J Electr Eng Technol Vol. 8, No. 4: 863-871, 2013
http://dx.doi.org/10.5370/JEET.2013.8.4.863

ISSN(Print) 1975-0102
ISSN(Online) 2093-7423

Adaptive Control of Pitch Angle of Wind Turbine using a Novel Strategy for Management of Mechanical Energy Generated by Turbine in Different Wind Velocities

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Abstract – Control of pitch angle of turbine blades is among the controlling methods in the wind turbines; this measure is taken for managing mechanical power generated by wind turbine in different wind velocities. Taking into account the high significance of the power generated by wind turbine and due to the fact that better performance of pitch angle is followed by better quality of turbine-generated power, it is therefore crucially important to optimize the performance of this controller. In the current paper, a PI controller is primarily used to control the pitch angle, and then another controller is designed and replaces PI controller through applying a new strategy i.e. alternating two ADALINE neural networks. According to simulation results, performance of controlling system improves in terms of response speed, response ripple, and ultimately, steady tracing error. The highly significant feature of the proposed intelligent controller is the considerable stability against variations of wind velocity and system parameters.

Keywords: ADALINE neural network, Adaptive controller, Pitch angle, Wind turbine.

I. Introduction

Use of renewable energies including wind energy has had a remarkable growth in the recent years. Fig. 1 illustrates growing trend of electricity generation using wind energy since late 2009 until latter half of 2011 [1]. Improvement of control process of wind turbines is vitally necessary due to exponential spread in electricity generation by wind [2].

The classic PID controller is among the most common controllers in industrial systems, which have excellent structural properties including signal tracking, low sensitivity to the measurement noise and robustness against the process' parameters and load disturbances despite its simple structure.

So, it has taken a special place to control of the linear and/or nonlinear systems [3].

However, it should be noted that the derivative part of the controller is sensitive to noise in practice. On the other hand, tuning the PI controller has to be done for a specific condition. Because, in some cases which provide a new condition due to the varying inputs or system parameters and system dynamic the controller fails to operate in its optimal performance based on its primary tuning [4].

Two application instances of this controller for controlling the wind turbines have been mentioned in [5-6].

Nonetheless, logically, use of the simple PI controller will not yield desirable results in systems like wind turbines which embrace non-linear and indefinite factors. This originates from the fact that parameters of control system change with variations of wind velocity (and hence change of working point of system), and also the fact that system parameters need to be readjusted.

Alleviation of aforementioned pitfall is possible in two ways: use of classic non-linear control methods (adaptive/ robust) and/or application of intelligent control methods. The classical method of sliding mode (which is among the oldest and meanwhile most well-known non-linear robust control techniques) was used in references [7] to control the wind turbine system.

In [8], the performance of a robust controller based on H_∞ for wind turbines is presented. Ref [9] has presented a new method to estimate the fault-tolerant to design a wind turbine.

Moreover, in Ref [10] a nonlinear control based on a wind speed estimator is used. In addition, neural-fuzzy techniques were utilized in references [11-13] to achieve

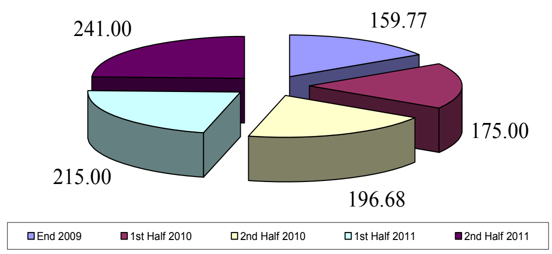

Fig. 1. Global trend of wind-generated electricity

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Received: April 30, 2012; Accepted: November 29, 2012

ideal answers in design of controlling systems of wind turbines.

In reference [14], the MLP neural network and the RBF neural networks were used to control the pitch angle. Simulation results attest better performance of RBF controller in providing the favorable nominal output power. Nevertheless, it must be explained that none of the above mentioned controllers, despite relatively large structure and diversity of inputs, are capable of full elimination of overshoot. Furthermore, a step-wise function served as the wind velocity model.

In [15], coefficients of the PID controller to control the pitch angle for a given wind speed profile were designed, and the obtained performance and results which were based on disturbance observer just for the given wind speed profile were accessible. It should be noted that the coefficients of this PID controller were tuned just for the given wind speed profile.

Moreover, a feed-forward non-linear controller (designed according to aerodynamic attributes of turbine rotor) was applied in reference [16] to compensate the weakness of the classic PID controller. Output of feed-forward non-linear controller is added to the PID controller output and generates the ideal input of pitch angle system.

In [17], a self-adjusting pitch angle controller was proposed based on adaptive control method of reference model. This controller is composed of two neural networks: one for comprehending plant's behavior (pitch angle system) and the other one for comprehending its reverse behavior (aimed at realizing reverse controlling strategy of the plant). Also, pitch angle was controlled with the aid of a robust controller in [18] so as to be compatible with systematic uncertainties (variation of wind turbine dynamics affected by wind velocity fluctuations). Pitch angle control was carried out in [19] using a non-linear controller for establishing equilibrium between the generated electrical power of wind field and the required load power.

It should be noted that the most significant weak point of the abovementioned studies was their failure in the on-line tracking regarding compatibility with variations of operation point and system parameters.

The coefficients of the PI/PID controller for wind turbines in a specific operating condition such as given wind speed profile and/or defined dynamic parameters can be determined to operate in an optimal performance of the controller can be seen in [15].

But, variation of the wind speed profile and/or the system's dynamic parameters causes the PID controller coefficients deviate form the optimal performance, and to achieve the optimal the recital, the coefficients are required to be rearranged.

In this paper, a self adjustable controller based on consecutive alternating two ADALINE neural networks to ideal regulation of pitch angle is designed. ADALINE neural network is characterized by its simple structure and accordingly high operation speed.

According to the simulation results, the proposed controller in terms of response speed, steady-state tracking error and response ripple performance is better than a PID controller. It should be noted that one of the most important features of the proposed controller (unlike the PI/PID controllers) is that the proposed controller is robust, stable and self adjustable under system variations.

The following parts of the paper are organized as below: Wind velocity model used in the simulation section is explained in section 2. The formulas pertaining to mechanical power and also power efficiency of wind turbine will be introduced in section 3. Following a brief description of single-layer ADALINE neural network and the procedures of determining reference pitch angle in section 4, designing mechanism of the proposed pitch-angle controller with application of two successive (alternating) ADALINE neural networks will be explained, and finally, the paper ends with presenting the conclusions in section 6.

II. Wind Velocity Model

Wind velocity can be supposed as summation of four components [20]:

- Average wind velocity (v_{av})
- Slope or ramp velocity (v_r)
- Gale velocity (v_g)
- Turbulence velocity (v_t)

The wind velocity can be therefore written as:

$$v = v_{av} + v_g + v_r + v_t \tag{1}$$

Average wind velocity component represents mean value of wind velocity in specified time intervals. Slope velocity component is in fact defines constant increase of wind velocity in steady state which is determined via a multi-rule function:

$$v_r = \begin{cases} \mathbf{0} & t < T_{sr} \\ A_r \frac{(t-T_{sr})}{(T_{er}-T_{sr})} & T_{sr} < t < T_{er} \\ A_r & t > T_{er} \end{cases} \tag{2}$$

where, A_r is an amplitude of slope velocity, and T_{sr} and T_{er} are considered as initial and final times of slop wind blowing, respectively. Gale velocity component in [20] was modeled as follows:

$$v_g = \begin{cases} \mathbf{0} & t < T_{sg} \\ A_g \left\{ \mathbf{1} - \cos\left[\mathbf{2}\pi \frac{(t-T_{sg})}{(T_{eg}-T_{sg})} \right] \right\} & T_{sg} < t < T_{eg} \\ \mathbf{0} & t > T_{eg} \end{cases} \tag{3}$$

where, A_g is a storm amplitude, and T_{sg} and T_{eg} respectively represent beginning and ending times of storm. Turbulence component which describes the random state of wind velocity will be denoted as below:

$$v_t = 2\sum_{i=1}^{N}\left[S_v(\omega_i)\Delta\omega\right]^{1/2}\cos(\omega_i t+\phi_i) \tag{4}$$

where $\omega_i=\left(i-\frac{1}{2}\right)\Delta\omega$ and ϕ_i is a random variable with uniform probability density in the interval 0 to 2π. Also, $S_v(\omega_i)$ is the spectrum density function proposed by WIKITIS [21] as below:

$$S_v(\omega_i)=\frac{2K_N F^2|\omega_i|}{\pi^2\left[1+(F\omega_i/\mu\pi)^2\right]^{4/3}} \tag{5}$$

where K_N = 0.004, F = 2000, and μ is an average velocity in high elevation. In [22], it was concluded that the parameter values of $N=50$ and $\Delta\omega$ between 0.5 and 20 would be suitable for the simulation.

III. Characteristics of Wind Turbines

Mechanical power of wind turbines is in fact a percentage of total power of wind energy and is calculated via the following formula:

$$P_r=\frac{\rho}{2}AC_P(\lambda,\beta)\,V^3 \tag{6}$$

where, ρ is the air density, C_P is the power efficiency coefficient, β is the pitch angle, A is the swept area by the rotor, and finally, V is the wind velocity, λ is the ratio of edge velocity which is also defined as below:

$$\lambda=\frac{\omega_r R}{V} \tag{7}$$

where R is the rotor's radius and ω_r is the rotor angular speed.

Due to constant values of parameters ρ, A and the fact that wind velocity is not under control, therefore, it is realized in Eq. 6 that P_r can be ideally controlled through adjusting C_P, which is in turn a function of λ and β parameters.

It should be explained that for higher wind velocities than rated velocity, C_P tuning is done by parameter β and in wind velocities lower than rated velocity (of course in turbines with variable speed) C_P tuning is done by parameter λ.

Using numerical approximation methods [23], the relation between C_P and parameters λ and are achieved in the following closed form:

$$C_P(\lambda,\beta)=c_1\left(\frac{c_2}{\lambda_i}-c_3\beta-c_4\right)e^{\frac{-c_5}{\lambda_i}}+c_6\lambda \tag{8}$$

Where

$$\lambda_i=\left(\frac{1}{\lambda+0.08\beta}-\frac{0.035}{\beta^3+1}\right)^{-1} \tag{9}$$

C_P attribute is plotted in Fig. 2 versus λ for different values of β

According to Fig. 2, wind turbine works with maximum power efficiency where $\beta=0$ and λ is in nominal value (which is obtained for nominal wind velocity and rotor rotation at nominal velocity). In these conditions, nominal mechanical power is delivered by the turbine.

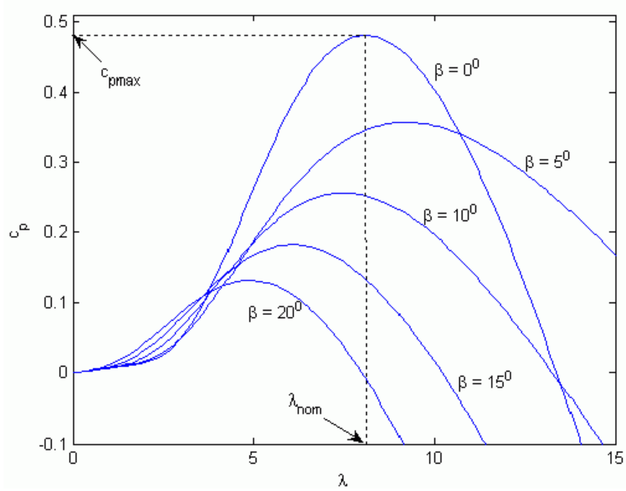

Fig. 2. Attribute of power efficiency in terms of edge velocity ratio and for different values of pitch angle [23]

IV. Controlling the Pitch Angle

A. ADALINE *neural network*

Main nucleus of all artificial neural networks is simple operational element called neuron; these elements are derived from biological neural systems. Variety of available artificial neural networks (including diverse structures: feed-forward and feed-backward) are derived through special arrangement of neurons in different layers.

Procedures to construct an artificial neural network respectively include:

- Selection of suitable network structure in accordance with problem requirements and based on experience.
- Selection of appropriate number of neuron layers and number of neurons in each one (which are normally determined through a trial and error process and by training the network).

- Training the network (determination of unknown weights).

Presence of rich training data is among the important factors affecting successful performance of a neural network. These data shall cover different circumstances that might occur during the operation so that trained neural network can experience different conditions and can yield suitable results in application where possible.

Block diagram of ADALINE neural network is shown in Fig. 3 which is a single-layer network with linear activity functions and the following input-output relation:

Single-layer Adeline neural network with a network of linear functions and the input - output equation is presented as follows:

$$\underline{a} = purelin(\underline{\underline{W}}\,\underline{P} + \underline{b}) = \underline{\underline{W}}\,\underline{P} + \underline{b} \tag{10}$$

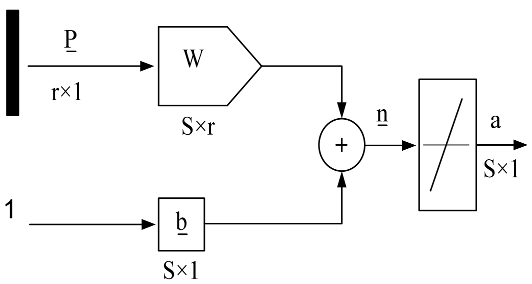

Fig. 3. Block diagram of ADALINE neural network

where, $\underline{p}$ and $\underline{a}$ are respectively input and output vectors of network and $\underline{\underline{W}}$ & $\underline{b}$ respectively represent weight vector and bias vector (adaptive or fitting parameters of network).

ADALINE neural network is trained by the famous least square error algorithm (LMS) algorithm. This function basically works on the assumption of square error for error function of the network:

$$F(\underline{\underline{W}},\underline{b}) \overset{\Delta}{=} e^2(\underline{\underline{W}},\underline{b}) \tag{11}$$

Obviously, network error function in general is a function of all fitting parameters of the network (i.e. $\underline{\underline{W}}$ & $\underline{b}$). Fitting parameters of the network are adjusted through an iterated process based on classical optimization algorithm of highest slope. Having assumed omission of bias term, the related equations are as below:

$$\underline{\underline{W}}_{k+1} = \underline{\underline{W}}_k + \nabla\underline{\underline{W}}_k \tag{12}$$

$$\nabla\underline{\underline{W}}_k = -lr \cdot \nabla F(\underline{\underline{W}})|_{\underline{\underline{W}}_k} \tag{13}$$

where:

$\underline{\underline{W}}_{k+1}$ and $\underline{\underline{W}}_k$ respectively are new and current values of network weight vector, $\nabla\underline{\underline{W}}_k$ is variations matrix, $\nabla F(\underline{\underline{W}})|_{\underline{\underline{W}}_k}$ is gradient matrix and finally parameter "lr" represents training rate of the network. Assuming absence of bias term, output vector, and consequently, error vector of network (for certain training data) will be as follows:

$$\underline{a} = \underline{\underline{W}} \cdot \underline{p} \;\Rightarrow\; e(\underline{\underline{W}}) \overset{\Delta}{=} \underline{t} - \underline{a} = \underline{t} - \underline{\underline{W}} \cdot \underline{p} \tag{14}$$

where:

$\underline{t}$ is ideal output vector of network for input vector $\underline{p}$. Now, it is written for calculation of gradient matrix $\nabla F(\underline{\underline{W}})|_{\underline{\underline{W}}_k}$:

$$\nabla F(\underline{\underline{W}})\Big|_{\underline{\underline{W}}} = \nabla_{\underline{\underline{W}}}\, e^2(\underline{\underline{W}}) = \nabla_{\underline{e}}\, \underline{e}^2(\underline{\underline{W}}) \cdot \nabla_{\underline{\underline{W}}}\, e(\underline{\underline{W}}) \tag{15}$$

where:

$$\nabla_{\underline{\underline{W}}}\, e(\underline{\underline{W}}) = -\underline{p}^T \tag{16}$$

Through combining the Eqs. 15 and 16 with Eqs. 12 and 13, there will be:

$$\nabla\underline{\underline{W}}_k = \mathbf{2} \cdot lr \cdot \underline{e}_k \cdot \underline{p}^T \tag{17}$$

$$\underline{\underline{W}}_{k+1} = \underline{\underline{W}}_k + \mathbf{2} \cdot lr \cdot \underline{e}_k \cdot \underline{p}^T \tag{18}$$

And also, Eq. 19 is used for network bias:

$$\underline{\underline{b}}_{k+1} = \underline{\underline{b}}_k + \mathbf{2} \cdot lr \cdot \underline{e}_k \tag{19}$$

where $\underline{\underline{b}}_{k+1}$ and $\underline{\underline{b}}_k$ are new and current values of bias matrix of network, respectively. Additionally, mean square error for each epoch is:

$$MSE = \frac{\mathbf{1}}{n}\sum_{i=\mathbf{1}}^{n} e_i^{\mathbf{2}} \tag{20}$$

where:

n is number of training models in each epoch and e_i is the error for the i^{th} training model calculated via Eq. 14. It should be noted that the equations above are extracted from reference [24].

B. Controlling system of pitch angle

In wind velocities below the nominal wind velocity, value of pitch angle must be considered zero for achieving the maximal possible energy from wind. If wind velocity exceeds its nominal value, generation power of turbine is still maintained in its nominal level through suitable adjustment of pitch angle. Block diagram of pitch-angle controlling system of turbine is illustrated in Fig. 4 where the controller the needed command is sent to pitch angle system based on tracing error of pitch angle.

In this figure, "Look up table" block contains the information of reference pitch angle proportional to each wind velocity and nominal velocity of rotor. Fig. 5 demonstrates how this flowchart is prepared. In flowchart of Fig. 5, V_C and V_e respectively are minimal and maximal wind velocities for which the turbine generates power, and, P_{rs} is nominal mechanical power of turbine. Block diagram of pitch angle system is shown in Fig. 6.

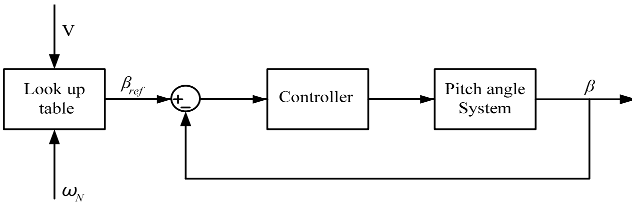

Fig. 4. Block diagram of pitch-angle controlling system

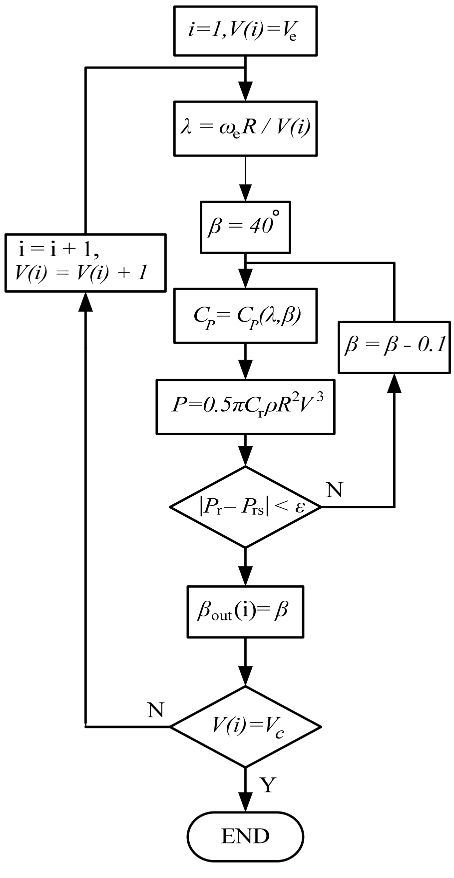

Fig. 5. Flowchart of calculation procedures of reference pitch angle [17]

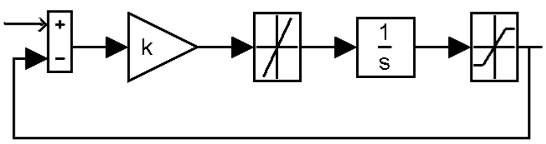

Fig. 6. Block diagram of pitch-angle controlling system

C. New strategy of controlling pitch angle

Due to non-linear nature of wind turbine and with the intention of maintaining favorable performance of the control system, the time-consuming process of coefficient adjustment in PI linear controller must be normally repeated for different wind velocities (working points). Two measures can be taken to resolve this problem:

- The PI linear controller can be replaced by an intelligent system (using fuzzy-neural structures).
- Adjustment of PI controller parameters with the aid of on-line training techniques for compatibility with new working conditions and even variations of system parameters.

In the current paper, a PI controller is used for desirable control of a default wind velocity profile (Fig. 9, simulation section). It must be remembered that controlling coefficients of PI are determined using ZIGLER NICOLS.

In the next steps, another controller is designed and substitutes the former one using a new strategy aimed at alleviating the structural weak points of linear PI controller of pitch angle (for variations of working point and system parameters). As observed in Figs. 7 and 8, the proposed controller is composed of two alternate ADALINE neural networks. Two ADALINE neural networks are used in order to maintain the structural power of the network, and particularly, styled observance of its training process.

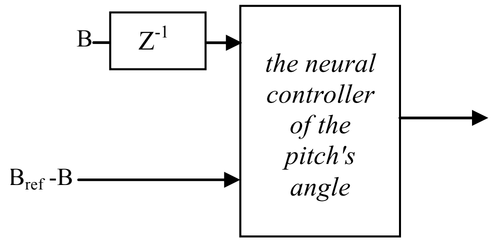

Fig. 7. Block diagram of the intelligent pitch-angle controller

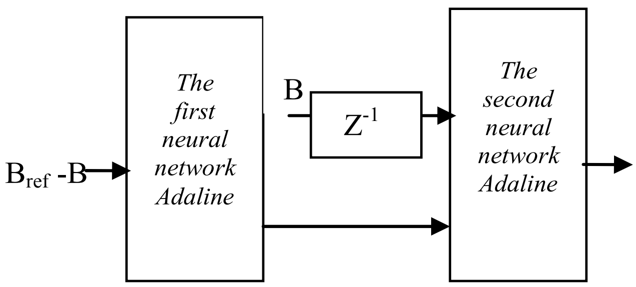

Fig. 8. Details of the neural block in Fig. 7

C1. The new controlling structure of neural network

Behavior of a PI controller is first studied. It is observed that the control signal exits from the PI controller for a certain value of error introduced to the system and consists of two parts:

- Instantaneous control signal which nullifies the error of the same instant
- The controlling signal which has been already available and nullifies the errors of former instants.

Finally, control signal for a new input of the PI controller is the sum of these two aforementioned control signals. As a novel method of control method, a model is built based on the PI controller and a neural network controller has been designed on the same basis. This neural network controller is composed of two neural networks connected in series.

The first ADALINE neural network generates the instantaneous control signal for the error at the same instant; behavioral input-output knowledge of PI controller is used for training this network. The second ADALINE neural network also sends a more optimal control signal to the pitch angle controller compared PI controller; its performance is based on instantaneous control signal (the output of the first neural network) and the output of pitch-angle control related to one instant before.

C2. Training the neural networks

200 values from difference interval of pitch angle and reference pitch angle are uniformly introduced to the PI controller; the maximal and minimal values among these 200 data respectively are the lowest and largest difference between the pitch angle and the reference pitch angle. These values are input in PI controller one by one in the form of the step function the same domain, and, the steady output value of PI controller for each input will be considered as the desirable output of the same input. As such, 200 training models are created for the first neural network.

Out of these 200 training models, 160 models were used for training and the rest 40 models for testing the first neural network. Training procedures are as below:

- Selection of random values for network weights
- Introducing training model to the neural network and achieving the output using Eq. 10.
- The error is computed using Eq. 14. And subsequently mean square error of each epoch is obtained via Eq. 20. If this error is less than 0.0001, the training procedures will end.
- Weights and biases and network are revised using Eqs. 18 and 19 and the procedure returns to step 1.

In this state, the first neural network will end after 63 epochs with MSE=0.00098.

In the interval of pitch angle variations, 20 values are selected between the maximal and minimal values in a way that its highest and lowest values equal the maximal and minimal values of pitch angle value. Also, 20 values are chosen between the maximal and minimal output values of the first neural network like the pitch angle values. Through permutation of two selected 20-value groups, 400 states will be obtained for two values. The generated 400 states are introduced to the PI controller one by one in the form of two-level step function whose domain in the first level equals the previous instantaneous pitch angle, and, the domain in the second level equals output of the first neural network. The steady output for the same input is considered as its desirable output, and in this manner, 400 training models are created for the second neural network.

For the second neural network, 30 models are used for training and 50 models for testing the second neural network. The training procedure of the second neural network is also similar to that of the first network while the two are trained independently. The second neural network ends in epoch 84 with MSE=0.00091. For both networks, training rate is taken 0.05 for the first network.

These two series ADALINE neural networks yield better non-linear performance capability to the neural network controller, proposed for the first time in the current paper as a novel method to be used in the design of intelligent controllers.

V. Simulation

All simulations were performed using MATLAB software lasting 400 seconds with nominal wind velocity of 12 m/s in all runs.

The default wind velocity profile is demonstrated in Fig. 9. In the initial 300 seconds when wind velocity is below the nominal value, pitch angle must be zero, and for the last 100 seconds during which wind velocity exceeds the nominal value (12m/s)., this value must equal 2.2 degrees according to “Look up table” depicted in Fig. 5.

Fig. 10 illustrates the reference pitch angle, response of pitch-angle controlling system in the case of using PI controller, and response of pitch-angle control system in the case of using the proposed controller.

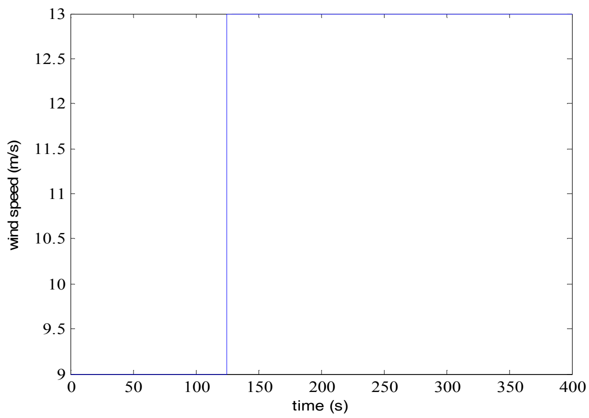

Fig. 9. Wind velocity profile.

To have the possibility of better comparison, the detailed form of Fig. 10 is presented in the interval 120-140 seconds in Fig. 11.

Fig. 11 reflects better performance of the proposed controller compared to the conventional PI controller in terms of overshoot elimination, response speed, and steady tracing error.

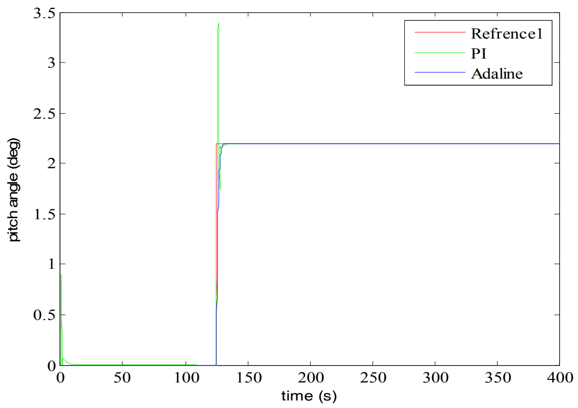

Fig. 10. Pitch angle variations for both types of controllers for $0 \le t \le 400s$

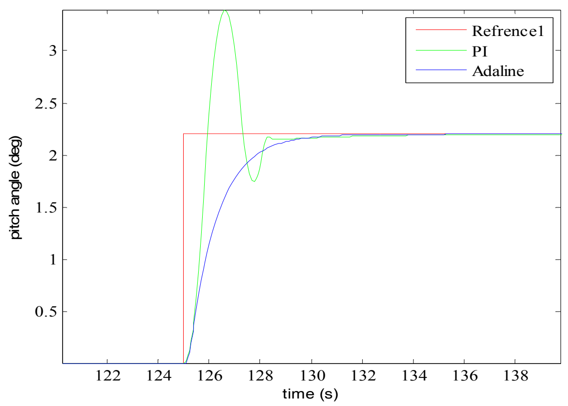

Fig. 11. Detailed form of Fig. 10 in 120-140 seconds interval

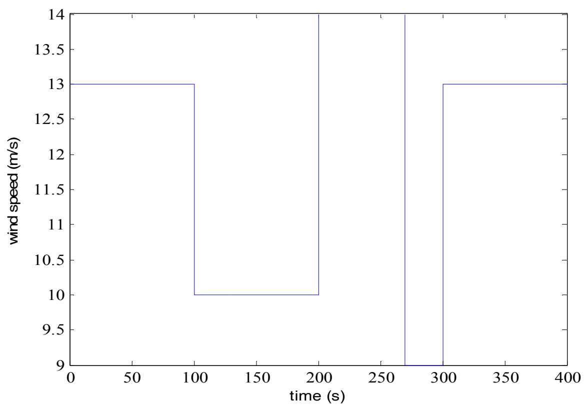

Fig. 12. Wind velocity profile

Nevertheless, in order to manifest the remarkable structural capability of the proposed intelligent controller for variations of working point and system parameters, Fig. 13 shows the performance of this controller versus velocity profile of Fig. 12 (which is somewhat different from velocity profile in Fig. 9); here, the change in the integrating coefficient of the pitch-angle system (K) is 80%. Fig. 13 also illustrates performance of PI controller in the new condition.

Comparison of recent years confirms excellent alignment

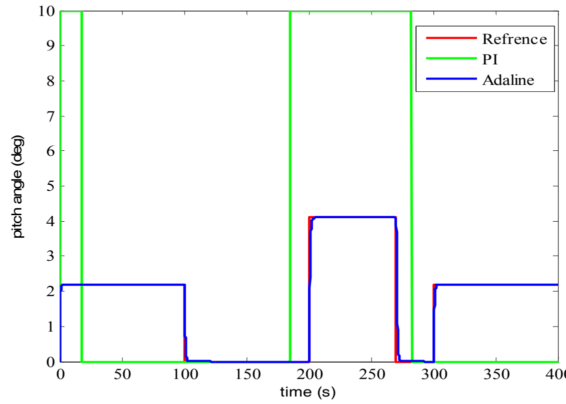

Fig. 13. Pitch angle variations for both types of controllers

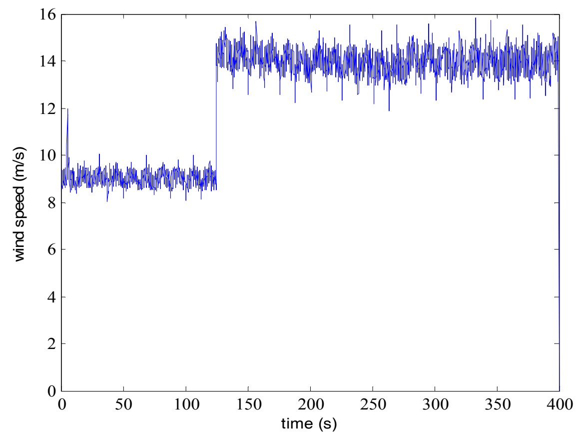

Fig. 14. Wind Velocity profile

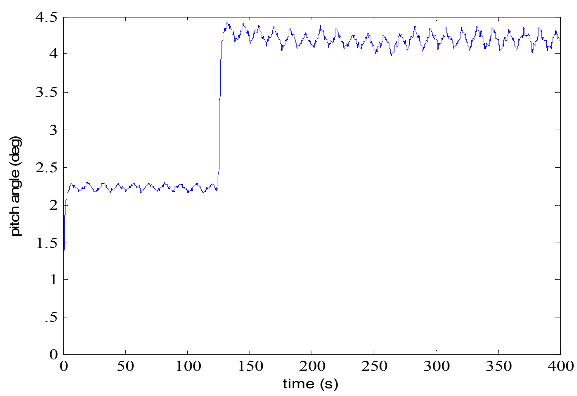

Fig. 15. Pitch angle variations for the proposed controller

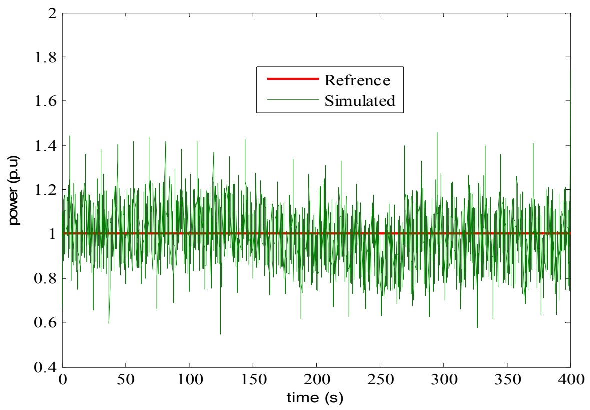

Fig. 16. Mechanical power curve of wind turbine

of the intelligent controller with the new condition while PI controller (which was adjusted for the previous condition) did not exhibit an unfavorable behavior.

For demonstrating excellent match of the proposed controller in fluctuating wind velocities, performance of this controller is shown in Fig. 15 versus the velocity profile of Fig. 14 (taken from the wind velocity model explained in section 2). Fig. 16 also plots the mechanical power of wind turbine for wind velocity profile of Fig. 14.

VI. Conclusions

Efficient control of power and speed in wind electricity generation systems is highly significant due to variability and at the same time uncontrollability (uncertainty) of wind velocity. Using a novel strategy in the current paper, a controller consisting of two alternate ADALINE neural networks was designed for controlling the pitch angle of turbine. The reason for selecting ADALINE neural network was its simplicity and hence high execution speed. According to simulation results, the following notable features can be listed for the proposed controller:

More favorable quality compared to controllers of the former research works in terms of steady and transient behavior indices while having a simple structure (higher quality regarding response speed, response ripple, and steady tracing error).

Excellent adaptability with working point variations (wind velocity profile) and system parameters (with change of working point and system parameters, there is no need for repeating the design but the model will be automatically revised and maintains its optimal performance).

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