A variable speed wind generator maximum power tracking based on adaptative neuro-fuzzy inference system

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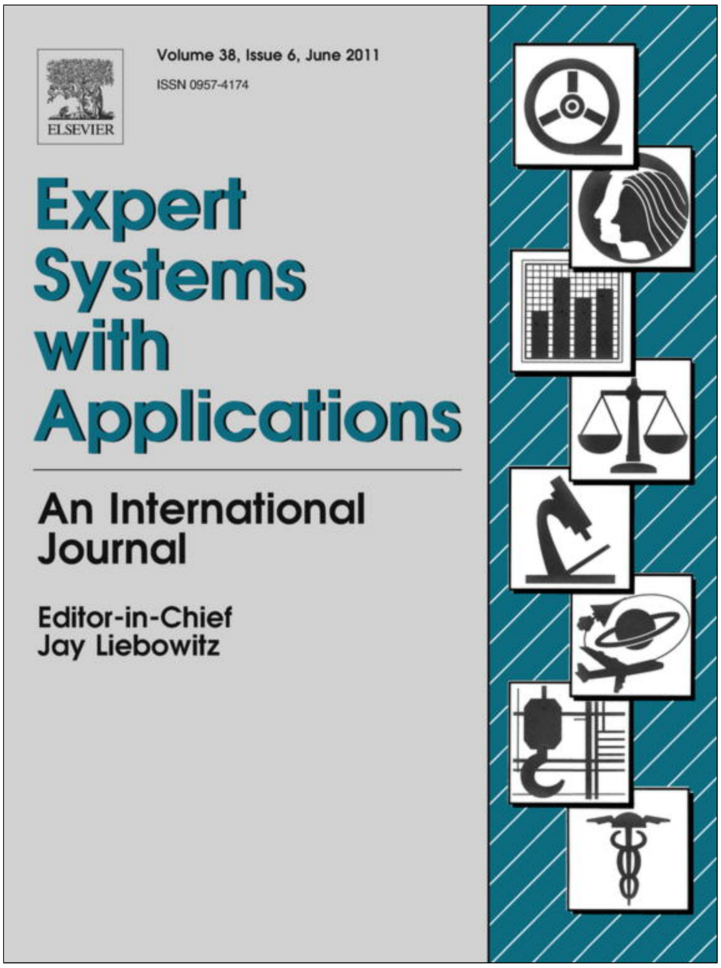
Mustapha Hatti
UDES Unité de Développement des Equipements Solaires

A. Boudghene Stambouli
Université des Sciences et de la Technologie d'Oran Mohamed Boudiaf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A variable speed wind generator maximum power tracking based on adaptative neuro-fuzzy inference system

A. Meharrar *, M. Tioursi, M. Hatti, A. Boudghène Stambouli

Faculty of Electrical Engineering, University of Sciences and Technology of Oran, BP 1505, EL M'Naouer, Oran, Algeria

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ABSTRACT

The power from wind varies depending on the environmental factors. Many methods have been proposed to locate and track the maximum power point (MPPT) of the wind, such as the fuzzy logic (FL), artificial neural network (ANN) and neuro-fuzzy. In this paper, a variable-speed wind-generator maximum-power-point-tracking (MPPT) based on adaptative neuro-fuzzy inference system (ANFIS) is presented. It is designed as a combination of the Sugeno fuzzy model and neural network. The ANFIS model is used to predict the optimal speed rotation using the variation of the wind speed as the input. The wind energy conversion system (WECS) employing a permanent magnet synchronous generator connected to a DC bus using a power converter is presented. A wind speed step model was used in the design phase. The performance of the WECS with the proposed ANFIS controller is tested for fast wind speed variation. Simulation results showed the possibility of achieving maximum power tracking for the wind and output voltage regulation for the DC bus simultaneously with the ANFIS controller. The results also proved the good response and robustness of the control system proposed.

1. Introduction

Electric power generation using non-conventional sources is receiving considerable attention throughout the world due to exhaustion of fossil fuels, and environmental issue. The wind energy, which is the clean energy source and infinite natural resources, is one of the available non-conventional energy sources (Senjyu et al., 2006).

The power generation using wind energy is possible in two ways, constant speed operation and variable speed operation using power electronic converts. The variable speed operation for wind generator is attractive because of its characteristic to achieve maximum efficiency at all wind velocities. Therefore, variable speed control of permanent magnet generator which applied vector control is needed.

The wind systems are, by nature, non-linear power sources that need accurate on-line identification on the optimal operating point. Also, the power from wind varies depending on the environmental factors such as the wind velocity v (m/s).

Aiming at optimizing such systems to ensure optimal functioning of the unit, new techniques are used today such as the fuzzy logic (FL), artificial neural network (ANN) and neuro-fuzzy.

ANFIS is used in many areas such as (Sorousha & Parisa, 2009) forecasting (Aznarte et al., 2007), classifying (Ozturk, Arslan, & Hardalac, 2008; Sengur, Turkoglu, & Ince, 2007), controlling (Elmas, Ustun, & Sayan, 2008), recognition (Avci & Avci, 2007; Avci, Hanbay, & Varol, 2007) and diagnosing (Güler & Ubeyli, 2004; Polat & Gunes, 2007; Übeyli, 2008).

In this study, the ANFIS controller is designed and adapted to tracking a maximum power of the wind. Neural network (NN) is used to adjust input and output parameters of membership function in the fuzzy logic controller (FLC). The back propagation learning algorithm is used for training this network. This intelligent controller is implemented using Matlab/Simulink and the performances are investigated.

2. Wind energy conversion subsystem (WECS)

The block diagram of the wind energy system adopted in this paper is shown in Fig. 1. It consists of a horizontal axis wind turbine compiled to a permanent magnet synchronous generator (PMSG). A detailed description of the wind model can be found in Eminoglu (2009).

The system is designed to achieve maximum power tracking (MPT) and output voltage regulation within a wide range of wind speed variation by means of MPPT block.

3. Control of the WECS

The WECS includes the wind turbine; the PMSG and the rectifier (Fig. 2).

* Corresponding author.
E-mail address: meharrar_aoued@yahoo.fr (A. Meharrar).

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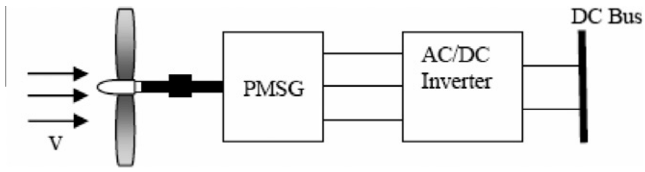

Fig. 1. Wind generation system configuration.

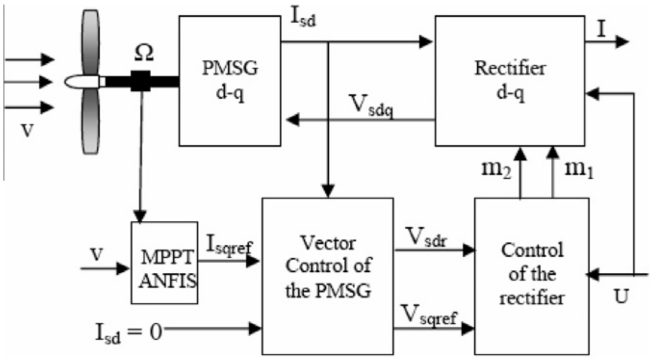

Fig. 2. Energetic macroscopic representation of the WECS.

The rectifier makes it possible to control the PMSG flux and consequently the speed of generator. The Block MPPT wind provides the value I_{sqref} corresponding to the value of the reference electromagnetic torque. In this study, the vector control strategy applied to the PMSG, which consists in imposing a reference of the forward current I_{sdref} to zero, is applied (Ansel & Robyns, 2006).

4. Wind turbine model

The power extracted from the wind is given in Eq. (1). It is rewritten here as (El-Shatter, Eskander, & El-Hagry, 2006):

$$P_t = \frac{1}{2}\rho A C_p v^3 \tag{1}$$

where ρ is the air density in (kg/m^3), A is the area swept by the rotor blades in (m^2), v is the wind velocity in (m/s), and C_p is called the power coefficient or the rotor efficiency and is function of tip speed ration and pitch angle.

The tip speed ration is defined as:

$$\lambda = \frac{\Omega R}{v} \tag{2}$$

where Ω is the rotational speed of the wind turbine in (rad/s) and R is the blade radius in (m).

Manufactures usually give an experimental relationship between C_p and λ parameters, for several values of the rotation speed Ω. In order to evaluate the C_p coefficient, interpolation functions are used to approximate this experimental relationship, within each range of instantaneous values of λ. From this process, the following expressions result:

$$C_p = -v^3(0.12992\lambda^3 - 0.11681\lambda^2 + 0.45406\lambda) \tag{3}$$

The mechanical system is represented by the following equation:

$$J\frac{d\Omega}{dt} = T_m - T_{em} - f\Omega \tag{4}$$

where J is the total inertia which appears on the shaft of the generator in (kg m^2), T_m is the mechanical torque in (N m), T_{em} is the electromagnetic torque in (N m), Ω is the rotational speed of the wind turbine in (rad/s) and f is a viscous friction coefficient in (N m s rad^{-1}).

5. Adaptive neuro-fuzzy inference system (ANFIS)

A neuro-fuzzy system is simply a fuzzy inference system trained by a neural network-learning algorithm. ANFIS is a hybrid of two intelligent systems models (Avci & Akpolat, 2006). It combines the low level computational power of a neural network with the high level reasoning capability of a fuzzy inference system. The advantages of ANFIS over the two parts of this hybrid system are: ANFIS uses the neural network's ability to classify data and find patterns; It then develop a fuzzy expert system that is more transparent to the user and also less likely to produce memorization errors than neural network; Furthermore, ANFIS keeps the advantages of a fuzzy expert system, while removing (or at least reducing) the need for an expert. Also, ANFIS has the ability to divide the data in groups and adapt these groups to arrange a best membership functions that clustering the data and deducing the output

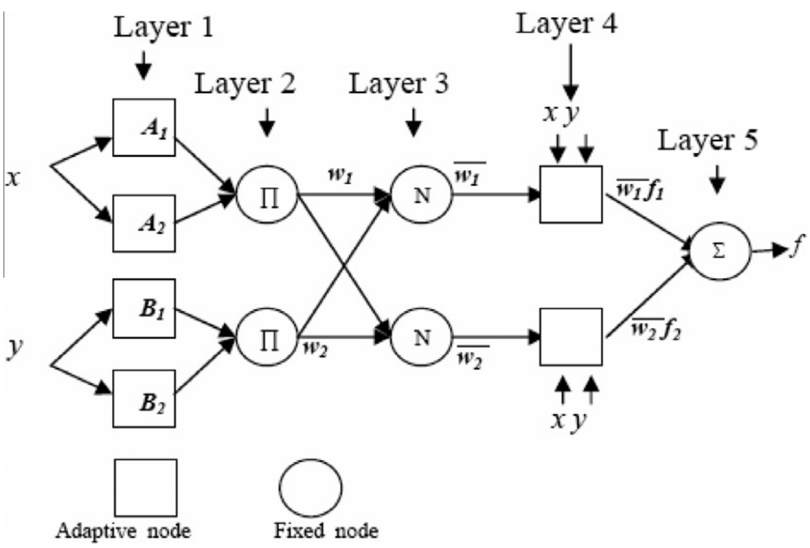

Fig. 3. ANFIS architecture.

desired with minimum epochs. The learning mechanism fine-tunes the underlying fuzzy inference system. Using a given input/output data set, ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone, or in combination with a least squares type of method. This allows your fuzzy systems to learn from the data they are modeling.

Fig. 3 shows a Sugeno fuzzy system (Jang, 1993) with two inputs, one output and two rules and below it, the equivalent ANFIS system is presented (Tashnehlab & Menhaj, 2001). This system has two inputs x and y and one output, where its rule is:

Rule i:

$$\text{if } x \text{ is } A_i \text{ and } y \text{ is } B_i, \text{ then } f_i = p_i x + q_i y + r_i; \quad i = 1, 2 \tag{5}$$

where f_i is output and p_i, q_i and r_i are the consequent parameters of ith rule. A_i and B_i are the linguistic labels which are represented by fuzzy sets whose membership function parameters are premise parameters (Wang, Taha, & Elhag, 2008). The so called firing strength or degree of fulfillment of a pair.

Output of each node in every layer is denoted by O_i^l where i specify the neuron number of next layer and l is the layer number. The performance of each layer is as follows (Buragohain & MahantaA, 2008).

The first layer is the fuzzifying layer in which A_i and B_i are the linguistic labels. The output of the layer is the membership functions of these linguistic labels are given as:

$$O_i^l = \mu_{A_i}(x) \tag{6}$$

$$O_i^l = \mu_{B_i}(y) \tag{7}$$

where $\mu_{A_i}(x)$ and $\mu_{B_i}(y)$ are membership functions that determine the degree to which the given x and y satisfy the quantifiers A_i and B_i.

The second layer calculates the firing strength for each rule quantifying the extent which any input data belongs to that rule. The output of the layer is the algebraic product of the input signals as can be given as:

$$w_i = \mu_{A_i}(x) \Lambda \mu_{B_i}(y); \quad i = 1, 2 \tag{8}$$

"Λ" denotes a fuzzy T-norm operator which is a function that describes a superset of fuzzy intersection (AND) operators, including minimum or algebraic product. In this study algebraic product was used.

The third layer is the normalization layer. Every node in this layer calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths

$$\bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \tag{9}$$

The output of every node in fourth layer is (Negnevitsky, 2002):

$$\bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \tag{10}$$

The fifth layer computes the overall output as the summation of all incoming signals, which represents the results of wave height or wave period as can be given as:

$$O_i^5 = \frac{\sum_{i=1}^{2} w_i f_i}{\sum_{i=1}^{2} w_i}. \tag{11}$$

6. The ANFIS learning algorithm

There are two methods that ANFIS learning employs for updating membership function parameters:

- Backpropagation for all parameters (a steepest descent method).
- A hybrid method consisting of backpropagation for the parameters associated with the input membership functions, and least squares estimation for the parameters associated with the output membership functions (Jang, 1991; Jang, Sun, & Mizutani, 1997).

In order to improve the training efficiency, a hybrid learning algorithm is applied to justify the parameters of input and output membership functions. In this way a two-step process is used for the learning or adjustment of the network parameters. In the first step, the premise parameters are kept fixed and the information is propagated forward in the network to Layer 4, where the consequent parameters are identified by a least-squares estimator. In the second step, the backward pass, the consequent parameters are held fixed while the error is propagated and the premise parameters are modified using a gradient descent algorithm. The only user-specified information is the number of membership functions for each input and the input–output training information. So, the output can be written as:

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2 \tag{12}$$

7. ANFIS control of the WECS

From the variation of the wind speed v, a neuro-fuzzy model made up of radial basis functions computes the optimal speed rotation and thus the aerodynamic torque T_{mref}. This computation is based on the mechanical characteristics of the wind turbine. The optimal torque gives the q-axis reference current I_{sqref}. The d- and q-axis reference currents applied to two PI regulators and two decoupling stages give the d- and q-axis reference voltages V_{sdref} and V_{sqref}. These voltages applied to two modulators provide the switching functions of the rectifier which gives the modulated current I_l. The control strategy of the WECS, previously described, is illustrated in Fig. 4.

8. The ANFIS model

In this study, the ANFIS model uses a hybrid learning algorithm to identify parameters of Sugeno-type fuzzy inference systems. It applies a combination of the least-squares method and the backpropagation gradient descent method for training FIS membership functions (MFs) parameters to estimate a given training data set.

The ANFIS model was simulated by using MATLAB software package that uses 200 training data, and three gbell membership functions, Fig. 5 displays membership functions before and after

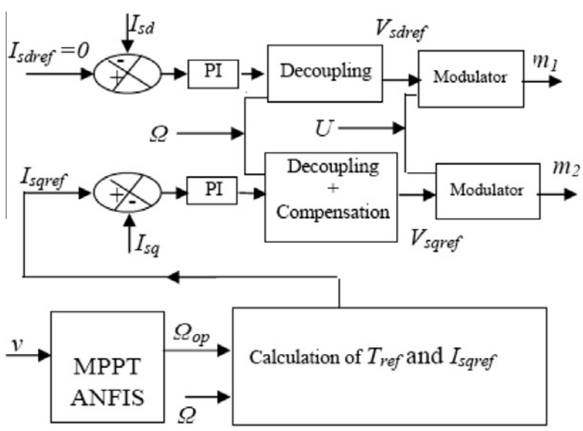

Fig. 4. ANFIS control of the WECS.

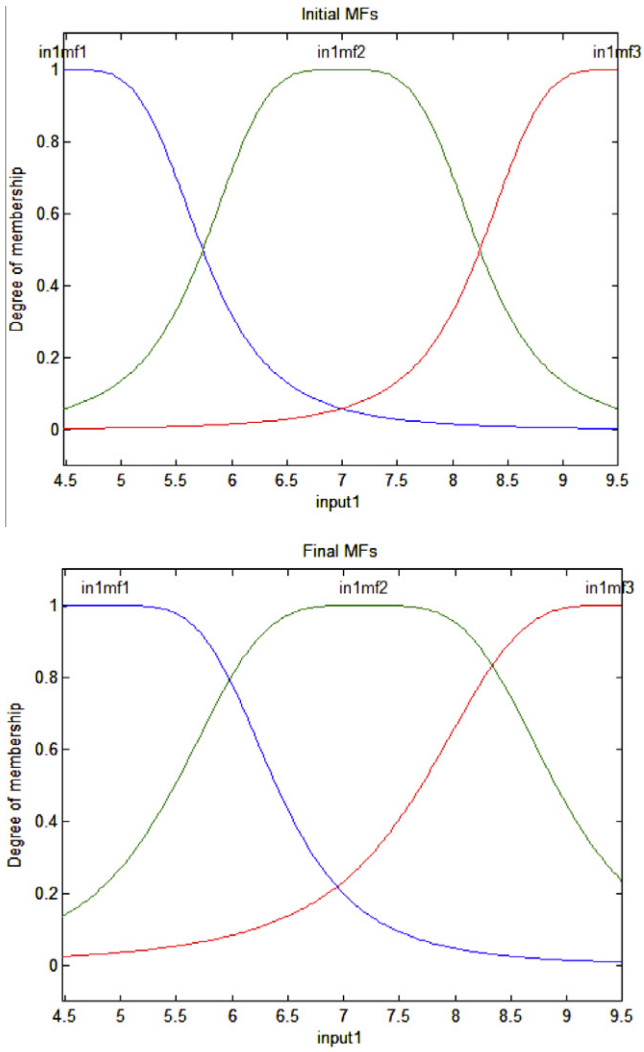

Fig. 5. Membership functions before (initial) and after (final) learning.

ANFIS modeling. In this model the membership function 'gbell' is selected. The training error is shown in Fig. 6.

9. Simulation results

The ANFIS has been simulated using the Matlab/ Simulink. Two cases studies are considered and described as follows:

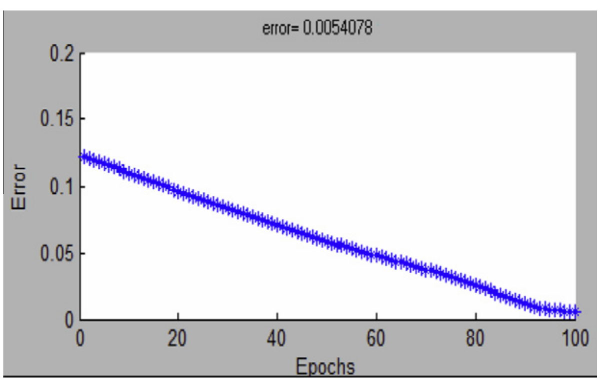

Fig. 6. Training error.

Case 1: Step model of wind velocity.

Simulation results for this case are shown in Figs. 7–11. In Fig. 7 wind speed is shown in the form of fast step variation.

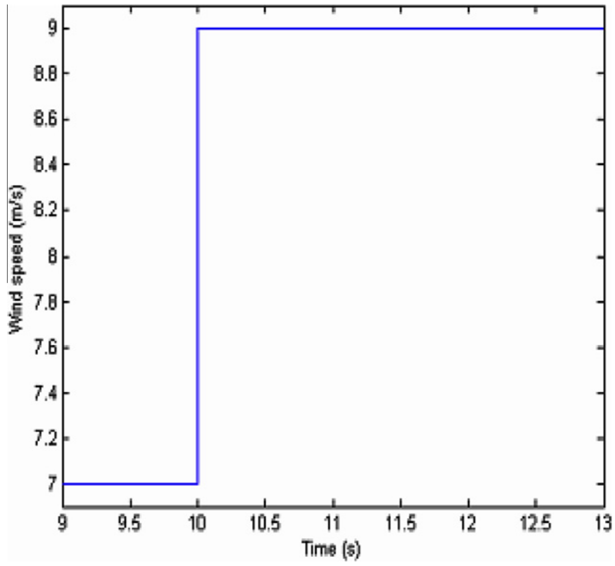

Fig. 7. Setup function of wind speed.

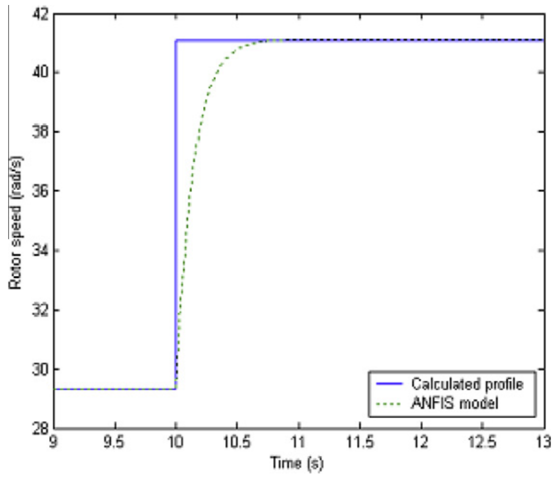

Fig. 8. Rotor speed response.

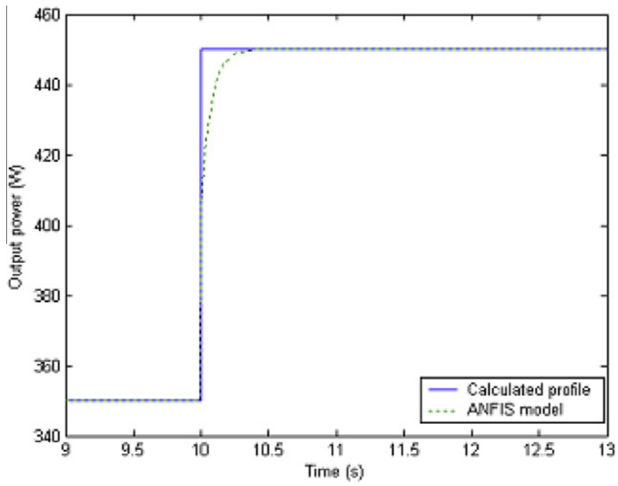

Fig. 9. Output power response.

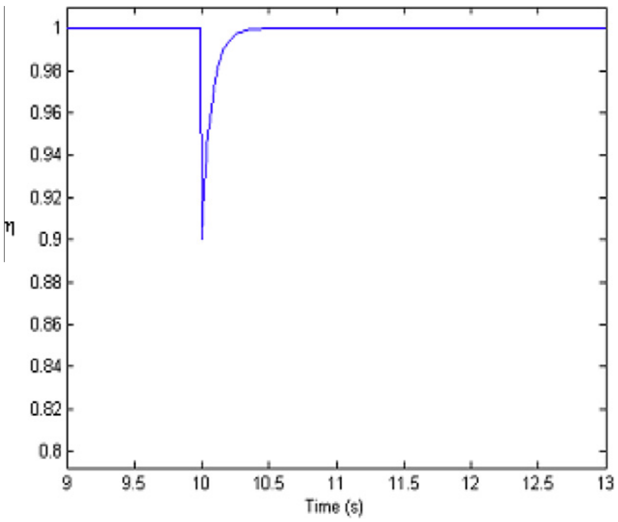

Fig. 10. Efficiency.

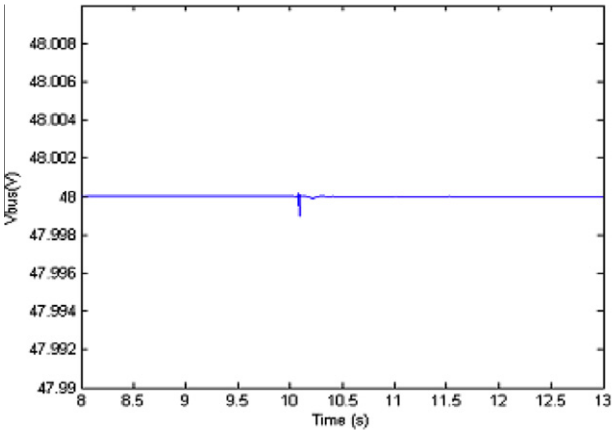

Fig. 11. DC bus voltage response.

Respectively, in Figs. 8 and 9, the output rotor speed and the output power obtained are presented. Fig. 10 gives the system efficiency calculated according to Eq. (13) and Fig. 11 gives the output voltage of DC bus (V_{dc}).

This result shows the fast response and exact maximum power tracking capabilities of the ANFIS controller.

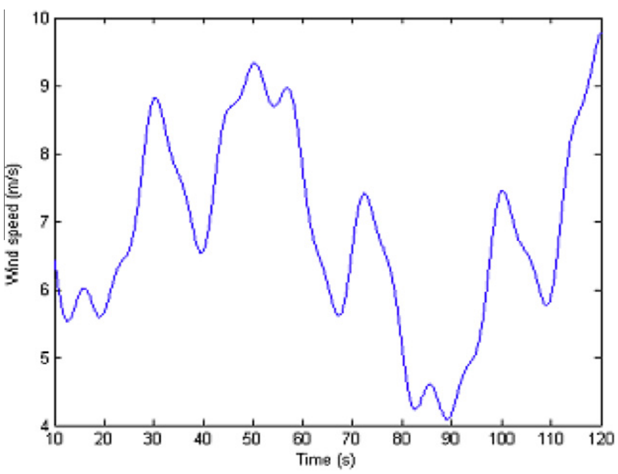

Fig. 12. Wind speed.

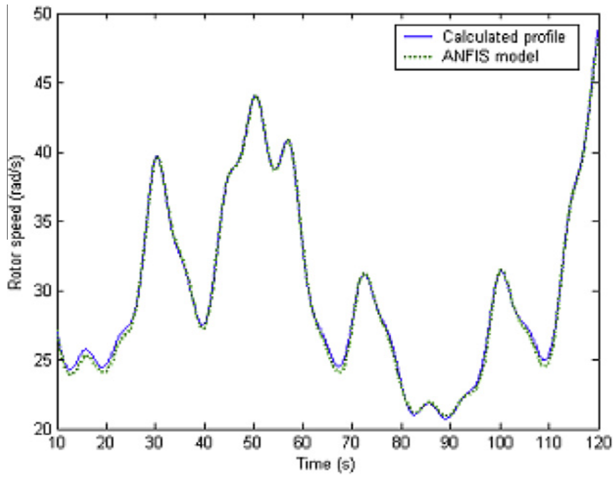

Fig. 13. Rotor speed response.

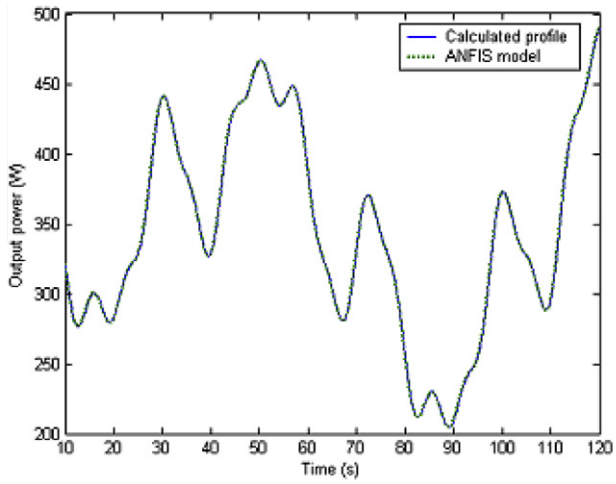

Fig. 14. Output power response.

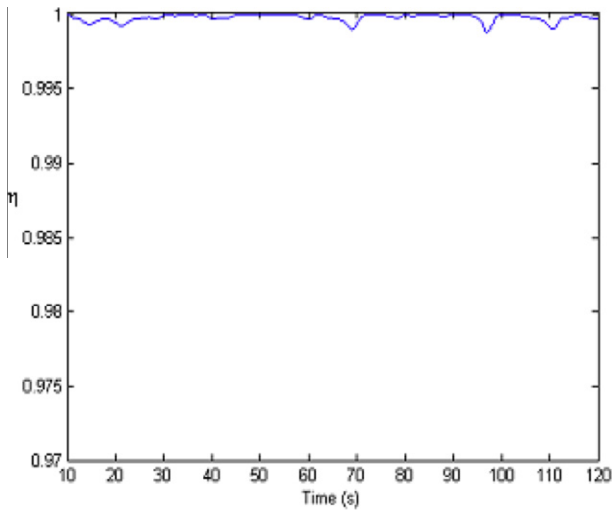

Fig. 15. Efficiency.

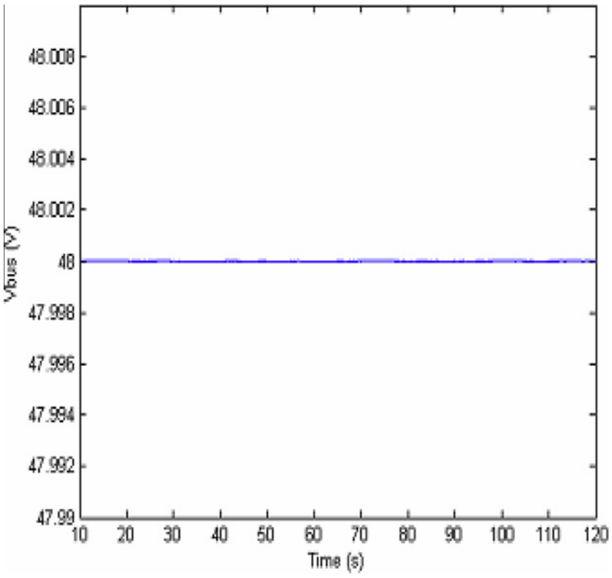

Fig. 16. DC bus voltage response.

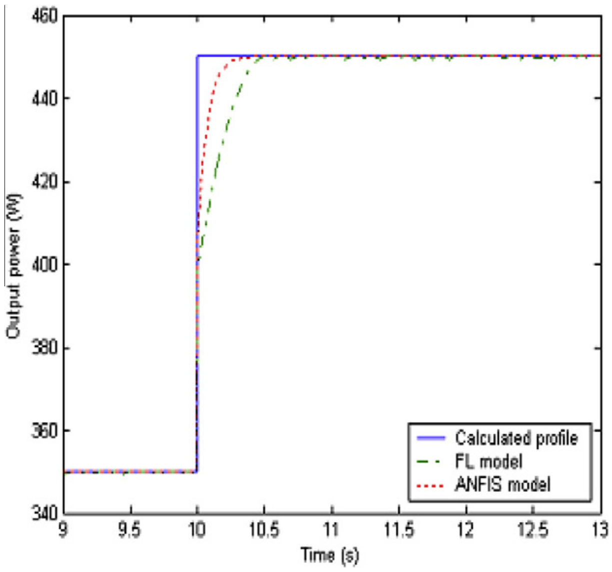

Fig. 17. Comparative output power response with ANFIS and FL.

Case 2: Fast variation of wind velocity.

In this case, the wind speed ranging between 4 and 10 m/s with an average value of 7 m/s is presented in Fig. 12. This sequence is obtained by adding a turbulent component to a slowly varying signal. Respectively, in Figs. 13 and 14, the rotor speed and the output power obtained after using ANFIS model are presented. Fig. 15 gives the system efficiency calculated according to Eq. (13) and Fig. 16 gives the output voltage of DC bus V_{dc}.

$$\eta = \frac{P_{MPPT}}{P_{op}} \tag{13}$$

It is easy to check that in these two cases, the two profiles P_{max} and P_{out} are very close and the results proved the fast response and the capabilities of this controller to tracking the maximum power input. On the other hand, Fig. 17 showed that ANFIS model has a better response compared to fuzzy logic model.

10. Conclusion

In this paper, the WECS was modeled using d-q rotor reference frame.

A variable speed wind generator maximum power point tracking based on an adaptative neuro-fuzzy-inference-system (ANFIS) was presented. The feasibility of this controller is demonstrated and the simulation results for both cases proved the robustness, fast response, and exact maximum power tracking capabilities of the ANFIS control strategy.

The results show also that ANFIS model has a better response compared to fuzzy logic model.

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