International Journal of Engineering and Applied Sciences (IJEAS)
Vol.2, Issue 3(2010)40-46

WIND ENERGY CONVERSION SYSTEMS CONTROL USING INVERSE NEURAL MODEL ALGORITHM

M. Bayat[1], M. Sedighizadeh[1,2] and A. Rezazadeh[1]
1-Faculty of Electrical and Computer Engineering, Shahid Beheshti University, G. C , Evin 1983963113, Tehran, Iran.
2-Faculty of Engineering and Technology, Imam Khomeini International University, Ghazvin, 34194, Iran
Email: m_sedighi@sbu.ac.ir

Accepted Date: 10 March 2010

Abstract

In this paper, a neural inverse model controller to achieve maximum power tracking for wind energy conversion systems (WECS's) employing a double- fed induction generator (DFIG) is proposed. Changes on the firing angle of the inverter can control the operation point of the generator. This purpose complies with a neural network (NN) controller. Its feasibility and effectiveness are demonstrated by simulation results of a typical turbine/generator pair.

Keywords: Double- fed induction generator; Neural inverse model controller; Wind energy conversion systems

1. Introduction

Motivated by the high dependence of global economies on fossil fuels and concerns about the environment, increasing attention is being paid to alternative methods of electricity generation [1]. Clean renewable energy sources such as solar and wind, have been developed over recent years. Wind is now on the verge of being truly competitive with conventional sources. The cost, weight, and maintenance needs of mechanical gearing between the wind turbine and the electrical generator pose a serious limitation to the further increase in WECS's power ratings [2]. Control plays a very important role in modern WECS's. In fact, wind turbine control enables a better use of the turbine capacity as well as the alleviation of aerodynamic and mechanical loads, which reduce the useful life of the installation [1]. The main drawback is that the resulting system is highly nonlinear and thus, a nonlinear control strategy is required to place the system in its optimal generation point. Among others, adaptive PID control [3, 4], predictive control [5], and fuzzy systems [6, 7, and 8] have been proposed as feasible control alternatives.

Nowadays, considerable attention has been focused on use of artificial neural network in system modelling and control applications. The NN has several key features that make it suitable for controlling nonlinear system. These features include parallel and distributed processing, as well as efficient nonlinear mapping between inputs and outputs without an exact system model [2]. The most successful topologies for this purpose are multilayer perceptron (MLP) [9]. A neural network-based structure for WECS's is proposed in [10]. Moreover, in [3, 10, and 11] an adaptive controller using NN is suggested for wind turbine control. This paper describes the principles of the NN control scheme and shows simulation results.

This paper is organized as follows: Section II derives the model of the system to be controlled. It consists of a wind turbine linked to an induction, wound rotor electric generator. Section III deals with the novel proposed controllers strategies. Section V shows the simulation results. Finally, Section V resumes the conclusions.

2. Wind Energy Conversion Systems

Since the inception of the wind energy technology, machines of several types and shapes were designed and developed around different parts of the world. WECS's are usually found in two schemes: fixed-speed, and variable-speed. Fixed-speed WECS's operate with optimum conversion efficiency only at a single wind speed. In order to make a better use of the turbine, variable-speed WECS's were subsequently developed [1].

2.1 Wind Turbine Characteristics

In this section, we present the application of wind turbine. Most of today's commercial machines are horizontal axis wind turbine (HAWT).

Commonly, the output mechanical power and the torque developed by the wind turbine are expressed in terms of non-dimensional power (C_p) and torque (C_Q) coefficients as follows [1]:

$$P = \frac{1}{2}\rho\pi R^2 C_p V_\omega{}^3 . \tag{1}$$

$$T_t = \frac{1}{2}\rho\pi R^3 C_Q V_\omega{}^2 . \tag{2}$$

Where C_p and C_Q satisfy

$$C_Q = {}^{C_p}\!/_{\lambda} . \tag{3}$$

The two coefficients are given as a nonlinear function of the parameter λ

$$\lambda = {}^{\omega R}\!/_{V_\omega} . \tag{4}$$

Where ρ is the air density, R is the radius of the turbine, V_ω is the wind speed, and ω is the rotational speed. Usually, C_p is approximated as $C_p = \alpha\lambda + \beta\lambda^2 + \gamma\lambda^3$; where α, β and γ are constructive parameters for a given turbine. Fig. 1 depicts typical C_p versus turbine speed curves, with V_ω as a parameter. It can be seen that C_{pmax} , the maximum value for C_p, is constant for a given turbine. That value, when replaced in (1), gives the maximum output power for a given wind speed. This corresponds to an optimal relationship (λ_{opt}) between ω and V_ω. Fig. 2 shows the torque/speed curves of a typical wind turbine, with V_ω as a parameter. Superimposed to those curves is the curve of C_{pmax} . It can be seen that the maximum C_p (and thus, maximum generated power) and the maximum torque are not obtained at the same speed. Optimal performance is achieved when the turbine operates at the C_{pmax} condition. This will be the control objective in this paper [10].

2.2 Induction Generators and Slip Power Recovery

There are basically two variable-speed WECS's: Direct drive synchronous generator and Double fed (wound rotor) induction generator (DFIG).

In DFIG, the stator winding is directly connected to the grid. However, the rotor winding is fed through a rectifier and inverter known as static Kramer drive which can change the electrical frequency as desired by the grid. Variations on the firing angle (α) of the inverter can control the operation point of the generator. Typical configuration of such a system is shown in Fig. 3.

The torque developed by the generator/Kramer drive combination is [3]:

$$T_g = \frac{3R_{eq}{V_s}^2}{s\omega_s\left[(R_s + {R_{eq}}/{s})^2 + (X_s + X_r)^2\right]}. \tag{5}$$

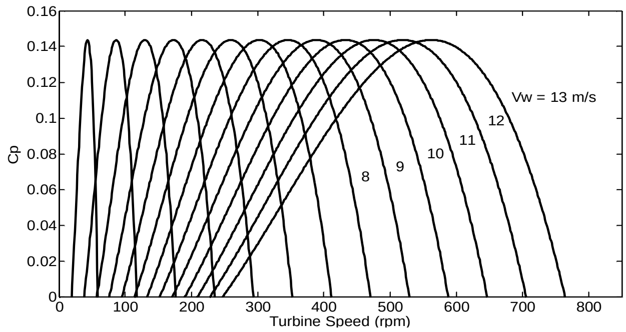

Fig. 1. Power coefficient C_p versus turbine speed [10]

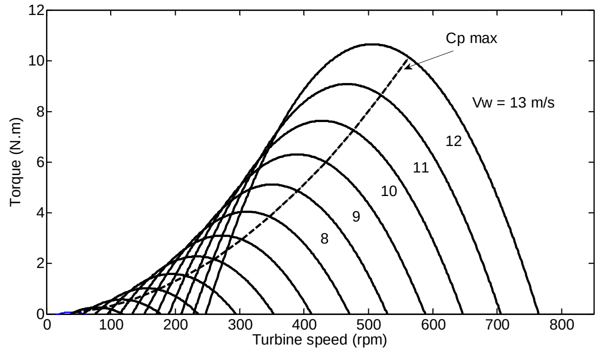

Fig.2. Torque/speed curves (solid) of a typical wind turbine. The curve of C_{pmax} is also plotted (dotted) [10].

Where

$$R_{eq} = f(s,\alpha). \tag{6}$$

and

R_s Stator resistance;
X_s Stator dispersion reactance;
X_r Rotor dispersion reactance;
ω_s Synchronous pulsation;
α firing angle;
s slip.
(All values referred to the rotor side).

2.3 Turbine- Generatore Model

The dominate dynamics of the whole system (turbine pulse generator) are those related to the total moment of inertia. Thus, ignoring torsion in the shaft, generator's electric dynamics, and other higher order effects, the approximate dynamic model of the system is:

$$J\omega^{\bullet} = T_t(\omega, V_\omega) - T_g(\omega,\alpha) \tag{7}$$

Where J is the total moment of inertia. Regarding (2) and (5), the system model becomes:

$$\omega^{\bullet} = \frac{1}{J}\Big(\frac{1}{2}\rho\pi R^3 C_Q V_\omega{}^3 - \frac{3R_{eq}V_s{}^2}{s\omega_s\left[(R_s + {R_{eq}}/{s})^2 + (X_s + X_r)^2\right]}\Big) \tag{8}$$

Where R_{eq} depends nonlinearly on the control action *cos(α)* according to (6). C_p, λ, and V_ω also depend on ω in a nonlinear way (3). Moreover, it is well known that certain generator parameters, such as wound resistance, are strongly dependent on factors such as temperature and aging. Therefore, a nonlinear control strategy seems very attractive. Its objective is to place the turbine in its maximum generation point in despite of wind gusts and generator's parameter changes. Thus, the proposed control strategy consists of changing α to produce a generator's torque that this torque settles the turbine on the ω_{opt}, $T_{t(opt)}$ [10].

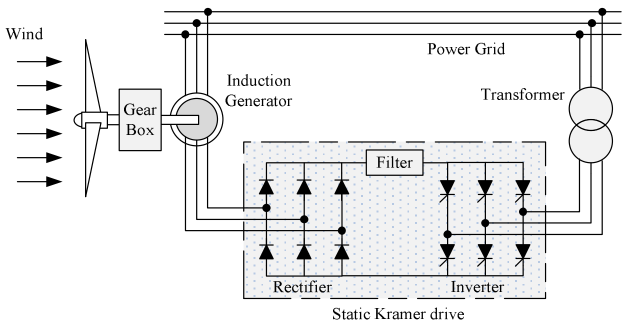

Fig.3. Basic Power Circuit of a DFIG

3. Proposed Control Strategy

This section presents a description of algorithms and the architecture of NN controller.

Nowadays, considerable attention has been focused on use of NN in system modelling and control applications. One of the simplest approaches for the implementation of the neuro-controller is the direct inverse model control approach. The principle of this is that if the process can be described by:

$$\begin{aligned} y(t+1) = F\big[&y(t), y(t-1), ..., y(t-n+1), \\ &u(t), u(t-1), ..., u(t-m+1)\big] \end{aligned} \tag{9}$$

Where $y \in \Re$ denotes the output, $u \in \Re$ is the input, t is the discrete time index, n and m are non-negative integers and $F(.)$ is a non-linear function.

The task is to learn how to control the plant described in (9) in order to follow a specified reference $y_d(t)$, minimizing some norm of the error:

$$e(t) = y_d(t) - y(t)\,. \tag{10}$$

A network is trained as the inverse of the process:

$$\begin{aligned} u(t) = F^{-1}\big[&y(t+1), y(t), ..., y(t-n+1), \\ &u(t-1), ..., u(t-m+1)\big] \end{aligned} \tag{11}$$

Before considering the actual control system, an inverse model must be trained. Two strategies for obtaining the inverse model are existed: general training and specialized training. First architecture used in this paper.

The network used for identification of an inverse model of the WECS is a two-layer feed-forward neural network with the error back-propagation learning algorithm that consists of input, one hidden and output layers is depicted in Fig. 4. In this architecture, we calculate the variation $\Delta u(t) = u(t) - u(t-1)$ and $\Delta y(t) = y(t) - y(t-1)$ .The activation function for all neurons is unipolar sigmoid and, thus signals normalized. The $\Delta y(t+1)$ feature output variation will allow us achieve a one- step predictive control.

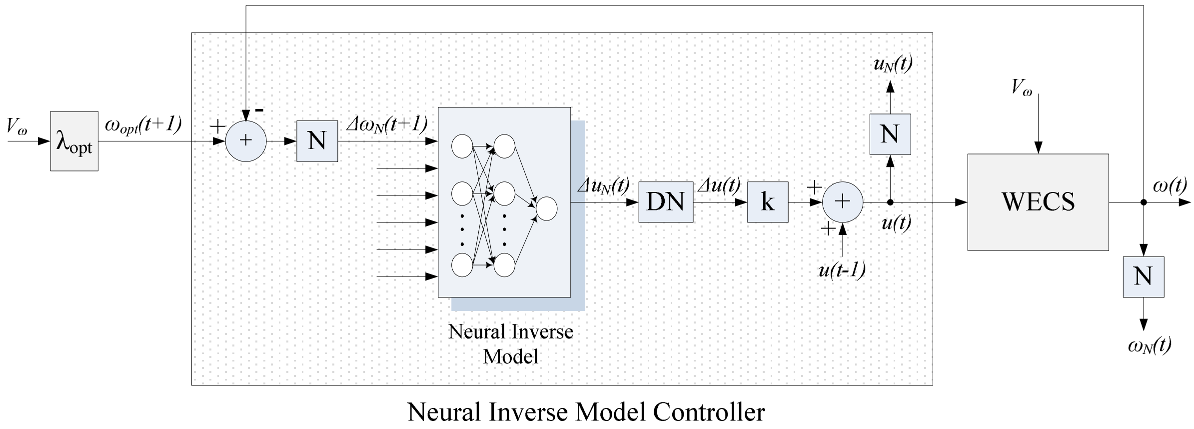

Figure 5. Closed loop block diagram

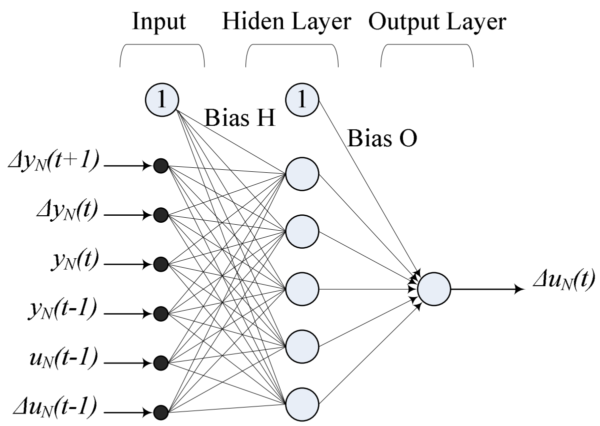

Fig.5. Structure of multi-layer neural networks

For this case study, *y(t)* is rotor speed *ω*; and control signal *u(t)* is *cos(α)*. A NN, as mentioned, includes 6 neurons in input layer, and 7 neurons in hidden layer. Random inputs will be applied to the model to generate the training data. The weights and biases are initialized with random alue of uniform distribution between -1 and 1. The adaptation gain is chosen 0.02.

When the identification model is completed, the NN controller will be used for the purpose of tracking the desired set point by inserting the desired output $y_d(t+1)$, instead of the output $y(t+1)$. This controller can be implemented directly with the previously identified plant model as shown in

Fig. 5. The network output signal, after having been de- normalized and multiplied by a k gain, is added to the applied control at the previous sampling time. The k gain value has an influence over the closed-loop stability. We set it 0.2. The steady state error is nil thanks to the presence of integral control.

4. Simulation Results

In this section, NN controller is implied to the WECS's and results are depicted. In Fig. 6, a step sequence of step-shaped wind gusts is applied to the system. The resulting evolution of the closed loop converges rapidly to the desired optimal rotational speed. Variation of *cos*(α), control signal is shown in Fig. 7.

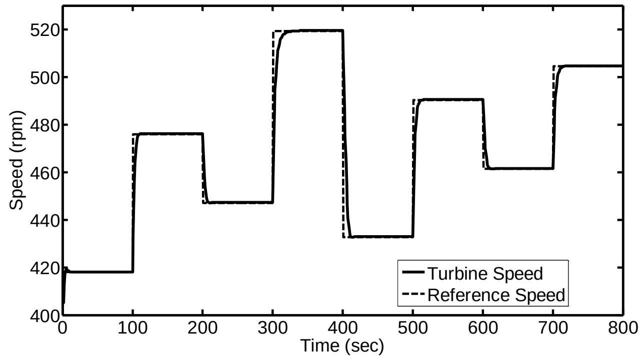

Fig.6. Inverse neural model controller Responses to a sequence of wind gusts

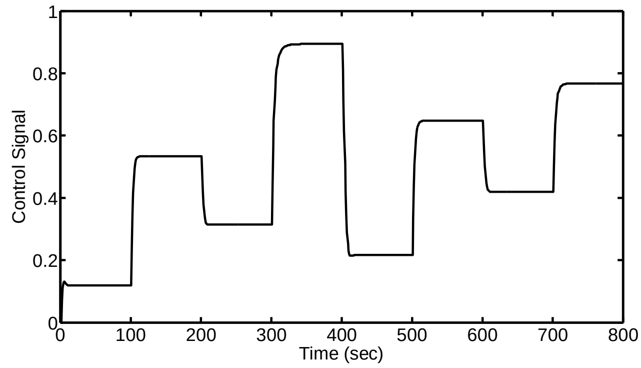

Fig.7. Variation of *cos*(α), control signal

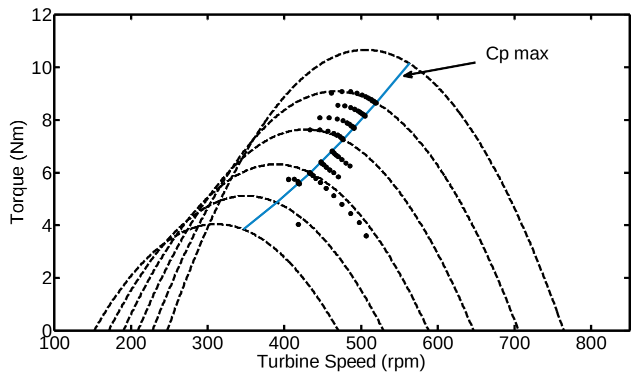

Fig.8. System response on torque/speed coordinates, for the same input sequence of Fig. 6. developed torque (points) converges to the maximal torque curve, ensuring optimal operation.

Moreover, Fig. 8 depicts the turbines developed torque versus rotational speed for the same input sequence. In addition, the turbine characteristic curves are displayed (dashed line).It can be seen that the torque trajectories of the controlled system converge to the points belonging to the maximum torque curve. The proposed controller can be efficiently implemented in signal processors.

5. Conclusions

This paper discussed the application of NN in the implementation of off-line controllers for WECS's. A NN controller was developed to perform the optimal power control of wind generation systems. The utilized approach, based on a MLP, allowed fast convergence to a nonlinear dynamic behavior. The system performance was studied by simulation to validate the concepts and principles. Simulation results indicated that the proposed controller could realize stable tracking control for WECS's. It was strongly robust for system distribution. The presented algorithm is universal and can be applied to other systems.

References

[1] F. D. Bianchi, H. De Battista and R. J. Mantz, *Wind Turbine Control Systems Principles, Modelling and Gain Scheduling Design* .Springer-Verlag London Limited 2007.

[2] M. N. Eskander, "Neural network Controller for a permanent magnet generator applied n a wind energy conversion systems," 2002.

[3] M.Sedighizadeh and A.Rezazadeh, "Adaptive PID control of wind energy conversion systems using RASPI mother wavelet basis function Networks," *Proceeding of World Academy of Science, Engineering and Technology*, vol. 27, February 2008.

[4] M.Sedighizadeh and A.Rezazadeh, "Adaptive PID controller based on reinforcement learning for wind turbine control," *Proceeding of World Academy of Science, Engineering and Technology*, vol. 27, February 2008.

[5] M. Bayat, H. K. Karegar, "Application of Predictive Control in DFIG Wind Turbines" unpublished.

[6] P. Simoes, B. K. Bose, and R. J. Spiegel, "Fuzzy logic-based intelligent control of a variable speed cage machine wind generation system," *IEEE Trans*. Power Electron., vol. 12, no. 1, Jan. 1997.

[7] Z. Chen and S. A. Gomez and M. McCormick, "A Fuzzy logic controlled power electronic systems for variable speed wind energy conversion systems,".

[8] K. Narendra and K. Parthasarathy, "Identification and control of dynamical systems using neural networks," *IEEE Trans*. Neural Networks, vol. 1, Mar. 1990.

[9] S. Haykin, *Neural Networks, a Comprehensive Foundation*. New York: Macmillan, 1994.

[10] M. A. Mayosky, G. I. E. Cancelo, "Direct adaptive control of wind energy conversion systems using Gaussian networks", *IEEE Trans.* Neural Networks, vol. 10, no. 4, July 1999.

[11] M. Sedighizadeh, M. Bayat, A. Rezazadeh, "Nonlinear model identification and adaptive control of variable speed wind turbine using recurrent neural network," unpublished.