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Optimal control for variable-speed wind generation systems using General Regression Neural Network

Chih-Ming Hong [a], Fu-Sheng Cheng [b], Chiung-Hsing Chen [a,*]

[a] Department of Electronic Communication Engineering, National Kaohsiung Marine University, Kaohsiung 811, Taiwan, ROC
[b] Department of Electrical Engineering, Cheng-Shiu University, Kaohsiung 833, Taiwan, ROC

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ABSTRACT

An induction generator (IG) speed drive with the application of an optimal controller and a proposed General Regression Neural Network (GRNN) 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 GRNN with adaptive ant colony optimization (AACO) torque compensation is feed-forward to increase the robustness of the wind driven induction generator system. An optimal control loop for the wind power system is designed. The optimality of the whole system is defined in relation with the trade-off between the wind energy conversion maximization and the minimization of the induction generator torque variation that is responsible for the frequency fluctuations. This is achieved by using a combined optimization criterion, resulting in a LQ tracking problem with an infinite horizon and a measurable exogenous variable (wind speed). The proposed controller is designed to drive the turbine speed to extract maximum power from the wind and adjust to the power regulation.

1. Introduction

Wind energy is an inexhaustible, sanitary and renewable resource. Many governments are attracted by the WECS with its simple structure, easy maintenance and management. On account of the development and the wide application of power electronics, the technologies of generating electricity by wind energy have proceeded quickly. It has becomes a vital renewable resource for environmental protection adopted worldwide.

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 cannot 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, optimal control [2–4] and fuzzy systems [5–7] have been proposed as feasible control alternatives. All those control strategies can enhance the robustness of the system to capture the maximal wind energy and improve the dynamic performance [8–10]. 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 GRNN 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 optimal control, and a GRNN based controller [11–14].

2. Wind turbine generator system

A simple block-diagram of a wind generation system is shown in Fig. 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 [15], [16]. Standalone systems are found with battery chargers for applications such as illumination, remote radio

* Corresponding author. Tel.: +886 7 3617141x3318; fax: +886 7 3650833.
E-mail address: chiung@webmail.nkmu.edu.tw (C.-H. Chen).

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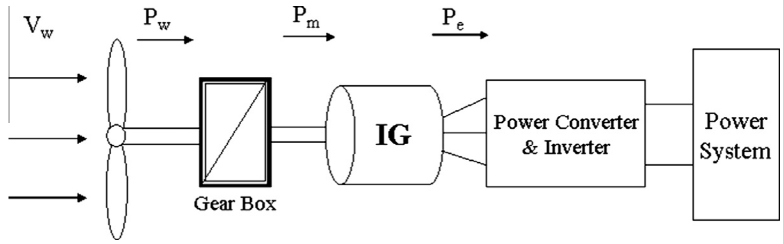

Fig. 1. Block diagram of the wind turbine.

repeaters, and sailboats. Hybrid systems are used in small to medium autonomous applications, combining wind turbines with diesel and solar generators.

2.1. Wind profile

The wind models describe the fluctuations in the wind speed, which will influence the power quality and control characteristics of the wind farm. A wind speed model simulates the wind speed fluctuations that influence the power fluctuations of the wind turbines [17], [18].

Wind speed changes continuously and its magnitude is random over any interval. To simulate the wind speed, it is common to assume that the mean value of the wind speed is constant for some intervals. To simulate the wind velocity V_ω can be expressed as

$$V_\omega = x\left(1 - 0.09\cos\left(\frac{2\pi t}{20}\right) - 0.09\cos\left(\frac{2\pi t}{60}\right)\right) \tag{1}$$

or

$$V_\omega = 1 - 0.1 \cdot x \cdot \cos\left(\frac{\pi t}{5}\right) \cdot e^{\frac{t}{30}} + 0.5 \cdot \sin\left(\frac{\pi t}{20}\right) \tag{2}$$

where x is a chosen number. To simulate wind gusts, the magnitude and frequency of the sinusoidal fluctuations is increased.

2.2. Model of wind turbine

In order to capture the maximal wind energy, it is necessary to install the devices of power electronics between the WT and the grid where frequency is constant. For a wind turbine, the torque produced by the turbine could be described as [19]

$$T_m = \frac{1}{2\lambda}\rho\pi C_p(\lambda,\beta)R^3V_\omega^2 \tag{3}$$

where ρ is the density of the air, R is the radius of the blade, V_ω is the wind speed (m/s), and $C_p(\lambda,\beta)$ is the power coefficient, and is given as a nonlinear function of the parameter λ by

$$\lambda = \frac{\omega_r R}{V_\omega} \tag{4}$$

with ω_r the rotational speed (rad/s). Power coefficient C_p is approximated by $C_p(\lambda,\beta) = C_1(\beta)\lambda + C_2(\beta)\lambda^2 + C_3(\beta)\lambda^3$, where $C_1(\beta)$, $C_2(\beta)$, and $C_3(\beta)$ are constructive parameters for a given turbine. Typical C_P versus λ curves for the pitch angle changing from zero to 10° are shown in Fig. 2. At the point λ_{opt}, $C_p = C_{pmax}$, the maximal power can be captured. It can be seen that C_{pmax}, the maximum value for C_p, is a constant for a given turbine. The dynamic performance of WT could be described as

$$J\frac{d\omega_r}{dt} = T_m - T_e \tag{5}$$

where J is the inertia moment of WT, T_e is electromagnet moment of the generator, and B is the coefficient of the friction. The power captured by the WT could be described as

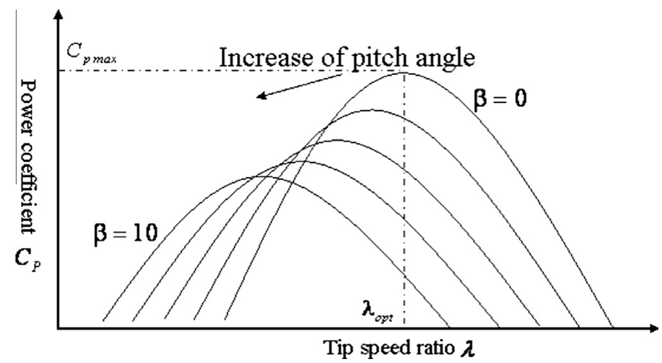

Fig. 2. Typical C_P versus λ curve.

$$P_m = \frac{1}{2}\rho\pi C_P(\lambda,\beta)R^2V_\omega^3 \tag{6}$$

The turbine power P_m and generator speed ω_r, can be related to generator power P_e approximated as

$$P_m = J\omega_r\frac{d\omega_r}{dt} + P_e \tag{7}$$

2.3. Induction generator model

2.3.1. Mathematical model of IG

In this paper, the d-q model of IG in the arbitrary reference frame is used since it provided the complete solution for dynamic analysis and control. The voltage equations of the d-q model are based on the stator current and rotor flux and are given as

$$\begin{bmatrix}0\\0\\0\\0\end{bmatrix} = \begin{bmatrix} R_s + L_s\sigma p & \omega L_s\sigma & \frac{L_m}{L_r}p & \frac{L_m}{L_r}\omega \\ -\omega L_s\sigma & R_s + L_s\sigma p & -\frac{L_m}{L_r}\omega & \frac{L_m}{\sigma L_s L_r T_r} \\ -\frac{L_m}{L_r}R_r & 0 & \frac{R_r}{L_r}+p & \omega-\omega_r \\ 0 & -\frac{L_m}{L_r}R_r & \omega-\omega_r & \frac{R_r}{L_r}+p \end{bmatrix} \begin{bmatrix} i_{qs}\\ i_{ds}\\ \lambda_{qr}\\ \lambda_{dr}\end{bmatrix} + \begin{bmatrix}V_{qs}\\V_{ds}\\V_{qr}\\V_{dr}\end{bmatrix} \tag{8}$$

where $\sigma = 1 - \frac{L_m^2}{L_s L_r}$, $p = \frac{d}{dt}$

The electromagnetic torque is given by

$$T_e = \frac{3}{2}\frac{P}{2}\frac{L_m}{L_r}(\lambda_{dr}i_{qs} - \lambda_{qr}i_{ds}) \tag{9}$$

where V_{qs}, V_{ds}, i_{qs}, and i_{ds} are the stator voltages and current. V_{qr}, V_{dr} are the rotor voltages. λ_{qr}, λ_{dr} are the rotor fluxes. R_s, L_s, R_r and L_r are the resistance and the inductance of the stator and the rotor, respectively. L_m is the magnetizing inductance.

2.3.2. Indirect field orientation control (IFOC) of the IG

A block diagram of indirect field-oriented IG system is shown in Fig. 3, 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