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A RBF Neural Network based MPPT Method for Variable Speed Wind Turbine System

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Abstract: Wind turbine system due to its aerodynamic and generator components is a nonlinear and strongly coupled system. These characteristics influence the efficiency and performance of the systems output. In order to improve the efficiency of Maximum Power Point Tracking (MPPT) and to produce more green energy, a novel control strategy which is based on RBF neural network is designed. The proposed algorithm depends on the optimal tip speed ratio and adjusts rapidly the output of torque with the random wind. Finally, to validate and demonstrate the performance of the proposed method, the FAST and Matlab/Simulink are used to test under different conditions of Wind.

Keywords: wind turbine; MPPT, torque control; RBF neural network.

1. INTRODUCTION

As a renewable and green energy source, wind energy has increased rapidly in the past years. According to global wind report for 2013 by the global wind energy council(GWEC), a new installed wind energy capacity all over the world was up to the 3,5289MW in the last year and sustained the first scale in the family of renewable energy. Chinese wind market has been the biggest one in both the cumulative capacity and the new installed capacity(Zhang, Andrews-Speed, & Zhao, 2013). In the next five years, a new installed wind energy capacity will rise over 10% annual rate. Wind energy is still a promising energy in the future(Lo, 2014). Hence, the research of wind turbine system is of great significance.

The variable speed variable pitch wind turbine system has accounted for a great deal of market, especially in the high-power generators, because of advantage of the high reliability and high efficiency. When wind speed is between the rated speed and cut-in speed called low wind region(LWR) and shown in Figure 1, the main challenge of this class of wind turbines is to tracking the maximum power point(MPP) by regulating rotor speed. Whereas in high wind region(HWR) which the wind speed exceeds the rate value and does not reach the cut-out speed, the crucial issue is to restrict the absorption power of wind wheel by altering the pith angle. Considering of the limit power in the HWR, this paper mainly focus on the LWR for capturing power. By improving the efficiency in the LWR, it will increase the total power in the all wind region.

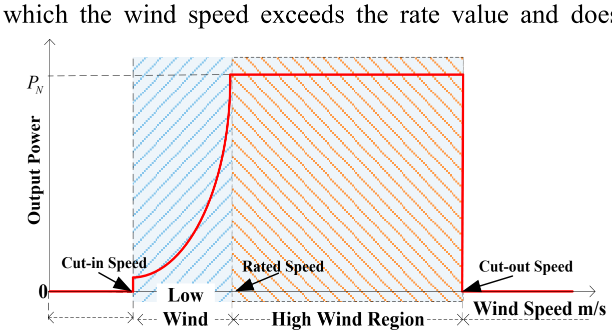

Figure 1. The power curve of wind turbine

However, the turbulent wind and the characteristic of wind turbine system, such as nonlinearity, time-varying, weaken the performance seriously in the LWR. Considering these issues, researchers have proposed a lot of methods. These methods can be mainly divided into three categories:

The first one is based on the optimal power curve in the LWR. The reference of torque can be calculated by the power curve(Bottasso, Croce, Nam, & Riboldi, 2012) or directly by the torque curve. There are several models for power curve, such as quadratic power curve (Carrillo, Obando Montaño, Cidrás, & Díaz-Dorado, 2013), cubic power curve(Thapar, Agnihotri, & Sethi, 2011). This method depends on the accurate power curve. However, to acquire the high-precision power curve needs to take numerous experiments and cost plenty of time and money.

The second category is based on the optimal tip speed ratio(TSR) (Munteanu, Bratcu, & Ceangǎ, 2009). When the TSR is optimal value, the power coefficient will be the maximum. If the available wind is measured precisely, the output of power can reach the peak value, theoretically. But, the feature of turbulent wind makes the result incredible.

The third category is derived from the mathematical searching technique, such as hill climb searching (Raza Kazmi, Goto, Hai-Jiao, & Ichinokura, 2011). When the operation point is closely to peak, it requires a small step-size so that the output power can be stable. But if the operation point is far away from the MPP, it needs a big step-size to follow the new MPP rapidly. Thus, the crucial issue is to

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select an appropriate step-size for different operation points with wind speed(Lin & Hong, 2010).

In order to improve the efficiency of MPPT, a novel controller with adaptive tracking strategy is proposed by using radial basis function neural network (RBFNN). As we know, neural networks are powerful for a function mappings (Shuang, Yongping, & Yongqian, 2007). It has been used in many fields, such as wind and power prediction. Here, the RBFNN is proposed to approach the optimal torque. This control method does not need the well parameters knowledge of the wind turbines. It has a short adjustment time, thus it can track rapidly the dynamic wind and improves the MPPT efficiency.

The following of this paper is organized as follows: In the next section II, the wind turbine rotor and drive trains models will be briefly presented. And in Section III, the torque controller which is based on RBFNN is designed. Then in Section IV, FAST and Matlab/Simulink based numerical results are illustrated. Finally, some conclusion remarks are shown in Section V.

2 WIND TURBINE SYSTEM MODELLING

2.1 Wind Turbine Rotor Model

Generally, wind turbine systems consist of the wind turbine rotor, drive trains and so on. The aerodynamic power which is captured by the rotor can be described as (Inthamoussou, Bianchi, De Battista, & Mantz, 2014):

$$P_r = \frac{1}{2}\rho\pi R^2 v^3 C_p(\lambda,\beta) \tag{1}$$

where ρ , R and v denote respectively, the air density, the blade radius and the available wind speed. And the above variable $\lambda = \omega_r R / v$ is the ratio of tip speed, and ω_r is the rotor speed.

The Power coefficient which is denoted as $C_p(\lambda,\beta)$ varies according to the values of the pitch angle β and λ . And its corresponding model can be written as follows

$$C_P(\lambda,\beta) = 0.5176\cdot(\frac{116}{\lambda_i} - 0.4\cdot\beta - 5)\cdot e^{\frac{-21}{\lambda_i}} + 0.0068\cdot\lambda \tag{2}$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\cdot\beta} - \frac{0.035}{\beta^3 + 1} \tag{3}$$

The aerodynamic torque is formulated as

$$T_r = \frac{1}{2}\rho\pi R^3 v^2 \frac{C_p(\lambda,\beta)}{\lambda} \tag{4}$$

In the LWR, the pitch angle β is usually maintained zero so as to ensure the power coefficient maximum. While in the HWR, the aerodynamic torque tends to reach the rating value by changing the pitch angle so that the produced power of the generator won't exceed the rating value.

2.2 Drive trains model

Considering the stiffness and the damping factors for the drive shafts in the wind turbine system, the drive trains model can be written as(Beltran, Ahmed-Ali, & Benbouzid, 2009):

$$J\dot{\omega}_r = T_r - K_t\omega_r - B_t\theta_r - T_g \tag{5}$$

where J is the equivalent inertia at Low-speed shaft (LSS) side, K_t and B_t are respectively the equivalent damping coefficient and stiffness coefficient, and $T_g = T_{em} / N_g$ is the equivalent generator torque at LSS side.

Usually, the stiffness coefficient which is generally $B_t << K_t$ very small can be ignored here, Thus then the drive trains model can be proposed as follow:

$$J\dot{\omega}_r = T_r - K_t\omega_r - T_g . \tag{6}$$

3 CONTROLLER DESIGN

3.1 Structure of neural network

The control module of wind turbine system divided into torque control system and pitch control system, as shown in Figure 2. Firstly, we will design the torque control system. In the LWR, the speed of rotor will reach the optimal speed by changing torque value for capturing the MPP. At this time, the pitch angle is usually fixed at zero so that power coefficient of wind turbine can reach the peak. In torque control system, we will introduce a RBF neural network briefly. Secondly, an additional pitch controller will be used for the HWR. In the HWR, the reference of generator torque and rotor speed will not be changed and maintained at constant value. During this period, if pitch angles are still kept as zero, the capture power will exceed the rating power and it cannot run well at last. Thus, the pitch angle controller extends the work area for wind turbine system.

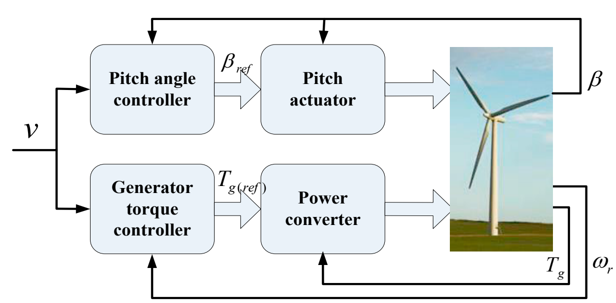

Figure 2. Sturture of wind turbine system for torque and pitch control

3.2 Neural network based torque controller design

Generally, neural network has three layers: input layer, middle layer and output layer and shown in Figure 3.

The output of middle layer is written as follow(Bin & Lijun, 2010):

$$\varphi_i(u_1,u_2) = \exp(-\frac{\|u - c_i\|}{2\delta^2}) \tag{7}$$

where c_i is the centre of the receptive field. δ is the width of the Gaussian function, and the notation of $\|\bullet\|$ represents a 2-norm term.

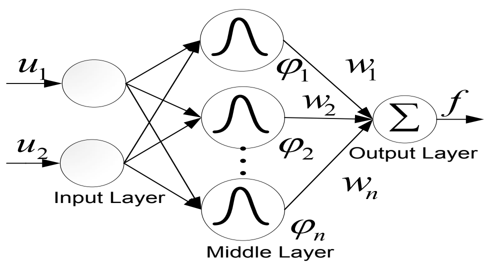

Figure 3. Structure of three layers of RBFNN (2-n-1 type)

Therefore, the output f can be obtained as follow:

$$f = \sum \varphi_i w_i \tag{8}$$

The output can be changed by modifying the weight w_i, according to special rules. Usually, the rule are selected as gradient descent method.

According to the equation (6), the drive trains model can be written as follow:

$$\begin{cases} \dot{\omega}_r = h(T_g + K_t\omega_r - T_r) \\ h = -1/J \end{cases} \tag{9}$$

Assuming $f(\omega_r, v) = (T_r - K_t\omega_r)/J$, then we can get the rotor speed:

$$\dot{\omega}_r = f(\omega_r, v) + hT_g \tag{10}$$

Thus, the nonlinear function $f(\omega_r, v)$ can be approximated by neural networks. The approximation errors satisfies $|d(\omega_r, v)| \le d_{\max}$. So the $f(\omega_r, v)$ can be expressed as

$$f(\omega_r, v) = \varphi(\omega_r, v)w + d(\omega_r, v) \tag{11}$$

The estimated approximate function can be written as:

$$\hat{f}(\omega_r, v) = \varphi(\omega_r, v)\hat{w} \tag{12}$$

where $\hat{w}$ is the estimated weight. the error of weight is defined as

$$\tilde{w} = w - \hat{w} \tag{13}$$

The error of rotor speed is defined as

$$e = \omega_{r\_opt}(v) - \omega_r = \lambda_{opt} v / R - \omega_r \tag{14}$$

Then, the output of torque can be selected as

$$\hat{u} = T_g = \frac{1}{h}[-\varphi(\omega_r, v)\hat{w} + k \cdot e] \tag{15}$$

where k is a positive constant.

By according to e-moderation method (Chowdhary, Mühlegg, & Johnson, 2014; Yadmellat, Samiei, & Talebi, 2009), the proposed learning algorithms can be chosen as follow

$$\dot{\hat{w}} = -\beta_1[\varphi^T(\omega, V_w)e + \zeta\,|e|\,\hat{w}] \tag{16}$$

where $\zeta > 0$ is a constant.

Proof: choose the Lyapunov candidate function as follow

$$V = e^2 + \frac{1}{2\beta_1}\tilde{w}^T\tilde{w} \quad ,$$

(17)

where $\beta_1 > 0$ is a constant and need to ensure.

According to (17), its corresponding derivative can be calculated as

$$\begin{aligned}
\dot{V} &= e\dot{e} + \frac{1}{2\beta_1}\dot{\tilde{w}}^T\tilde{w} + \frac{1}{2\beta_1}\tilde{w}^T\dot{\tilde{w}} \\
&= e\left(\frac{\lambda_{opt}\dot{v}}{R} - f(\omega_r, v) - hT_g\right) - \frac{1}{\beta_1}\tilde{w}^T\dot{\hat{w}} \\
&= e\left(\frac{\lambda_{opt}\dot{v}}{R} - \varphi(\omega_r, v)w + d(\omega_r, v) - (-\varphi(\omega_r, v)\hat{w} + k\cdot e)\right) - \frac{1}{\beta_1}\tilde{w}^T\dot{\hat{w}} \\
&= e\left(\frac{\lambda_{opt}\dot{v}}{R} - \varphi(\omega_r, v)\tilde{w} + d(\omega_r, v) - k\cdot e\right) - \frac{1}{\beta_1}\tilde{w}^T\dot{\hat{w}} \\
&= e\left(\frac{\lambda_{opt}\dot{v}}{R} - \varphi(\omega_r, v)\tilde{w} + d(\omega_r, v) - k\cdot e\right) + \tilde{w}^T\varphi^T(\omega_r, v)e - \zeta\,|e|\,\tilde{w}^T\hat{w} \\
&= e\left(\frac{\lambda_{opt}\dot{v}}{R} + d(\omega_r, v) - k\cdot e\right) - \zeta\,|e|\,\tilde{w}^T\hat{w}
\end{aligned}$$

Assuming that the rate of change for optimal rotor speed ω_{r_opt} is bounded:

$$|\omega_{r\_opt}| = \left|\frac{\lambda_{opt}v}{R}\right| < d_r \tag{18}$$

Since $d(\omega_r, v)$ is bounded and it is $|d(\omega_r, v)| < d_{\max}$. Therefore, the $\dot{V}$ satisfies as follow:

$$\begin{aligned}
\dot{V} &\le |e|[(d_{\max} + d_r) - k\cdot e - \zeta\tilde{w}^T\tilde{w} + \zeta\tilde{w}^T w] \\
&= |e|[(d_{\max} + d_r) - \zeta\tilde{w}^T\tilde{w} + \zeta\tilde{w}^T w] - k\cdot e^2 \\
&= \zeta\,|e|\left[\frac{(d_{\max} + d_r)}{\zeta} - \tilde{w}^T\tilde{w} + \tilde{w}^T w - \frac{w^T w}{4} + \frac{w^T w}{4}\right] - k\cdot e^2 \\
&= \zeta\,|e|\left[\frac{(d_{\max} + d_r)}{\zeta} - \left(\tilde{w} - \frac{w}{2}\right)^T\left(\tilde{w} - \frac{w}{2}\right) + \frac{w^T w}{4}\right] - k\cdot e^2
\end{aligned}$$

If $\delta_w = \|\tilde{w}\|$ is defined and meets the following condition

$$\delta_w \geq \frac{w}{2} + \sqrt{(d_{\max} + d_r)/\zeta + (w^2/4)}\ ,$$

One ensures $\dot{V} \leq 0$. Hence, it is stable.

3.3 Pitch controller design

In the HWR, the output of torque holds the rated value. And a PID controller will use to keep the output electrical power as a rated value by changing the pitch angle. Usually, this controller takes effect only if wind speed is over the rating value. During this period, if there is not pitch controller and not decline the power coefficient, the output rotor speed will be increased and over the rating value because of rotor torque is over the rating value. if we left it unchecked, the entire wind turbine system will be damaged. However, if we change the pitch angle and reduce the power coefficient, the rotor torque will decrease and the rotor speed will not increase even decline. Here, we use a incremental PID controller to maintain drive train balance. The output of pitch controller is written as follow:

$$\Delta\beta = K_p N_g \Delta\omega_r + K_i \int N_g \Delta\omega_r dt + K_d N_g \Delta\dot{\omega}_r \quad (19)$$

where K_p, K_i, K_p, K_i, K_d is the proportional, integral, and derivative coefficients respectively.

Considering nonlinearity factor in the pitch actuator, one adds a saturation and rate limiter modules in simulation (Shown in the Figure 4).

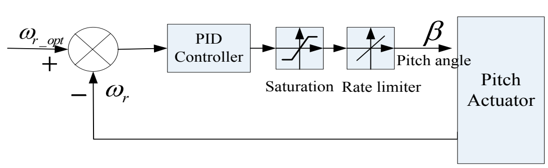

Figure 4. Stucture of pitch control system

4 NUMERICAL SIMULATION RESULTS

In the context, a FAST (Fatigue, Aerodynamices, Structures and Turbulence) model which is developed by the National Renewable Energy Laboratory(NREL) and Matlab/Simulink are used. The FAST which has been utilized by many enterprises and institutes for designing and checking a wind turbine system, has a Matlab/Simulink interface (Jason M Jonkman & Buhl Jr, 2005). Here, one chooses a 5-MW wind turbine for offshore system to verify the performance of the propose MPPT controller. The relevant parameters of the wind turbine system can been found in (Jason Mark Jonkman, Butterfield, Musial, & Scott, 2009) and shown in Table I. The torque controller is designed by S-Function codes.

TABLE I. THE MAIN PARAMETER OF WIND TURBINE SYSTEM

Parameter Description	Value
Rated Power	5 *MW*
Rotor Radius	63 m
Gear Box Ratio	97
Cut-in Wind Speed	3 *m/s*
Cut-out Wind Speed	25 *m/s*
Rated Speed	1173.7 *rpm*
Rated Torque	43.093 *KN.m*

4.1 Piecewise constant wind

Firstly, one considers two different constant wind speeds of 9 m/s and 15 m/s to test the performance. And the control parameters are selected as $\beta_1 = 2\times10^4$ and $\zeta = 1$.

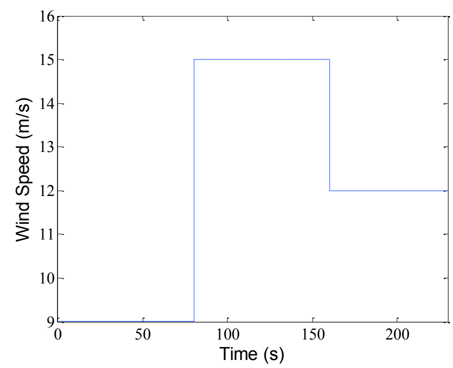

Figure 5. Wind speed profile

The production of the generator power and the maximum available power of wind turbine curve is shown in Figure 5. The input of generator torque and speed of generator are shown respectively in Figures 6 and 7. From the Figures, it takes nearly 50 seconds to reach the balance. After 50 seconds, the weights trend to the ideal values which are shown in Figure 8 under constant wind speed of 9 *m/s*. When the wind continues to grow, the steady weights will also increase. Here, the parameters of β_1 and ζ for the four weights are selected correspondingly as a same constant.

And from figure 8, its corresponding optimal generator speed is 999.06 *RPM* compared to the real generator speed of 999.90 *RPM*. During this period, the output power is 2.55MW and it is far less than the rated power. Whereas, the blade pitch angle is zero.

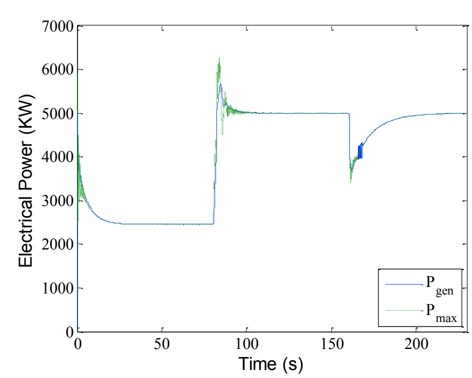

Figure 6. The curve of electrical power and the maximum capture power of wind turbine

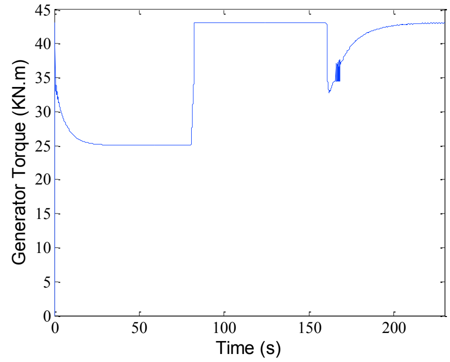

Figure 7. Generator torque of wind turbine

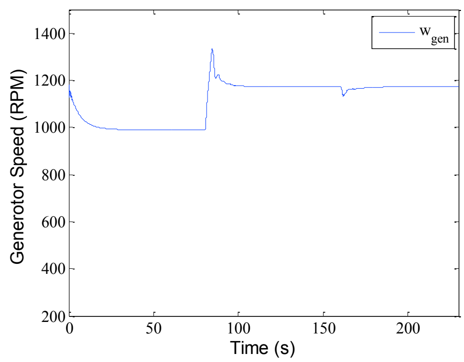

Figure 8. Generotor speed of wind turbine

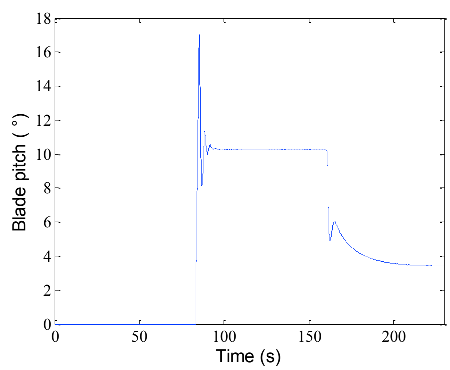

Figure 9. Blade pitch angle

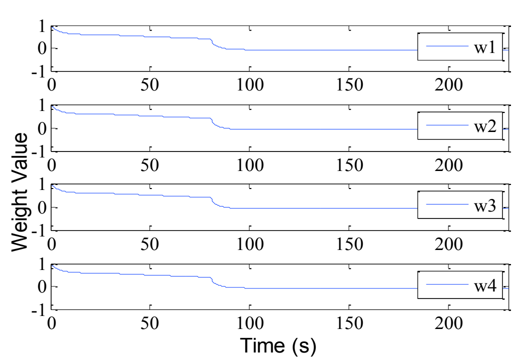

Figure 10. Weights of RBFNN (2 input,4 neurons in middle, and 1 output)

When the wind speed become 15 *m/s* which it is in the HWR, the output power is limited in rated range by changing the blade pitch angle and the generate speed reach to the rated speed. For 15 *m/s*, the optimal blade pitch angle is 10.45 ° and the pitch error is 0.9 ° .

4.2 Stochastic variable wind

Secondly, a stochastic wind whose mean value is 8 m/s is selected. The wind data which is also designed by NERL in FAST is generated by the TurbSim subsystem (Shown in Figure 11). The generator power and maximum available power are shown in Figure 12. The torque and generator speed curve are shown respectively in Figures 13 and 14.

From these Figures, the generator speed trend to the optimal speed. Its dynamic curves of weights which are shown in Figure 15 can be noticed that its corresponding values of weights are changed with the variations of wind.

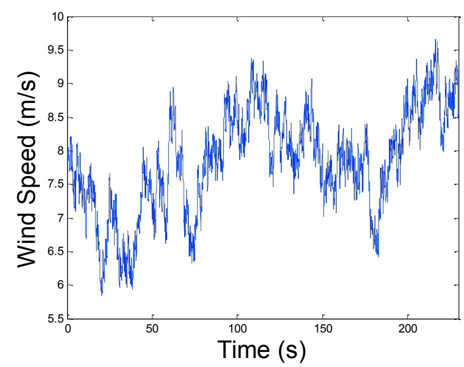

Figure 11. Wind speed profile (mean vaule is equaled 8 m/s)

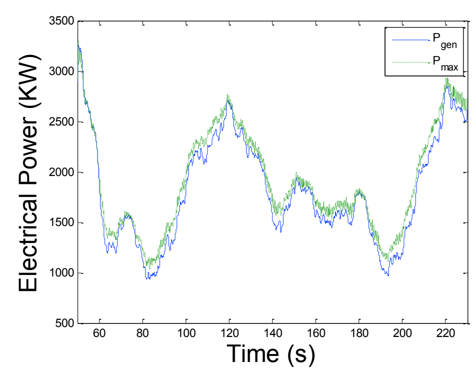

Figure 12. Electrical and maximum capture power of wind turbine

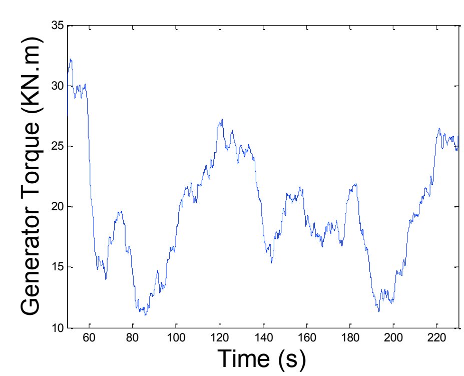

Figure 13. Generator torque of wind turbine

5 CONCLUSIONS

In this paper, a MPPT control which is composed on a torque and pitch controller is presented for wind turbine system. The referred torque controller which is developed based on RBFNN is only dependent on the optimal TSR. And to validate and demonstrate the performance of the proposed MPPT control, two different conditions of a constant and stochastic wind have been tested in the co-simulation mode of FAST and Matlab/Simulink. Noting that under the constant wind, the generator of speed can reach its corresponding optimal value. While under the stochastic wind, the output speed fluctuations are maintained within an accepted certain range. The stability of entire proposed method can be ensured under piecewise constant or stochastic wind input conditions between the LWR and HWR. In the near future, the proposed controller will be planed to compare and implemented in more realistic platforms.

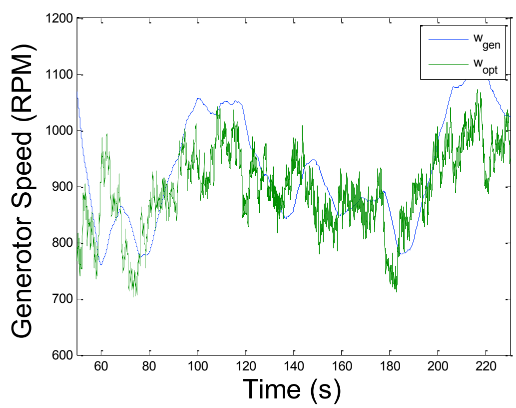

Figure 14. Generotor speed of wind turbine

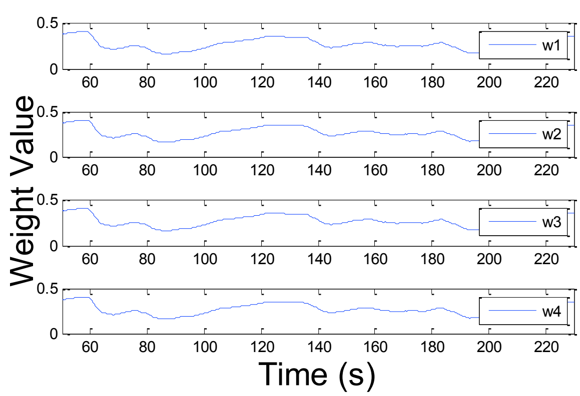

Figure 15. The weigh of RBF neural network(2 input,4 neurons for middle layer,and 1 output)

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