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ANFIS modeling and validation of a variable speed wind turbine based on actual data

Authors

Vahid Fazlollahi [a]
Mostafa Taghizadeh [a*]
Farzad A.Shirazi [b]

[a] School of Mechanical and Energy Engineering, Shahid Beheshti University, Tehran, Iran

[b] School of Mechanical Engineering, University of Tehran, Tehran, Iran

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ABSTRACT

In this research paper, ANFIS modeling and validation of Vestas 660 kW wind turbine based on actual data obtained from Eoun-Ebn-Ali wind farm in Tabriz, Iran, and FAST is performed. The turbine modeling is performed by deriving the non-linear dynamic equations of different subsystems. Then, the model parameters are identified to match the actual response. ANFIS is an artificial intelligent technique which creates a fuzzy inference system based on input and output information of the model. In this research, the ANFIS algorithm combines neural network and fuzzy logic with 5 layers which utilize different node functions for learning and setting fuzzy inference system parameters. After learning, by assuming constant parameters, a hybrid method is used to update the results. Employing the proposed method, computation time and complexity are remarkably reduced. Results of the proposed method are then compared and validated with the actual data of Eoun-Ebn-Ali wind farm in Tabriz. It is shown and concluded that the proposed model matches favorably well with the actual data and FAST model.

Keywords: Wind Turbine, ANFIS, Validation, FAST.

1. Introduction

Wind turbine technology because of the environmental, social and economic benefits has become the fastest-growing green energy against other energy resources considering the installed capacity per year [1]. Unlike the other alternative sources, wind turbines industry has attained full-grown commercial stage. In spite of that, wind turbines are ceaselessly increasing size and rated power capacity in order to achieve more competitive cost of energy compared to fossil fuel sources. Wind turbines are divided into fixed and variable turbines are widely used nowadays because speed turbines according to generator operating conditions. Variable-speed wind of their increased extracted energy from wind, and reduced loads on the structure [1-4].

Modeling is a basic tool for analysis that requires experience, repetition and enough accuracy of the system modeler. Almost in all branches of engineering, much effort is being done to gain information about different aspects of a system, which is known as system analysis. System analysis is performed through inputting test signals and observing responses. However, this method is not always possible because the changing range of physical system parameters is limited. Thus, there is a limitation of the range of inputs. A simplified representation

* Corresponding author: Mostafa Taghizadeh
School of Mechanical and Energy Engineering, Shahid Beheshti University, Tehran, Iran
Email: mo_taghizadeh@sbu.ac.ir

of the system is the solution which is called system model.

A plethora of methods has been used to model variable speed wind turbines. Velastimir et al. [5] utilized a model combined with a stochastic wind model for simulation purposes. Aamer and Xiaodong [6] proposed a hybrid intelligent learning based adaptive neuro-fuzzy inference system (ANFIS) for online estimation of effective wind speed from instantaneous values of wind turbine tip speed ratio (TSR), rotor speed and mechanical power. Singh [7] presented manufacturer-specific models of wind turbines for use in wind power interconnection studies. While they are detailed and accurate, their usage is limited to the terms of the non-disclosure agreement, thus stifling model sharing. The primary objective of the work proposed was to develop universal manufacturer-independent wind power plant models that can be shared, used, and improved without any restrictions by project developers, manufacturers, and engineers. Sahasakkul [8] focused on three important topics: (i) development of the combined offshore wind turbine system model with the 13.2 MW wind turbine, a floating semi-submersible platform, and a mooring system; (ii) the entire procedure involved in modeling and analyzing first-order hydrodynamics using two codes, Multi Surf and WAMIT; and (iii) assembling of the integrated aero-hydro-servo-elastic model considering hydrodynamics in order to verify the steady-state and stochastic response of the integrated wind turbine system. Manyonge et al. [9] proposed a mathematical model of wind turbine. A mathematical model is essential in understanding the behavior of the wind turbine over its region of operation because it allows for the development of comprehensive control algorithms that aid in optimal operation of a wind turbine. Modeling enables control of wind turbine's performance. This paper attempts to address part or whole of these general objectives of wind turbine modeling through examination of power coefficient parameter. Rolan et al. [10] analyzed a typical configuration of a Wind Turbine Generator System (WTGS) equipped with a Variable Speed Generator. Moreover, the concept of the Maximum Power Point Tracking (MPPT) has been presented in terms of the adjustment of the generator rotor speed according to instantaneous wind speed. Junyent-Ferré et al. [11] presented the modeling of wind turbine generator systems and the model of a doubly fed induction generator, along with the corresponding converter, crow bar protection electrical grid is described. Sanchez and Medina [12] represented three principal parts (blades, gearbox, and generator) by using the bond-graph methodology. Then, they are combined together in order to simulate the complete system. The complete aerodynamic model is simulated and validated using real data provided in the open literature (blade profile and gearbox parameters for a 750 kW wind turbine).

As mentioned above, ANFIS modeling of Vestas 660 kW wind turbine is done based on actual data obtained from Eoun-Ebn-Ali wind farm in Tabriz, Iran. ANFIS has a combination of fuzzy systems and neural networks advantages which uses fuzzy theory for presenting knowledge and employs the capability of learning from a neural network to optimize the parameters [13-19].

The structure of this paper is as follows. In section 2, the wind turbine performance is discussed. In section 3, a model of the wind turbine is presented. Model validation with actual data is done in section 4. ANFIS modeling is discussed in section 5. Finally, the last section shows the conclusion.

Nomenclature

A	Area (m^2)
B	Shaft damping coefficient (Nm.s.rad^{-1})
C_P	Power coefficient
F_T	Thrust force (N)
J_{gen}	Generator shaft moment of inertia (kgm^2)
J_r	Rotor shaft moment of inertia (kgm^2)
K_s	Shaft stiffness coefficient (N.mrad^{-1})
N_{gear}	Gearbox gear ratio
P	Power (kW)
P_a	Aerodynamic power (kW)

T_a	Aerodynamic torque (Nm)
T_{gen}	Generator torque (Nm)
T_1	Applied torque to the low-speed shaft (Nm)
T_h	Applied torque to the high-speed shaft (Nm)
V_N	Rated wind speed (ms^{-1})
V_o	Wind speed proportion to the Rated power (ms^{-1})
V_{wind}	Wind speed (ms^{-1})
β	Pitch angle (deg)
β_{opt}	Optimum pitch angle (deg)
ε	Rotor angular speed error ($rads^{-1}$)
λ	Blade tip speed ratio
λ_{opt}	Optimum blade tip speed ratio
ω_r	Rotor angular velocity ($rads^{-1}$)
ω_{gen}	Generator angular velocity ($rads^{-1}$)

2. Wind turbine performance

Wind turbines supply required power for generating electricity by converting wind kinetic energy to torque. The amount of energy that is absorbed by blades, depends on the area of rotor, air density, blades design, and wind speed.

$$P_{wind} = \frac{1}{2}\rho A V_{wind}^3 \tag{1}$$

$$P_a = C_P P_{wind} \tag{2}$$

When wind blows in the turbine blades with sufficient speed, blades move and cause low-speed shaft rotation. This shaft is connected to a gearbox to increase rotational speed. When high-speed shaft reaches rated speed of generator, it drives the generator and electrical energy is produced [20-22].

Typically, to explain the performance of wind turbines, non-dimensional characteristic curves can be used to indicate the actual performance of the wind turbine in different operating conditions. These curves are described as below.

2.1. $C_P - \lambda$ Performance curve

A common method to show the performance of wind turbines is the dimensionless curve of power coefficient-blade tip speed ratio. In variable speed wind turbines the maximum amount of power coefficient is approximately equal to 0.48 which is obtained at blade tip speed ratio of 8.1. Mentioned value is lower than the value determined by Betz (maximum possible extracting energy from wind by turbine) [23]. One the reason for this difference is the reduction of power coefficient in actual values, which occurs at blades. Nevertheless, reaching Betz value is rarely possible since blades design cannot be flawless and perfectly accurate [24, 25]. In Fig. 1, this curve is depicted for a three-blade wind turbine.

Figure 2 shows the 2D diagram of $C_P(\lambda, \beta)$.

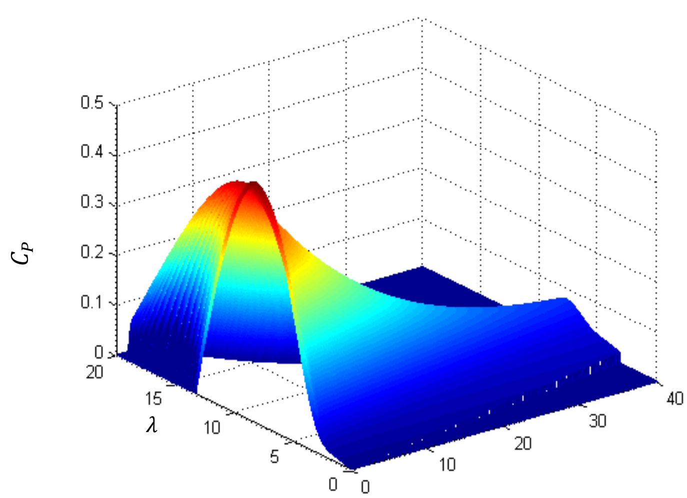

Fig. 1 3D diagram of $C_P(\lambda, \beta)$

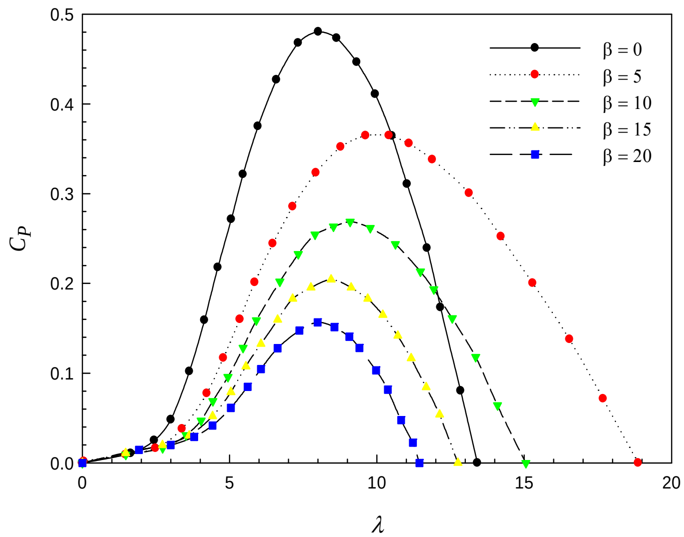

Fig. 2 2D diagram of $C_P(\lambda, \beta)$

2.2. Variable speed wind turbine performance regions

Performance regions of variable speed wind turbines are shown in Fig. 3. Variable speed wind turbine performance regions are shown in Fig. 3. Accordingly, wind turbines consist of three different regions.
Region 1 – in this region because of the cost considerations turbine is not working.
Region 2 – in this region torque controller is activated to control generator torque for extracting maximum energy of the wind.
Region 3 – in this region, when speed and power of the turbine reach its rated values, pitch angle control is activated in order to speed of the generator is fixed by increasing pitch angle, which prevents any exceeding from its rated power. Therefore, the output power and generator speed of the turbine are kept constant at their rated values [26].

3. Wind turbine modeling

The process of creating a model is not linear. It passes consequent steps to prepare an improved progressing model and several simplifying assumptions are considered in these steps. General assumptions considered in this study are as follows.

General assumptions:

- Nonlinear modeling is considered and no linearization is performed in subsystems.
- Wind turbine blades assumed perpendicular to the wind direction.
- The phenomenon of wind shear ignored.

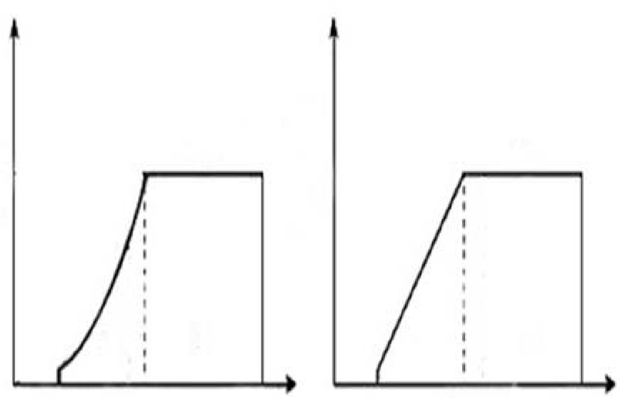

Fig. 3 wind turbines performance regions

In this paper, the variable speed wind turbine divided to aerodynamic, drive train, electrical and pitch angle actuator subsystems. In the following, modeling of the aerodynamic subsystem is explained. Equation (3) shows the available power in the wind. It can be inferred from Eq.(4) that power coefficient is a function of tip-speed ratio and pitch angle.

$$P_{wind} = \frac{1}{2}\rho A V_{wind}^3 \tag{3}$$

$$C_P(\lambda, \beta) = \frac{P_a}{P_{wind}} \tag{4}$$

In Eq. (5) the absorbed aerodynamic power by the rotor is shown. Based on this equation it is obvious that aerodynamic power of turbine has relationship with wind speed powered by 3.

$$P_a = \frac{1}{2}\rho \pi R^2 C_P(\lambda, \beta) V_{wind}^3 \tag{5}$$

The relation between power and aerodynamic torque is stated in Eq. (6).

$$P_a = T_a \omega_r \tag{6}$$

$$F_T = \frac{\rho \pi R^2}{2} C_T\left(\frac{\omega_r R}{V_{wind}}, \beta\right) V_{wind}^2 \tag{7}$$

$$T_a = \frac{\rho \pi R^3}{2} C_Q\left(\frac{\omega_r R}{V_{wind}}, \beta\right) V_{wind}^2 \tag{8}$$

In Eq. (8), torque coefficient is obtained by Eq.(9).

$$C_Q(\lambda, \beta) = \frac{C_P(\lambda, \beta)}{\lambda} \tag{9}$$

In this section, the modeling of drive train subsystem is provided. In order to model drive train, the dynamic of low-speed shaft is obtained by Eq. (10).

$$J_r \frac{d^2}{dt^2}\theta_r = T_a - T_1 - \frac{d}{dt}\theta_r \tag{10}$$

Also, the dynamic of the high speed shaft is calculated by Eq. (11).

$$J_{gen} \frac{d^2}{dt^2}\theta_{gen} = T_h - T_{gen} - \frac{d}{dt}\theta_{gen} \tag{11}$$

Then, the gearbox is modeled as a gear ratio in Eq. (12).

$$T_h = \frac{T_1}{N_{gear}} \tag{12}$$

Torsion of drive train subsystem is modeled by a torsional spring and damping coefficient.

$$T_1 = K_s \delta\theta + B \frac{d}{dt}\delta\theta \tag{13}$$

$$\delta\theta = \theta_r - \frac{\theta_{gen}}{N_{gear}} \tag{14}$$

$$\delta\omega = \omega_r - \frac{\omega_{gen}}{N_{gear}} \tag{15}$$

$$\frac{d}{dt}(\delta\theta) = \delta\omega = \omega_r - \frac{\omega_{gen}}{N_{gear}} \tag{16}$$

By replacing Eq. (16) in (13), Eq. (17) is obtained.

$$T_1 = K_s \delta\theta + B\omega_r - \frac{\omega_{gen}}{N_{gear}} \tag{17}$$

By replacing Eq. (13) in (10), Eq. (18) is obtained.
Similarly, by replacing Eq. (13) in (12), and then in (11), Eq. (20) is gained.
Finally, dynamic of the drive train is defined by Eqs. (18) to (20).

$$J_r \frac{d}{dt}\omega_r = [T_r - (k_s \delta\theta + B\delta\omega) \tag{18}$$

$$\delta\omega = \omega_r - \frac{\omega_{gen}}{N_{gear}} \tag{19}$$

$$J_{gen} \frac{d}{dt}\omega_{gen} = \left[\frac{1}{N_{gear}}(k_s \delta\theta + B\delta\omega) - T_{gen}\right] \tag{20}$$

- Note that the viscose friction of low and high-speed shafts are ignored since their values are unelectable.

In wind turbines, the output power can be obtained through Eq. (21).

$$P_e = \omega_{gen} T_{gen} \tag{21}$$

However, it should be noted that the efficiency of the generator is relatively high, it is not 100% and there is an amount of loses which is considered in Eq. (22).

$$P_e = \eta_{gen}\omega_{gen}T_{gen} \tag{22}$$

As can be observed in Eq. (21) and (22), output power changes with the variation of generator torque.
Finally, dynamics of generator subsystem is calculated by Eq. (23).

$$\dot{T}_{gen} = \frac{1}{\tau_{gen}}(T_{g,ref} - T_{gen}) \tag{23}$$

In this paper, two mass modelings is used to model wind turbine, which is demonstrated in Fig. 4 in details.

The pitch actuator is a nonlinear servo system, which is compatible with the rotation of the whole or a part of blades. In a closed-loop system, pitch actuator can be model as a dynamic system with perfect range and the output signal can be derived. This control system prevents excessive loads on wind turbine structure at higher speeds and keeps the generator speed and power constant at their nominal value [27-29]. Here, a linear dynamics is assumed for the pitch actuator as Eqn. (24) which is valid for the range the pitch angle changes in this study.

$$\dot{\beta} = -\frac{1}{\tau}\beta + \frac{1}{\tau}\beta_{opt} \tag{24}$$

4. Model validation with actual data and FAST

In this section, in order to validate the model in section 3, obtained actual data (wind speed, pitch angle, generator speed, generator torque, and output power) from Eoun-Ebn-Ali wind power plant is utilized. Curve depicted in Fig. 6, is obtained from actual data of Eoun-Ebn-Ali wind power plant.

In order to validate the proposed model, at first inputs to the real wind turbine (wind speed, pitch angle and generator torque) considered as inputs to the model (presented in section 3) in MATLAB software. Then obtained the output power of simulation is compared with real wind turbine output power. Also, in order to validate the proposed model with FAST, inputs to the real wind turbine (wind speed, pitch angle and generator torque) considered as inputs to the FAST open-loop model and then output power of FAST model is compared with actual data and data obtained from Simulink model. As shown in the Fig. (7-9), output power of the real wind turbine (That obtained from Eoun-Ebn-Ali wind farm in Tabriz, Iran) and the simulation results and FAST, are compared. These figures show that the amount of output power in three curves are matched with proper accuracy. It should be noted that to simulate in Matlab software and FAST model, wind turbine is considered as an open-loop system. In Table 1, real wind turbine and simulation data are listed.

You can see the open loop block diagram of wind turbine in Fig. 5.

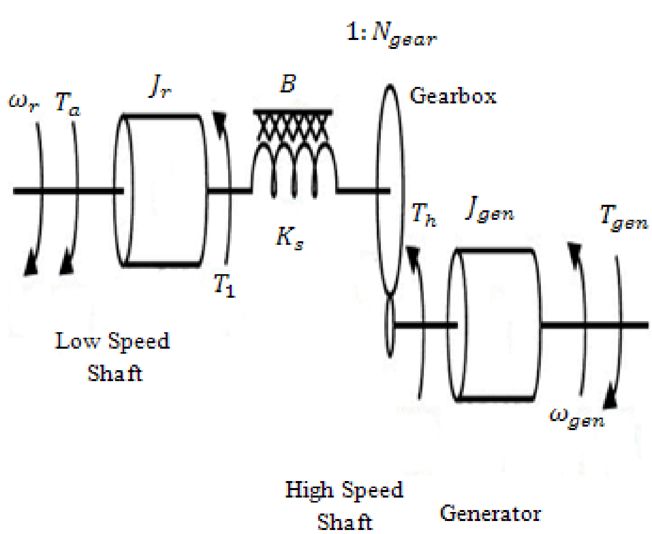

Fig 4. Two mass model of wind turbine

Table 1. Real wind turbine and simulation data

Item	Value	Units (SI)
Rotor diameter	47	(m)
Gear ratio	52.65	-
Rated Power	660	(kW)
Cut in wind speed	4	(ms^{-1})
Rated wind speed	15	(ms^{-1})
Cut out wind speed	25	(ms^{-1})
Air density	1.225	(kgm^{-3})
Rotor inertia	354000	(kgm^{2})
Generator inertia	37.5	(kgm^{2})
Shaft stiffness coefficient	293563	($Nm.rad^{-1}$)
Shaft damping coefficient	10363	($Nm.s.rad^{-1}$)
Tower height	40	(m)
Optimal pitch angle	0	(deg)
Optimal tip speed ratio	8.1	-

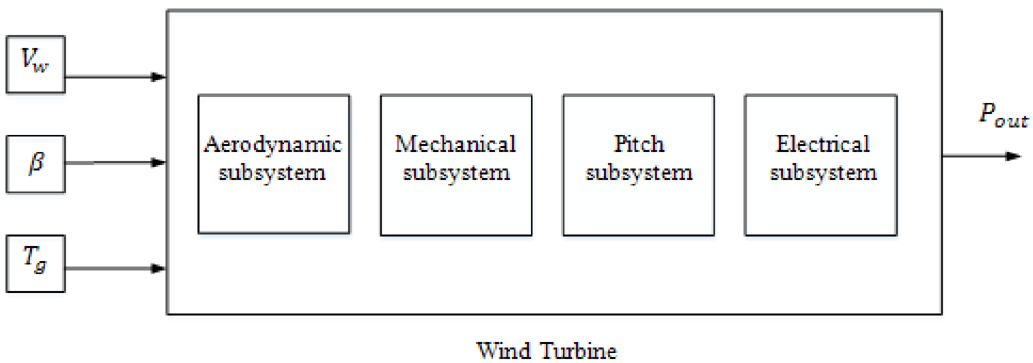

Fig. 5 block diagram of open loop wind turbine

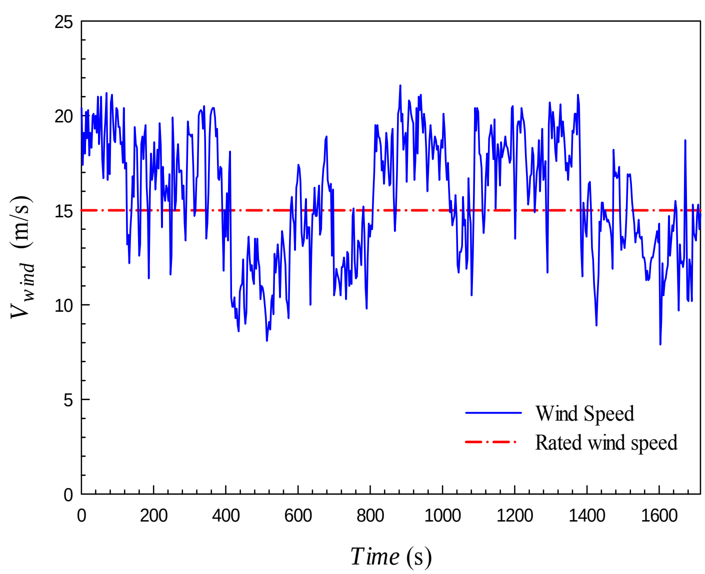

Fig. 6 Wind speed curve used in simulation

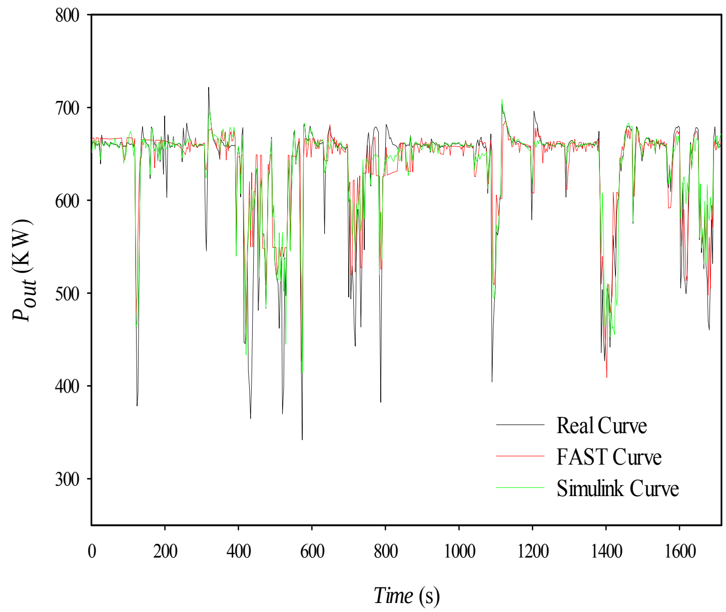

Fig. 7 Comparison of wind turbine output power in Simulink, FAST and real curves

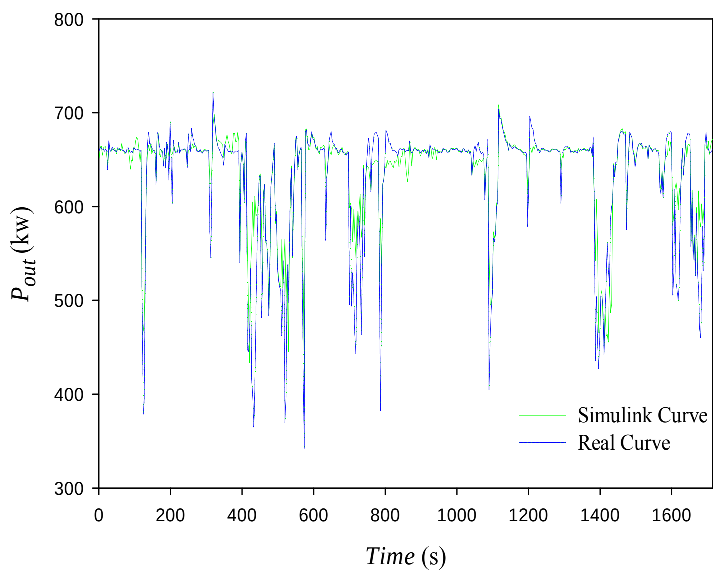

Fig. 8 Comparison of wind turbine output power in Simulink and real curves

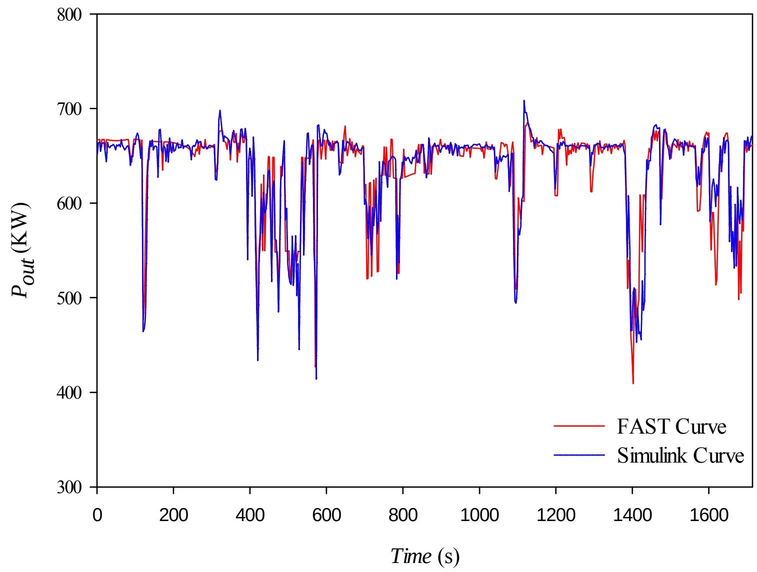

Fig. 9 Comparison of wind turbine output power in Simulink and FAST curves

5. ANFIS modeling

ANFIS system is an artificial intelligent technique which creates a fuzzy inference system based on input and output information of the model. This system combines neural network and fuzzy system. ANFIS can be used in a wide range of applications in modeling, decision making, and signal processing and control. This system is a class of adaptive networks which is a function of fuzzy inference system. ANFIS algorithm is consisted of combining neural network and fuzzy logic with 5 layers which utilize different node functions for learning and setting fuzzy inference system parameters. After learning, considering the parameters are constant, least-square estimation method is used to update results [30]. ANFIS system is a Sugeno type fuzzy model which is in the framework of an adaptive system in order to facilitate adaption and learning capabilities. Furthermore, this capability makes fuzzy controller more regulated and less dependent on expert knowledge.

As shown in Fig. 8, ANFIS has 5 layers. First and fourth layers are constructed from adaptive (settable) nodes and the other three layers are constructed from constant (non-settable) nodes.

First layer, fuzzification: each node in this layer is adaptive. The output of this layer is the degree of membership of inputs which is stated as follows.

$$O_{ij}^{(1)} = \mu_{ij}\,(x), \quad i = 1, \dots, P \text{ and } j = 1, \dots, n \tag{25}$$

$O_{ij}^{(1)}$ are outputs of each node in each layer which represent ith node in the first layer, in proportion to input j. For instance, a bell membership function at first layer is obtained as follows.

$$\mu_{ij}(x_j) = \frac{1}{1 + \left|\frac{x_j - c_{ij}}{a_{ij}}\right|^{2b_{ij}}} = \frac{1}{1 + \left(\left(\frac{x_j - c_{ij}}{a_{ij}}\right)^2\right)^{b_{ij}}} \tag{26}$$

While parameters a_1, b_1 and c_1 are for the first implication of first layer and the rest of similar parameters are for second to fourth implication of the first layer.

Second layer, rules layer: each node in this layer is a constant node and non-adaptive and shown with circle. The output of each layer is equal to the multiplication of its inputs which is demonstrated as follows.

Figure 10 shows the equivalent structure of ANFIS for Sugeno model.

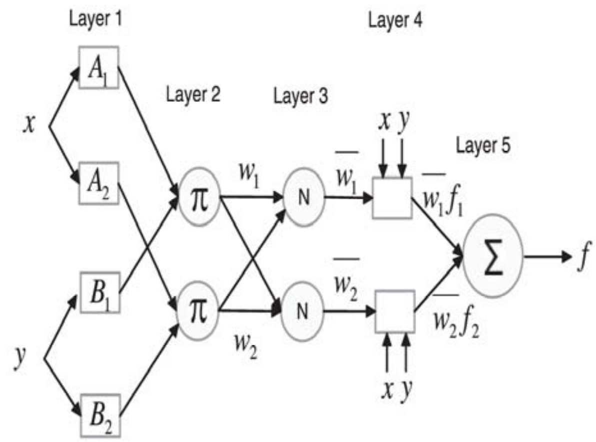

Fig.10. ANFIS structure

$$O_i^2 = w_i = \prod_k \mu_{ik} \quad (27)$$
$i = 1, \dots, P$

The output of each node (w_i) is the firing strength of each rule.
In this layer, instead of multiplier operator, any fuzzy operator that can satisfy AND can be used.

Third layer: each node in this layer is constant. The output of i^{th} node is equal to the i^{th} firing strength divided by the total firing strength of all rules.
Outputs of this layer are known as normalized firing strength.

$$O_i^3 = \overline{w}_i = \frac{w_i}{\sum_{k=1}^{P} w_k} \quad (28)$$
$i = 1, \dots, P$

Fourth layer, defuzzification layer: each node in this layer is adaptive. An output of this layer is consisted of multiplying later first-order Sugeno fuzzy command in $\overline{w}_i$ coefficients.

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i \left(\sum_{k=1}^{n} q_{ik} x_k + r_i \right) \quad (29)$$
$i = 1, \dots, P$

where $\overline{w}_i$ is normalized firing strength that is obtained from third layer.

Fifth layer, summation neuron: the sole node in this layer is constant which the final output is from the summation of all outputs from the fourth layer.

$$O^5 = y = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (30)$$
$i = 1, \dots, P$

It worth to mention that second, third and fifth layers are constant, while the first and fourth layers are adaptive. In other words, learning of the network is changing the parameters of these two layers to reach desired results. ANFIS structure is learned automatically by least square method and backpropagation algorithm, or hybrid learning.

6. Simulation results

In this paper, for ANFIS modeling actual data obtained from Eoun-Ebn-Ali wind farm in Tabriz, Iran, is used. For this purpose 572 pairs of actual data is utilized. 300 pairs of them are used for training and 272 pairs of them is used for checking. In this modeling pitch angle, wind speed and rotor angular velocity considered as inputs and output power considered as output. The block diagram of that is depicted in Fig. 11. As it is shown in Fig. 11 the fuzzification unit converts crisp information to linguistic variables which enter the rules block as input. A set of rules based on previous knowledge of system is written in rules block. Then, learning algorithm block for leaning neural network is placed to select a proper set of rules. For control signal this stage is critical. Finally, the output of the neural

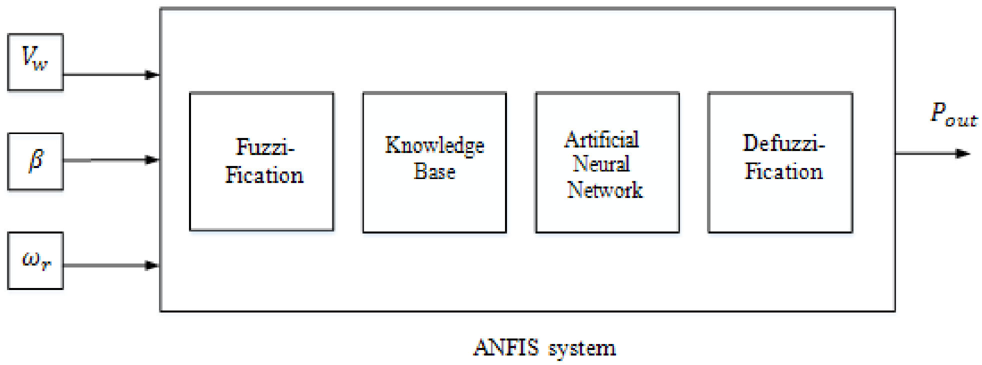

Fig. 11 block diagram of ANFIS modeling with actual data

network is defuzzified and linguistic functions are converted to crisp form.

In this research, the following steps are done for ANFIS modeling.

- At first, training data and checking data are loaded in ANFIS editor in MATLAB software. As you can see that in Fig. 12. Then FIS parameters are generated in ANFIS editor in MATLAB software.
- Then by using hybrid method in ANFIS editor the training has been done in order to the error tolerances reduce to the defined range. It is demonstrated in Fig. 13. Then by using test FIS section in ANFIS editor and selecting the training and testing options, the actual data is compared with the ANFIS parameters. You can see them in Fig. 14 and Fig. 15.

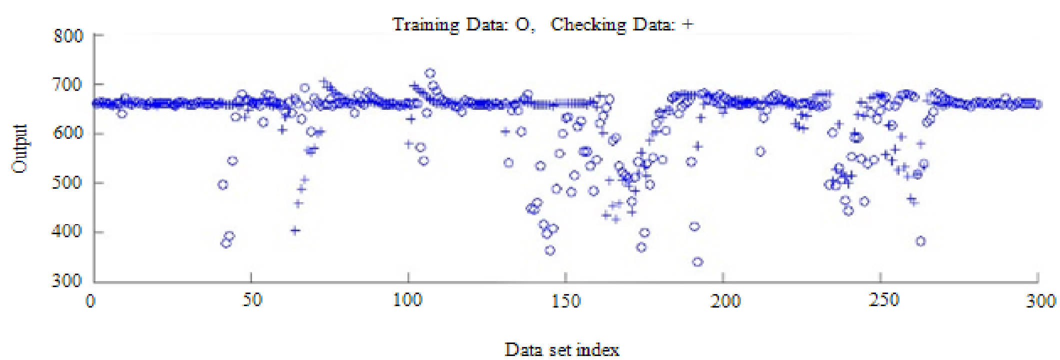

Fig. 12 Training data and checking data

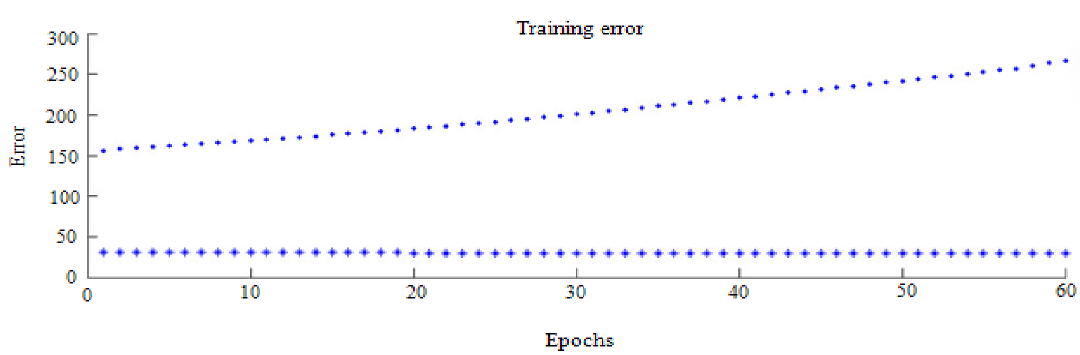

Fig. 13 Training error of modeling in ANFIS editor

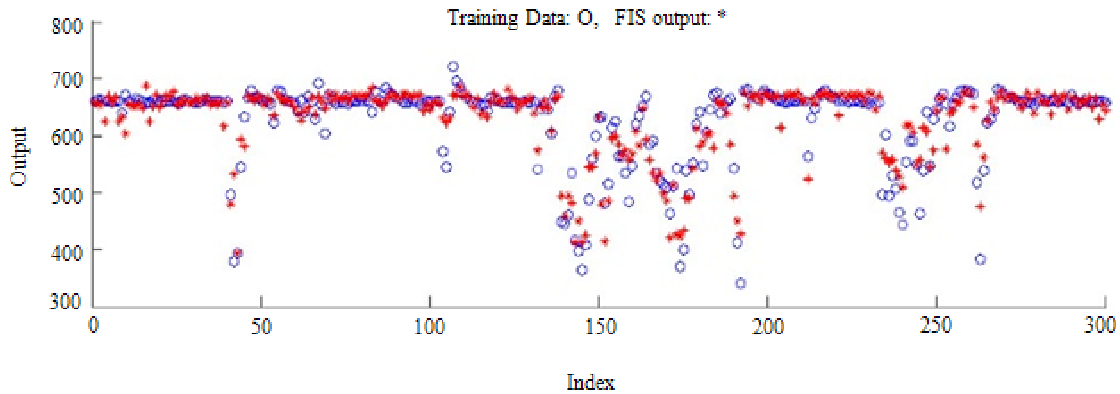

Fig. 14 Training data and FIS output

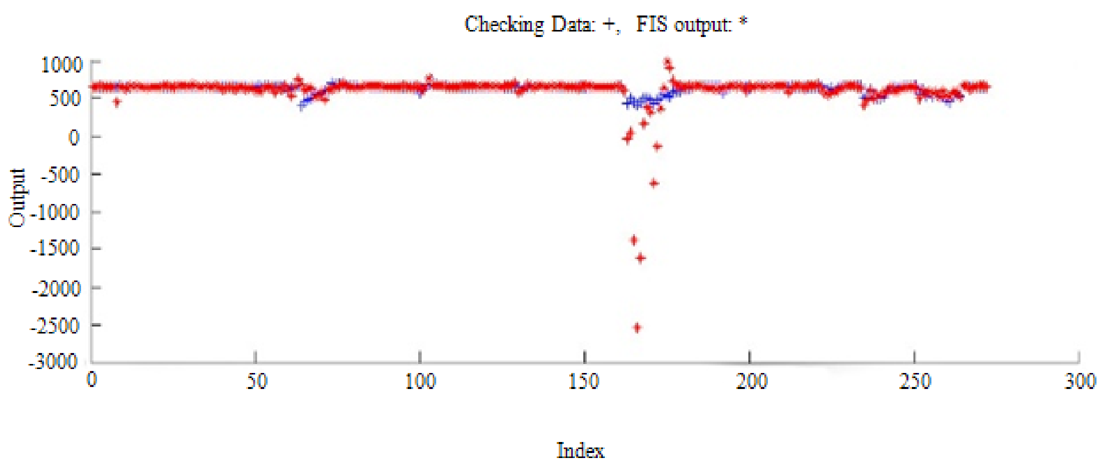

Fig. 15 Checking data and FIS output

7. Conclusions

In this research, ANFIS modeling and validation of Vestas 660 kW wind turbine is done by using actual data obtained from Eoun-Ebn-Ali wind farm in Tabriz, Iran, with Simulink and FAST model. One important aspect of a proposed method is a combination of fuzzy systems and neural networks, so it has a advantage of both of them, which uses fuzzy theory for presenting knowledge and employs the capability of learning from neural network to optimize the parameters. Employing the proposed method, computation time and computation complexity are remarkably reduced. To illustrate the effectiveness of the proposed methodology, the results of the proposed method are then compared and validated with the actual data of Eoun-Ebn-Ali wind farm in Tabriz and FAST. It is shown and concluded that the proposed model matches favorably well with the actual data.

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