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Fuzzy Logic Control of Wind Energy Systems

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Abstract

Wind energy has gained an increasing worldwide interest due to the continuous increase in fuel cost and the need to have a clean source of energy. The main objective of most of the wind energy systems is to extract the maximum power available in the wind stream. However, the wind regime varies continuously and thus the system controllers should be updated to follow these variations. This paper is intended to apply fuzzy logic control techniques to overcome the effect of the wind speed variations on the parameters of the wind turbines and their controllers.

1. Introduction

Wind energy generation has brought about many challenges to electrical power system engineers [1]. The problems encountered in the electrical network comprising wind energy systems are due to the continuous variations in the wind regime [2]. These variations may inflect undesirable fluctuation in the network and thus has limited the capacity of the wind energy systems which can be integrated with the network to a modest penetration factor.

Various techniques have been proposed to cope with the variations in the wind speed to ensure high performance and steady output for the wind energy systems and hence contribute to allow for higher penetration factor.

The effect of the variation in the wind speed may result in:

1- Change in the output voltage
2- Change in the output frequency
3- Change in the output power
4- Shift in the operating point

The change in the output voltage and frequency is solved in this paper by adopting the system which employs a doubly fed induction generator connected to the network. The voltage and frequency in this case are dictated by the main network the variation in the output power is addressed in a companion paper by using a storage battery to smooth the changes in the output power [3].

The shift in the operating point occurs due to the variation in the wind turbine characteristics at different speed and other climate variations. These variations require that the parameters of the controller should be continuously updated to ensure that the wind turbine operating at the optimal point. To cope with the fact the wind speed change in unpredictable manner, it is proposed to use fuzzy logic controllers [4]&[5].

System under study

Fig. 1 shows the system under study which comprises a doubly-fed induction generator connected to the electric network [6]. The generator is driven by a wind turbine. The system is controlled by modulating the slip power extracted from the rotor circuit to implement the required control strategy.

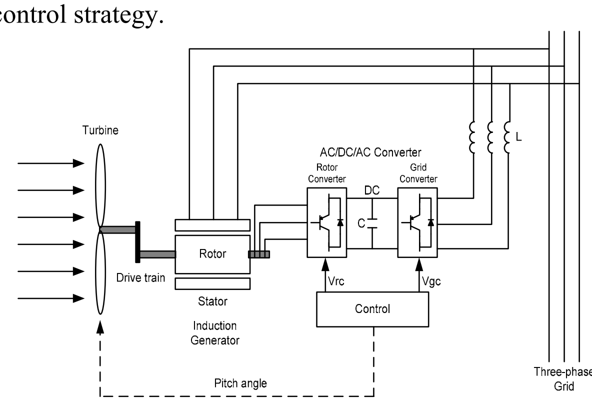


Fig. 1. System under study.

Fuzzy logic controller

The mechanical output power at a given wind speed is drastically affected by the turbine's tip speed ratio (TSR). At a given wind speed, the maximum turbine energy conversion efficiency occurs at an optimal TSR. Therefore, as wind speed changes, the turbine's rotor speed needs to change accordingly in order to maintain the optimal TSR and thus to extract the maximum power from the available wind resources.

Previous research has focused on three types of maximum wind power extraction methods, namely TSR control [7], power signal feedback (PSF) control [8] and hill-climb searching (HCS) [9]. TSR control regulates the wind turbine rotor speed to maintain an optimal TSR. This technique can't adapt itself for the parameters' changes of the wind turbine which lead to changing the optimal TSR. PSF control requires the knowledge of the maximum power curve of the wind turbine. The lack of adaptation results in power losses in case of aerodynamic changes, such as air density changes.

Fuzzy logic provides a convenient method for constructing a maximum power point tracking algorithms. An adaptive fuzzy logic technique for maximum power point tracking (MPPT) under different aerodynamic conditions is proposed. The adaptive feature allows the algorithm to be robust under wind turbine parameters uncertainties.

2. Wind turbine modeling

The output power of a wind turbine is given by the following equation:

$$P_m = \frac{1}{2} C_p(\lambda, \beta) \rho A V_{wind}^3 \quad (1)$$

P_m is the mechanical output power of the turbine (W), C_p is the performance coefficient of the turbine, ρ is the air density (kg/m^3), A is the turbine swept area (m^2), V_{wind} is the wind speed (m/s), λ is the tip speed ratio, and β is the blade pitch angle (deg.). Eq.(1) can be normalized. In the per unit (p.u.) system we have:

$$P_{m\_pu} = K_p C_{p\_pu} V_{wind}^3 \quad (2)$$

A generic equation is used to model $C_p(\lambda, \beta)$.The equation, based on the modeling turbine characteristics [10]:

$$C_p(\lambda, \beta) = C_1 \left(\frac{C_2}{\lambda_i} - C_3 \beta - C_4 \right) e^{\frac{-C_5}{\lambda_i}} + C_6 \lambda \quad (3)$$

with

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1} \quad (4)$$

The coefficients $C_1$to C_6 are: C_1= 0.5176, C_2 = 116, C_3 = 0.4, C_{41} = 5, C_5 = 21 and C_6 = 0.0068. The wind model which is used in the simulation study is based on the available MATLAB/SIMULINK model for the wind turbine [11].The maximum value of C_p (C_{p-max}= 0.48) is achieved for $\beta = 0$ degree and for λ = 8.1. This particular value of λ is defined as the nominal value (λ _nom).

3. Uncertainties of the power curves

The power curves illustrate the mechanical power of a wind turbine versus the rotor speed at different wind velocities. Power curves are found by field measurements, where an anemometer is placed on a mast reasonably close to the wind turbine (not on the turbine itself or too close to it, since the turbine rotor may create turbulence, and make wind speed measurement unreliable).

In reality, a swarm of points spreads around each power curve. The reason is that in practice the wind speed always fluctuates, and one cannot measure exactly the column of wind that passes through the rotor of the turbine. Moreover, the wind speed has different values at each point of the blade. The mechanical power developed by the wind turbine not only depends on the wind speed (which is difficult to measure) but also it depends on the air density and the turbine performance coefficient.

According to the ideal gas law, the density of a gas is proportional to its pressure and inversely proportional to its temperature; see Eq. (5).

$$\rho = \frac{M.P}{R.T} \quad (5)$$

where P is the absolute pressure, M is the molar mass, R is the gas constant (8.314472 JK^{-1}mol^{-1}), and T is the absolute temperature.

If the pressure increases by 10% and the temperature decreases by 15%, the air density will increase about 30%. Fig. 2 shows the effect on the air density on the power curves. When the air density increases, the maximum mechanical power output increases, which results in shifting the maximum power point line.

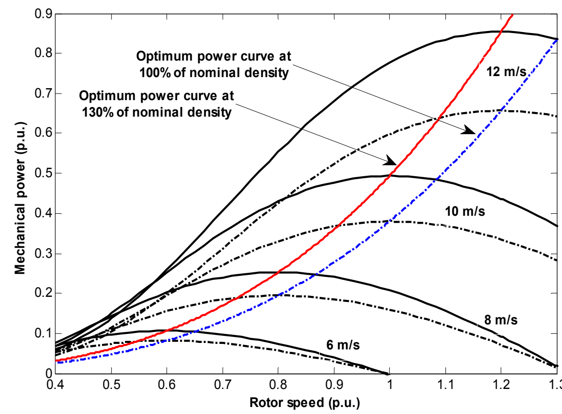


Fig. 2. The effect of air density on the power curves.

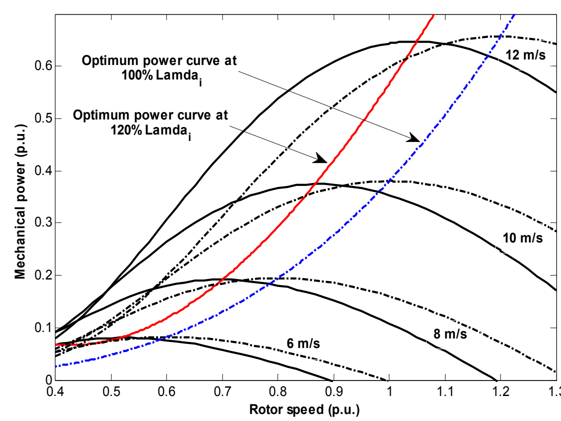


Fig. 3. The effect of changing λ_i on the power curves.

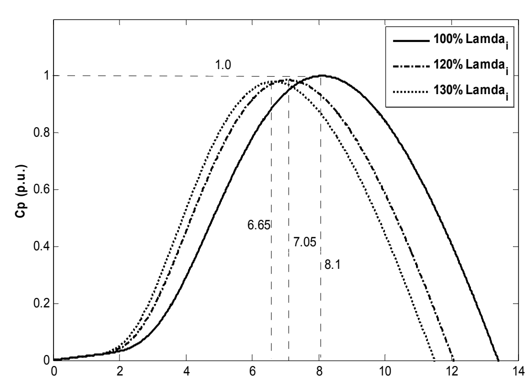


Fig. 4. The effect of changing λ_i on the performance coefficient.

To detect the effect of performance coefficient uncertainty on the power curves, assume that λ_i increases by 20% of its calculated value, Eq. (4). As shown in Fig. 3, when λ_i increases the maximum power decreases slightly, but it occurs at different rotor speed, which results in shifting the maximum power loci. Fig. 4 shows the effect of λ_i on the performance coefficient. It is noted that as λ_i increases, the performance coefficient decreases slightly, but C_{p-max} occurs at lower tip-speed-ratio.

4. Maximum power tracking via fuzzy systems

To overcome the previously mentioned uncertainties, we propose a fast and efficient fuzzy based MPPT technique. The proposed method is designed and simulated for a Doubly-Fed Induction Generator (DFIG) variable-speed WECS, see Fig. 1. The traditional power tracking loop, which will be replaced by our proposed fuzzy systems, is shown in Fig. 5. The block diagram of the proposed fuzzy based MPPT is shown in Fig. 6. The proposed method consists of two parts: First, the main fuzzy MPPT, and second, the fuzzy HCS adaptation. The main fuzzy MPPT replaces the traditional PSF method which is used for MPPT; see Fig. 7. The main fuzzy MPPT has one input, the measured rotor speed, while the output is the reference Q-axis current.

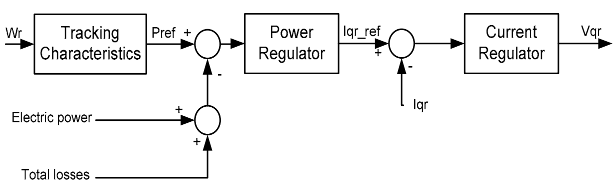


Fig. 5. The traditional power tracking loop.

In order to obtain the TSK fuzzy model, the subtractive clustering method [12] for partitioning the input-output space is combined with the Adaptive Neuro-Fuzzy Inference System (ANFIS) as an optimization technique [13]. The identification of this TSK fuzzy model implies the existence of a knowledge base consisting of a set of input/output measured data samples. To generate the training data used to build this fuzzy model, We used a ramp wind speed profile with a sample interval (50 sec) greater than the maximum settling time of the traditional PSF method, to be sure that the algorithm reaches the reference current that results in the maximum power.

The ramp wind speed changes from the minimum speed (5 m/s) to the nominal speed (12 m/s). For each wind speed sample, the corresponding rotor speed and the reference Q-axis reference current are recorded.

The resultant fuzzy system has three Gaussian membership functions assigned to the rotor speed, three linear functions assigned to the reference output current, and three rules. Table 1 shows the mean, the variance of each membership function assigned to the rotor speed, and the corresponding consequent.

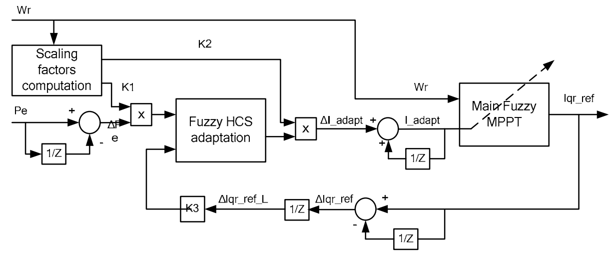


Fig. 6. The block diagram of the proposed fuzzy based MPPT.

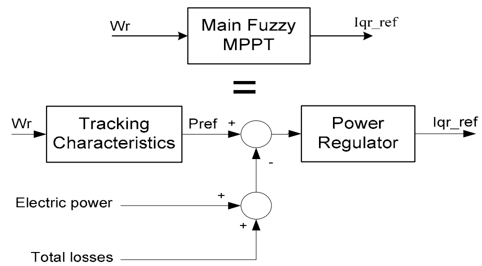


Fig. 7. The main fuzzy MPPT.

Table 1. Rule base of the main fuzzy MPPT

Rule	Rotor Speed		Consequent
	Variance	Mean	
1	0.1538	1.136	$0.7999\omega_r - 0.4248$
2	0.0354	0.6263	$22.06\omega_r - 15.49$
3	0.02694	0.7743	$0.828\omega_r - 0.4211$

The shaded rule in Table 1 is read as follows:

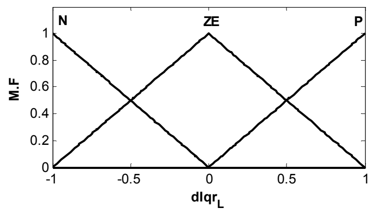
IF **the rotor speed** around 1.136, THEN **reference current** is around $0.7999\omega_r - 0.4248$.

The main fuzzy MPPT gives the reference current to the current control loop. This reference current is continuously adjusted using the fuzzy HCS adaptation. This fuzzy HCS tunes the main fuzzy MPPT by adding a constant term to the consequent part of the rules. The fuzzy HCS is constructed based on the basic HCS method.

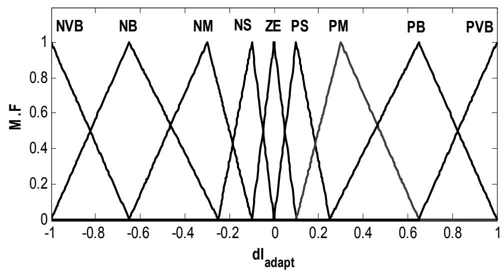
If the variation of the measured electric power (ΔP_e) is positive with the last positive variation of the reference Q-axis current ($\Delta I_{qr\_ref\_L}$), the adaptation (I_{adapt}) is kept in the same direction. If, on the other hand, $+\Delta I_{qr\_ref\_L}$ causes negative $-\Delta P_e$, the adaptation direction is reversed. Let the letter N, Z, P, S, M, B, V stand for the linguistic terms negative, zero, positive, small, medium, big, and very, respectively.

The variables $-\Delta P_e$, ΔI_{adapt}, and $\Delta I_{qr\_ref\_L}$ are described by triangular membership functions, see Fig. 8. The control laws are given by Table 2. The shaded rule in Table 2 is read as follows:

IF $\boldsymbol{\Delta P_e}$ is PVB (positive very big) AND $\boldsymbol{\Delta I_{qr\_ref\_L}}$ is N (negative), THEN $\boldsymbol{\Delta I_{adapt}}$ is NVB (negative very big).



(a)



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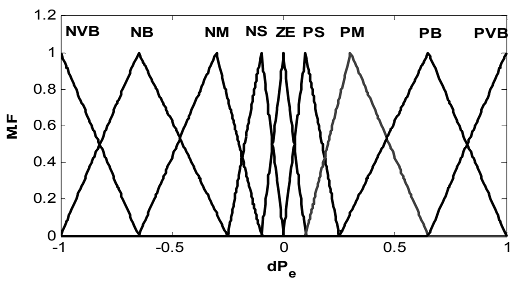

(c)

Fig. 8. Membership functions of the fuzzy HCS adaptation system.

Table 2. Rulebase for the fuzzy HCS adaptation

ΔP_e	$\Delta I_{qr\_ref\_L}$		
	P	Z	N
PVB	PVB	PVB	NVB
PB	PB	PVB	NB
PM	PM	PB	NM
PS	PS	PM	NS
Z	Z	Z	Z
NS	NS	NM	PS
NM	NM	NB	PM
NB	NB	NVB	PB
NVB	NVB	NVB	PVB

The membership functions of ΔP_e and ΔI_{adapt} are symmetrical around the zero value, giving more sensitivity as the variables approach the zero value. The scaling factors K1 and K2, shown in Fig. 8, are functions of the rotor speed, so that the control becomes somewhat insensitive to speed variation [14]. The scaling factor expressions are given, respectively, as

$$K1 = a_1\omega_r^3 \quad (6)$$
$$K2 = a_2\omega_r^3 \quad (7)$$

a_1 and a_2 are constant coefficients that are derived from simulation studies.

The advantages of fuzzy HCS adaptation are obvious. It provides adaptive step size in the MPPT that leads to fast convergence, and the main fuzzy can accept inaccurate and noisy signals. The proposed method does not need any wind velocity information, and its real time based search is insensitive to system parameter variation and the uncertainties of the power curves which make the traditional PSF method fail to search the maximum power.

5. Simulation Results

The simulation results are based on the MATLAB/SimPowerSystem model of the DFIG. A power system has a wind farm consists of six 1.5 MW wind turbines connected to a 25 kV distribution system exporting power to a 120 kV grid through a 30 km 25 kV feeder. A 2300V, 2 MVA plant consisting of a motor load (1.68 MW induction motor at 0.93 PF) and of a 200 kW resistive load is connected on the same feeder at bus B25. A 500 kW load is also connected on the 575 V bus of the wind farm. The single-line diagram of this system is illustrated in Fig. 9. The parameters of the DFIG are reported in Table 3.

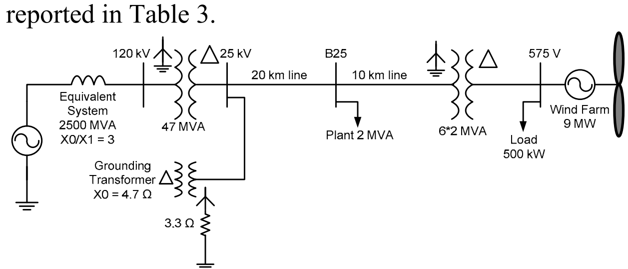

Fig. 9. Single-Line Diagram of the Wind Farm Connected to a Distribution System.

Table 3. The DFIG parameters

Nominal wind turbine mechanical output (MW)	1.5
Generator type	Three-phase wound rotor Induction generator
Generator nominal power (MW)	1.5/0.9
Nominal phase to phase voltage (V)	575
Stator resistance (p.u.)	0.00706
Rotor resistance	0.005
Stator leakage inductance (p.u.)	0.171
Rotor leakage inductance (p.u.)	0.156
Magnetizing inductance (p.u.)	2.9
Base frequency (Hz)	60
Pairs of poles	3
Inertia constant (s)	5.04
Friction factor (p.u.)	0.01

The following simulation studies are performed to compare between three power tracking systems, namely, the traditional power tracking, see Fig. 5, and the proposed fuzzy power tracking with and without the fuzzy HCS adaptation.

First, we will apply a step changing wind speed profile, see Fig. 10. Fig. 11 shows the extracted power from the WECS as compared to the available mechanical power which can be extracted. Fig. 12 shows the output electric power that results from the three systems. All of the three systems extract the same mechanical power.

That it is because the main fuzzy MPPT system is trained based on the PSF method and the nominal power curves.

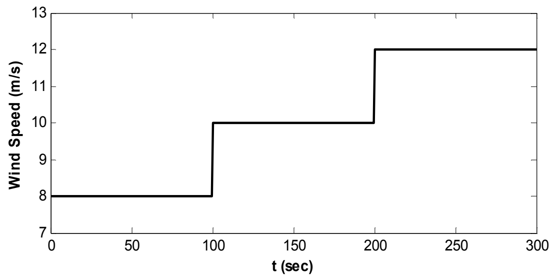

Fig. 10. A step change wind speed profile.

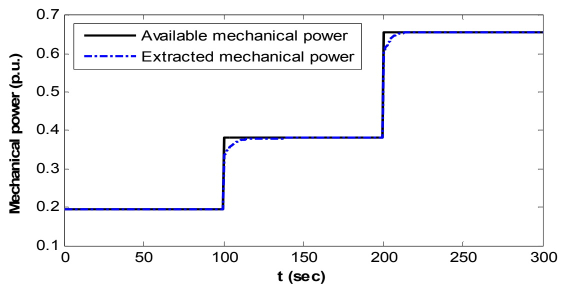

Fig. 11. The mechanical power under the step change wind speed profile.

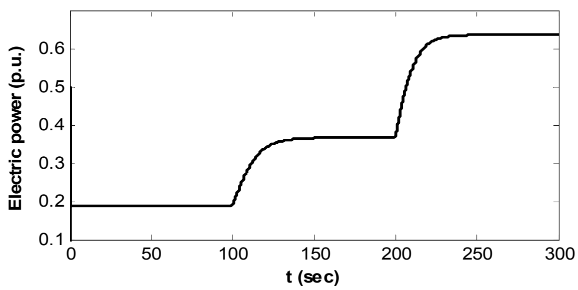

Fig. 12 The electric power under step change wind speed profile.

The next step is examining the performance of the three systems under uncertain conditions. We assumed that the air density is increased by 30% of its nominal value and λ_i, see Eq. (4), is increased also by 30%. Under these assumptions, the optimum power curve which is used by the PSF method will be changed. To ensure the effectiveness of our proposed method, a random wind speed profile is applied, see Fig. 13.

Fig. 14 shows the extracted mechanical power by the three control systems. Fig. 15 shows the resultant electric power by the three systems. The PSF and the non-adaptive fuzzy MPPT system have the same mechanical and electric power, because the main fuzzy MPPT was trained based on the PSF method. It is obvious; the adaptive fuzzy MPPT results in more extracted mechanical power and more generated electric power.

Although the adaptation method depends on the HCS search, the overall maximum power tracking system is fast, because the main fuzzy MPPT is trained based on the PSF method. The percentage root mean squares are calculated as follow:

$$\%RMSE = \sqrt{\frac{1}{T}\int_0^T \Delta P^2(t)dt} * 100 \qquad (8)$$

Where: T is the integration interval (3000 s), ΔP is the difference between the available mechanical power and the extracted mechanical power. Table 4 compares the %RMSE of the three methods. As shown in Table 4, the adaptive fuzzy system produces more power than the traditional power tracking under uncertain conditions.

Table 4
THE %RMSE COMPARISON

Method	%RMSE
Adaptive fuzzy system	0.91%
Non-adaptive fuzzy system	7.95%
PSF method	7.95%

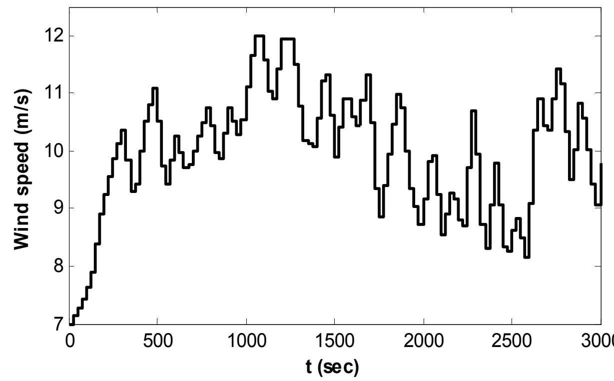

Fig. 13. A random wind speed profile.

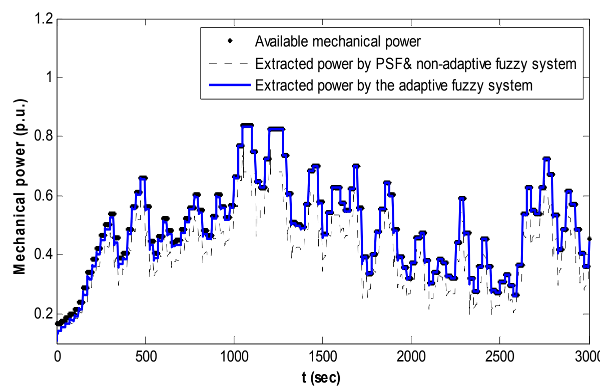

Fig. 14. The mechanical power under the random wind speed profile and uncertain conditions.

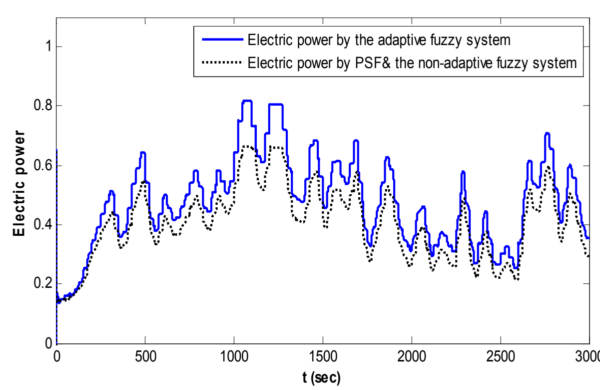

Fig. 15. The electric power under the random wind speed profile and uncertain conditions.

6. Conclusion

The impact of the variation and uncertainty in the wind speed on the performance of the wind energy system is investigated in the paper. An adaptive fuzzy logic controller is proposed in this paper to cope with wind speed variations. The capability of the proposed controller is verified by using the MATLAB/SIMULINK model and it is found that it has a fast response in tracking the maximum power point which is manifested by higher output electrical power.

Acknowledgement

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References

[1] J. Laks, L. Pao and Wright, "Control of Wind Turbines: Past, Present and Future", ACC June 2009.

[2] P. Odgaard, C. Damgaard and Nielsen, "on-Line Estimation of Wind Turbine Power Coefficients Using Unknown Input Observers", IFAC, Seoul, Korea, Jul 6-11, 2008.

[3] M. Ibrahim, A. Khairy, H. Hagrass. M. Zaher, A. El-Shafi, A.Shaltout and N. Abdel-Rahim, "Studying the Effect of Decentralized Battery Storage to Smooth the Generated Power Storage to Smooth the Generated Power of a Grid Integrated Wind Energy Conversion System", Paper Submitted to MEPCON'11, Dec. 2010.

[4] L. Wang, "Adaptive Fuzzy System and Control", Prentice-Hall, New Jersey, 1994.

[5] V. Galadi, A. Piccolo and Siano, "Designing an Adaptive Fuzzy Controller for Maximum Wind Energy Extraction", IEEE Trans. On Energy Conversion, Vol. 23, pp559-569, 2008.

[6] R. Pena, J.C. Clare and G.M. Ashre, "Doubly-Fed Induction Generator Using Back to Back PWM Converters and its Application to Variable Wind-Energy Generation"' IEEE Proceedings-Electrical Power Applications, Vol. 143, no. 3, pp. 231-241, May 1966.

[7] T. Thiringer and J. Linders, "Control by variable rotor speed of a fixed pitch wind turbine operating in a wide speed range," *IEEE Trans. Energy Conv.*, vol. EC-8, pp. 520–526, Sept. 1993.

[8] R. Chedid, F. Mrad, and M. Basma, "Intelligent control of a class of wind energy conversion systems," *IEEE Trans. Energy Conv.*, vol. EC-14, pp. 1597–1604, Dec. 1999.

[9] I. K. Buehring and L. L. Freris, "Control policies for wind energy conversion systems," *Proc. Inst. Elect. Eng. C*, vol. 128, pp. 253–261, Sept.1981.

[10] Siegfried Heier, "Grid Integration of Wind Energy Conversion Systems," John Wiley & Sons Ltd, ISBN 0-471-97143-X, 1998.

[11] http://www.mathworks.com/help/toolbox/physmod/powersys/ref/windturbinedoublyfedinductiongeneratorphasortype.html, accessed September 2010.

[12] S.L. Chiu, ''Fuzzy model identification based on cluster estimation,'' *J.Intel. Fuzzy Syst.*, vol. 2, pp. 267-278, 1994.

[13] Jang, J.-S.R., "ANFIS: Adaptive Network-based Fuzzy Inference Systems," *IEEE Transactions on Systems*, Man and Cybernetics, 23(3), 665–685, 1993.

[14] M. G. Simoes, K. Bose, and R. J. Spiegel, "Design and performance evaluation of a fuzzy-logic-based variable-speed wind generation system," *IEEE Trans. Ind. Applicat.*, vol. IA-33, pp. 956–964, July/Aug. 1997.