

Intelligent Control for the Variable-Speed Variable-Pitch Wind Energy System

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Abstract: In this paper, a new type of multi-variable compensation control method for the wind energy conversion systems (WECS) is presented. Based on wind energy conversion systems, combining artificial neural network (ANN) control and PID, a new type of PID NN intelligent controller for steady state torque of the wind generator is designed, by which the steady state torque output is regulated to track the optimal curve of wind power factor and the blade pitch angle is regulated to keep the stable power output. Also, the LPV model of the WECS, LPV compensator for the wind generator is designed to effectively compensate output of the wind generator torque and the blade pitch angle. Finally, simulation models of the control system based on a realistic model of a 8kw wind turbines are built up based on the Dspace platform. The results show that the proposed method can reduce interferences caused by disturbed parameters of the WECS, mechanical shocks of the wind generator speed are reduced while capturing the largest wind energy fluctuation range of wind generator power output is reduced, and the working efficiency of the variable pitch servo system is improved.

Keywords: ANN, Dspace, PID NN, Wind Energy Conversion Systems.

1. Introduction

As environmental issues become more prominent, energy generated by wind has gradually increased year by year. Application fields of wind energy have been gradually extended to the industrial areas from agricultural irrigation, navigation and grinding. However, due to the randomness of wind power, WECS (wind energy conversion systems) may implement either VSWT (variable speed wind turbines) or VSVPWT (variable speed variable pitch speed wind turbines) [1-6]. When the wind speed is below the rated value, wind energy conversion efficiency is used for improving the wind energy conversion efficiency. The commonly control strategy for capturing most wind energy is maximum power point tracking (MPPT) [7], and corresponding control methods include PI [8] control, LPV [9] control, neural network control [10,11], etc. However, the above control methods for energy conversion systems have an undesirable effects, as the existence of many nonlinear and uncertain facts caused by the wind. As the PID control of the WECS based on the fuzzy logic ruler has good adaptive capacity, the effect applied to the VSWT WECS is ideal [12]. Giuseppe and Pietro [13] developed a method for predicting working state of

wind turbines with neural network control. Sargolzaei and Kianifar [14] presented a control strategy for improving the power quality with neural network control. Yurdusev et al. [15] developed a method for tracking optimal tip speed ratio with the neural network. Compensation control of neural network is proposed to suppress interference of wind power systems [16]. RBF neural network is applied in the variable-pitch control system [17]. When the wind speed is above the rated value, LPV compensator for VSWT WECS is designed to regulate the high frequency output of wind generator torque and blade angle pitch, combining neural network control with PID control, a new type of PID neural network intelligent controller for VSVPWT WECS is designed for dynamic compensate steady-state output. The training algorithms used are gradient descent algorithm with momentum factor, which presents the on-line version of auto-tuning algorithm for PID control parameter. A hardware platform for multi-variable compensation control of the VSVPWT WECS is built up based on Dspace. The results confirm the superiority of the proposed control (multi-variable in this paper) scheme to the conventional ones (traditional multi-variable). Fathabadi [18] proposed a novel fast and highly accurate universal maximum power point (MPP) tracker for hybrid fuel cell/photovoltaic/wind power generation systems. The tracker called "universal tracker" because it used a unified algorithm and controller to concurrently track the MPPs of the photovoltaic (PV), fuel cell (FC) and wind energy conversion subsystems of a hybrid FC/PV/wind power system. Soufi et al. [19] proposed a

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particle swarm optimization based sliding mode control of squirrel cage induction generator of a variable speed wind energy conversion system. The proposed method had good transient performance and fast convergence. Hong et al. [20] presented a artificial neural network for optimal control for variable-speed wind generation systems.

The rest of this paper is organized as follows. Section 1 discusses the constant power control problem and the modeling of the WECS from the multi-variable control point of view. Section 2 depicts an overview of the proposed control structure, presents a new LPV dynamic compensation control method for the variable-speed variable-pitch WECS. Section 3 presents a new PID neural network control structure, explain the training algorithm of the multi-variable controller. Section 4 presents the experimental results with the proposed control method based on a 8000 watt wind turbine. Section 5 concludes this work and represents one of the main contributions in this paper.

2. LPV Modeling of Variable WECS

The aerodynamic model of a wind wheel is computed from Eq. (1) [7, 15].

where is $C=0.5\pi\rho R^3$, $\Gamma(t)$, ρ and R are the torque of the rotor, the air density and wind wheel radius respectively.

$$\Gamma(t) = Cv(t)^2 C_T(\lambda, \beta) \quad (1)$$

The parameter $C_T(\lambda, \beta)$ is the torque coefficient that depends on the blade pitch angle β and the tip-speed ratio λ determined from Eq. (2):

$$C_T(\lambda, \beta) = C_p(\lambda, \beta)/\lambda \quad (2)$$

where $C_p(\lambda, \beta)$ is the power coefficient, and the tip-speed ratio is $\lambda = \Omega_l R/v$. Hereafter, the augmented system will be analyzed (see Figure 1 for a block diagram of the VSVPWT WECS), wind energy captured by the rotor of a wind wheel is computed from Eq. (3),

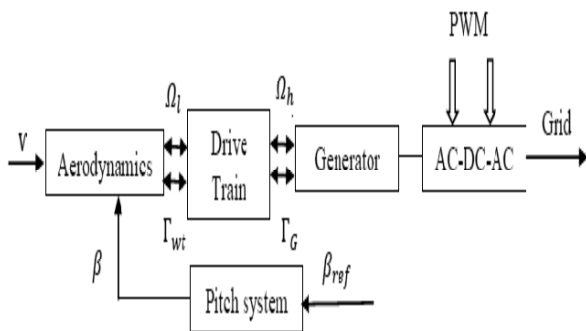


Fig. 1. Block diagram of the VSVPWT WECS

$$P_{wt}(t) = C/R v(t)^3 C_p(\lambda, \beta) \quad (3)$$

The nonlinear wind turbine is linearized around the steady-state operating point so as to obtain linear model of VSVPWT WECS [22]. Defining the error $\Delta x = x - \bar{x}$, and the normalized errors $\overline{\Delta x} = \Delta x / \bar{x}$. As the uncertainty of wind, we take the wind speed as stochastic processes of non-statistics, so it includes two part:

$$v = \bar{v} + \Delta v \quad (4)$$

where, \bar{v} is low-frequency wind speed, Δv is high-frequency wind speed:

$$\Delta v = -\frac{1}{T_w \Delta v} + \frac{1}{T_w} \xi \quad (5)$$

where, ξ is Gaussian white noise, T_w is filter time constant, and $T_w = L_t / \bar{v}$, L_t is turbulence length of the wind speed. Linear parameter-varying (LPV) model for VSVPWT WECS can be expressed as [6, 18]:

$$\begin{cases} \dot{x}(t) = A(Q)x + B(Q)u + L(Q)x \\ \dot{z}(t) = Cx + Du \end{cases} \quad (6)$$

where, state vector x , input vector $u(t) = [\overline{\Delta \Gamma_G} \quad \overline{\Delta \beta_{ref}}]^T$, $\theta = \gamma$. Where, \bar{v} where, $\overline{\Delta v} = \Delta v / \bar{v}$, $\overline{\Delta \Omega_l} = \Delta \Omega_l / \bar{\Omega}_l$, $\overline{\Delta \Gamma_{wt}} = \Delta \Gamma_{wt} / \bar{\Gamma}_{wt}$, $\overline{\Delta \Gamma_G}$ is normalized wind wheel torque, $\overline{\Delta \beta_{ref}}$ is normalized generator torque, $\overline{\Delta v}$ is normalized wind speed. Parameters $L(\theta) = [0 \quad 0 \quad (2-\gamma)/T_w]^T$, $B(\theta)$ and $A(\theta)$ can be expressed as:

$$B(\theta) = \begin{bmatrix} -1/J_T & 0 \\ 0 & 1/T_\beta \\ -\gamma/J_T & \xi/T_\beta \end{bmatrix} \quad (7)$$

$$A(\theta) = \begin{bmatrix} 0 & 0 & 1/J_T \\ 0 & -1/T_\beta & 0 \\ \gamma/T_w & \frac{\xi}{T_w} - \frac{\xi}{T_\beta} & \gamma/J_T - 1/T_w \end{bmatrix} \quad (8)$$

In Eq. (8), γ depends on the operating points of the WECS. it defines as $\gamma = \frac{\lambda C_p(\lambda, \beta)}{C_p(\lambda, \beta)} - 1$, $C_p(\lambda, \beta) = dC_p(\lambda, \beta) / d\lambda|_{\lambda=\bar{\lambda}, \beta=\bar{\beta}}$ and $\bar{\lambda} = R\Omega_l / \bar{v}$.

J_T is mechanical time constant of transmission system and define as follows:

$$J_T = \frac{J_l \bar{\Omega}_l}{\bar{\Gamma}_{wt}} = \frac{J_h \bar{\Omega}_h}{\bar{\Gamma}_{wt}}$$

Affine coefficient matrix in the LPV model depending on the parameter vector Θ , which can be expressed as:

$$\begin{cases} A(\theta) = A_0 + \theta A_1 \\ B(\theta) = B_0 + \theta B_1 \\ L(\theta) = L_0 + \theta L_1 \end{cases} \quad (9)$$

3. Designing of Multi-Variable Controller Based on the NN PID

3.1 Multivariable Control Strategy

PID algorithm can be expressed as following:

$$u(k) = K_p e(k) + K_I \sum_{j=0}^n e(j) + K_D [e(k) - e(k-1)] \quad (10)$$

$u(k)$ is output of PID controller. To achieve better performance, a nonlinear multi-variable controller for the VSVPWT WECS have been proposed in [2]. Multi-variable controller includes two layers, the first layer is generator torque controller, which is to regulate the output torque; the second layer is blade pitch angle controller, which is used to make the controller less complex and as the rotor speed regulation objective is partly guaranteed by the pitch controller. When the wind speed is above rated value, classical multi-variable control structure of the VSVPWT WECS is the following (Figure 2), two PID controllers are used as equations (11) and (12), [6, 21]:

$$\Gamma_{ar}^g = e_{\Omega} (k_{p1} + \frac{k_{i1}}{s} + k_{d1}s) \quad (11)$$

$$\beta_r^g = e_{pa} (k_{p2} + \frac{k_{i2}}{s} + k_{d2}s) \quad (12)$$

Where $e_{\Omega} = \Omega_{hr} - \Omega_h$, which is the generator speed tracking error, and $e_{pa} = P_{ar} - P_a$, which is the generator output power tracking error, k_{p1} and k_{p2} are the proportional coefficient, k_{i1} and k_{i2} are the integral coefficient, k_{d1} and k_{d2} are the differential coefficient.

However, the classical method depends on the linear operating point of the WECS, when the system is operating far from the steady operating point, the rotor speed and power unfortunately presents large variations. The controllers (see Eq.(10)) are unable to obtain control rules with the input variable sum-of-error $\sum_{j=0}^k e(j)$, that is integral error, because the steady state value of integral error is unknown for VSVPWT WECS control systems. The proposed method (see Figure 3 for PID NN multi-variable control structure of the VSVPWT WECS), the PID neural

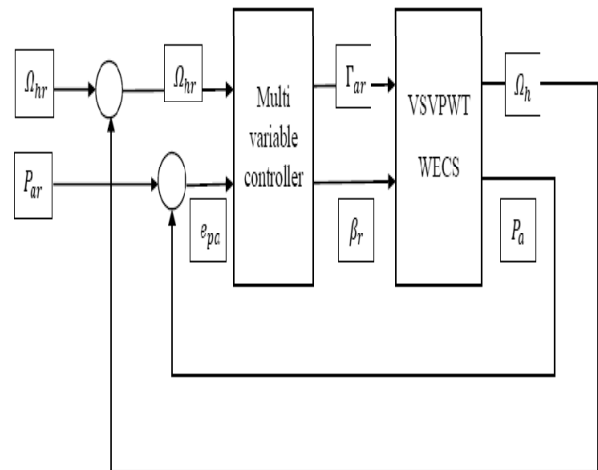


Fig. 2. Classical multi-variable control structure of the VSVPWT WECS

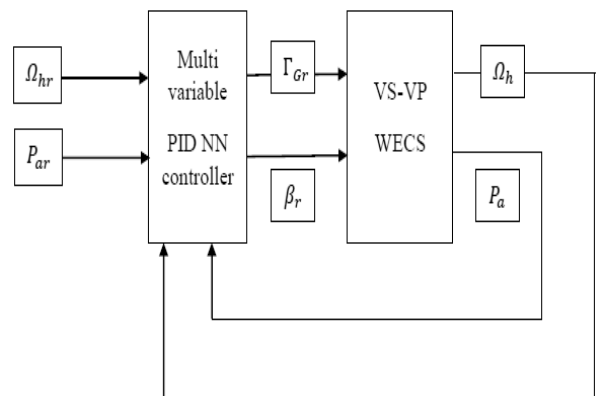


Fig. 3. PID NN multi-variable control structure of the VSVPWT WECS

network can. This controller completes the online tuning of proportion, integral and differential parameters, and the network training algorithm by employing momentum factor will not be easy to fall into a local minimum value.

3. 2. PID Neural Network Controller

In order to assist the torque controller to regulate the wind turbine electric power output, while avoiding significant loads and maintaining the rotor speed within acceptable limits, a proportional pitch controller is added upon the rotor speed tracking error:

As is shown in Figure 4, there are two same 2-3-1 structure PID neural network controller for the multi-variable controller. Here we just give the torque controller [24, 25]:

Two inputs of neural network are x_1^i and x_2^i , where, x_1^i is

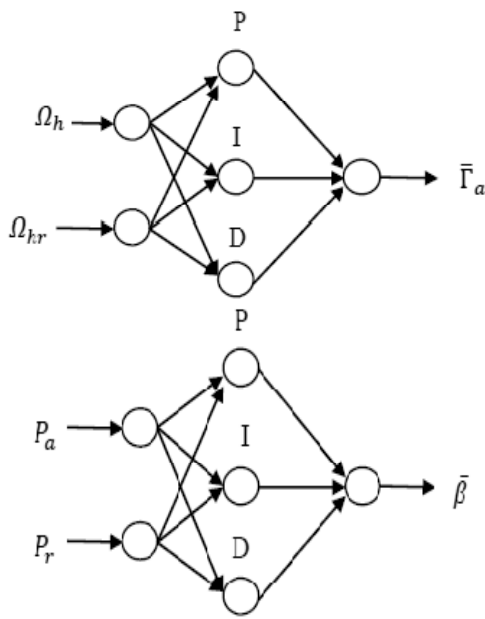


Fig. 4. PID NN controller

the speed reference value Ω_{href} of wind turbines. x_2 is the actual rotational speed Ω_h of wind turbines. The output of the input layer is $y_j^1 = f^1(net_j^1)$, $j=1, 2$. The state function of neurons is $u_j^2(k) = (net_j^2)$. Hidden layer includes three neurons, proportional element, integral element, differential element. The sum of input weight which in hidden layer neurons is $net_i^2 = \sum_{j=1}^2 y_j^1$. w_{ij}^2 , $i=1, 2, 3$, w_{ij}^2 is the input weights of the i -th neurons which in the hidden layer.

The state of proportional element is:

$$u_1^2(k) = net_1^2 \tag{13}$$

The state of integral element is:

$$u_2^2(k) = u_2^2(k-1) + net_2^2 \tag{14}$$

The state of differential element is:

$$u_3^2(k) = net_3^2(k) - net_3^2(k-1) \tag{15}$$

Output layer includes one neuron. The sum of neurons input weight is $net_1^3 = \sum_{i=1}^3 y_i^2$, w_{i1}^3 is the input weights of the i -th neurons which in the output layer, and $i=1$. The output of the output layer is $y_1^3 = f^3(net_1^3)$. The state function of neurons is $u_1^3(k) = (net_1^3)$. The output functions of input layer and hidden layer are f^1 and f^2 , which are Tan-sig function. The output function of output layer is f^3 ,

which is purelinand wavelet function. The initial weights from input layer to hidden layer are $w_{ij}^2 = 1$, $w_{ij}^2 = -1$. The initial weights from hidden layer to output layer are the output ratio of PID controller, integration k_I , differentiation k_D . k_P is proportional coefficient, k_I is integral coefficient, k_D is differential coefficient. The network training target can be expressed as:

$$E_t(p) = \frac{1}{2} \sum_{p=1}^m [y_{tp} - y_{op}]^2 \tag{16}$$

Where, y_{op} is actual output of the neural network, y_{tp} is expected output of the neural network, m is sample size. PID neural network weight is to train by the gradient descent algorithm with momentum factor, the final training steps can be express as equations (17) and (18):

$$\frac{\partial E}{\partial w_{li}^3} = -\frac{1}{m} \sum_{k=1}^m \delta(k) y_i^2(k) \tag{17}$$

where, $\delta'(k) = 2[y_{tp} - y_{op}]$, equation (17) is weight correction from hidden layer to output layer.

$$\frac{\partial E}{\partial w_{ij}^2} = -\frac{1}{m} \sum_{k=1}^m \delta(k) y_i^2(k) \tag{18}$$

where, $\delta(k) = \delta(k) w_{li}^3 \text{sgn} \frac{y_i^2(k) - y_i^2(k-1)}{net_i^2(k) - net_i^2(k-1)}$ equation (18) is weight correction from input layer to hidden layer.

3. 3. LPV Gain Scheduling Control

Full state feedback controllers is expressed as equation (19)[21]:

$$u = K(\theta)x \tag{19}$$

The closed-loop system can be expressed as:

$$\begin{aligned} x^g &= \bar{A}(\theta)x + L(\theta)\xi \\ z &= C(\theta)x \end{aligned} \tag{20}$$

where, $\bar{A}(\theta) = A(\theta) + B(\theta)K(\theta)$, $\bar{C} = C + DK(\theta)$.

where, $C = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$, $D = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$.

Gain matrix of parameter state feedback controller given by matrix inequality can be expressed as follows [23, 26]:

$$K(\theta) = R(\theta)V^{-1} \tag{21}$$

where, V and $R(\theta)$ are symmetric positive definite matrix.

The Control structure of the variable-speed WECS with

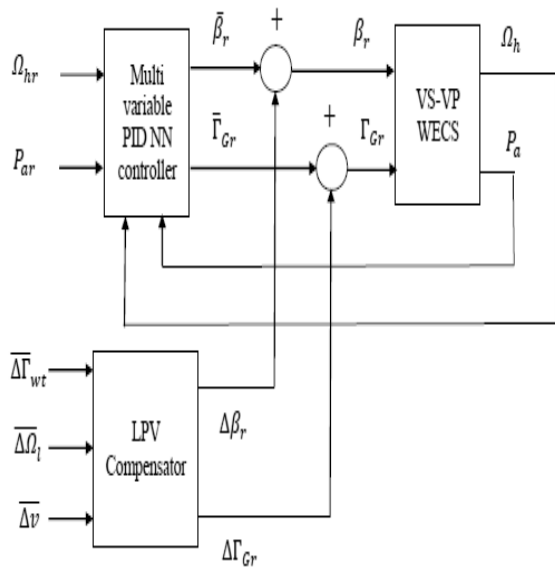


Fig. 5. Control structure of variable-speed WECS with torque compensator

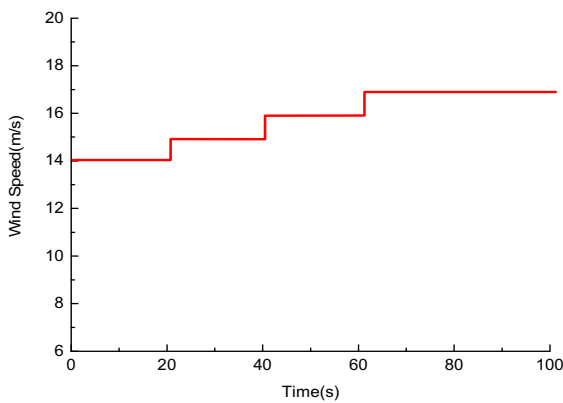
torque compensator is shown in Figure 5, As given in equations (22) and (23), where $\bar{\Gamma}_{Gr}$ is the output of the torque controller, $\bar{\beta}_r$ is the output of the blade pitch angle controller. Both the two controllers and the LPV compensator which outputs are $\Delta\beta_r$ and $\Delta\Gamma_{Gr}$ regulate the output power.

$$\Gamma_{Gr} = \bar{\Gamma}_{Gr} + \Delta\Gamma_{Gr} \quad (22)$$

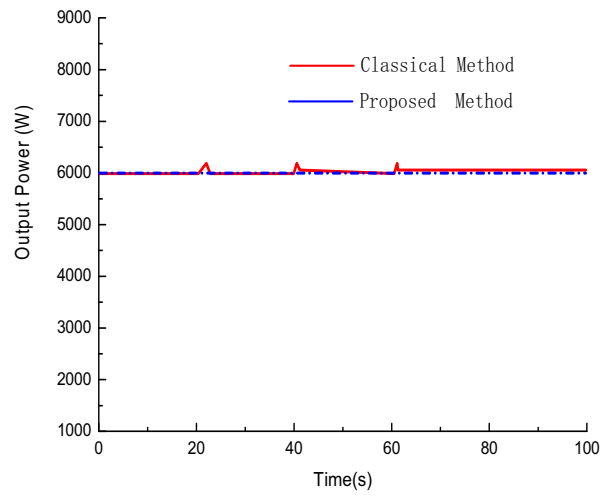
$$\beta_r = \bar{\beta}_r + \Delta\beta_r \quad (23)$$

3. 4.SimulationResearch

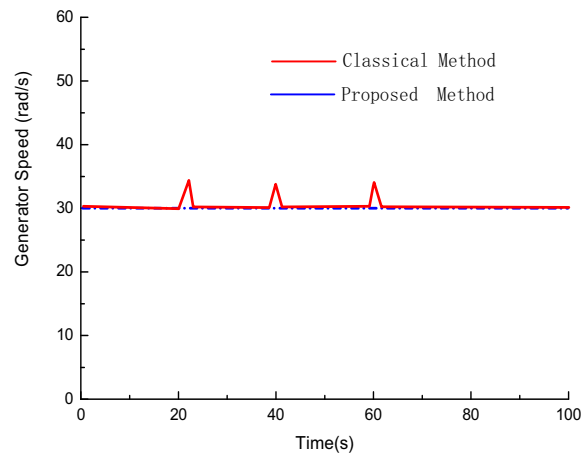
The simulation model is set up so as to verify the control



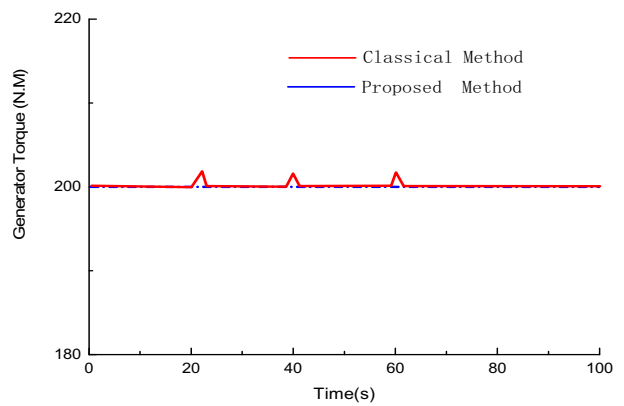
(a) Wind speed



(b) Gower output



(c) Generator speed



(d) Generator torque

Fig. 6. Blade pitch angle controller output

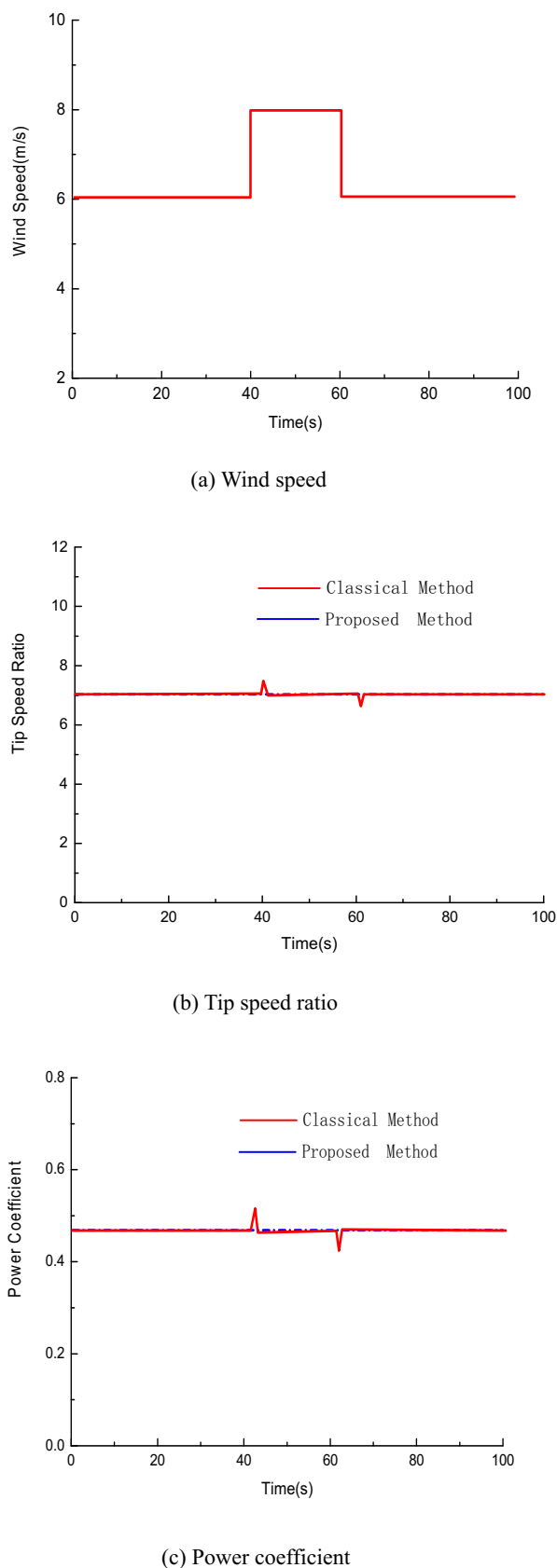


Fig. 7. Torquecontroller output

effect. There are two cases, the one is to test the blade pitch angle controller effect of PID neural network (see blade pitch angle controller output in Figure 6). It can be seen from Figure 6(b) to Figure 6(d), when changes of wind speed are immediate, system output has less disturbances with the PID neural network controller than the PID controller.

The second is to test the torque controller effect of PID neural network (see torque controller output in Figure 7). As is shown in the Figures 7(b) and 7(c), wind power output can track the maximum power coefficient, and disturbances with the PID neural network controller are less than the PID controller, so this method can keep the stable output of the VSVPWT WECS.

4. Experiment Results and Analysis

The Dspace experiment platform is shown in Figure 8, including Matlab/Simulink model, RTW model, Compiler model, RTI model, Control Desk model. Downloading the model compiled to processor through the establishment of Matlab/simulink model, the platform includes electric motor and wind generator [23]. Corresponding parameters of the VSVPWT WECS including: wind generator power is 8000 watt, gear ratio is 6.25, transmission efficiency of wind turbine is 0.95, time constant of filter is 10second, air density is 1.25 kg/m^3 , rated wind speed is 12.5 m/s . Wind generator speed output reference is 30 rad/s , wind generator torque output reference is 200 N.M . Dspace experiment platform is set up so as to verify the control effect of the proposed Multi-variable controller.

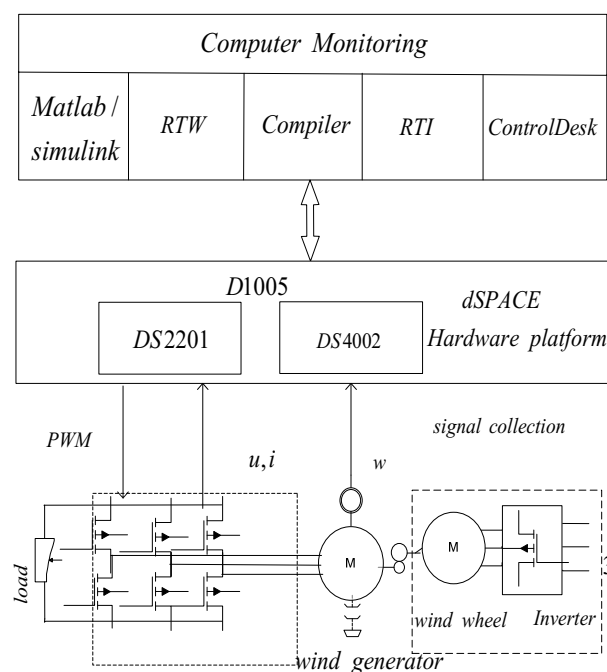
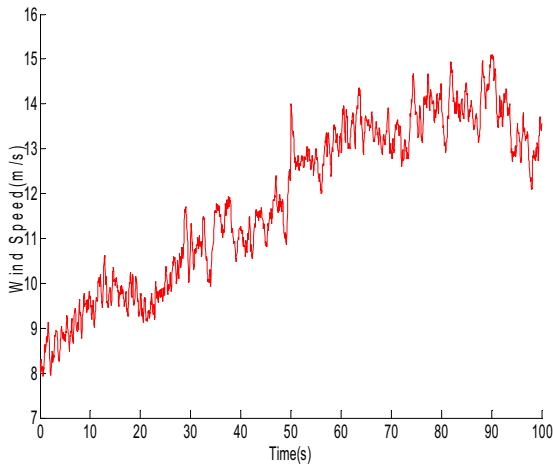


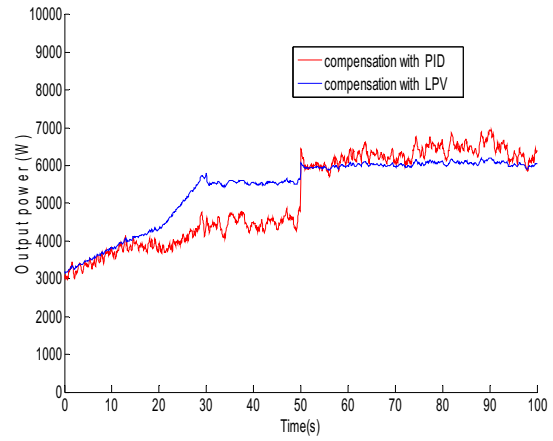
Fig. 8. Dspace experiment platform

The wind speed shown in Figure 9(a) is above rated value after 50 s, the Multi-variable controller based on hardware-in-loop simulation output shown in the Figures 9(b)

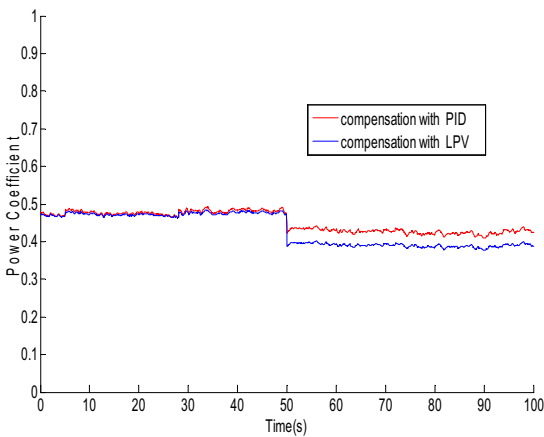
and 9(g) have been selected here since they show some key characteristic of wind turbine dynamic behavior. Firstly, time evolution of the power coefficient, tip speed



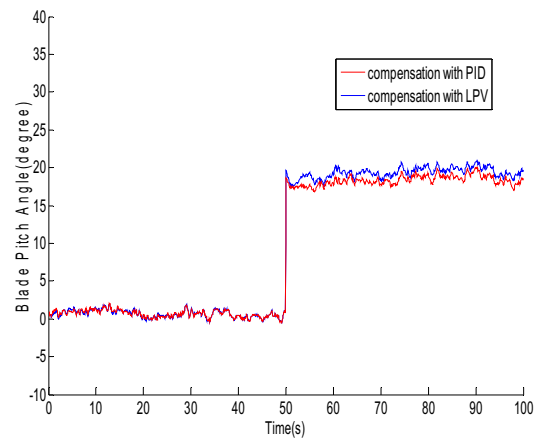
(a) Wind speed



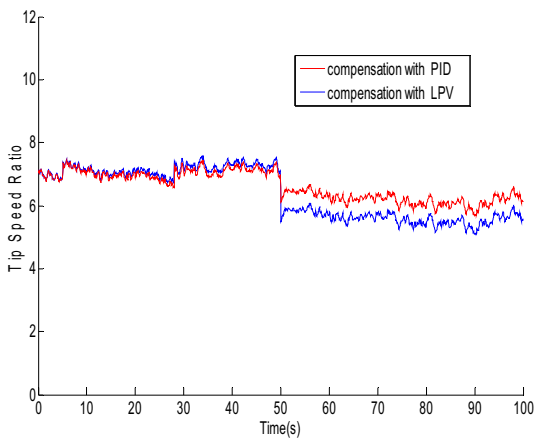
(d) Output power



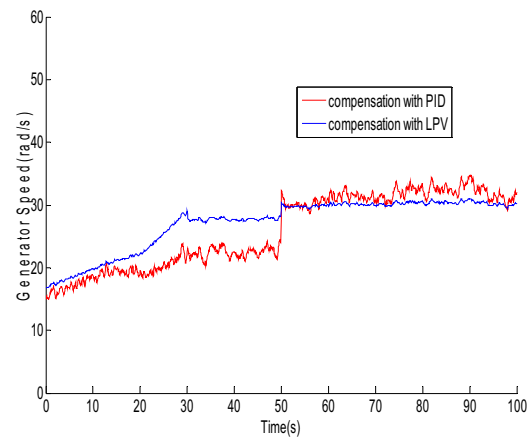
(b) Power coefficient



(e) Blade pitch angle



(c) Tip speed ratio



(f) Generator speed

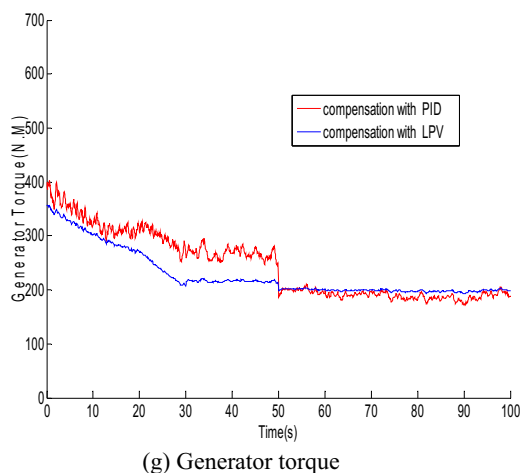


Fig. 9. Multi-variable controller based on hardware-in-loop simulation output

ratio presented in Figures 9(b) and 9(c) remains close to the optimal value before 50-second, but standard deviation becomes large after 50-second. Both the torque controller and the blade pitch angle controller with the PID neural network have better control effect, and LPV compensation control has shown better control performances as compared to the classical PID compensation control, which can be obtained with a reasonable control effort. Secondly on the Figures 9(d) and 9(g), the responses of output power, blade pitch angle, generator speed, generator torque with the compensation control methods to the step change in wind speed are shown. A sudden change in wind speed, the output responses can obtain the optimal values before 50-second and stably remain close to the rated values after 50-second. The results comparison of wind turbine with LPV compensation and classical PID compensation reflect that the LPV compensation control has more expected control performance. Therefore, it is clear that classic approach to Multi-variable controller design are assumed to be constant. This is the reason why the wind turbines cannot follow the optimal work performance during the changes in wind speed. The proposed method can handle better changes in wind speed resulting in faster control of wind turbines, because this method can not only improve the sensitivity of the system by the PID neural network controller when the wind speed is below the rated value, but also assure reducing the system vibration caused by fast dynamic resulted from the action of the turbulent wind speed.

5. Conclusion

In this brief, a framework for a generalized predictive control method is presented. The Hammerstein-Wiener model

identification is used to establish the predictive model of variable pitch WECS, the model can quickly and accurately approaches the controlled object, so it provides a good model foundation for predictive control. In the design of rolling optimization, the brief takes the CPSO algorithm as the rolling optimization strategy. In view of the rapidity, real-time and stability, the rolling optimization can be realized, the control requirements of rapidity and real-time are achieved. Finally, the method has been demonstrated on a realistic nonlinear simulation of the variable pitch WECS with two inputs and one output. The simulation results show a more stable output of speed and power for generator, it provides a good control scheme for variable pitch WECS.

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