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Neural Network Approach to Pitch Angle Control in Wind Energy Conversion Systems for Increased Power Generation

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Abstract: Presented in this study is an artificial intelligence approach to pitch angle control in wind turbine for the enhancement of power generation efficiency of wind energy conversion systems. A two-input neural network model was developed, trained using backward propagation technique and employed in adjusting the pitch angle of the turbine in response to the speed of the turbine generator and the rate of change of the speed. Ten-year real-life data on the wind speeds of a study location was used to validate the approach. At a peak performance, power output of 1300 W was obtained through the NN-based control as compared to 950 W from the non-NN adjustment. This shows that the method performs well in controlling the power above the turbine's rated wind speed. The approach is thus recommended for an effective management of the wind energy conversion systems towards improving reliability in electric power supply.

Keywords—*pitch control, wind turbine, neural network, model training, model validation*

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1 Introduction

Electric power systems hold the key to national development. Adoption of renewable energy resources, among which wind energy is prominent, is thus persistently gaining attention as the world experiences unabated increase in demand for electricity. Wind energy becomes most popular renewable energy option due to its cleanliness and minimal maintenance requirements of the energy's conversion facilities [1]. Wind energy conversion (WEC) technology has expanded significantly over several decades and has become the most cost-effective approach to renewable energy harvesting at present [2–4]. In the technology, WEC systems transform the kinetic energy of wind-flow to electricity. The kinetic energy then converts to mechanical power by the rotation of wind turbine blade, while the turbine generator, in turn, employs the mechanical power to generate electricity [5].

Since the flow of wind fluctuates, there is a corresponding fluctuation in the developed mechanical power, with consequential fluctuations in the magnitude of the electric power generated. To this end, wind turbines are intended to only function within wind power availability constraints [6, 7] to avoid severe weather that may cause damage to them. Proper wind turbines control is thus critical in the deployment of the technology as this promotes efficient use of the capacity of WEC systems and alleviates aerodynamic and mechanical stresses [8].

Turbines with variable speeds perform in two distinct areas: above-rated and below-rated power; to capture the most wind speed whenever the power output falls under the expected values. Whenever the flow rate of the wind is less than the cut-in speed, the rotational speed of the wind turbine generator (WTG) is zero and thus produces no power [9, 10]. If the wind is below the rated speed and above the cut-in, maximum power can be collected from the wind by some controlling mechanism call maximum power point tracking (MPPT) technique [11]. At the above-rated-speed range, the primary goal becomes maintaining consistent power output without damage to the system. This is usually done by reducing the amount of wind energy collected, which is performed by adjusting the pith angle of the blades [12, 13]. Therefore, in addition to alleviating mechanical stress, robust power quality management and manipulation of reactive resource usage are other reasons for system control in WEC systems.

Oscillation in the output energy, as a result of changing wind speed, is a major challenge of WEC systems; and adjustment of the blade angle has been the major solution to this fluctuation of power [14]. By adjustment, wind speed beyond the rated value is checked by triggering pitch angle control mechanism [8] in order to keep the power output constant at its rated value. Management of the pitch angle is a method in which the turbine blade angle is varied as the power control variable beyond the wind speed rated value [15]. Proportional-integral (PI) controller has been commonly used as pitch angle adjuster; but despite its simplicity, [14, 15] submit that the controller cannot reach the optimized performance due to the non-linear dynamics of WTG. Therefore, different control structures like nonlinear PI (N-PI) [15] and fractional order PI (F-PI) [16]; have been in use. As well, structural cascade control [13] and the control fault tolerant [17] are used in compensating unknown time-varying nonlinearity and disturbances. Some other available techniques are observer-based blade pitch control [18] and fuzzy logic control [19–21]. In addition, pitch angle control has been improved through model predictive control (MPC) approach, but with related prediction computing complexity [22]. Another way by which pitch control has been improved is that instead of relying on prediction, the control is accomplished using a future knowledge of wind conduct and the wind speed data sent to WTG from one another [23]. Such signal may then be provided for the MPC to ensure best possible response [18–19]. Information on future wind conditions aids MPC to provide optimal solutions while considering system constraints [20]. The MPC can also predict future behavior using a plant model, and as a result, the WTG control system has shown significant gains [21]. From a practical standpoint, however, the online solution of quadratic program is the main drawback of the MPC [20, 21]. As a result, a better method for controlling pitch angle is required; hence, this present study proposes the use of artificial neural networks (ANN) for the control.

At the core of the concept of the approach presented in this study is the design of an MPC-based controller that is capable of constantly maintaining minimum fluctuation in the power output of WEC systems [22]. The strategy

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involves providing wind speed data to the wind turbine ahead of time using backward propagation neural networks (BPNNs). In the literature, neural networks (NNs) have been used to build nonlinear control systems. It is therefore employed in this study for pitch control in WEC system to maintain a constant power output level in the region over the rated output power. The controller is designed to perform an advance optimal control action and minimize undesired power fluctuations [24–26]. This proposed method is demonstrated using a software-based simulation platform with wind turbine model and a real-life windspeed data.

The remaining parts of this paper are arranged as follows: while methodology of the study and materials used are presented in Section 2, Section 3 contains and discusses the results of the demonstration of the approach, and Section 4 draws the conclusion of the study.

2 Methodology

A model of the WEC system whose pitch angle was controlled using neural network (NN), was developed on the simulation environment of MATLAB/Simulink. Figure 1 is a blocked diagram that depicts the modeling. While inputs to the NN are the current speed of the turbine generator and the change rate of the speed, its singular output is the shifting angle of the differential pitch of the wind turbine. The mechanical power developed by this turbine is thus a product of the varying angle of the pitch.

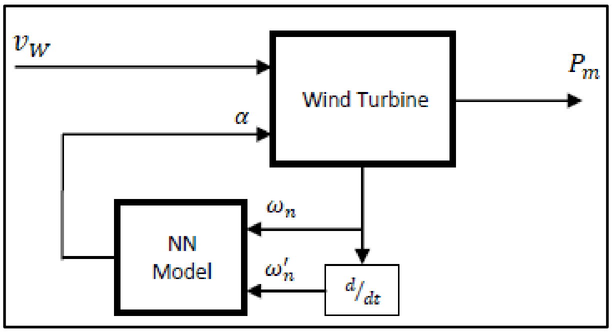

Fig.1. Block diagram of the NN-based control of pitch angle in WEC system

The operational characteristics of a typical WEC system are as represented by the plots in Figure 2 that show the relationship among the parameters of the system. WEC system is generally characterized by tip speed ratio (λ) and power coefficient (C_p) that is described in [27] as:

$$\lambda = \frac{\text{Hub Speed}}{\text{Wind Speed}} = \frac{\omega R}{v_W} \text{ and } C_p = k_1\left[\frac{k_2(\gamma - k_9\lambda)}{\lambda(\alpha^3+1)-\Lambda} - \beta\right]\exp^{-\frac{k_7(\gamma-k_9\lambda)}{\lambda(\alpha^3+1)-\Lambda}} \quad (1)$$

Where ω represent turbine speed, R stands for radius of the swept area of the turbine rotor, v_W is the wind speed, α is the pitch angle, $\beta = k_3\alpha + k_4\alpha^{k_5} + k_6$, $\gamma = \alpha^3 + k_8k_9\alpha + 1$, and $\Lambda = k_8(\alpha^3 + 1)\alpha$.

By general description, approximately mechanical power, P_m, developed by the turbine blades from the wind flow is [31–33]:

$$P_m = 0.5\rho A C_p v_W^3 \quad (2)$$

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Where ρ stands for the air density and A for the swept area of turbine rotor blade. If ω stands for the turbine speed, then $\omega_{\max}$ represents the maximum turbine speed at which maximum mechanical power is developed from wind flow. Therefore, the wind speed, v_W^*, at which the maximum mechanical power is harvested is [27]:

$$v_W^* = \omega_{\max} R\left[\frac{(\alpha^3+1)(k_1k_7\beta+k_1k_2)+k_1k_2k_7k_9}{k_1k_2k_7\gamma+\Lambda(k_1k_7\beta+k_1k_2)}\right] \quad (3)$$

Thus, the maximum mechanical power accruable from the wind by the turbine is a function of α and $\omega_{\max}$ as [27]:

$$P_{m_{\max}} = 0.5\rho\pi R^5\left\{k_1\left[\frac{k_2(\gamma-k_9\lambda)}{\lambda(\alpha^3+1)-\Lambda}-\beta\right]\exp^{-\frac{k_7(\gamma-k_9\lambda)}{\lambda(\alpha^3+1)-\Lambda}}\left[\frac{(\alpha^3+1)(k_1k_7\beta+k_1k_2)+k_1k_2k_7k_9}{k_1k_2k_7\gamma+\Lambda(k_1k_7\beta+k_1k_2)}\right]^3\right\}\omega_{\max}^3 \quad (4)$$

Adapting the turbine speed to rotational speed of the turbine generator requires a gear system with ratio $r_g = \frac{\omega_n}{\omega}$, where ω_n is the generator speed. This generator speed thus relates with mechanical power as [27]:

$$P_{m_{\max}} = \frac{0.5\rho\pi R^5}{r_g^3}\left\{k_1\left[\frac{k_2(\gamma-k_9\lambda)}{\lambda(\alpha^3+1)-\Lambda}-\beta\right]\exp^{-\frac{k_7(\gamma-k_9\lambda)}{\lambda(\alpha^3+1)-\Lambda}}\left[\frac{(\alpha^3+1)(k_1k_7\beta+k_1k_2)+k_1k_2k_7k_9}{k_1k_2k_7\gamma+\Lambda(k_1k_7\beta+k_1k_2)}\right]^3\right\}\omega_{n_{\max}}^3 \quad (5)$$

Thus, from equation (3), the relationship among wind speed, pitch angle and generator speed is obtained as [27]:

$$v_W^* = \frac{\omega_{n_{\max}}}{r_g} R\left[\frac{(\alpha^3+1)(k_1k_7\beta+k_1k_2)+k_1k_2k_7k_9}{k_1k_2k_7\gamma+\Lambda(k_1k_7\beta+k_1k_2)}\right] \quad (6)$$

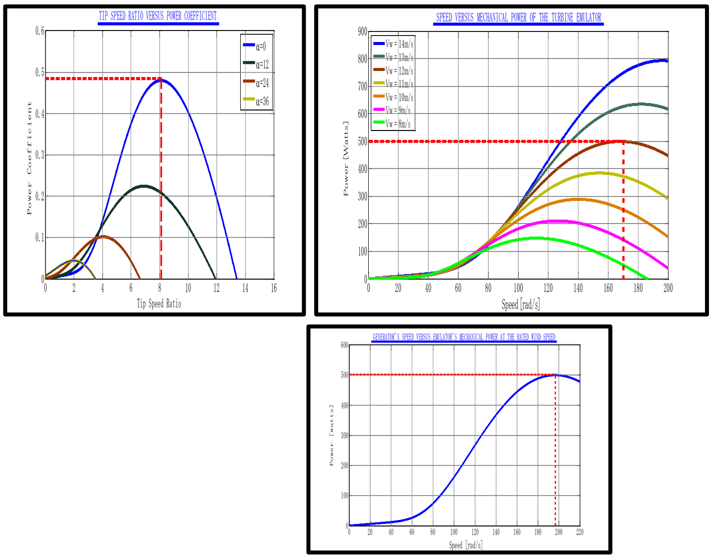

Fig. 2. Operational characteristics of a typical WEC system. Adapted from [27]

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Training procedures and computations in neurons and layers of the NN model are carried out using Levenberg-Marquardt (LM) algorithm. LM is a second-order algorithm [28, 29] that can solve complex problems [30]. The block diagram of the NN model developed with two hidden layers of 16 neurons altogether is display in Figure 3. Present generator speed, ω_n , and rate of change of the speed, ω_n' are the two inputs into the model; while the output is the varying pitch angle which determines the power quality generated. Generally, NN is expressed as [30]:

$$Y = X^T W \tag{7}$$

Where;

X represent input;

W for the weight, and

Y *for* the target / output.

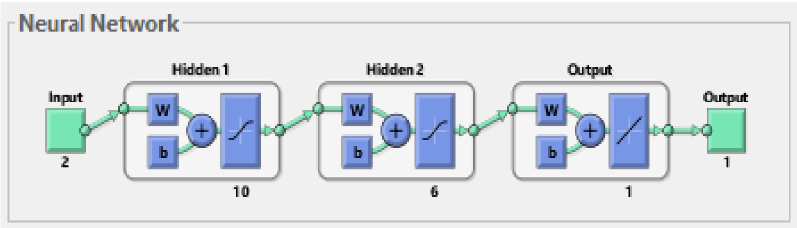

Fig. 3. Block diagram of the NN model

The procedures followed for the multi-layer perceptron learning are:

Step one: Data propagation layer to the output from the input; forward propagation

Step two: The actual and the predicted outcome differences are determined as; calculative error on the output bases.

Step three: The network and updated model with respect to each weight are obtained as derivative error; error back-propagation.

Step four: Steps 1to3 were to learn ideal weight over multiple epochs; and

Step five: to obtain the predicted class labels, the output via a threshold function is taken.

The hidden layer activation unit $a_1(h)$ is calculated in the first step as [30]:

$$Z_1(h) = a_0(in)w_{0,1}(h) + a_1(in)w_{1,1}(h) + \cdots + a_i(in)w_{k,1}(h) \tag{8}$$

$$a_1 h = \emptyset\big(Z_1(h)\big) \tag{9}$$

The activation unit results is the application of activation function, $\emptyset$, to the z value. This is differentiable for weight learning using gradient descent. The activation function is mostly the sigmoid (logistic) functions.

$$\emptyset(z) = \frac{1}{1+e^{-z}} \tag{10}$$

In order to solve complex problems like image processing, the nonlinearity needed is allowed. The hidden layer activation is also represented as [30]:

$$z(h) = a(in).w(h) \tag{11}$$

Where the output later is:

$$Z(out) = A(h).w(out) \tag{12}$$

Wherein,

$a(in)$ = i^{th} value is the input layer

$a_i(h)$ = i^{th} unit is the hidden layer

$a_i(out)$ = i^{th} value in the output layer

$a_0(in)$ = The corresponding weight w_0 with bias unit

$w_{k,j}(i)$ = from layer *1* to layer *i+1* is the weight coefficient

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Training, validation, and testing of the NN algorithm was achieved using 70%, 15% and 15% respectively, of the wind speeds data; while mean square error (MSE) was used as evaluation index. The data, which is ten-year real-life wind speeds in the city of Ibadan (Nigeria) as recorded per minute for the period, was obtained from Climate Hazards Group Infrared Precipitation Station (CHIPPS). Performances of the proposed control mechanism are evaluated by investigating the behavior of the turbine to the wind speeds that are greater than the rated capacity of the turbine. The output mechanical power relates to the variations in the pitch angle, which is a function of the turbine generator's speeds.

3 Results and Discussion

Results obtained from the demonstration of the pitch controller are here presented and discussed. Regression analysis, training, and validation of the NN model, as well as mechanical power output behavior of the WEC system based on the approach of this study are described.

Shown in Figure 4 are the regression analysis curves wherein outputs are plotted against targets. The four plots: training, validation, test, and all; are presented, with the all-plot giving an overall performance of the algorithm. The closer the target to the output, the better the regression plots. Likewise, the more the regression value is to 1, the better. The output value represents the equation of a straight line. The coefficient of the target is the gradient, and the constant value is the intercept on output axis. Also, the more the slope is to unity and the intercept to zero, the better the regression plot. The curves show regression values of 0.97343, 0.97512, 0.99185 and 0.97651 for the training, validations, tests, and all, respectively. The all-plot's regression of 0.97651 was considered to be good value, and so the algorithm was deployed for the pitch angle control.

In Figure 5 is revealed the performances of the algorithm. The best validation performance of the NN model was 22.1343 at epoch 91. This validation value implied that the model could be deployed for the proposed prediction.

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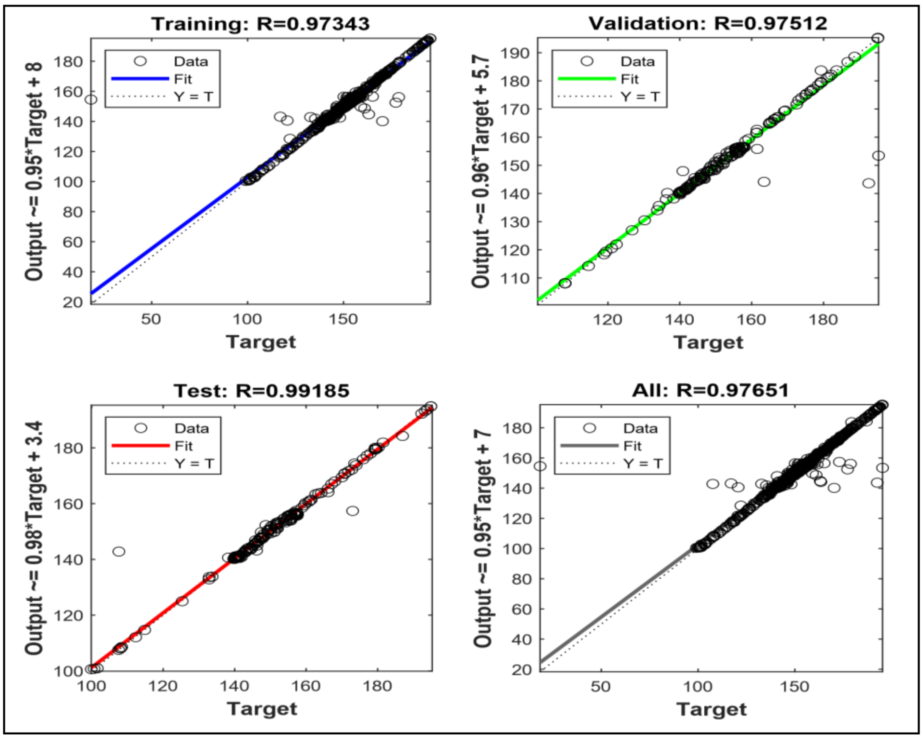

Fig. 4. Plots showing the results of regression analysis.

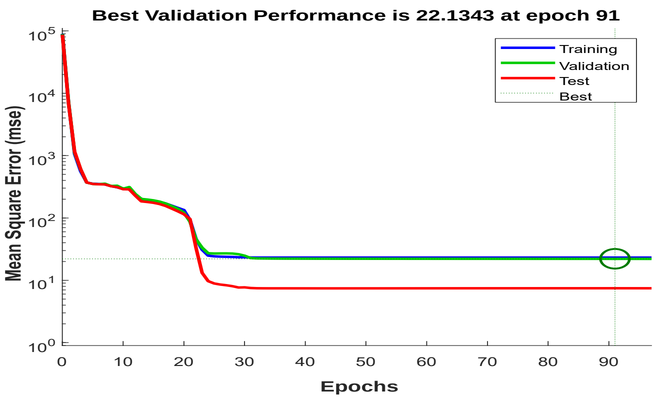

Fig. 5. Performances of the model at training and validation

Figures 6 and 7 respectively show the pitch angle adjustment using the NN-based controller and the corresponding mechanical power developed, as compared with the defaults. While in Figures 6 the actual and the predicted values of the pitch angle are compared, the mechanical power developed in response to the pitch adjustment is presented in Figure 7. At a peak performance on the figure, power output of 1300 W was obtained through the NN-based control as compared to 950 W from the default method. This shows 38.89% increase in the power developed by the turbine.

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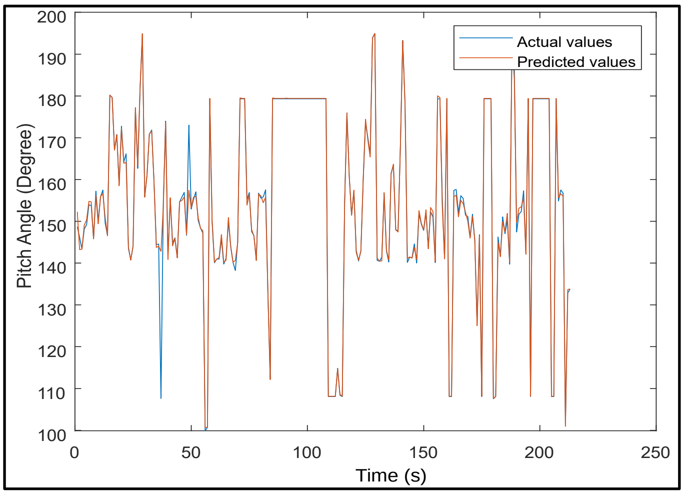

Fig. 6. Comparison between the actual and the NN predicted pitch angle.

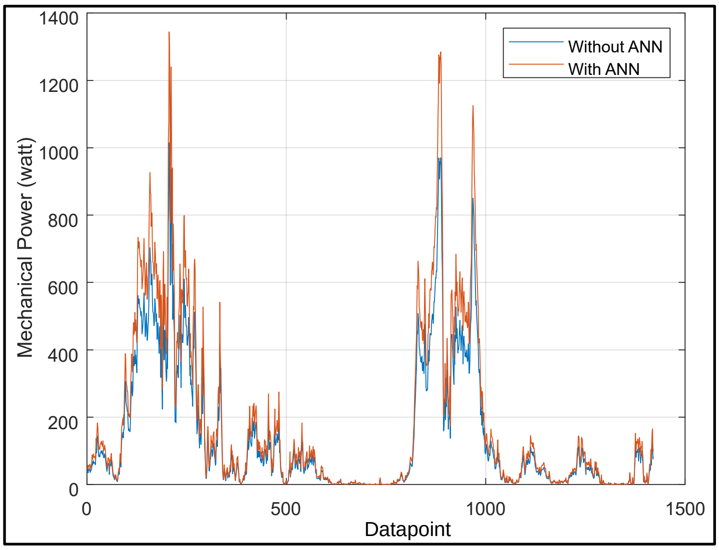

Fig.7. Mechanical power developed using the NN-Based pitch angle controller.

4 Conclusion

With the simulation experiments carried out, this study has found out that the NN-based pitch angle control of wind turbines performs well in controlling the mechanical power developed by wind energy conversion systems above the turbine's rated wind speed. The control mechanism performs well in the above-rated-wind-speed region of operation, with increase in the mechanical power developed by the turbine. The approach is thus recommended for the enhancement of pitch angle control and the overall efficiency of wind energy conversion systems for better reliability of electric power supply. For hierarchy of decision-making, however, the control mechanism can be developed further using deep neural network.

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