

A novel SC-PI with ANFIS compensation for wind turbine pitch control

Shenghua He¹, Hong Huang^{2,}, Bishuang Fan¹, and Xiaowei Huai³*

¹College of Electrical and Information Engineering, Changsha University of Science and Technology, Changsha, 410004, China

²SPIC Jiangxi Electric Power Co., LTD.

³State Key Laboratory of Disaster Prevention and Reduction for Power Grid Transmission and Distribution Equipment, Human Disaster Prevention Technology Co., Ltd.

Abstract. As a common control method for blades, variable pitch technology is used to regulate the output power of the turbine in region 3. To cope with the random variation of wind speed, a novel pitch angle controller is designed in this paper. The proposed method applies a self-coupled PI (SC-PI) to obtain the desired speed tracking performance, and employs an adaptive neuro-fuzzy inference system (ANFIS) to compensate the controller for disturbance damping capability. A contrast experiment with a baseline PI is conducted in Matlab/Simulink. The performance superiority of the proposed hybrid control method is thus confirmed.

1 Introduction

As the problem of global warming becomes more acute, the world is seeking to decarbonize in a variety of areas [1]. One of the most direct ways to move away from dependence on fossil energy is through the energy transition. This path has brought increasing attention to clean and environmentally friendly renewable energy. As a traditional renewable energy source, the total installed capacity of wind energy has been growing steadily in recent years [2]. To meet the growing demand for energy, wind turbines are required to capture more energy from the air. For the absorption of low wind speeds, the technique used is maximum power point tracking (MPPT) [3]. And for the constancy of the output power at high wind speed more use the variable pitch control technique [4]. Adjustability of the blades greatly increases the efficiency and flexibility of the wind turbine. To this end, a control strategy needs to be designed to obtain the optimal pitch angle to guide the blade action in a rational manner.

The traditional method uses a PI controller to obtain the reference pitch angle [5]. This method is simple to implement and works reliably, but the nonlinear tracking capability is not strong. Later, state-space-based methods such as adaptive control and sliding mode control were applied to pitch control [6-8]. Although the robustness of the system is improved, the acquisition of controller parameters became more difficult. In recent years, expert control algorithms have made a splash for a variety of control tasks in wind turbines.

* Corresponding author: honghuang_21@163.com

In this paper, an SC-PI with ANFIS compensation is selected to control the pitch angle by summarizing the previous methods. The proposed method is simulated and compared with the baseline PI in Matlab/Simulink to verify its feasibility.

2 Model of wind turbine

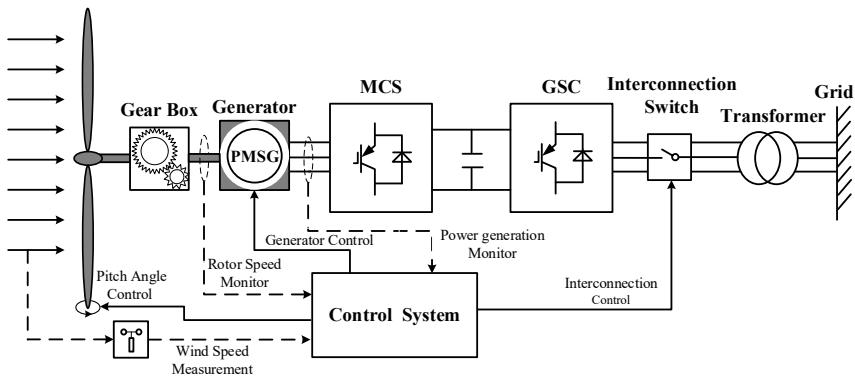


Fig. 1. The structure of direct-drive wind turbine system.

The simplified structure of a grid-connected direct-drive wind turbine system is shown in Figure 1.

According to the Betz aerodynamic theory, the energy absorbed by the wind turbine from the air can be expressed as:

$$P_m = \frac{1}{2} \pi \rho R^2 v_w^3 C_p(\lambda, \beta) = T_m \cdot \omega_r \quad (1)$$

where ρ is the air density, R is the wind turbine rotor radius, v_w is the wind speed, C_p is the wind energy utilization coefficient, T_m is the mechanical torque, and ω_r is the rotor angular velocity. And C_p exists as a function of tip speed ratio λ and blade pitch angle β as follows:

$$\begin{cases} C_p(\lambda, \beta) = 0.5 \left(\frac{116}{\lambda_i} - 0.4\beta - 5 \right) e^{-\frac{21}{\lambda_i}} + 0.0068\lambda \\ \frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{1 + \beta^3} \\ \lambda = \frac{\omega_r R}{v_w} \end{cases} \quad (2)$$

By analysing Eqs. (1) and (2), it can be seen that the main function of pitch control is to make the power coefficient C_p vary with the wind speed v_w by adjusting the pitch angle β , so that P_m remains relatively constant.

The energy captured by the wind turbine blades is used to produce electricity by directly dragging the rotor shaft of the generator at a lower speed. Therefore, the generator side satisfies the following equation:

$$T_m - T_e = J \frac{d\omega_r}{dt} + B\omega_r \quad (3)$$

where T_e is the generator electromagnetic torque, J is the generator rotational inertia, and B is the generator damping factor.

3 Design of pitch control system

In order to obtain the desired wind turbine response performance, a variable pitch system is designed and its structure is shown in Figure 2.

3.1 Self-coupled PI

The mechanical power P_m absorbed and converted by the wind turbine will also show a nonlinear variation due to the nonlinear effect of the wind speed v_w . This is bound to bring more frequent fluctuations in its rotor speed. Considering the lifetime of the wind turbine mechanical components, a novel self-coupled PI is used to obtain the desired speed tracking performance. The most important feature of this controller, compared to the conventional PI, is that the two links of the controller with different physical properties, proportional and integral, are coupled into a synergistic control signal by a speed factor z_c :

$$\begin{cases} k_p = 2z_c \\ k_i = z_c^2 \end{cases} \quad (4)$$

Thus, the number of parameters to be adjusted is reduced from two to one, and the workload is greatly reduced. In addition, an adaptive adjustment of the z_c parameters based on the system response state was adopted:

$$z_c = \frac{\alpha}{T_t} [1 - 0.9 \exp(-\beta t)] \quad (5)$$

where $\alpha \in (0, 100)$, $\beta = 1/T_t$, T_t is the transition time of the system from transient to steady-state response, and t is the current response time of the system.

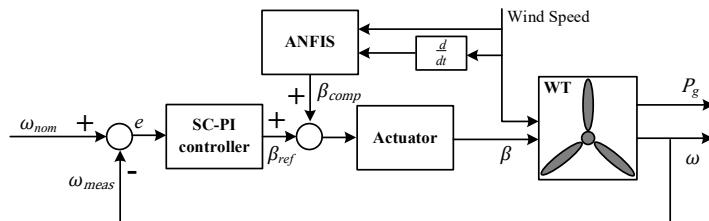


Fig. 2. Proposed pitch angle control system.

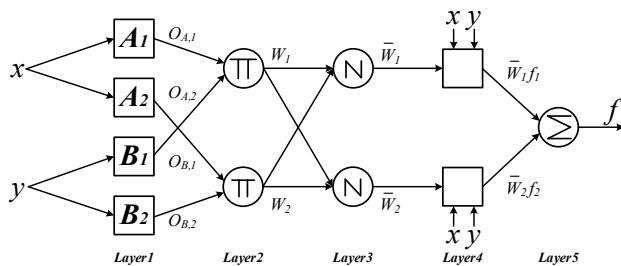


Fig. 3. The structure of ANFIS.

3.2 Adaptive neuro-fuzzy inference system

An ANFIS based on wind speed variation information is used to compensate the control in order to improve the damping effect of the SC-PI controller on disturbances.

ANFIS is a special kind of fuzzy inference system combining neural network and fuzzy theory [9]. Taking a two-input single-output system as an example, a five-layer structured adaptive neuro-fuzzy inference system is given by Figure 3.

The first layer is the fuzzification layer. Each function in this layer corresponds to a linguistic variable represented by a membership function. And the function corresponding to the variable can be a traditional membership function, for example, a Gaussian function as:

$$L_i = \mu_{A_i}(x) = \exp\left[-\frac{(x - c_i)^2}{b_i^2}\right] \quad (6)$$

Here i is the number of membership functions corresponding to each input variable, and c_i and b_i are the mean and standard deviation of the i -th membership function.

The second layer is the fuzzy inference layer. The main work of this layer is to calculate the firing strength of each fuzzy rule. The fuzzy rules as:

$$\text{Rule } i : \text{IF } x \text{ is } A_i \text{ and } y \text{ is } B_i, \text{ Then } Y_i = p_i x + q_i y + r_i$$

The corresponding firing strength is:

$$L_2 = W_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y) \quad (7)$$

The third layer is the standardization layer. This layer performs a firing strength normalization operation. The standardization is done in the following way.

$$L_3 = \bar{W}_i = \frac{W_i}{\sum W_i} = \frac{W_i}{W_1 + W_2} \quad (8)$$

The fourth layer is the defuzzification layer. The role of this layer is to calculate to get the product of each normalized ignition intensity and the corresponding post-rule piece, which is calculated as shown in equation (9).

$$L_4 = \bar{W}_i \cdot Y_i = \frac{W_i}{W_1 + W_2} \cdot (p_i x + q_i y + r_i) \quad (9)$$

The fifth layer is the output layer, which accumulates the output of the previous layer to obtain the total output value of the ANFIS.

$$L_5 = \sum \bar{W}_i \cdot Y_i = \frac{\sum W_i Y_i}{\sum W_i} \quad (10)$$

By endowing the self-learning and self-organizing ability of neural networks to the fuzzy inference system, its approximation ability for nonlinear systems is greatly improved from the original base.

Table 1. Wind turbine simulation parameters.

Parameters of wind turbine	Value	Parameters of PMSG	Value
Rated power	2MW	Rated power	2MW
Rotor radius	35.78m	Stator resistance	0.821mΩ
Cut-in wind speed	3m/s	Friction factor	0.001189 N.m.s
Cut-out wind speed	20m/s	Pole pair	26
Rated wind speed	12m/s	Rotor flux linkage	5.826 Wb
Blade inertia	$6.3 \times 10^6 \text{ kg.m}^2$	Generator inertia	48 000 kg.m^2

4 Results and discussions

In order to verify the feasibility of the proposed algorithm, a 2MW wind turbine simulation model was built based on the 'Wind Turbine' module in Matlab/Simulink, and the parameters of the simulation are shown in Table 1.

As shown in Fig. 4(a), a three-step wind speed (14m/s, 16m/s, 18m/s) was used as the input signal to verify the response performance of the wind turbine system. The proposed method is compared with the baseline PI for experiments.

From Fig. 4(b), it can be seen that the hybrid control strategy has a shorter rise time for wind speed variation. It is able to guide the blade action more rapidly to achieve a reasonable pitch angle.

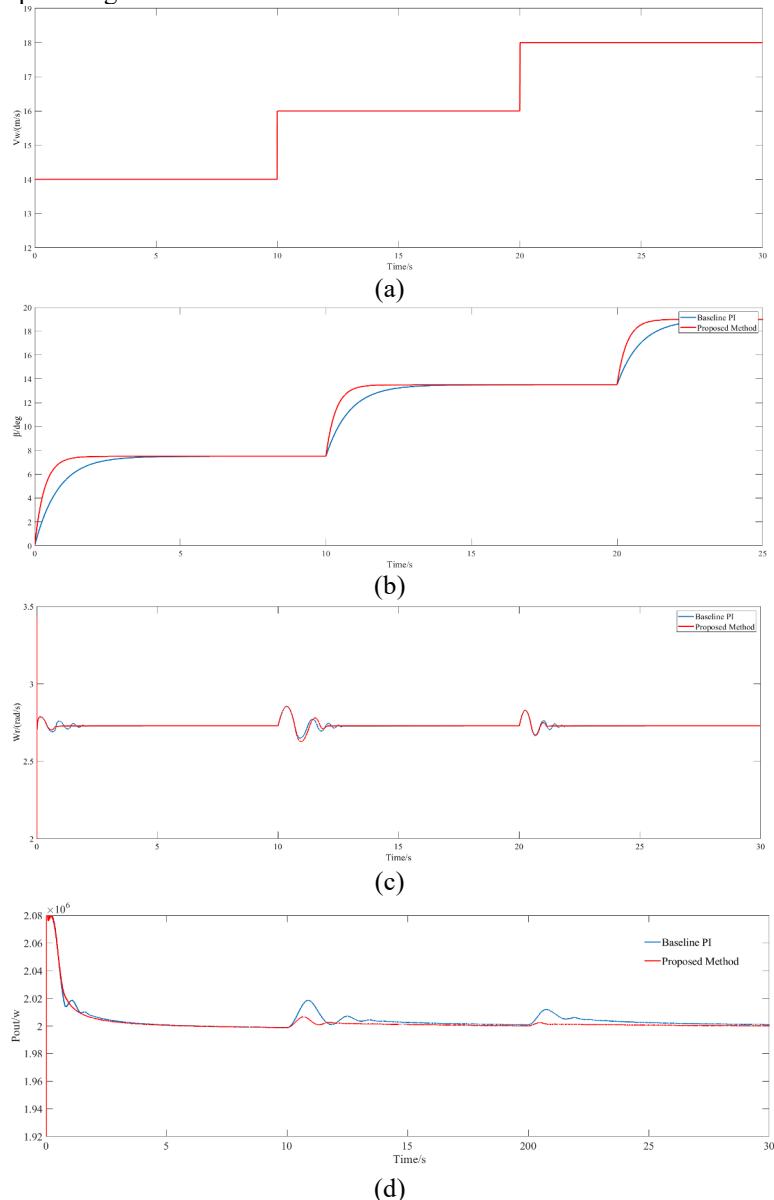


Fig. 4. Simulation result.

Observing Fig. 4(c), it can be found that the proposed scheme takes 1-2s for rotor speed regulation to reach stability, while the baseline PI takes 2-3s to stop fluctuation. Therefore, the superior performance of the designed scheme for speed regulation is verified.

Similarly, the usefulness of the designed controller in terms of power limitation is demonstrated in Fig. 4(d). The curve of the proposed method is closer to 2 MW for most of the time of the response process.

5 Conclusion

In this paper, a novel hybrid pitch angle control scheme is proposed to address the challenges posed by the stochastic nature of wind speed to the performance of the wind turbine system. A SC-PI with parameter adaptation is used to obtain the desired speed tracking performance. Meanwhile, ANFIS with wind speed information as input is employed to compensate the SC-PI control in order to improve the damping effect of the system against disturbances. The implemented control scheme is simulated and compared with the baseline PI, and its superior performance for wind turbine speed and power regulation is highlighted.

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