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 VSVPWT 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
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 an 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, presents a new LPV dynamic compensation control method for the variable-speed variable-pitch WECS. 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],

\[ \Gamma(t) = C_v(t) C_p(\lambda, \beta) \]  

where \( C_v \) is the power coefficient, \( \lambda \) is the tip-speed ratio, and \( \beta \) is the blade pitch angle. 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),

\[ P_{wt}(t) = C/R \nu(t) C_p(\lambda, \beta) \]  

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 \( \Delta \nu = \nu - \bar{\nu} \), and the normalized errors \( \Delta x = \Delta x/\bar{x} \). As the uncertainty of wind, we take the wind speed as stochastic processes of non-statistics, so it includes two part:

\[ \nu = \nu + \Delta \nu \]  

where, \( \nu \) is low-frequency wind speed, \( \Delta \nu \) is high-frequency wind speed:

\[ \Delta \nu = -\frac{1}{T_w \Delta \nu} + \frac{1}{T_w} \xi \]  

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

\[ \begin{cases} x(t) = A(Q)x + B(Q)u + L(Q)x \\ z(t) = Cx + Du \end{cases} \]  

where, state vector \( x \), input vector \( u(t) = [\Delta \nu \ \Delta \theta]^T \), \( \theta = \gamma \). Here, \( \Delta \nu = \nu - \bar{\nu} \), \( \Delta \theta = \theta - \bar{\theta} \), \( \bar{x} \), \( \Delta \nu \), \( \Delta \theta \) are normalized wind wheel torque, \( \bar{\nu} \) is normalized generator torque, \( \bar{\nu} \) is normalized generator speed. Parameters \( A(\theta) = \begin{bmatrix} 0 & 0 & 1/T_w \\ 0 & 1/T_w & 0 \end{bmatrix} \), \( B(\theta) \) and \( A(\theta) \) can be expressed as:

\[ \begin{bmatrix} -1/\gamma \tau_w & 0 \\ 0 & 1/\gamma \tau_w \end{bmatrix} \]  

In Eq. (8), \( \gamma \) depends on the operating points of the WECS, it defines as \( \gamma = \frac{c_4(\lambda, \beta)}{c_3(\lambda, \beta)} = 1 - \frac{\nu c_6(\lambda, \beta)}{\nu c_4(\lambda, \beta)} \) and \( \lambda = \frac{\rho \omega}{\nu} \).

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

\[ J_T = \frac{J_\Omega}{J_{wt}} = \frac{J_\beta J_\gamma}{J_{wt}} \]
Affine coefficient matrix in the LPV model depending on the parameter vector $\Theta$, which can be expressed as:

$$
\begin{align*}
A(\Theta) &= A_0 + \Theta A_1 \\
B(\Theta) &= B_0 + \Theta B_1 \\
L(\Theta) &= L_0 + \Theta L_1
\end{align*}
$$

(9)

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

3.1 Multivariable Control Strategy

PID algorithm can be expressed as following:

$$
u(k) = K_p e(k) + K_i \sum_{j=0}^{n} e(j) + K_d [e(k) - e(k - 1)]$$

(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]:

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

(11)

$$
\beta_{ar}^g = e_{pu} (k_{p2} + \frac{k_{i2}}{s} + k_{d2}s)
$$

(12)

Where $e_\omega = \omega_r - \omega_s$, which is the generator speed tracking error, and $e_{pu} = p_{ar} - p_u$, 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 $E_\infty e(j)$, 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 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 $x_1$ and $x_2$, where, $x_1$ is
Fig. 4. PID NN controller

3.2. Full State Feedback Control

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

\[ u = K(\theta)x \] (19)

The closed-loop system can be expressed as:

\[ \dot{x} = A(\theta)x + L(\theta)\xi \]

\[ z = C(\theta)x \] (20)

where, \( A(\theta) = A(\theta) + B(\theta)K(\theta), C = C + DK(\theta). \)

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

\[ K(\theta) = R(\theta)V^{-1} \] (21)

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

The Control structure of the variable-speed WECS with
torque compensator is shown in Figure 5. As given in equations (22) and (23), where $\Gamma_{Gr}$ is the output of the torque controller, $\beta_r$ 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.

\[
\Gamma_{Gr} = \bar{\Gamma}_{Gr} + \Delta \Gamma_{Gr}
\]

(22)

\[
\beta_r = \bar{\beta}_r + \Delta \beta_r
\]

(23)

3.4. Simulation Research

The simulation model is set up so as to verify the control
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/m³, 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.

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![Fig. 7. Torque controller output](image)

![Fig. 8. Dspace experiment platform](image)
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...
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.

References


M. Heidari was born at 1978 in Iran. He is an assistance professor of the Faculty of Engineering at Aligudarz Branch, Islamic Azad University, Aligudarz, Iran. Heidari is interested in noise and vibration, structural dynamics, noise and vibration control (AVC, ANC), rotor dynamics, and fault detection. He has published more than 30 conference and journal papers and has more than 10-year professional experiences in cement and oil industries. He has done over 10 industrial projects. Heidari received his B.S. and M.S. degrees from Shiraz University, Shiraz, Iran, and Ahvaz University, Ahvaz, Iran, respectively.