(t)\theta(k)^T$, and k is the learning number. The step of learning algorithm of quasi-ARX neural network is described by,

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 (16) to update $\aleph(k,\phi(t))$
5) stop if pre-specified conditions are met and update $\aleph(\phi(t))$ by using $\aleph(k,\phi(t))$, 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

The quasi-ARX prediction model is improved to guarantee system stability expressed by

$$y(t,\phi(t)) = \phi^T(t)\aleph(\phi(t),\chi(t)) \quad (18)$$
$$\aleph(\phi(t),\chi(t)) = \chi(t)W_2\Gamma W_1(\phi(t)+B)+\theta. \quad (19)$$

where $W_2\Gamma W_1(\phi(t)+B)$ is nonlinear part, θ is linear part. Obviously, through introducing the switching function $\chi(t)$, the improved quasi-ARX neural network model is different from the conventional quasi-ARX model. When $\chi(t)$ = 1, it is a nonlinear prediction model which can insure the prediction accuracy. And when $\chi(t)$ = 0, it is a linear prediction model which can insure the control stability [18].

The linear part error and nonlinear part error, respectively is defined as follows :

$$e_1(t) = y(t+d) - \phi(t+d)^T\theta. \quad (20)$$
$$e_2(t) = y(t+d) - \phi(t+d)\aleph(\phi(t+d)). \quad (21)$$

The switching criterion function are described as follows:

$$J_i(t) = \sum_{l=k}^{t} \frac{a_i(l)(\|e_i(l)\|^2 - 4\triangle^2)}{2(1+a_i(l)\phi(l-k)^T\phi(l-k)} + c\sum_{l=t-N+1}^{t}(1-a_i(l)\|e_i(l)\|^2), i=1,2 \quad (22)$$

$$\chi(t) = \begin{cases} 1, & \text{if } J_1(t) > J_2(t) \\ 0, & \text{otherwise} \end{cases} \quad (23)$$

The value of $\triangle$ is determined by designer where $\triangle \leq \phi(t)\aleph(\phi(t))$. The detail of switching technique and its stability analysis refer to [18].

A minimum variance controller is used for WECS, define as follows,

$$M(t+1) = \left(\frac{1}{2}(y(t+d) - y^*(t+d))^2 + \frac{\lambda}{2}u(t)^2\right) \quad (24)$$

where λ is a weight of control input, the controller can be obtained by solving,

$$\frac{\partial M(t+1)}{\partial u} = 0 \quad (25)$$

In the case where a conventional neural network is used as a prediction model, a controller can not be derived directly from an identified model because of the nonlinearities. However, the quasi-ARX neural network model is linear in the input variable $u(t)$. Therefore, a controller is derived from the proposed model [8], [18]:

$$u(t) = \frac{\hat{b}_1(t)}{\hat{b}_1^2(t)+\lambda}((\hat{b}_1(t) - \hat{b}(q^{-1},\phi(t))q)u(t-1) + y^*(t+1) - \hat{a}(q^{-1},\phi(t))y(t)) \quad (26)$$

IV. Simulation and Results

To further demonstrate the effectiveness of the proposed MPPT control strategy, the control action is to arrange blade pitch ratio β to track angular velocities of turbine operating in MPPT point. The pitch angle command signal is determined by the wind speed and pitch angle. Wind speed is generated by ARMA model with the mean observed wind speed of $\mu(t)$ = 12 m/s and the standard deviation of the observed wind speed of $\sigma(t)$ = 1.5. The results of simulation in detail are shown in Fig. 7 - Fig. 13. In order to obtain maximum output power from a wind turbine generator system, it is necessary to drive the wind turbine at an optimal rotor speed for a particular wind speed.

The kernel of MIMO multi layer parceptron neural networks has one hidden layer, n_u=3, n_y=4, and m=n_u+n_y=7. The parameter of switching criterion c=1.2 and N=3. Fig. 7 and Fig. 8 illustrate the WECS response in the MPPT operating point. Before $t = 0s, V = 12.48m/s$, MPPT power tracking $1.45MW$, $\beta = 0deg$, angular velocity

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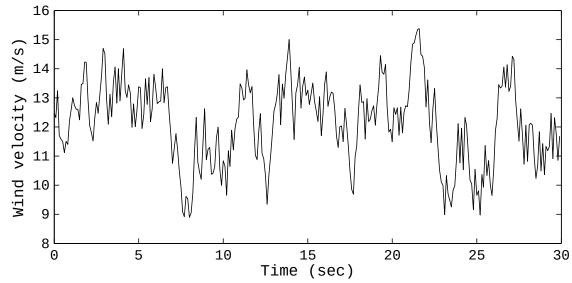

Fig. 7. Wind speed.

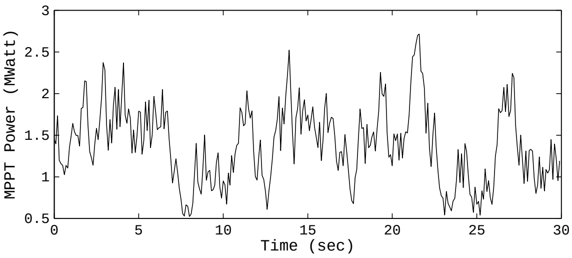

Fig. 8. MPPT aerodynamic power.

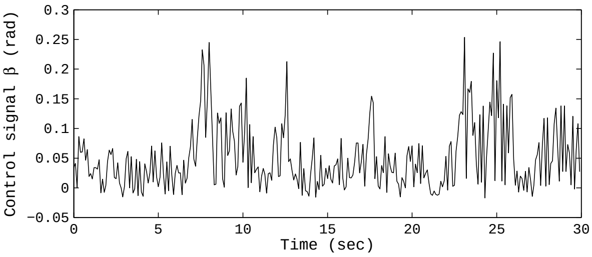

Fig. 9. Control signal.

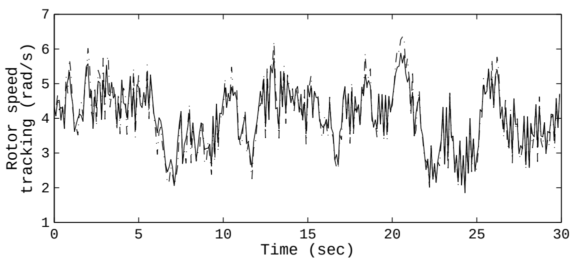

Fig. 10. Trajectory of ω_t of minimum variance controller with switching based quasi-ARX model.

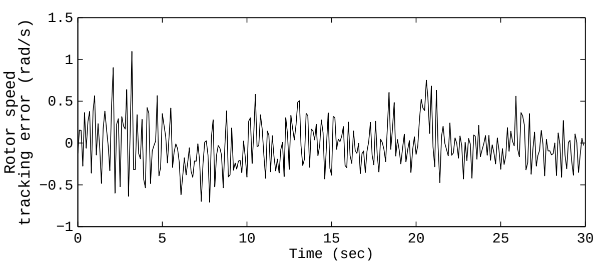

Fig. 11. Tracking error of turbine angular velocity.

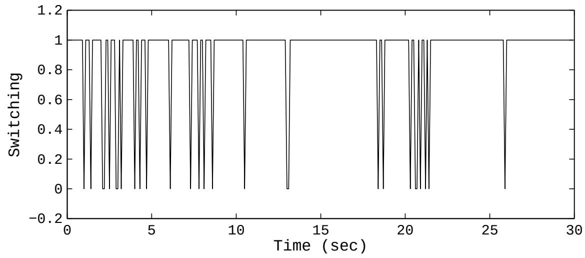

Fig. 12. Switching sequance.

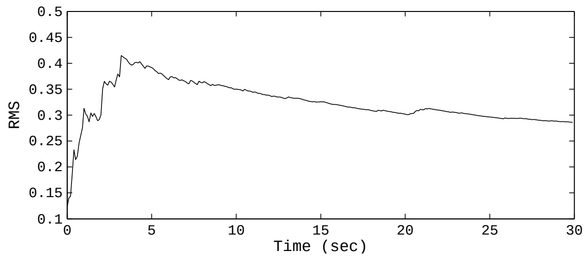

Fig. 13. RMS error versus time.

$\omega_t = 4.12 rad/s$. When the wind speed change to decrease or increase the MPPT power also should be change in order to keep maximum operating point of WECS with arrange turbine rotor speed ω_t by controlling blade pitch ratio β. Fig. 9 and Fig. 10 shows the control signal and wind turbine rotor speed tracking. The dot dash line denotes the output of system using proposed method and solid line denotes rotor speed reference ω_t in MPPT operating point, respectively.

The tracking error of turbine rotor speed is shown in Fig. 11. Switching function between nonlinear and linear part to keep system stability and control accuracy is shown in Fig. 12. The performance of the proposed controller is also measured by the rooted mean squared (RMS) error index versus time shown in Fig. 13 defined as,

$$RMS = \sqrt{\frac{\sum_{t=1}^{N}(y^*(t) - y(t))^2}{t}} \qquad (27)$$

where $y^*(t)$ is the reference signal and $y(t)$ is the controlled system output.

V. Conclusion

In this paper, quasi-ARX neural network model is used to identification and prediction nonlinear system. The controller design is derived from the proposed model with switching function to keep system stability. Switching law a made by logical signal 0 for linear part and 1 for nonlinear part, as we know quasi-ARX neural network model is divided into two part; nonlinear and linear. The quasi-ARX model also has good properties, it is used to modeling a system into linear correlation between regression vector and its coefficients, so it is easy to derive the controller law by using local linear properties in nonlinear system such as minimum variance controller. By using minimum variance controller with switching law, the proposed model successfully is used to track maximum power point tracking (MPPT) of WECS.

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