NNPID-based Stator Voltage Oriented Vector Control for DFIG based Wind Turbine Systems

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Abstract: Doubly fed induction generators are widely adopted for the wind turbine systems since it is cheap and reliable. Based on the traditional stator voltage oriented vector control method, the performance of the proposed vector control is largely influenced by the variations of the DFIG parameters. And the classical PID algorithm cannot achieve the maximum power point tracking (MPPT) in time (owing to the transient wind). Hence, in this paper, to eliminate parameters variations on the power output and capture the MPPT rapidly, we propose a stator voltage oriented vector control which is based on a Neural Network PID (NNPID) technology. The weights which are being similar to the PID coefficients are adapted by Hebb rule to decrease the power error online according to the error gradient descent method, while the classical PID coefficients will be a constant. The effectiveness of the proposed method is demonstrated by corresponding simulation results: even in the case of wind mutation change, the proposed NNPID can track the variation of the wind energy, and robust to the DFIG parameters variations.

Keywords: wind turbine system; maximum power point tracking; DFIG; NNPID;

1. Introduction

As a renewable and clean energy, wind energy which growths rapidly worldwide and attracts widespread attention by governments [1]. Recently, high efficiency and low cost power production control methods and technologies are always an eternal working goal for researchers and engineers.

Doubly fed induction generators (DFIG) which are widely adopted for the wind turbine systems occupy most parts of the global market because of the lower-cost and smaller inverter capacity. However, the DFIG’s characteristics of non-linearties, strong coupling, and varying parameters as well as the wind randomness are intractable problems. It also reduces the efficiency of the wind energy. Moreover, the model of wind is complicated, and affected by many factors. Besides, dynamic and static characteristics of nature wind need to be reflected by the wind model. And wind turbine system also requires an appropriate wind model for different performances. The emitted power usually cannot catch up with capture wind energy because of both the transient wind and the lag inertia of the blades. Considering wind uncertainties and wind turbine systems nonlinearities, it is difficult to selecting appropriate classical PID coefficients to obtain good performances. In addition, these coefficients usually maintain constant once the PID controller is installed. Recently, artificial intelligent controls have been developed rapidly and applied gradually to wind turbine systems, such as neural network control and fuzzy control are discussed in [2-4]. However, to achieve good control performance needs complex computations in the neural network based control algorithms. A rule table for fuzzy control is also difficult to design [6]. For fuzzy controllers which select this rule table by self-adjusting needs to spend a longer time in calculations.

In this paper, to improve the efficiency of capturing wind energy and simplify the referred control methods computations, a particular PID controller which is based on a single-neuron network is developed and called Neural Network PID (NNPID). Known that three layers of neural networks (NNs) can be used to approximate an arbitrary input-output mapping [7]. The weights of the proposed NNPID can be adjusted adaptively online with tracking errors. This used adaptive mechanism is useful to overcome both the wind turbine systems external disturbances and parameters uncertainties.

The rest paper is organized as follows: a wind model is presented in 2^{nd} section. And in 3^{rd} section, a wind turbine model which includes an aerodynamic model of the wind turbine rotor, DFIG model and drive trains model is described. After that, for the considered system, a fundamental stator voltage oriented vector control method and a NNPID controller is developed in 4th section. Then to validate the proposed method**,** some numerical simulation results are illustrated in 5th section. Finally, some conclusion remarks are presented in 6th section.

2. Wind Model

A natural wind which is a dynamic stochastic process can be mainly divided into two categories. The first one which builds by the meteorological data such as location information and altitude is applied for large-scale wind farm and forecasting wind speed. The second one which is developed on probability and statistics methods is called as a statistical model [8]. In this paper, the statistical model is used and can be defined as follow

$$v = v_s + v_r \tag{1}$$

where, v_s is the average component, which reflects the wind speed long-term characteristic and maintains constant, v_r is the turbulence component, and it is related to the turbulence intensity which depends upon the roughness of a wind farm surface. The von Karman's or Van der Hoven's models are used to express the dynamic turbulence characteristics [9]. Because of the major drawback, that the turbulence component is regarded as a stationary random process which cannot reflect the complete wind information by using the Van der Hoven's model. As a result, the von Karman's model is chosen. In this model, the non-stationary turbulence component can be simulated by the following shaping filter which is defined as:

$$H_t(s) = K_F \frac{0.4T_F s + 1}{(T_F s + 1)(0.25T_F s + 1)} \tag{2}$$

where parameters of K_F and T_F are decided by the average component. And the input of the shaping filter is a white noise. Hence the turbulence component v_r can be deduced as:

$$v_r(t) = \frac{1}{2\pi} \int H_t(s)\varepsilon(s)e^{st} ds \tag{3}$$

where $\varepsilon(s)$ represents a zero mean white - noise signal.

Generally, the above wind model can be used to simulate approximately a real wind. However, in order to demonstrate the following proposed control methods performances, some extreme wind cases are also tested, such as signals of step or ramp type.

3. Wind Turbine and Driver Train Models

3.1 Wind turbine rotor model

The wind turbine will absorb part of energy when the airflow runs through it [10]. And the available captured power can be represented as

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

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

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08 \cdot \beta} - \frac{0.035}{\beta^3 + 1} \tag{6}$$

where R is the radius of wind turbine, ρ is the air density, $C_P(\lambda, \beta)$ is the power coefficient, $\lambda = \omega_T R / v$ is the tip speed ratio, ω_T is the angular speed for the wind wheel, and β is the pitch angle. Cp is affected by both λ and β. When the wind overrides the rated wind, the capture power will exceed its capacity. So in the field, the pitch angle will be adapted to maintain a constant rated power. The output torque on the wind turbine is represented as

$$T_L = P / \omega_T \tag{7}$$

3.2 The drive train model

To simplify wind drive train model and fulfil the control requirements, we choose a one-mass model [11]. When the stiffness and the damping factor are neglected, its corresponding motion equation is described as:

$$T_L - T_e = \frac{J}{n_p} \frac{d\omega_r}{dt} = \frac{J}{n_P} \frac{d^2\theta}{dt^2} \tag{8}$$

where T_e is the generator torque, T_L is the wind turbine torque which equals to the torque of generator side, J is the equivalent moment inertia, n_p is the number of pole pairs, ω_r is the rotor electrical angular speed, and θ is the rotor position angle of DFIG.

3.3 DFIG model

In the motor reference frame as in [12-13], the dynamic equations of DFIG can be developed by vector transformation dq-axis voltage and flux equations as follows

$$\begin{cases} \vec{u}_s = R_s\vec{i}_s + j\omega_s\vec{\Psi}_s + p\vec{\Psi}_s \\ \vec{u}_r = R_r\vec{i}_r + j\omega_{sl}\vec{\Psi}_r + p\vec{\Psi}_r \end{cases} \quad (9)$$

$$\begin{cases} \vec{\psi}_s = L_s\vec{i}_s + L_m\vec{i}_r \\ \vec{\psi}_r = L_r\vec{i}_r + L_m\vec{i}_s \end{cases} \quad (10)$$

where L_m is the mutual inductance, L_s is the stator self-inductance, L_r the rotor self-inductance, R_s and R_r are the stator and rotor resistances, ω_s is the angular frequency of the grid, $\omega_{sl} = \omega_s - \omega_r$ is the slip angular frequency, and u_{sq}, u_{sd}, u_{rq} and u_{rd} are stator and rotor voltages in the dq reference frame. And

$\vec{u}_r = u_{rd} + ju_{rq}$,

$\vec{u}_s = u_{sd} + ju_{sq}$,

$\vec{i}_s = i_{sd} + j \cdot i_{sq}$,

$\vec{i}_r = i_{rd} + j \cdot i_{rq}$,

$\vec{\psi}_s = \psi_{sd} + j\psi_{sq}$,

$\vec{\psi}_r = \psi_{rd} + j\psi_{rq}$.

4. Design of NNPID Controller

In this section for the considered DFIG model, we propose a stator voltage oriented vector control which is based on a Neural Network PID (NNPID) technology to track the available maximum power. Its control architecture is illustrated in Figure 1.

Under this scheme, firstly the rotor dq axis current references which are used for optimal power tracking are calculated from the active and reactive power. They are decoupled by the following referred stator voltage oriented vector control. Then, with the application of the proposed NNPID, one ensures the maximum output power tracking.

4.1 Stator voltage oriented vector control method

According to the magnetic flux conservation principle, the DFIG three-phase dynamic model can be simplified into a two-phase dp dynamic model. Without the proposed stator voltage oriented vector control [14], the calculated flux are easily affected by generator parameters, such as inductance cannot be accurately obtained.

Thus under stator voltage reference frame, one obtains

$$\begin{cases} u_{sq} = 0 \\ u_{sd} = u_s \end{cases} \quad (11)$$

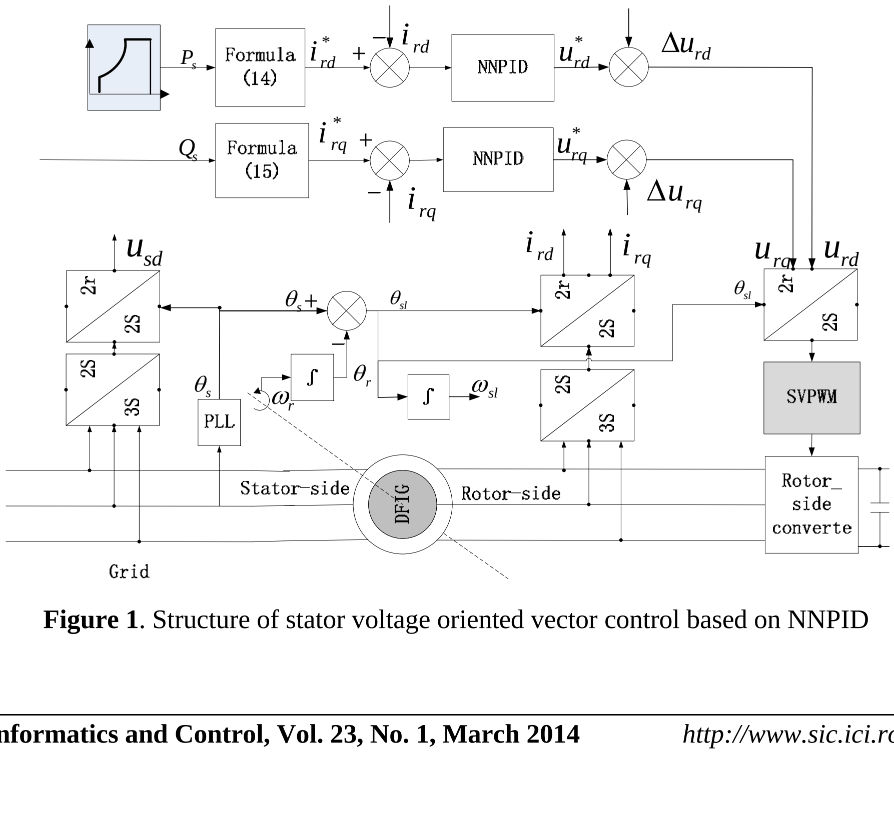

Figure 1. Structure of stator voltage oriented vector control based on NNPID

where u_{sd} and u_{sq} are voltages under dq-axis.

In wind turbine systems, the wind energy is mainly transferred to power through the stator side to grid. When the DFIG runs on the state of super-synchronous condition, a part of power will flow across the rotor-side converter. In steady-state working condition, the stator resistance can be ignored which means $R_s << \omega_s L_s$. And according to power equation, the following active and reactive power can be calculated as follows

$$P_s = -\frac{3}{2}(u_{sd} i_{sd} + u_{sq} i_{sq}) \approx -\frac{3}{2}\frac{L_m}{L_s} u_s i_{rd} \tag{12}$$

$$Q_s = -\frac{3}{2}(u_{sd} i_{sq} - u_{sq} i_{sd}) \approx \frac{3}{2}(\frac{L_m}{L_s} u_s i_{rq} + \frac{u_s^2}{\omega_s L_s}) \tag{13}$$

Thus from the above equations, the following current references of i_{rd}^* and i_{rq}^* can be calculated as

$$i_{rd}^* \approx -\frac{2L_s}{3u_s L_m} P^* \tag{14}$$

$$i_{rq}^* = \frac{2L_s}{3u_{sd} L_m} Q^* - \frac{u_s}{\omega_s L_m} \tag{15}$$

The reactive power reference Q^* which can be adapted with variation values of grid is selected to be ‘zero’ here. And it is important to note that the active power reference P^* which is calculated from the wind turbine optimal power curve (illustrated in Figure 2) can be easily obtained with measurements of rotor angular speed.

Substituting (10) and (11) in (9), the dp-axis compensated voltages can be calculated as

$$\Delta u_{rd} = -\omega_{sl}(L_r \sigma i_{rq} + \frac{L_m}{L_r}\frac{u_s}{\omega_s}) \tag{16}$$

$$\Delta u_{rq} = \omega_{sl} L_r \sigma i_{rd} \tag{17}$$

with the leakage factor $\sigma = 1 - L_m^2 / L_s L_r$.

Hence the input of SVPWM convertor can be presented as

$$u_{rd} = u_{rd}^* + \Delta u_{rd} \tag{18}$$

$$u_{rq} = u_{rq}^* + \Delta u_{rq} \tag{19}$$

where u_{rd}^* and u_{rq}^* are reference voltages which are calculated by the NNPID and described in the next subsection.

4.2 Neural Network PID

Traditionally, a classic PID controller performances whose three coefficient values are difficult to select are normally affected by systems nonlinearities and external disturbances [15]. Thus in this subsection, a Neural Network PID (NNPID) which presents self-learning and adjusting abilities on coefficient weights online is developed[16]. Here the detailed of designing d-axis NNPID is

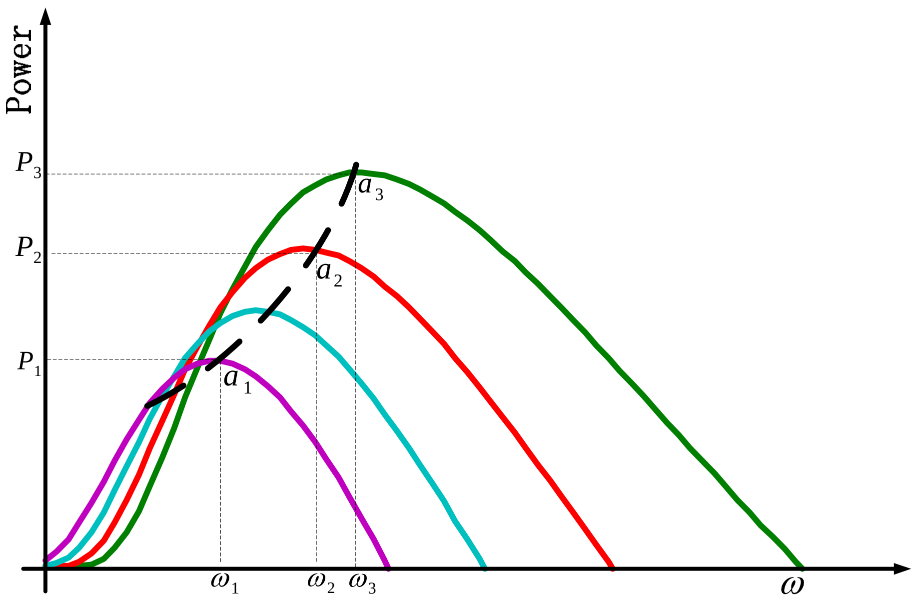

Figure 2. Optimal wind turbine power curve

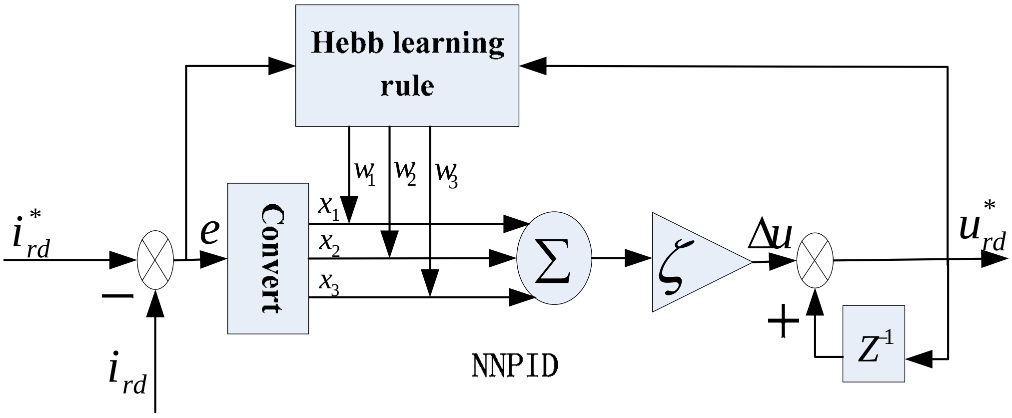

Figure 3. Structure of NNPID

only presented because the q-axis one is similarly to d-axis.

The input of NNPID in d-axis is the current error $e_{rd}(k) = i_{rd}^*(k) - i_{rd}(k)$. The output of NNPID is the d-axis voltage $u_{rd}(k)$,which is illustrated in Figure 3.

The output of NNPID can be written as follow

$$u_{rd}^*(k) = u_{rd}^*(k-1) + \zeta \sum_{i=1}^{3} x_i(k) w_i(k) \qquad (20)$$

where ζ is the proportion coefficient which relates to the stability of the closed-loop system, and the coefficients of w_1, w_2 and w_3 are represents the proportional, integral and differential constants for a classical incremental discrete PID controller. $x_i(k)$ is the error polynomials and written as follows

$$\begin{cases} x_1(k) = e_{rd}(k) - e_{rd}(k-1) \\ x_2(k) = e_{rd}(k) \\ x_3(k) = e_{rd}(k) - 2e_{rd}(k-1) + e_{rd}(k-2) \end{cases} \qquad (21)$$

In this paper, the error function is defined as

$$E = \frac{1}{2} e_{rd}(k)^2 = \frac{1}{2}(i_{rd}^* - i_{rd})^2 \qquad (22)$$

According to the Hebb learning rule [17] and avoiding local minima[18], an improved algorithm for adjusting the weights is proposed and deduced as follows

$$\begin{cases} w_i(k) = w_i(k-1) + \Delta w_i(k) + \alpha_i(w(k-1) - w(k-2)) \\ \Delta w_i(k) = -\eta e_{rd}(k) u_{rd}(k) x_i(k) \end{cases} \qquad (23)$$

where η_i is the learning factor, $e(k)$ is equal to the error between the reference and measurements, and α_i is the inertia coefficient.

In the summary, the NNPID algorithm can be shown in Figure 4.

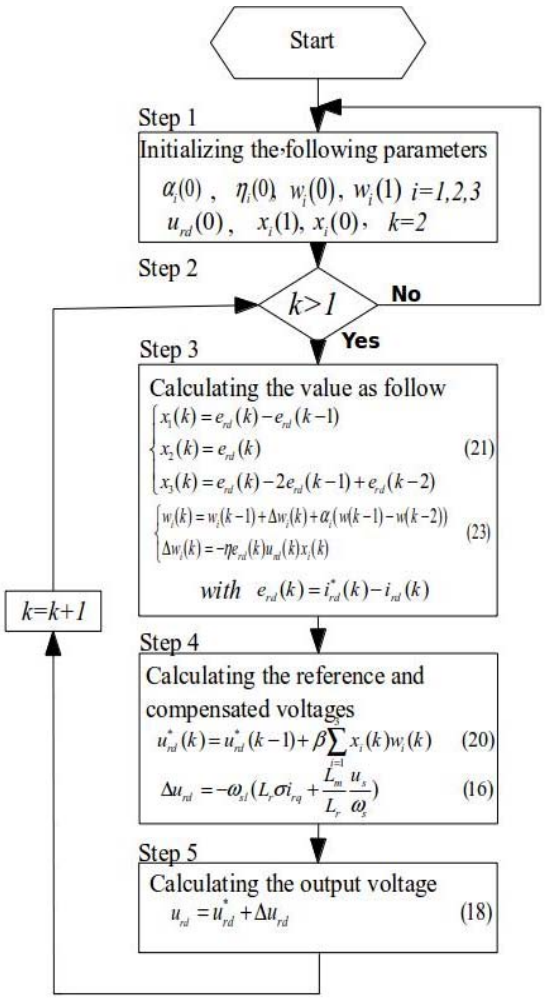

Figure 4. NNPID process algorithm

5. Numerical Simulation

In this section, we validate the proposed NNPID based control strategy for the considered wind turbine system on Matlab/Simulink. The controlled system parameters are shown in Table 1.

Table 1. Parameters of the wind turbine system

Parameter	Value
Blade radius	40m
Rated Power	1.5MW
air density	1.25kg/m^3
Rated Voltage	690V
Frequency	50Hz
Number of poles pair	2
Stator resistance	1.1mΩ
Rotor resistance	2.3mΩ
Stator leakage inductance	0.007mH
Rotor leakage inductance	0.0075mH
Stator-rotor mutual inductance	2.9936mH
Wind turbine moment of inertia	4.95M kg.m^2
Generator moment of inertia	90 kg.m^2
Gearbox ratio	83.53

To demonstrate the proposed controller performance, we consider an external wind input signal which contains mainly three different types of step, ramp and stochastic signal and illustrated in Figure. 5. In addition, to validate the robustness of NNPID, the stator resistance is selected for changing at 7.5th second from the value of R_s to $1.2*R_s$. Because its value is easily changed with the variation of temperature. Under these testing conditions and without considering the wind turbine system linked to the grid, their corresponding control results which includes the power coefficient, rotor speed, reference and actual power, and tracking error are illustrated respectively in Figure 5 to Figure 9.

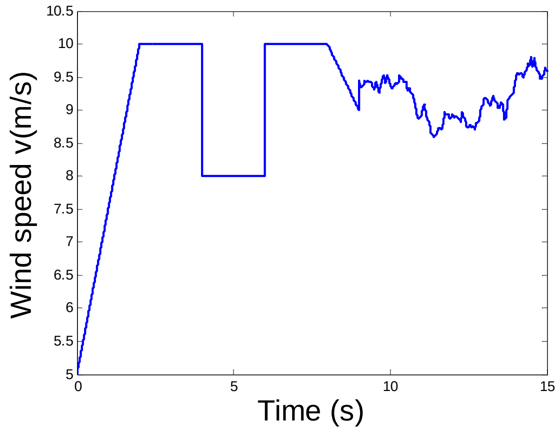

Figure 5. Evolution of the wind speed parameter

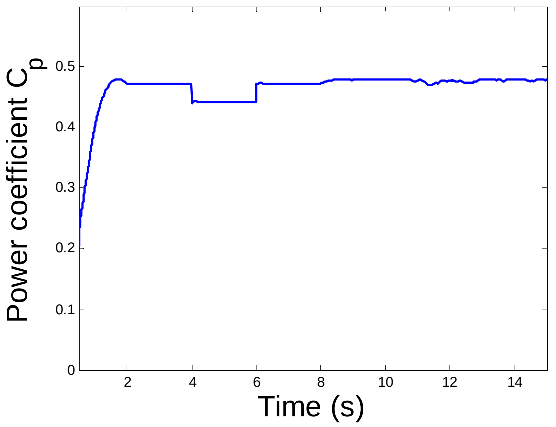

Figure 6. Power coefficient

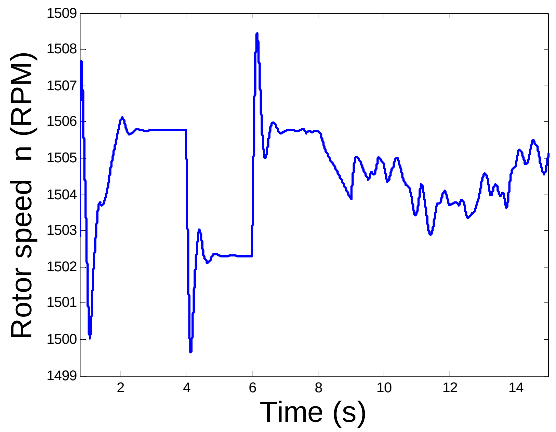

Figure 7. Rotor speed

It is important to note that, from Figure. 8 and Figure. 9, with the proposed NNPID technology, the actual power output tracks very well the available maximal power point, even under the variation of wind speed and system parameter variations.

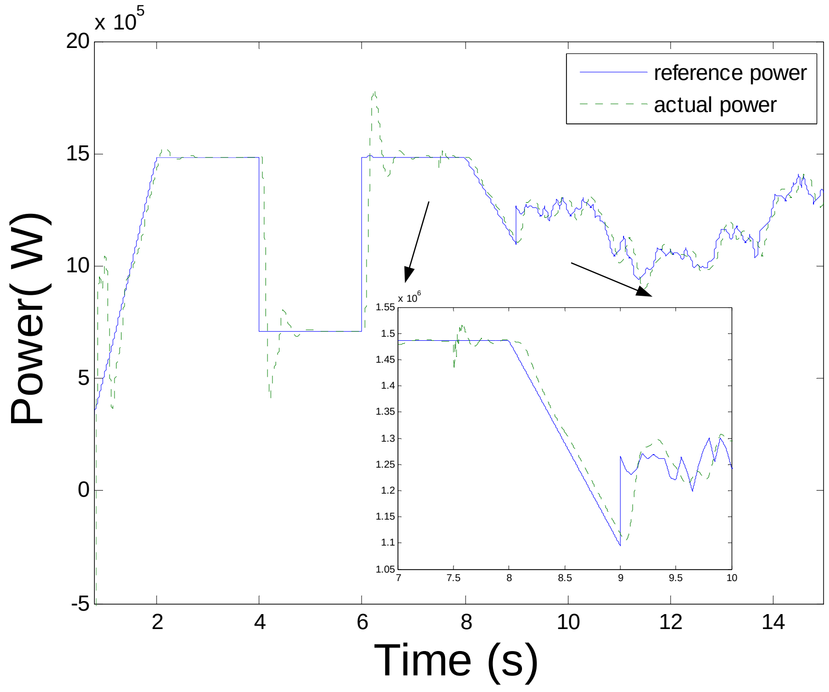

Figure 8. Reference and actual power

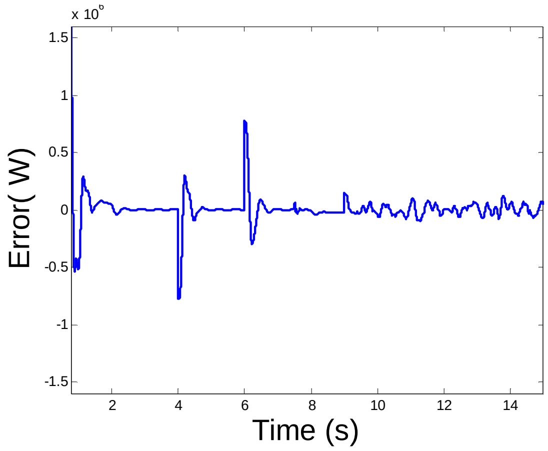

Figure 9. Power error between reference and actual power

6. Conclusion

In this paper, a NNPID based stator voltage oriented vector control is designed and implemented to a DFIG based wind turbine system. The advantages of the proposed control are that its corresponding control weights can be adapted online by Hebb rule by according to power error. And the effectiveness of the proposed method is demonstrated by corresponding numerical simulation results, even in cases of wind mutation changes.

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