Energy 106 (2016) 137–146

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

New neural network and fuzzy logic controllers to monitor maximum power for wind energy conversion system

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ARTICLE INFO

Article history:
Received 4 January 2016
Received in revised form
24 February 2016
Accepted 6 March 2016
Available online 1 April 2016

Keywords:
Neural network
Fuzzy logic
Controllers
Maximum power
Wind energy conversion system

ABSTRACT

This work presents a new control strategy to ensure maximum power point tracking for a DFIG (doubly fed induction generator) based WECS (wind energy conversion system). The proposed strategy uses neural networks and fuzzy logic controllers to control the power transfer between the machine and the grid using the indirect vector control and reactive power control techniques. This transfer is ensured by controlling the rotor via two identical converters. The first converter is connected to the RSC (rotor side) and the second is connected to the GSC (grid side) via a filter. The DC (Direct Current) link voltage is controlled by a fuzzy controller. This control strategy is used to control the rotor side currents and to protect the generator by limiting the output current (or voltage).

1. Introduction

In the area of wind power generation systems, where the wind speed varies considerably, VSG (variable speed generation) is more interesting than fixed speed systems [1,2]. In these systems, a MPPT (maximum power point tracking) adjusts a system quantity to maximize turbine power output [3,4]. The generator that operates at variable speeds is extremely attractive. So to exploit these advantages in wind power generation area, new control strategies should be designed, by taking into account all the parts of the system such as the grid, the structure complexity of the DFIG (doubly fed induction generator) with respect to the quality of the energy to be generated. In the absence of suitable control of the produced active and reactive powers many problems may appear when the generator is connected to the grid, such as, low power factor and harmonic pollution [4,5]. Several designs and arrangements have been investigated by using predictive functional and internal mode controllers, where satisfactory results in power response compared with those of the traditional methods, using a conventional PI (Proportional Integral) controller. However, these new methods are hard to implement, due to their complicated structures [6,7].

Among control objectives of WECSs (wind energy conversion system) much work has been achieved in the control of variable speed TSR (Time Speed Ratio) and/pitch controlled wind turbines with the main goal to bring them to the optimum operating point for maximum power conversion [3,6,8]. Many control schemes has been proposed for this purpose [9–13].

Adaptive control [14,15], which is a promising approach since it provides controllers the ability of learning and auto-adjustment as systems and/or environment change [16,17]. This feature is particularly useful for DFIGs which are immersed in highly stochastic and varying winds [18,19]. Different adaptive control schemes were proposed for achieving maximum power capture in WECSs in Ref. [20], the authors proposed an adaptive fuzzy control of a PMSG-based wind turbine, which dealt successfully with the uncertainties in the turbine parameters, in Ref. [21] an adaptive control scheme using radial basis function was proposed, in both works, a sliding supervisory term is introduced, this last can be a source of chattering and complexity, another limitation of this approach is the boundedness assumptions made on the control gain, its derivative and on the structural error [20], and the dynamics field vector [21].

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http://dx.doi.org/10.1016/j.energy.2016.03.026
0360-5442/

List of abbreviations

Ωt	Rotational speed of the turbine (m/s),
Ct	Turbine torque (N.m),
Ωmec	Mechanical speed of the turbine (m/s),
Cmec	Mechanical torque (N.m),
C_{em}	Electromagnetic torque (N.m),
C_{aero}	Aerodynamic torque (N.m),
Cp (λ,β)	power coefficient,
B	Orientation angle of the blades,
λ	Specific speed,
V_{wind}	Wind speed (m/s),
R	Ray of the blades (m),
f	Coefficient of friction (Ns/m),
J	Inertia (Kg/m^2),
G	Multiplier,
ρ	Air density (Kg/m^3),
V_{ds}, V_{qs}	Stator voltage direct (V),
I_{ds}, I_{qs}	Stator current direct (A),
V_{dr}, V_{qr}	Rotor voltage direct (V),
I_{dr}, I_{qr}	Rotor current Quadrature (A),
R_s, R_r	Resistance of stator and rotor (Ohm),
R_f	Filter resistance (Ohm).
V_g, I_g	Voltage and current side network (V), (A),
L_g	Inductance side network (H),
φ_{ds}, φ_{qs}	Stator flow direct (Weber),
φ_{dr}, φ_{qr}	Rotor flow Quadrature (Weber),
L_s,L_r	Stator and rotor inductance (H),
M	Mutual inductance (H),
ω_s, ω_r, ω_{gli}	Stator, rotor and slip angular speed (rd/s),
P	Number of the pair of the pole,
P_s, Q_s	Stator active and reactive power (Watt),
P_r, Q_r	Rotor active and reactive power (VAR),
P_g, Q_g	Active and reactive power side network (Watt), (VAR),

This paper is an alternative approach which has been proposed using optimized Neural Networks and Fuzzy Logic controllers to control the active and reactive powers through the rotor circuit, these types of controllers have been used due to their characteristics and benefits, such as their robustness, easy to understand and design, *via* the introduction of human expertise … etc [22–25].

The main objective of this work is to propose new neural network and adaptive fuzzy controller schemes for maximum wind power capture, applied to the doubly fed generator. The proposed schemes require controlling RSC (rotor side) and GSC (grid side). This paper is organized as follows. Section 1, briefly presents the model of the wind turbine, Section 2, presents a background of maximum power extraction objective. Section 3, presents modeling of asynchronous double feed Generator, the modeling of the indirect vector control power and the grid side converter, finalized by the DCLink voltages control. Section 5, outlines the proposed neural network and fuzzy logic controllers. Section 4, presents simulation results, Section 5 concludes the paper.

2. Wind turbine modeling

Fig. 1 represents the main parts of the studied WECS (wind energy conversion system).

The extracted power is expressed by: [26]

$$P_{\max} = \frac{1}{2} C_p(\lambda) \rho \pi R^2 V_{\text{wind}}^3 \tag{1}$$

$C_p(\lambda,\beta)$ is the power coefficient, expresses the aerodynamic efficiency of the turbine. With β is the pitch angle of the blades, so the ratio λ can be expressed as follows $\lambda = \frac{\Omega_t R}{V}$; C_P for 7.5 kW wind is defined as:

$$C_p(\lambda,\beta) = C_1 \left(\frac{C_2}{\lambda_i} - C_3 \beta - C_4 \right) e^{\frac{C_5}{\lambda_i}} + C_6 \lambda \tag{2}$$

With:

$$C_1 = 0.5176, C_2 = 116, C_3 = 0.4, C_4 = 5, C_5 = 21, C_6 = 0.0068 \tag{3}$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.008\beta} - \frac{0,035}{\beta^3 + 1}$$

The limit of Betz is defined by $C_p = 0.48$ for a specific speed $\lambda_{opt} = 8.1$ the WECS provides optimal power rating to determine the evolution of the mechanical speed from the total torque C_{mec}

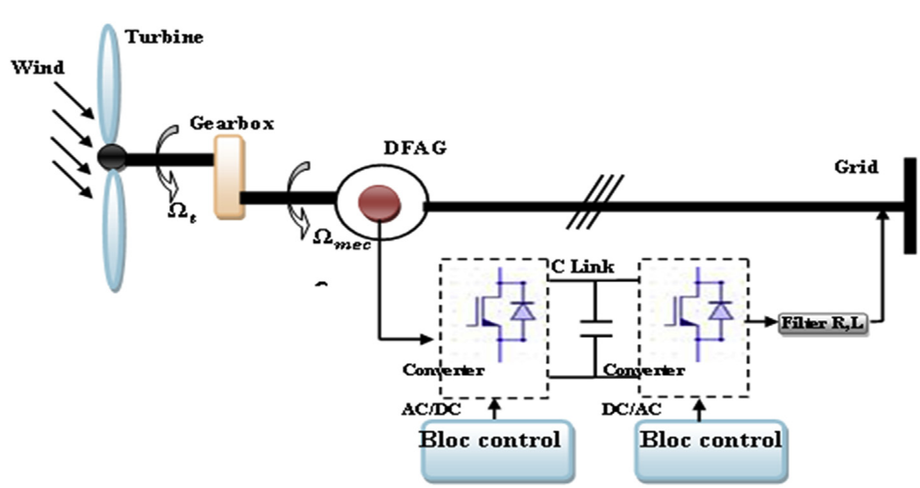

Fig. 1. The studied wind energy conversion system.