



The 6<sup>th</sup> International Conference on Applied Energy – ICAE2014

# Sliding Mode Control for Variable-Speed Wind Turbine Generation Systems using Artificial Neural Network

Chih-Ming Hong<sup>a</sup>, Cong-Hui Huang<sup>b,\*</sup>, Fu-Sheng Cheng<sup>c</sup>

<sup>a</sup>Department of Electronic Communication Engineering, National Kaohsiung Marine University, Kaohsiung 811, Taiwan, R.O.C.

<sup>b,\*</sup>Department of Automation and Control Engineering, Far-East University, Tainan 744, Taiwan, R.O.C.

<sup>c</sup>Department of Electrical Engineering, Cheng-Shiu University, Kaohsiung 833, Taiwan, R.O.C.

## Abstract

An induction generator (IG) speed drive with the application of a sliding mode controller and a proposed artificial neural network (ANN) controller is introduced in this paper. Grid connected wind energy conversion system (WECS) present interesting control demands, due to the intrinsic nonlinear characteristic of wind mills and electric generators. The ANN torque compensation is feed-forward to increase the robustness of the wind driven induction generator system. The proposed controller is designed to drive the turbine speed to extract maximum power from the wind and adjust to the power regulation. When sliding mode occurs on the sliding surface, the control system acts as a robust state feedback system. Moreover, a sliding mode speed controller is designed based on a sliding surface.

*Keywords:* sliding mode control (SMC), artificial neural network (ANN), wind turbine (WT), wind energy conversion system (WECS), induction generator (IG).

## 1. Introduction

The wind energy captured by the wind turbine (WT) depends on the wind speed, blade pitch and rotational speed [1]. The nonlinear aerodynamic performance of WT and the wide switching scope of wind added a volatile structure to the energy conversion systems. The effects of mechanical damping also varied with rotational speed. All above factors make it difficult to control WECS. The traditional control strategy based on the linearized model can not guarantee a satisfactory control under a large-scale wind change. WECS can be found in standalone, hybrid, and grid-connected topologies. Traditionally, wind turbines are linked with asynchronous generators, squirrel cage or wound field, providing a robust and low maintenance system. The major drawback is that the resulting system is highly nonlinear, and a nonlinear control strategy is required to regulate the system to reach its optimal generation point. Among others, sliding mode control [2] and fuzzy systems [3] have been proposed as feasible control alternatives.

\* Corresponding author. Tel.: +886-6-5979566 ext. 5527

E-mail address: [ch\\_huang@cc.feu.edu.tw](mailto:ch_huang@cc.feu.edu.tw).

All those control strategies can enhance the robustness of the system to capture the maximal wind energy and improve the dynamic performance [4]. On the other hand, to preserve the robust performance under parameter variations and external mechanical disturbances, many studies have been engaged on the generator drives, including ANN feed-forward control of the torque compensation. This paper proposes a neural-network-based structure for WECS control. It consists of two combined control actions : a sliding mode control, and an ANN based controller [5].

### 2. Wind Turbine Generator System

A simple block-diagram of a wind generation system is shown in Figure 1. WECS has many interesting characteristics regarding simplicity, reliability and maintenance costs. WECS is the most cost competitive among all renewable energy sources. They are usually found in three basic topologies: standalone, hybrid, and grid connected installations [6]. Standalone systems are found with battery chargers for applications such as illumination, remote radio repeaters, and sailboats. Hybrid systems are used in small to medium autonomous applications, combining wind turbines with diesel and solar generators.

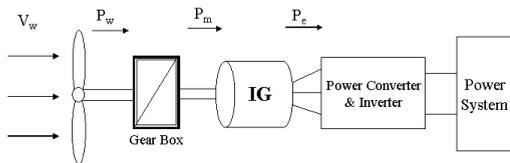


Fig. 1 Block diagram of the wind turbine

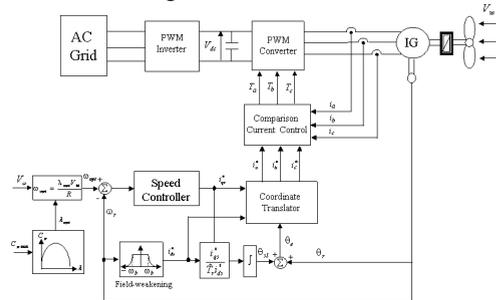


Fig.2 Indirect Field-Oriented IG system block diagram

A block diagram of indirect field-oriented IG system is shown in Figure 2, which consists of an IG, a current-controlled PWM voltage source converter (VSC), a field-orientation mechanism, including the coordinate translator, and a speed control loop. The IFOC dynamics for the induction machine of torque, slip angular frequency and voltage command can be derived from Equation (1)-(2), respectively at  $\lambda_{qr} = 0$ ,  $p\lambda_{qr} = 0$ ,  $p\lambda_{dr} = 0$ , and  $\omega = \omega_e$ . The torque equation and slip angular frequency for rotor field orientation are given in Equation (1) while the voltage commands of IFOC are given in Equation (2) by

$$T_e = \frac{3}{2} \frac{P}{L_r} \frac{L_m^2}{L_r} i_{qs}^e i_{ds}^e, \quad \omega_{sl} = \frac{1}{T_r} \frac{i_{qs}^e}{i_{ds}^e} \tag{1}$$

$$\begin{bmatrix} V_{qs}^e \\ V_{ds}^e \end{bmatrix} = \begin{bmatrix} \omega_e \lambda_{dr} \frac{L_m}{L_r} \\ 0 \end{bmatrix} - \begin{bmatrix} R_s + L_s \sigma p & \omega_e L_s \sigma \\ -\omega_e L_s \sigma & R_s + L_s \sigma p \end{bmatrix} \begin{bmatrix} i_{qs}^e \\ i_{ds}^e \end{bmatrix} \tag{2}$$

where  $i_{qs}^e$ ,  $i_{ds}^e$ ,  $T_r$ ,  $\omega_{sl}$ , and  $\omega_e$  are stator quadrature axis current, stator direct axis current, the rotor time constant, the slip angular frequency, and the angular frequency of the synchronous reference frame, respectively.

### 3. The Proposed Sliding Mode Speed Controller and Feed-forward Artificial Neural Network

The proposed sliding mode speed controller is shown in Figure 3 [7]. The state variables are defined by

$$x_1(t) = \varpi_{opt} - \omega_r(t) \tag{3}$$

$$\dot{x}_1(t) = -\dot{\omega}_r(t) = -x_2(t) \tag{4}$$

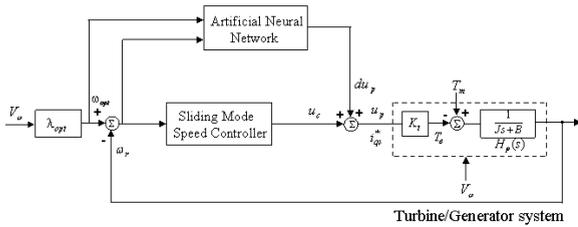


Fig. 3 Closed-loop system block diagram

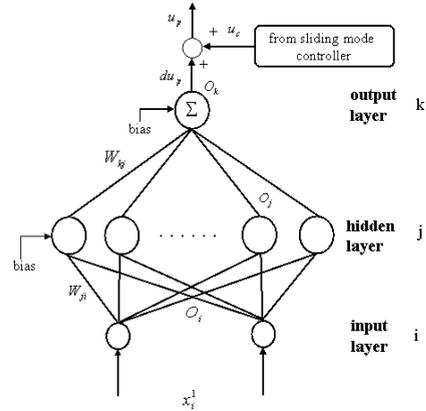


Fig. 4 The general three layer ANN

Then the IG drive system can be represented in the following state-space form by

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} 0 & -1 \\ 0 & -B/J \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} 0 \\ K_t/J \end{bmatrix} i_{qs}^*(t) + \begin{bmatrix} 0 \\ -1/J \end{bmatrix} \dot{T}_m \tag{5}$$

The above equation can be represented as

$$\dot{X}(t) = AX(t) + BU(t) + DT_m \tag{6}$$

where

$$A = \begin{bmatrix} 0 & -1 \\ 0 & -B/J \end{bmatrix}, B = \begin{bmatrix} 0 \\ K_t/J \end{bmatrix}, D = \begin{bmatrix} 0 \\ -1/J \end{bmatrix}, U(t) = i_{qs}^*(t) \tag{7}$$

and  $U(t)$  is output of the proposed sliding mode controller.

A three-layer neural network as shown in Figure 4 is adopted to implement the proposed ANN controller. The ANN input is  $x_1^1$  and  $x_2^1$  of the first layer, where  $x_1^1 = \omega_{opt} - \omega_r$  and  $x_2^1 = \dot{\omega}_{opt}$  in this study. The hidden and output layers contain several processing units with an associated sigmoidal function. The net input to a node  $j$  in the hidden layer  $net_j$  and output of node  $j$   $O_j$  are

$$net_j = \sum(W_{ji} \cdot O_i) + \theta_j, O_j = f(net_j) \tag{8}$$

where  $f$  is the activation function, which is a sigmoidal activation function

$$f(net_j) = \frac{1}{1 + e^{-net_j}} \tag{9}$$

and the net input to a node  $k$  in the output layer  $net_k$  and corresponding output  $O_k$  are

$$net_k = \sum(W_{kj} \cdot O_j) + \theta_k, O_k = f(net_k) = du_p \tag{10}$$

#### 4. Simulation Results

The overall system block diagram is depicted in Figure 3. The wind turbine generator system used for the simulation has the following parameters:

- (1) Parameters of Wind Turbine: rate of power  $P_{mec}=2.5KW$ , air density  $\rho=1.25N_s^2/m^4$ , turbine radius  $R=1.62M$ , moment of inertia  $J=0.0577N_msec^2$ , friction  $B=0.0088N_msec/rad$ ,  $C_1(\beta) = -0.1$ ,  $C_2(\beta) = 0.077$ ,  $C_3(\beta) = 0.08$ .
- (2) Parameters of Induction Generator: stator resistance  $R_s=0.17\Omega$ , rotor resistance  $R_r=0.05\Omega$ , stator inductance  $L_s=0.0062H$ , rotor inductance  $L_r=0.0064H$ , magnetization inductance  $L_m=0.0061H$ , gear ratio  $N1/N2=1$ .

The simulation results show that the wind velocity is well estimated with small errors in both cases. Note that the actual speed is closely tracked by reference speed obtained from the proposed controller. With the controlled rotor speed, the actual turbine power  $P_m$  and the generator power  $P_e$  can track the desired  $P_w$  closely. It shows a robust control performance, both in the wind speed tracking and power regulation. Power tracking performance for various control methods are shown in Tables 1. The control methods for the average power generation from the small to the large under any wind conditions during 50 sec are as follows: PI control, sliding mode with artificial neural network control.

Table 1. Performance comparison with various control methods

Controller Type	Average Power	Max. speed tracking error	Max. power tracking error
SMC with ANN Controller	805W	0.67 rad/sec	120W
PI Controller	770W	1.2 rad/sec	145W

## 5. Conclusion

This paper discussed the application of artificial neural network in the implementation of sliding mode controller for WECS. They were proposed to cope with the intrinsic nonlinear behavior of wind turbines/generators. The approach used, based on a combination of artificial neural network and a sliding mode controller, allowed fast convergence to a simple linear dynamic behavior, even in the presence of parameter changes and model uncertainties. This technique can maintain the system stability and reach the desired performance even with parameter uncertainties. The regulation of the electrical power is an important lecture to be considered.

## References

- [1] Mihet-Popa L, Blaabjerg F, and Boldea I. Wind Turbine Generator Modeling and Simulation Where Rotational Speed is the Controlled Variable. *IEEE Trans. Ind. Appl.* 2004; **40** (1):3-10.
- [2] Battista HD, Mantz RJ, and Christiansen CF. Dynamic sliding mode power control of wind driven induction generators. *IEEE Trans. Energy Conver.* 2005; **15** (4): 451-457.
- [3] Aissaoui AG, Tahour A, Essounbouli N, Nollet F, Abid M, Chergui MI. A Fuzzy-PI control to extract an optimal power from wind turbine. *Energy Conversion and Management.* 2013; **65**:688-696.
- [4] Lin WM, Hong CM, Ou TC, and Chiu TM. Hybrid Intelligent Control of PMSG Wind Generation System Using Pitch Angle Control with RBFN. *Energy Conversion and Management.* 2011; **52** (2): 1244-1251.
- [5] Sabanovic A, Jezernik K, Rodic M. Neural Network Application in Sliding Mode Control Systems. *IEEE workshop on Variable Structure Systems.* 1996; 143-147.
- [6] Sakamoto, Senjyu T, Kinjo T, Urasaki N, and Funabashi T. Output Power Leveling of Wind Turbine Generator by Pitch Angle Control Using Adaptive Control Method. *IEEE International Conf. on Power System Technology.* 2004; 834-839.
- [7] Lin FJ, Chiu SL, and Shyu KK. Novel sliding mode controller for synchronous motor drive. *IEEE Trans. Aerosp. Electronic Systems.* 1998; **34** (2):532-542.

**Chih-Ming Hong** was born in 1972. His Ph.D. EE degree from National Sun Yat-Sen University, Kaohsiung, Taiwan, R.O.C., in 2011. He has been with National Kaohsiung Marine University, Kaohsiung, Taiwan, R.O.C., since 2010. Dr. Hong's research interests include motor drive systems, power electronics, control theory applications, and renewable energy systems.

**Cong-Hui Huang** was born in 1979. His Ph.D. EE degree from the National Sun Yat-Sen University, Kaohsiung, Taiwan, in 2003 and 2008, respectively. He has been with Far East University, Hsin-Shih, Tainan County, Taiwan, since 2008. His research interests include power systems operation and security, and intelligent solar control systems.

**Fu-Sheng Cheng** was born in 1962. He received the Ph.D. degree from National Sun Yat-Sen University, Kaohsiung, Taiwan, R.O.C., in 2001. He has been with the Department of Electrical Engineering, Cheng-Shiu University, Kaohsiung, since 1990. He is interested in AI applications on distribution planning and power system operation.