Journal of Engineering and Development, Vol. 18, No.4, July 2014, ISSN 1813- 7822

Pitch Angle Control Design of Wind Turbine Using Fuzzy-Art Network

Lecturer. Dr. Ammar Abdulshaheed abdulhameed. Aldair
Electrical Engineering Department , Engineering College, University of Basrah
Emile: mmr.ali2@googlemail.com

Abstract:

Wind energy is by far the fastest-growing renewable energy resource. The power extracted from the wind can be optimized or restricted by adjusting the blades pitch angles of the wind turbine. The wind turbine model is highly nonlinear; therefore, an intelligent controller should be designed to adjust the pitch angles of the blades. In this paper, the fuzzy- ART (ART for Adaptive Resonance Theory) network has been used to control the angle between the incoming wind direction and the chord line of the blade. Simulation results show that the proposed controller is very effective to adjust the pitch angles.
Keywords: Wind turbine, Pitch angle control, Fuzzy-ART networks.

تصميم منظومة تحكم من نوع Fuzzy-Art للسيطرة على زاوية ميلان ريش مولد الكهرباء الهوائي

م.د. عمار عبد الشهيد الدير
قسم الهندسة الكهربائية / كلية الهندسة / جامعة البصرة

الخلاصة:

أن مولد الكهرباء الهوائي أصبح اليوم من أهم مصادر الاستفادة من الطاقة المتجددة لتوليد التيار الكهربائي. فمن خلال ضبط زاوية ميلان ريش المولد الكهربائي يتحقق الاستخلاص الأمثل للطاقة الكهربائية من الحركة الديناميكية للهواء. إن الموديل الرياضي الذي يصف مولد الكهرباء الهوائي يكون لأخطي لذا لابد من تصميم منظومة تحكم ذكية للسيطرة على زاوية ميلان الريش بصورة المثلى. لذا تم في هذا البحث تصميم منظومة تحكم من نوع Fuzzy-ART لتوليد الزاوية المثلى بين اتجاه الريح واتجاه حركة ريش المولد. بينت النتائج المستحصلة كفائة المنظومة المقترحة للتحكم بزاوية ميلان ريش المولد الكهرباء الهوائي.
كلمات مفتاحيه : مولد كهرباء هوائي، تحكم بزاوية ميلان الريش،المنطق المضبب.

1. Introduction:

During the last decades, the increasing concerns about the environment and the trends towards the diversification of the energy market have been reinforcing the interest in wind energy exploitation. The progress of wind power around the world in recent years has exceeded all the expectations, with Europe leading the global market. In numbers, the power generated from wind turbines farm is reached to 100 GW [1]. The cost of electricity provided by wind power facilities has been dropping drastically since the 1980s. These cost reductions are due to new technologies and higher production scales leading to larger, more efficient and more reliable wind turbines [2].

Wind turbine control is necessary to ensure low maintenance costs and efficient performance. The control system also guarantees safe operation, optimizes power output, and ensures long structural life. Turbine rotational speed and the generator speed are two keyareas that must be controlled for power limitation and optimization. Blade angle adjustment is known as pitch angle control, while, yaw control refers to the rotation of the entire wind turbine in the horizontal axis. The yaw control is slightly used to extract the power from wind because wind direction can vary quickly; the turbine may misalign with the oncoming wind and cause power output losses[3]. Many authors proposed control systems to adjust the angle between the incoming wind direction and the chord line of the blade [3-6].

The wind turbine system is highly nonlinear and it is very sensitive to external disturbances and parameters variations. Therefore, for power limitation and optimization, an intelligent and fast control system should be designed to change the angle of the blade with respect to wind speed. The artificial neural networks and fuzzy logic systems are good examples for the adaptive systems. Artificial Neural networks are good at recognizing patterns. However, they are not good at explaining how they reach their decisions. Fuzzy logic systems are good at explaining their decisions but they cannot automatically acquire the rules used to make those decisions. Furthermore, fuzzy system controllers are very fast control, but it is difficult to determine the optimal structure of those controller such as the shape of the membership functions and the exact rule number. These problems have been a central driving force behind the creation of intelligent hybrid systems where two or more techniques are combined in a manner that overcomes the limitations of the individual techniques. The Neurofuzzy system is a good example for such a hybrid system. Therefore, by using the neurofuzzy system, the disadvantages of the fuzzy logic systems and the artificial neural networks will be omitted. The neuro-adaptive training techniques provide a method for the fuzzy modelling procedure to train information about a data set. This technique gives the fuzzy logic capability to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input and output data. In order to process a fuzzy rule by neural networks, it is necessary to modify the standard neural network structure accordingly.

A much smarter (and algorithmically more complex) way of input space partitioning is the application of the Fuzzy-ART (ART for Adaptive Resonance Theory) algorithm proposed by Carpenter et al. in 1991[7]. The ART-type ANFIS model resembles the Scatter-type ANFIS model but it is much smarter in the clustering of input data. Being a well-known unsupervised learning technique, the fuzzy-ART algorithm creates input data categories exclusively on areas of the input space where data appear.

In this paper, the Fuzzy-ART network has been used to design control system for pitch angle of wind turbine.

2. Dynamic Modelling of the Wind Turbine

A wind turbine is a revolving machine that converts the kinetic energy from the wind into mechanical energy. By using the generators system, this mechanical energy is then converted into electricity that is sent to a power grid. The turbine components responsible for these energy conversions are the rotor and the generator. The rotor is the area of the turbine that consists of both the turbine hub and blades. As wind strikes the turbine's blades, the hub rotates due to aerodynamic forces. This rotation is then sent through the transmission system (gearbox) to increase the revolutions per minute. The output rotational motion of the gearbox is employed to run the generator to generate the required electricity. The construction of the wind turbine is shown in **Figure (1**).It includes the following main components: rotor hub, blades, low speed shaft, gearbox, high speed shaft and generator.

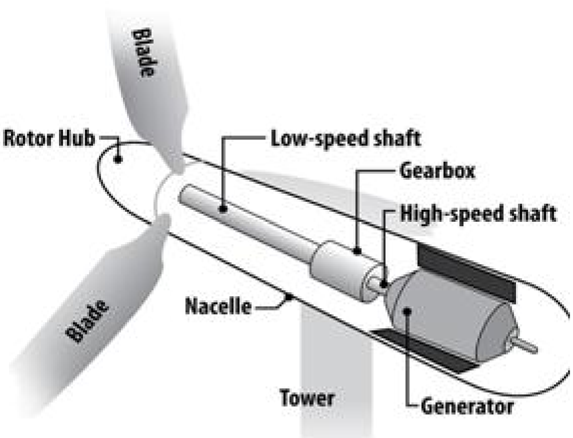

Fig .(1) the construction of wind turbine

The amount of surface area available for the incoming wind is the key to increasing or decreasing aerodynamic forces on the rotor blades. The angle at which the blade is adjusted is referred to as the angle of attack, β.

The ratio of the rotational speed of the rotor (ω_r)to the linear speed of the wind (v_w)is called the Tip Speed Ratio (TSR), λ ,as shown in **equation 1**.

$$\boldsymbol{\lambda} = \frac{\boldsymbol{\omega_r l}}{\mathbf{v_w}} \qquad (1)$$

where, l is the length of blade.

The ratio of the actual power to the ideal power extracted from the wind is called the power coefficient (C_P). The power coefficient is a function of TSR and angle blade as shown in **equation 2**[8]:

$$\mathbf{C_p} = (0.44 - 0.0167\beta)\sin\left(\frac{\pi(\lambda - 3)}{15 - 0.3\beta}\right) - 0.00184(\lambda - 3)\beta \qquad (2)$$

The usable power from the wind turbine can be calculated from **equation 3**[8]:

$$\mathbf{P_w} = 0.5\,\rho A C_p v_w^3 \qquad (3)$$

Where ρ is the air density (1.2929 Kg/m^3), A is the swept area by the blades.
The torque available from the wind can be given as[8]:

$$\mathbf{T_w} = \frac{\mathbf{P_w}}{\boldsymbol{\omega_r}} = 0.5\,\rho A l C_w v_w^2 \qquad (4)$$

where C_w is the torque coefficient which is given by $C_w = C_p/\lambda$.

By substituting **eq. (1) and eq. (2) in eq. (4)**, it is shown that T_w is function of the ratio of the rotational speed of the rotor (ω_r) and pitch angle β.

The fundamental dynamics of the variable-speed wind turbine are captured with the following simple mathematical model[8]:

$$\mathbf{J_t \dot{\omega}_r} = \mathbf{T_w} - \mathbf{T_m} \qquad (5)$$

where J_t is the moment of inertia of the turbine rotor and $T_m$is the mechanical torque necessary to turn the generator (it is assumed constant value commanded by the generator).

Figure .(2) shows the wind speed- output power curve.

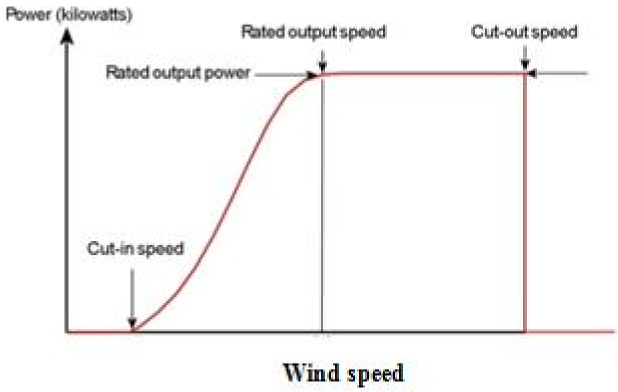

Fig .(2) wind speed-output power curve

The cut-in and cut-out speeds are the operating limits of the turbine. From **Figure .(2)**, it can be seen that the wind speed- output power curve is split into two distinct regions. In first region (low wind speed region) the wind turbine operates below the rate turbine power; therefore, the turbine is run at the maximum efficiency to extract all power from the wind (optimization the generated power). In other words, the pitch angle must be increase, causing the flat side of the blade to face further into the oncoming wind. In second region(high wind speed region),the wind turbine is run at the rated turbine power. Therefore, the pitch angle must be decreased to limit the generated power. Pitch angle adjustment is the most effective way to optimize or limit output power by changing aerodynamic force on the blade.

3. Description of Fuzzy-ART Network Operation:

Fuzzy ART is an unsupervised Adaptive Resonance theory network presented for classifying an arbitrary sequence of analogue input patters into stable recognition categories [9]. The standard Fuzzy-ART was used for online neural control [10]. The main advantage of Fuzzy-ART is that when new patterns are produced by the monitored process, Fuzzy-ART networks can continue to learn (without forgetting past learning) and incorporate new information[11]. The Fuzzy-ART is smarter type than the other types of adaptive fuzzy networks (Fuzzy-Grid network and Fuzzy-Scatter network) because it employs two algorithms for parameter learning: RLS algorithm and backpropagation algorithm, and one algorithm for automatic structure learning[12].

Figure .(3) depicts the structure of the multi input signal output Fuzzy-ART network. For the simplicity, the following assumptions will be assumed: (a) the model has three inputs x_1, x_2 and x_3 and one output y, (b) it has just three fuzzy rules.

The Fuzzy-ART network has two main parts: antecedent part and conclusion part. From **Figure .(3)** the Fuzzy-ART network has six layers, like the multilayer neural networks, each layer performs a specific task. The output of the i^{th} node in the l^{th} layer is denoted by $Out_i^{(l)}$, where every node in the same layer performs the same function as described below[13]:

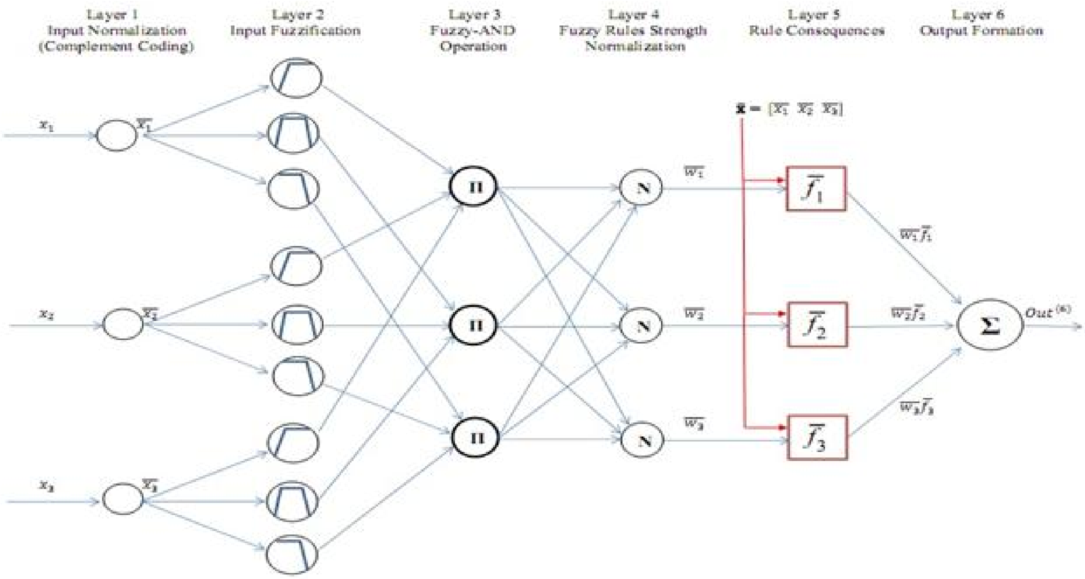

Fig .(3) The Structure of Fuzzy-ART Network

- ## Layer 1 (Input Normalization Layer):

The Fuzzy-ART uses the technique of complement coding from fuzzy-ART to normalize the input training data. Complement coding is a normalization process that replaces an n- dimensional input vector $X = [x_1, x_2, \dots, x_n]$with its 2n-dimensional complement coded form $\acute{X}$ such that:

$$\acute{\mathbf{X}} = [\bar{\mathbf{x}}_1, 1-\bar{\mathbf{x}}_1, \bar{\mathbf{x}}_2, 1-\bar{\mathbf{x}}_2, \dots, \bar{\mathbf{x}}_n, 1-\bar{\mathbf{x}}_n]$$

The I/O function of this layer can be given as:

$$\mathbf{Out_i^{(1)}} = \left(\overline{\mathbf{In_i^{(1)}}}, 1-\overline{\mathbf{In_i^{(1)}}}\right) \quad \mathbf{i} = \mathbf{1, 2, 3} \qquad \mathbf{(6)}$$

- ## Layer 2 (Input Fuzzification Layer):

The nodes belonging to this layer are called input-term nodes and each represents a term of an input-linguistic variable and functions as a 1-D membership function. Trapezoidal membership function is to fuzzify the input variables as following:

$$\mathbf{Out_i^{(2)}} = \mathbf{1} - \mathbf{g}\left(\mathbf{In_{ij}^{(2)}} - \boldsymbol{\upsilon}_{ij}^{(2)}, \boldsymbol{\gamma}\right) - \mathbf{g}\left(\mathbf{u_{ij}^{(2)}} - \mathbf{In_{ij}^{(2)}}, \boldsymbol{\gamma}\right) \quad \mathbf{i} = \mathbf{1, 2, 3} \qquad \mathbf{(7)}$$

Where $u_{ij}^{(2)}$ and $\upsilon_{ij}^{(2)}$are, the left-flat and right-flat points of the trapezoidal membership function of the jth input-term node of the ith input linguistic variable. $In_{ij}^{(2)}$is the input to the jth input-term node from the ith input linguistic variable (i.e. $In_{ij}^{(2)} = Out_i^{(1)}$). Also, the function g (.) is defined as:

$$g(\varrho,\gamma)=\begin{cases}1, & \text{if } \varrho\gamma>1\\ \varrho\gamma, & \text{if } 0\le\varrho\gamma\le 1\\ 0, & \text{if } \varrho\gamma<0\end{cases}$$

The parameter γ regulates the fuzziness of the trapezoidal membership function.

- **Layer 3 (Fuzzy-AND Operation Layer):**

This layer is called rule-antecedent layer. The conjunction operation is performed in this layer. The output of this layer comes from multiplying the incoming signals. The output of each node in this layer can be written as:

$$\mathbf{Out_k^{(3)}=w_k=\prod_{i=1}^{n}Out_{ik}^{(2)}\quad k=1,2,..,Nt} \qquad \textbf{(8)}$$

where Nt is the number on input terms. The output of each node in this layer represents the firing strength (or activation value) of the corresponding fuzzy rule. Note that the number of the fuzzy rules equals the number of input term nodes.

- **Layer 4 (Normalization of Each Rule Firing Strength):**

This layer is called normalization layer. The output of the kth node is the normalized of the kth firing strength wk. The output of any node in this layer can be given as:

$$\mathbf{Out_k^{(4)}=\bar{w}_k=\frac{Out_k^{(3)}}{\sum_{m=1}^{Nr}Out_k^{(3)}}} \qquad \textbf{(9)}$$

- **Layer 5 (Rule Consequences):**

Each node k in this layer is accompanied by a set of adjustable parameters $(a_{1k}, a_{2k}, a_{3k}, a_{0k})$ and implements the linear function:

$$\mathbf{Out_k^{(5)}=\bar{w}_k\bar{f}_k=\bar{w}_k(a_{1k}\overline{In_1^{(1)}}+a_{2k}\overline{In_2^{(1)}}+a_{3k}\overline{In_3^{(1)}}+a_{0k})} \qquad \textbf{(10)}$$

Those parameters are called consequent parameters or linear parameters of the Fuzzy-ART system and are regulated by RLS algorithm.

- **Layer 6 (Output Layer):**

This layer is called output layer. It computes the output of the Fuzzy-ART network by summing up the outputs of layer 5. The output of this layer is given by the following equation:

$$\mathbf{Out^{(6)}=\sum_{k=1}^{Nt}Out_k^{(5)}=\sum_{k=1}^{Nt}\bar{w}_k\bar{f}_k} \qquad \textbf{(11)}$$

4. Training Parameters of Fuzzy-ART Network

The trainable parameters of Fuzzy-ART Network (i.e. premise parameters ($u_{ij}^{(2)}$ and $\upsilon_{ij}^{(2)}$)) are trained by using the Error Back propagation at each iteration in order to minimize the following performance function (Mean Squared Error):

$$\mathbf{E(n) = \sum_{m=1}^{Nov} E_m(n)} \qquad (12)$$

where Nov is the number of output variables (in this case Nov = 1) , nis the iteration number and Em is the error signal between the desired output of mth data and the actual output of Fuzzy-ART model of mth data. The error signal Em is given as:

$$\mathbf{E_m(n) = 0.5\,[y_m^d(n) - Out_m^{(6)}(n)]^2} \qquad (13)$$

In layer 6, there is no parameter to be trained; just the derivative of the error signal to the respect of the output of the network should be calculated:

$$\mathbf{\delta_m^{(6)}(n) = -\frac{\partial E(n)}{\partial Out_m^{(6)}(n)} = y_m^d(n) - Out_m^{(6)}(n)} \qquad (14)$$

The consequent parameters in layer 5 are trained using the RLS algorithm. Therefore the back propagation dose not adjusted any parameter in this layer. The output of layer 6 is derived to the respect to the output of layer 5

$$\mathbf{\frac{\partial Out_m^{(6)}}{\partial Out_m^{(5)}} = 1} \qquad (15)$$

Similarly to layer 5, just the calculation of the error at each node is determined

$$\mathbf{\delta_k^{(4)}(n) = -\frac{\partial E(n)}{\partial Out_m^{(4)}} = -\sum_{m=1}^{Nov}\frac{\partial E_m(n)}{\partial Out_k^{(4)}} = -\sum_{m=1}^{Nov}\frac{\partial E_m(n)}{\partial Out_k^{(6)}}\frac{\partial Out_m^{(6)}}{\partial Out_{km}^{(5)}}\frac{\partial Out_{km}^{(5)}}{\partial Out_m^{(4)}}} \qquad (16)$$

From eqs. 14 and 15,eq.16 can be written as:

$$\mathbf{\delta_k^{(4)}(n) = \sum_{m=1}^{Nov}\delta_m^{(6)}(n)\frac{\partial Out_{km}^{(5)}}{\partial Out_m^{(4)}}} \qquad (17)$$

From eq.10, the quantity of $\frac{\partial Out_{km}^{(5)}}{\partial Out_{m}^{(4)}}$ can be given by

$$\frac{\partial Out_{km}^{(5)}}{\partial Out_{m}^{(4)}} = a_{1k}^{m}\overline{In_1^{(1)}} + a_{2k}^{m}\overline{In_2^{(1)}} + a_{3k}^{m}\overline{In_3^{(1)}} + a_{0k}^{m} = \bar{f}_k^{m} \tag{18}$$

The derivative of performance function to the respect of the output of layer three is calculated as:

$$\delta_k^{(3)}(n) = \frac{\partial E(n)}{\partial Out_k^{(3)}} = -\sum_{k1=1}^{Nr} \frac{\partial E}{\partial Out_{k1}^{(4)}} \frac{\partial Out_{k1}^{(4)}}{\partial Out_k^{(3)}}$$
$$= \sum_{k1=1}^{Nr} \delta_k^{(4)}(n) \frac{\partial Out_{k1}^{(4)}}{\partial Out_k^{(3)}} \tag{19}$$

The derivative of performance function to the respect of the premise parameters in layer 2 is given as:

$$-\frac{\partial E}{\partial \upsilon_{ij}^{(2)}} = -\frac{\partial E}{\partial Out_{ij}^{(2)}} \frac{\partial Out_{ij}^{(2)}}{\partial \upsilon_{ij}^{(2)}} \tag{20}$$

And

$$-\frac{\partial E}{\partial u_{ij}^{(2)}} = -\frac{\partial E}{\partial Out_{ij}^{(2)}} \frac{\partial Out_{ij}^{(2)}}{\partial u_{ij}^{(2)}} \tag{21}$$

Where

$$-\frac{\partial E}{\partial Out_{ij}^{(2)}} = \delta_k^{(3)} = -\frac{\partial E}{\partial Out_{k=j}^{(3)}} \frac{\partial Out_{k=j}^{(3)}}{\partial Out_{ij}^{(2)}}$$

Or

$$\delta_k^{(3)}(n) = -\delta_k^{(3)}(n) \frac{\partial Out_{k=j}^{(3)}}{\partial Out_{ij}^{(2)}} \tag{22}$$

From the premise parameters of the fuzzy rules the following hold:

$$\frac{\partial Out_{ij}^{(2)}}{\partial \upsilon_{ij}^{(2)}} = \begin{cases} \gamma & \text{if } 0 \le (In_{ij}^{(2)} - \upsilon_{ij}^{(2)})\gamma \le 1 \\ 0, & \text{otherwise} \end{cases}$$

$$\frac{\partial \mathrm{Out}_{ij}^{(2)}}{\partial u_{ij}^{(2)}} = \begin{cases} -\gamma & \text{if } 0 \le (u_{ij}^{(2)} - \mathrm{In}_{ij}^{(2)})\gamma \le 1 \\ 0, & \text{otherwise} \end{cases}$$

Finally, the update equations of the premise parameters are calculated from the following:

$$\upsilon_{ij}^{(2)}(n+1) = \upsilon_{ij}^{(2)}(n) + \eta\left(-\frac{\partial E}{\partial \upsilon_{ij}^{(2)}}\right) \tag{23}$$

$$u_{ij}^{(2)}(n+1) = u_{ij}^{(2)}(n) + \eta\left(-\frac{\partial E}{\partial u_{ij}^{(2)}}\right) \tag{24}$$

Where η is the learning rate.

5. Design the Fuzzy-ART Controller for wind turbine:

In this section, the development of the control strategy for the pitch angle of wind turbine is presented using the concept of Fuzzy-ART control scheme, the block diagram of which is shown in **Figure .(4).**

To start with, the controller is designed using the Fuzzy-ART scheme. Fuzzy logic is one of the successful applications of fuzzy set in which the variables are linguistic rather than the numeric variables. Linguistic variables, defined as variables whose values are sentences in a natural language (such as Negative, Positive, Large, Small and so on), may be represented by the fuzzy sets.

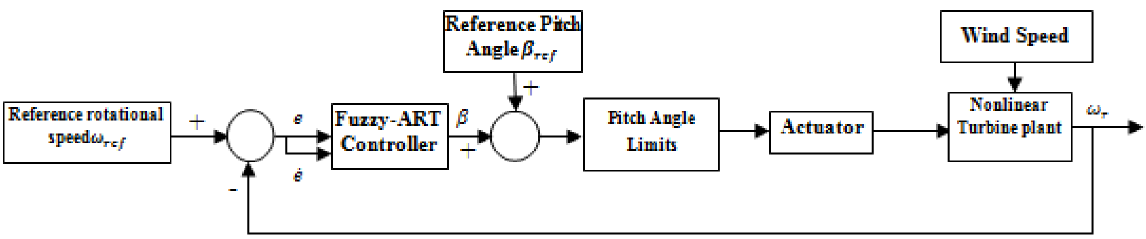

Fig .(4) The Structure of Proposed Controller

In **Figure 4**, the inputs to the Fuzzy-ART controller, i.e., the error and the change in error is modelled using the eq. 25 and eq. 26, respectively

$$e(T) = \omega_{ref} - \omega_r \tag{25}$$

$$\Delta e(T) = e(T) - e(T-1) \tag{26}$$

where ω_{ref} is the reference angular speed, ω_r the angular speed of the turbine rotor, e(T) the error and $\Delta e(T)$ is the change in error. The set of nine rules are written on the basis of previous knowledge/experiences in the rule based block (as shown in **Table 1**).

Table .(1) Rule Based Fuzzy-ART Control

<table>
<tr><td>Pitch angle</td><td colspan="4">Error</td></tr>
<tr><td rowspan="4">Change in Error</td><td></td><td>Neg</td><td>Zero</td><td>Pos</td></tr>
<tr><td>Neg</td><td>Neg</td><td>Neg</td><td>Zero</td></tr>
<tr><td>Zero</td><td>Neg</td><td>Zero</td><td>Pos</td></tr>
<tr><td>Pos</td><td>Zero</td><td>Pos</td><td>Pos</td></tr>
</table>

The rule base block is connected to the neural network block. Back propagation algorithm is used to train the neural network (using eq. 23 and eq. 24) to select the proper set of rule base (by reducing the value of error between the reference angular speed ω_{ref} and the angular speed of the turbine rotor ω_r). For developing the control signal, the training is a very important step in the selection of the proper rule base. Once the proper rules are selected and fired, the control signal required to obtain the optimal outputs is generated. The membership function of triangular type is used in our work. The proper rules are selected by the training of the neural network with the help of back propagation algorithm and these selected rules are employed to construct the Fuzzy-ART controller.

6. Simulation and Results

The Fuzzy-ART network is employed for controlling the rotor speed of wind turbine to generate a constant output power by adjusting the pitch angles of the blades. The proposed wind turbine speed control is simulated by MATLAB Simulink software package. Random input is used to simulate the wind speed input as shown in **Figure 5**. In this simulation, the reference rotational speed is assumed 2.9 rad/sec and the reference pitch angle is 900 (the reference angle between the incoming wind direction and the chord line of the blade).

The actuator shown in **Figure 4** is permanent magnet DC motor which is used to adjust the turbine blade angle.

When the incoming wind speed is changed, the Fuzzy-ART controller will exhibit a corresponding change in blade angle to keep the angular speed of the turbine rotor ω_r approximately constant about the reference angular speed ω_{ref}. **Figure 6** shows the change of the turbine blade angle. While, **Figure 7** shows the angular speed of the turbine rotor.

Figure 8 depicts the generated output power from the wind turbine. This figure shows that the output power is remained constant even the incoming wind speed is changed.

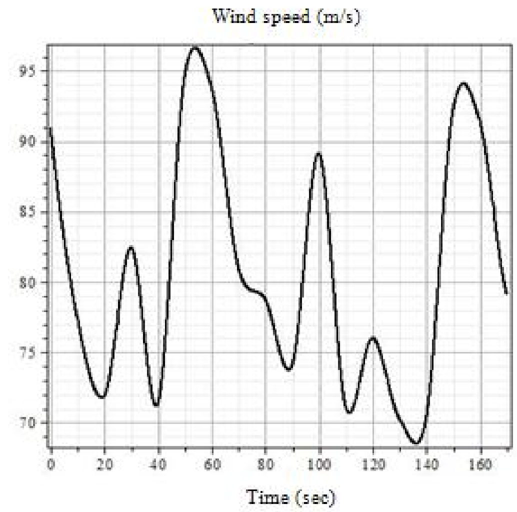

Fig .(5) Incoming wind speed

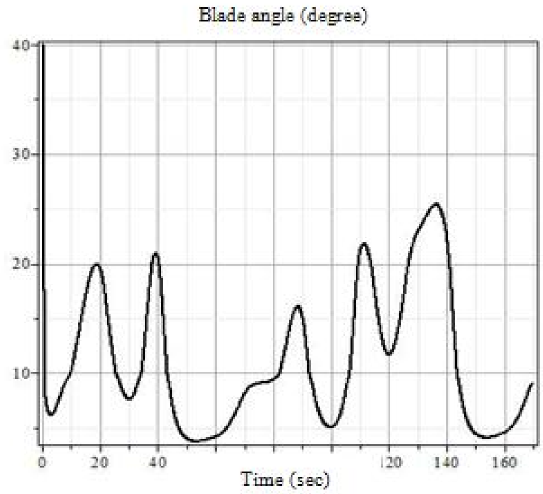

Fig .(6) Turbine blade angle

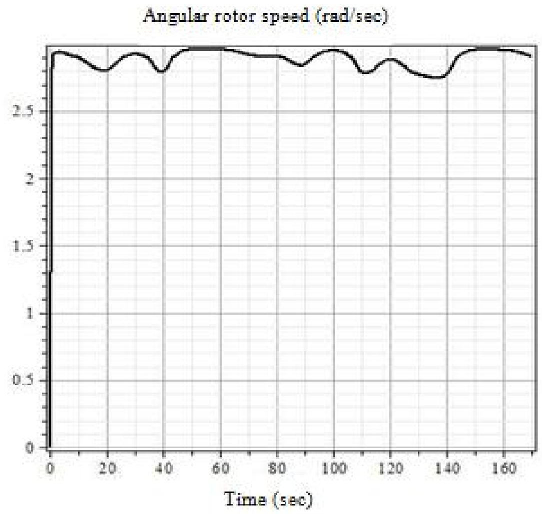

Fig .(7) The angular speed of the turbine rotor

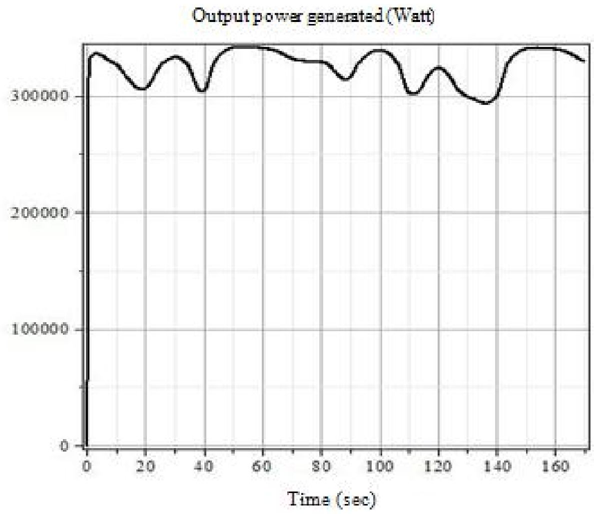

Fig .(8) Output power generated

7. Conclusion

A Fuzzy-ART controller is employed for turbine rotor speed control to generate a constant output power. For simulation issue, the wind speed is changed between 68 m/s to 97 m/s. In response, the control system will exhibits a corresponding change in blade angle between 3 degree to 26 degree in order to keep the rotor speed constant at the reference value (2.9 rad/s). Using of pitch angle fuzzy-ART control can improve electrical power response performance of wind turbine. The proposed controller is suitable to be employed to maximize the electrical output power of the wind turbine in the low wind speed (as shown at time 140 sec, the controller adjust the blade angle at 26 degree to extract maximum power from the wind) and remain the generated power at rated output power in the high wind speed (by adjusting the pitch angle of turbine blade at 3 degree as shown at time 55 to 60 sec and 155 to 160 sec). Therefore, by adjusting the blades pitch angles of the wind turbine using the proposed controller, the power generated from generator is almost remain at rated output and maximum power is extracted from the wind as shown in **Figure 8.**

References:

1. **EWEA, Wind industry factsheets. , in Technical report. 2012, European wind Energy Association**
2. **Ackermann, T. and L. Soder, An on=vweview of wind energy status. Renewable and Sustainable Energy Reviews, 2002. 6(67-127).**
3. **Clemens Jauch, et al., Design of a wind turbine pitch angle controller for power system stabilisation. Elsevier, Renewable Energy., 2007. 32: p. 2334-2349.**
4. **Musyafa, A., et al., Pitch Angle Control of Variable Low Rated Speed Wind Turbine Using Fuzzy Logic Controller. International Journal of Engineering and Technology, 2010. 10(5): p. 21-25.**
5. **Furat Abdal Rassul and M.A. Abdulsada, Simulation of Wind Turbine Speed Controil by Matlab. International Journal of Computer and Electrical Engineering, 2010. 2(5): p. 912-916.**
6. **E. Muljadi and C.P. Butterfiled, Pitch-Controlled Variable-Speed Wind Turbine Generation, in IEEE Industry Applications Society Annual Meeting. 2000: Phoenix, Arizona.**
7. **Carpenter G. A., Grossberg S., and Rosen B. D., Fuzzy ART: Fast Stab;e Learning and Categorization of Analog Patterns by an Adaptive Resonance System. neural Networks, 1991. 4: p. 759-771.**
8. **Fernando D. Bianchi, Hernan De Battista, and R.J. Mantz, Wind turbine control systems : principles, modelling and gain scheduling design. 2007, Verlag London: Springer.**
9. **G. A. Carpenter and S. Grossberg, Fuzzy ART: Fast stablity Learning and Categorization of Analogue Patterns by an Adaptive Resonance System. Neural Networks, 1991. 2(756-771).**
10. **D. D. Ediriweera and I. W. Marshall. Internally self organising Neural Network for online Learning od perception to action Mapping in Sensor Networks. in Proceeding sofLond on Communications Symposium. 2005. London, UK.**
11. **Massimo Pacella, Quirico Semeraro, and A. Anglani, Manufacturing quality control by means of a Fuzzy ART network trained on natural process data. Engineering Applications of Artificial Intelligence, ELSEVIER 2003. 17: p. 83-96.**
12. **M. Georgiopoulos, et al., 1999. Neural Networks, PERGAMON. 12: p. 837-850.**
13. **Cheng-Jian Lin and C.-T. Lin, An ART-Based Fuzzy Adaptive Learing Control Network. IEEE Transactions on Fuzzy System, 1997. 5(4): p. 477-497.**